



UNIVERSITAT
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Doctoral Thesis

**Optimal design of socially and
environmentally efficient
reinforced concrete precast
modular road frames under
constrained budgets**

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Doctoral thesis by article compendium

This doctoral thesis is presented as a compendium of articles previously published in peer-reviewed academic journals. The complete references for each paper that constitute the core content of this dissertation are presented below:

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Abstract

Transportation infrastructure is essential for human development, driving industry growth and societal evolution through enhanced interaction and connectivity. Transportation infrastructure construction acts as a catalyst for socio-economic transformations, stimulating local economies and streamlining the flow of workforce and resources. Growing recognition of the detrimental effects of unsustainable practices in construction engineering necessitates a shift towards more responsible methodologies. Historically, economic viability has dominated the priorities of structural engineering, but there is now an increasing emphasis on evaluating the life cycle impacts of projects. While this shift marks progress towards aligning structural design with sustainability goals, it does not fully capture the intricate and multifaceted nature of life cycle sustainability.

This doctoral thesis systematically unfolds the process of conceiving and substantiating a design framework that incorporates life cycle sustainability into the construction of transportation infrastructure. A precast modular approach is proposed for road frame projects as an attractive alternative to conventional cast-in-place methods. The structural design process and life cycle environmental and social impacts of the structure are encapsulated within a sophisticated mathematical model, facilitating the application of both single and multi-objective optimization alongside decision-making algorithms. Exact optimization methods are not a viable resort due to the extensive array of optimization variables and the mixed integer nature of the problem. Thus, the research deploys trajectory-based local search and hybrid metaheuristics for the single-objective cost-minimization of the structure. Simulated annealing and threshold accepting metaheuristics adjusted with longer chain lengths achieve high-quality results but demand substantial computational resources. A hybrid version of

simulated annealing, incorporating a mutation operator typically found in population-based algorithms, reaches comparable solutions with less computational effort. The hybridization of metaheuristics is identified as an effective strategy to enhance the exploratory capacities of these algorithms.

The life cycle assessment of diverse cost-optimized road frame layouts reveals distinct environmental advantages of the precast modular approach compared to the conventional cast-in-place method. However, the social implications present a more intricate relationship, emphasizing the importance of including life cycle impacts as objective functions in the optimization process. Additionally, this underscores the necessity to involve multi-criteria decision-making techniques to effectively score and rank alternatives, ensuring a balanced consideration of environmental and social impacts in the decision-making framework.

This research employs innovative crossover, polynomial mutation, and repair operators to effectively discretize the optimization problem, equipping novel genetic and evolutionary algorithms with the capabilities to tackle the mixed integer nature of the multi-objective optimization problem. The statistical-based repair operator algorithm is notably successful when incorporated with the non-dominated sorting genetic algorithms II and III and the reference vector-guided evolutionary algorithm. Despite their operational variances, the fair un choix adéquat decision-making technique yields the same rankings as the simple additive weighting method. This alignment also extends to the technique for order of preference by similarity to ideal solution, preference ranking for organization method for enrichment evaluation and multi-criteria optimization and compromise solution algorithms. An entropy theory-based strategy endows these multi-criteria decision-making techniques with a methodical and unbiased approach to criteria weighting. Integrating multi-objective optimization algorithms with multi-criteria decision-making techniques within a mathematical model-based design framework culminates in a sequence of ranked non-dominated optimal designs. These designs balance the economic, environmental, and social dimensions of life cycle sustainability.

Resumen

La infraestructura de transporte es fundamental para el desarrollo humano, ya que impulsa el crecimiento de la industria y la evolución social a través de mejoras en la interacción y conectividad. La construcción de infraestructuras de transporte se convierte en un catalizador para las transformaciones socioeconómicas, fomentando las economías locales y facilitando el movimiento de la fuerza laboral y los recursos. La creciente conciencia sobre los efectos negativos de las prácticas insostenibles en la ingeniería de construcción exige un cambio hacia métodos más responsables. Tradicionalmente, la viabilidad económica ha sido la principal prioridad en la ingeniería estructural, pero actualmente cada vez hay un mayor énfasis en la evaluación de los impactos a lo largo del ciclo de vida de los proyectos. Aunque este cambio representa un avance hacia la alineación del diseño estructural con los objetivos de desarrollo sostenible, no logra abarcar completamente la complejidad y diversidad de la sostenibilidad en el ciclo de vida.

Esta tesis doctoral presenta de manera sistemática el proceso de idear y fundamentar un marco de diseño que integre la sostenibilidad del ciclo de vida en la construcción de infraestructuras de transporte. Se sugiere un enfoque modular prefabricado para proyectos de estructuras viales como una opción más atractiva en comparación con los métodos tradicionales de hormigonado in-situ. El proceso de diseño estructural, así como los procesos del ciclo de vida ambiental y social de la estructura, se sintetizan en un modelo matemático avanzado. Esto permite la aplicación de optimización mono-objetivo y multiobjetivo en conjunto con algoritmos de toma de decisiones multicriterio. La aplicación de métodos de optimización exacta resulta inviable debido al elevado número y la diversa naturaleza de las variables del problema. Por lo tanto, la investigación recurre a metaheurísticas de búsqueda por en-

tornos e híbridas para minimizar el coste final de la estructura desde un enfoque de mono-objetivo. Las metaheurísticas de recocido simulado y aceptación por umbrales calibradas con cadenas de longitud más extensa logran resultados de alta calidad, aunque conllevan un considerable esfuerzo computacional. La versión híbrida del recocido simulado con un operador de mutación común en algoritmos basados en poblaciones consigue soluciones comparables con menor esfuerzo computacional. La hibridación de metaheurísticas conforma una estrategia eficaz para potenciar las capacidades exploratorias de estos algoritmos.

El análisis del ciclo de vida de distintas configuraciones de marcos con coste óptimo muestra claras ventajas ambientales del enfoque modular prefabricado frente a la estructura convencional de construcción in situ. No obstante, las implicaciones sociales presentan un panorama más complejo, resaltando la importancia de incluir los impactos del ciclo de vida como funciones objetivo en el proceso de optimización. Esto también subraya la necesidad de aplicar técnicas de decisión multicriterio para valorar y clasificar eficazmente las alternativas, garantizando una consideración equilibrada de los impactos ambientales y sociales dentro del marco de toma de decisiones.

Esta investigación desarrolla operadores de cruce, mutación y reparación para discretizar de manera efectiva el problema de optimización. Estos dotan a algoritmos genéticos y evolutivos con la capacidad de manejar la complejidad del proceso de optimización multiobjetivo. El algoritmo de operador de reparación estadístico destaca especialmente cuando se combina con los algoritmos genéticos NSGA-II y NSGA-III, así como con el algoritmo evolutivo RVEA. A pesar de sus diferencias, la técnica de toma de decisiones FUCA genera clasificaciones idénticas al método de ponderación aditiva simple. Esta congruencia también se extiende a técnicas como TOPSIS, PROMETHEE y VIKOR. Un proceso de computación basado en la teoría de la entropía proporciona a estas técnicas de decisión multicriterio un enfoque metódico e imparcial para la ponderación de criterios. La integración de algoritmos de optimización multiobjetivo con técnicas de decisión multicriterio en un marco de diseño basado en modelos matemáticos culmina en una clasificación de diseños óptimos no dominados. Estos diseños equilibran las dimensiones económica, ambiental y social de la sostenibilidad del ciclo de vida de la estructura.

Resum

La infraestructura de transport és fonamental per al desenvolupament humà, ja que impulsa el creixement de la indústria i l'evolució social a través de millores en la interacció i connectivitat. La construcció d'infraestructures de transport es convertix en un catalitzador per a les transformacions socioeconòmiques, fomentant les economies locals i facilitant el moviment de la força laboral i els recursos. La creixent consciència sobre els efectes negatius de les pràctiques insostenibles en l'enginyeria de construcció exigeix un canvi cap a mètodes més responsables. Tradicionalment, la viabilitat econòmica ha sigut la principal prioritat en l'enginyeria estructural, però actualment cada vegada hi ha un major èmfasi en l'avaluació dels impactes al llarg del cicle de vida dels projectes. Encara que este canvi representa un avanç cap a l'alineació del disseny estructural amb els objectius de sostenibilitat, encara no aconsegueix abastar completament la complexitat i diversitat de la sostenibilitat en el cicle de vida.

Esta tesi doctoral presenta de manera sistemàtica el procés d'idear i fonamentar un marc de disseny que integre la sostenibilitat del cicle de vida en la construcció d'infraestructures de transport. Se suggerix un enfocament modular prefabricat per a projectes d'estructures viàries com una opció més atractiva en comparació amb els mètodes tradicionals de formigonada in-situ. El procés de disseny estructural, així com els processos del cicle de vida ambiental i social de l'estructura, se sintetitzen en un model matemàtic avançat. Això permet l'aplicació d'optimització bonic-objectiu i multiobjectiu en conjunt amb algorismes de presa de decisions multicriteri. L'aplicació de mètodes d'optimització exacta resulta inviable a causa de l'elevat número i la diversa naturalesa de les variables del problema. Per tant, la investigació recorre a metaheurístiques de cerca per entorns i híbrides per a minimitzar el cost final de

l'estructura des d'un enfocament de mico-objectiu. Les metaheurístiques de recuita simulada i acceptació per lindars calibrades amb cadenes de longitud més extensa aconsegueixen resultats d'alta qualitat, encara que requereixen d'un considerable esforç computacional. La versió híbrida de la recuita simulada amb un operador de mutació comuna en algorismes basats en poblacions aconsegueix solucions comparables amb menor esforç computacional. La hibridació de metaheurístiques conforma una estratègia eficaç per a potenciar les capacitats exploratòries d'estos algorismes.

L'anàlisi del cicle de vida de diferents configuracions de marcs amb cost òptim mostra clares avantatges ambientals de l'enfocament modular prefabricat enfront del convencional de construcció in situ. No obstant això, les implicacions socials presenten un panorama més complex, ressaltant la importància d'incloure els impactes del cicle de vida com a funcions objectiu en el procés d'optimització. Això també subratlla la necessitat d'aplicar tècniques de decisió multicriteri per a valorar i classificar eficaçment les alternatives, garantint una consideració equilibrada dels impactes ambientals i socials dins del marc de presa de decisions.

Esta investigació desenvolupa operadors d'encreuament, mutació i reparació per a discretitzar de manera efectiva el problema d'optimització. Estos doten a algorismes genètics i evolutius amb la capacitat de manejar la complexitat del procés d'optimització multiobjectiu. L'algorisme d'operador de reparació estadístic destaca especialment quan es combina amb els algorismes genètics NSGA-II i NSGA-III, així com amb l'algorisme evolutiu RVEA. Malgrat les seues diferències, la tècnica de presa de decisions "fair un choix adequat" resulta en classificacions idèntiques al mètode de ponderació additiva simple. Esta congruència també s'estén a tècniques com TOPSIS, PROMETHEE i VIKOR. Un procés de computació basat en la teoria de l'entropia proporciona a estes tècniques de decisió multicriteri un enfocament metòdic i imparcial per a la ponderació de criteris. La integració d'algorismes d'optimització multiobjectiu amb tècniques de decisió multicriteri en un marc de disseny basat en models matemàtics culmina en una classificació de dissenys òptims no dominats. Estos dissenys equilibren les dimensions econòmica, ambiental i social de la sostenibilitat del cicle de vida de l'estructura.

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Chapter 1

Introduction and objectives

1.1 Background

The introductory Section of this doctoral dissertation provides a comprehensive backdrop, detailing the context relevant to the research area. Sections 1.1 and 1.2 underscore the thesis's motivation, significance, and innovative contributions, clearly defining the scope and presenting the research questions. Moreover, Section 1.3 comprehensively delineates the methodology utilized throughout the PhD research to attain the research goals. Conclusively, Section 1.4 outlines the dissertation's structure, summarizing the content of the following chapters.

1.1.1 Sustainable Development

Since its inception in the 1987 Brundtland Report, sustainable development has progressively garnered attention [1]. Fundamentally, it seeks to balance economic growth, environmental protection, and social inclusion, anchored by the principle that the strategies employed to reach this balance should be sustainable for future generations. While its core concept appears simple, sustainable development's nuanced implications and applications uncover a deeply complex landscape.

A wide array of stakeholders, encompassing national governments, the United Nations, social movements, and private sectors, have been instrumental in shaping and refining the concept of sustainable development [2]. Noteworthy landmarks include the formulation of Agenda 21 at the Earth Summit and the establishment of the Millennium Development Goals in 2000, which paved the way for adopting the 2030 Agenda in 2015 [3]. This agenda acts as a global blueprint for sustainability, presenting 17 sustainable development goals (SDGs) aimed at addressing pivotal challenges such as climate change, extreme poverty, and inequality, among others, through a systematic approach.

The SDGs act as a framework for the collective and proactive transformation of our global society across the three sustainability dimensions: economic, environmental, and social. They guide individuals, governments, private corporations, and non-profit organizations to align their actions with these global objectives, promoting transparency and accountability by clearly defining their progress. Furthermore, the integration of evaluation mechanisms such as environmental social and governance (ESG) scores [4], environmental product declarations (EPD) [5], and the mandate for thorough life cycle assessments (LCA) for products and services based on standard regulations not only motivates but also incentivizes entities for pursuing economic growth in a manner that responsibly addresses environmental and social ramifications.

1.1.2 The Role of Transportation Infrastructure Construction

Transportation infrastructure is indispensable to human development, serving as a keystone for enhancing societal progress, interaction, and connectivity. The strategic construction and investment in land transport infrastructure encompassing roads, bridges, and railroads transcend mere physical development, acting as catalysts for significant socio-economic transformations. Such projects stimulate local economies through direct job creation and facilitate population agglomeration by streamlining the flow of workforce and resources [6]. This dual effect significantly reduces geographical and temporal barriers, optimizing production efficiency and fostering sustained economic growth.

Moreover, the role of transportation infrastructure in promoting human development extends to inducing localized socio-economic shifts that yield indirect benefits. By facilitating access to education and healthcare, these infrastructural advancements contribute to a more educated and healthier population, enhancing the overall resilience and growth potential of the economy [7]. The construction of transportation infrastructure thus represents a multifaceted approach to development, producing a blend of direct and indirect advantages that collectively propel economic sustainability and human progress. Transportation infrastructure is of fundamental importance in creating a more interconnected, efficient, and thriving society.

However, despite enabling these advantages, the construction sector is marked by its heavy reliance on natural resources and significant energy consumption, commonly attributed to outdated and inefficient practices [8]. While leveraging the sector's role in economic growth is essential, addressing its inefficiencies' environmental and social implications is equally critical. A paradigm shift is required to align the sector's operations with sustainable development goals, ensuring its contributions continue to enhance rather than compromise our collective future [9].

Economic considerations have predominantly guided the feasibility assessment, risk analyses, and management strategies for construction projects within land transport infrastructure networks. This narrow focus, coupled with an oversight of the long-term impacts of substandard practices, presents an ongoing dilemma. Consequently, this approach has historically led to transportation infrastructure failing to contemplate environmental and social sustainability.

Integrating environmental and social factors into the intricate decision-making processes of construction planning and management is undoubtedly complex. However, it is imperative to overcome this challenge to guarantee that the construction and ongoing operation of transportation infrastructure are in harmony with sustainable development objectives. Tackling these intricate issues necessitates a comprehensive

strategy that equally weighs economic, environmental, and social goals, setting the foundation for a future where infrastructure development fosters a sustainable and thriving society.

1.1.3 Challenges for Integrating Sustainability

Considering the construction industry as a resource-based system [10], three approaches to enhancing the sustainability of transportation infrastructure development emerge: sufficiency, efficiency, and consistency [11]. Assessing current challenges in integrating sustainability in transportation infrastructure construction involves evaluating sustainability's three dimensions economic, environmental, and social through these distinct yet complementary perspectives.

The sufficiency paradigm aims to identify the minimum requirements for fulfilling specific needs, questioning their nature and underlying logic. In transport infrastructure construction, attaining economic sustainability through sufficiency involves crafting designs that meet operational requirements over the project's lifespan while ensuring that construction expenses are confined to the absolute minimum needed [12]. From an environmental standpoint, sufficiency involves reducing environmental impacts and adhering strictly to regulations, ensuring the project complies with legal benchmarks and strives to minimize ecological harm as much as possible. Social sustainability under the sufficiency lens entails carefully managing transport infrastructure demand. Emphasis should be placed on enhancing the accessibility of current infrastructure for the broadest of the community. This consideration includes advocating for projects that are adequately scaled to meet, but not exceed, the community's needs [13]. It can be discussed that, on occasion, this perspective highlights the value of expanding existing structures, favouring modest enhancements over grandiose, speculative ventures or those seeking acclaim for the professionals and firms involved.

The efficiency approach focuses on the optimal conversion of material resources into desired outcomes. Within the economic sustainability of the construction sector for contemporary transportation infrastructure, there is a pressing need to embrace solutions marked by highly efficient production processes [14]. Progress in this domain is often the result of extensive research, development, and the implementation of cutting-edge planning and design technologies. When considering the environmental facet, the efficiency paradigm underscores the importance of solutions that make prudent use of natural and energy resources [15]. A pivotal shift in construction machinery, moving from traditional dependence on fossil fuels to adopting systems powered by renewable energies, is essential. Integrating the social dimension of sustainability through an efficiency perspective focuses primarily on fostering meaningful

connections with the communities impacted by the construction projects. Minimizing and effectively managing disruptions throughout the infrastructure's life cycle is crucial [7]. Proactive engagement with local stakeholders is critical to developing transportation networks that satisfy technical and economic requirements and resonate with and contribute positively to the community's social fabric.

The consistency paradigm focuses on implementing renewable resources whose use does not incur definitive depletion or degradation to an irreversible state. Within economic sustainability, embracing consistency involves aligning construction processes with the principles of the circular economy. This approach entails strategies designed to reduce resource consumption by thoroughly planning the entire life cycle of structures, from their inception to decommissioning, thereby circumventing premature obsolescence [16]. It champions the prolonged use of materials through diligent maintenance and supports the recovery and recycling of resources at the end of their life cycle [17]. From an environmental standpoint, the consistency paradigm aims to synchronize the management of energy and material resources with the rhythms of natural cycles, thereby reducing ecological footprints. Prioritizing the research into and applying environmentally friendlier construction materials, such as sustainable concretes, and shaping legislative frameworks that encourage their use in transportation infrastructure is vital to achieving environmental consistency. Socially, the consistency approach emphasizes engaging with community members from the planning stages to incorporate their insights into the project, employing local labour and resources. Such practices ensure that the infrastructure serves people's needs while promoting social cohesion.

1.1.4 Reinforced Concrete Precast Modular Solutions

In advancing the construction industry's modernization, integrating digital tools and applying artificial intelligence can enhance the sustainability of structural solutions from the outset of the design phase. Precast modular solutions stand out as a functional alternative to traditional cast-in-place structures [18]. The controlled environment of industrialized in-plant manufacturing creates an optimal setting for developing, implementing, and refining innovative techniques [19]. Moreover, mass production enhances efficiency, sufficiency, and consistency across various facets, addressing the challenges outlined in Section 1.1.3.

Manufacturing structural components in a controlled environment diminishes variability in critical processes like concrete pouring, curing, and demolding. Quality control is more efficiently executed in a plant setting than in the inherently variable conditions of construction sites, enabling the consistent production of high-quality structural elements. Enhanced quality control and stable conditions improve the durability of pre-

cast concrete surfaces. Improved surfaces reduce the penetration of external agents, lessening maintenance requirements and potentially increasing the structures' lifespan. In transportation infrastructure, limiting maintenance to scheduled inspections results in fewer unexpected repairs over the service life, reducing disruptions for local communities and adhering to circular economy principles.

Cement, essential for the structural integrity of the concrete matrix, notably influences the environmental footprint of reinforced concrete structures. The accurate material adjustments possible in controlled in-plant pouring processes lead to more efficient use of cement [20]. This efficiency helps minimize waste and lower energy consumption throughout the structure's life cycle, decreasing economic costs and environmental impacts. Moreover, the controlled conditions of precast plants appear conducive to incorporating recycled materials into the prefabrication process, further aligning with sustainability principles.

The shift towards industrial manufacturing capitalizes on the features of serial production. Stable manufacturing processes provide a foundation for exploring and testing innovative solutions. When paired with performance-based design principles, it fosters the development of structurally sound precast modular assemblies that emphasize efficient functionality. Moreover, prefabrication in-plant moves energy consumption from construction sites to facilities better suited for integrating renewable energy sources, thus reducing the environmental impacts associated with the construction and dismantling phases.

Besides the manufacturing features of precast modular structures, their construction techniques set them apart from traditional cast-in-place solutions. After the structural components are transported to the worksite and prepared for installation, construction primarily involves assembling the modules to form the final structure. The simplicity of this approach significantly reduces the scale and duration of construction activities, facilitating cost-effective practices that limit environmental and social impacts to the essential minimum [21].

Decommissioning precast modular systems involves disassembly rather than the demolition associated with cast-in-place structures. This approach enables the salvage and potential reutilization under safety constraints and allows non-structural applications after service life. Specific components, like precast slabs, can be virtually fully recovered [19]. The ability to repurpose materials, granting them a second life, aligns the use of modular assemblies in transportation infrastructure construction with sustainable development.

Modular solutions significantly increase the flexibility and adaptability of transportation infrastructure construction, addressing the varied and specific requirements of

distinct projects and communities. This adaptability guarantees that transportation infrastructure is scalable and amenable to modifications or expansions. It also helps tailor projects to current needs, preventing the overestimation of future demands and ensuring resources are utilized efficiently and sustainably [22].

While integrating precast modular solutions offers potential advantages for constructing transportation infrastructure, recognizing and addressing their inherent constraints is crucial. A comprehensive understanding of precast modular solutions' standing within sustainable construction practices entails evaluating potential risks and limitations, ensuring a balanced and informed approach to their design and utilization.

Although precast modules offer versatility in common applications, their adaptability to unique or non-standard projects can be limited by the necessity for standardized designs. In contrast, cast-in-place methods afford on-site customization to address specific architectural needs and site conditions, more effectively meeting the demands of projects with unique requirements or intricate site layouts.

Transporting large precast modules to construction sites presents logistical challenges, particularly in remote, congested, or hard-to-reach areas. The need for specialized vehicles and lifting equipment raises costs and adds complexity to transportation logistics [23]. These issues can substantially affect project timelines and budget estimates if not effectively managed.

While precast modular solutions enhance the adaptability of transportation infrastructure, fluctuations in demand introduce challenges to scaling up precast production. Constraints in manufacturing or delays in producing extra modules can adversely affect project schedules and financial efficiency. This potential disparity between production capacity and project requirements, a concern less pronounced in traditional practices with established supply chains, underscores the critical need for precise demand forecasting to preserve operational efficiency [24].

The upfront costs of setting up a precast manufacturing facility and acquiring all necessary equipment are significant. This substantial initial investment must be meticulously weighed against the potential long-term advantages, assessing the economic feasibility of implementing precast modular construction solutions for particular applications.

Navigating compliance with construction codes, standards, and regulatory requirements can present obstacles for precast modular solutions. Traditional construction methods are aligned with established and continuously updated standards. Modifying precast designs and production processes to comply with these regulations might require extra time and resources [25]. Moreover, introducing innovative approaches

may face resistance from stakeholders familiar with conventional construction practices.

While precast modular solutions offer potential environmental and social advantages, material sourcing, manufacturing processes, transportation, and other considerations influence their overall sustainability performance. Utilizing LCA methods is necessary to understand the sustainability implications throughout the entire structure's life cycle [26].

Precast modular solutions offer potential avenues for overcoming sustainability challenges in constructing transportation infrastructure. Nonetheless, an ongoing critical evaluation of their performance relative to traditional cast-in-place solutions is crucial.

1.1.5 Knowledge Gap and Research Motivation

This doctoral research was undertaken at the Universitat Politècnica de València (UPV), within the University Institute of Concrete Science and Technology (ICITECH) facilities. The work detailed in this dissertation forms a core part of the hybrid life cycle optimization of bridges and mixed and modular structures with high social and environmental efficiency under restrictive budgets (HYDELIFE) project. The study builds upon the robust groundwork established by research group fellows, whose extensive efforts and publications in the field of research aimed towards enhancing infrastructure development have markedly contributed to enriching the academic discourse and structural engineering approaches.

A generalist and systematic methodology was adopted to delineate the research line relevant to this dissertation. A broad academic publication dataset was compiled through a series of targeted queries on reinforced concrete precast and modular road transportation infrastructure solutions within the Web of Science and Scopus databases. The dataset comprised research in the structural field aimed at advancing the sustainability of transportation infrastructure construction.

The initial database underwent a preliminary curing process. The screening phase focused on ensuring uniformity in document type and research quality, mandating the selection of peer-reviewed articles written in English and issued in the last 15 years. Figure 1.1 illustrates the number of papers per year at this specific stage, depicting an upward trajectory that underscores the escalating significance of the research domain.

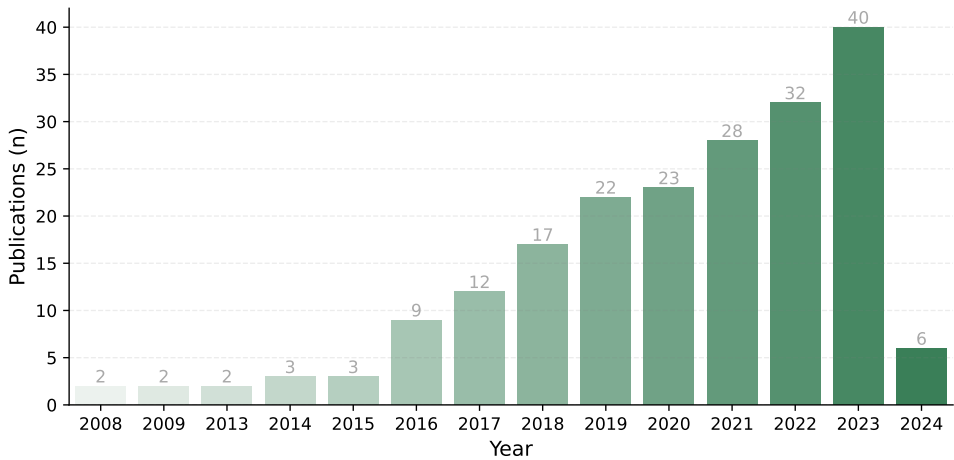


Figure 1.1: Annual trend in the number of academic publications pertinent to the research field.

The collection of papers was further scrutinized for thematic relevance following a consistency and quality assessment. This step involved discarding documents not aligning with the research focus and incorporating studies frequently referenced in already verified papers within the dataset. Figure 1.2 offers an overview of the geographical distribution of the academic affiliations of the authors considered in this phase, highlighting a worldwide engagement in the research area, with researchers contributing from Asia, Europe, and the Americas.

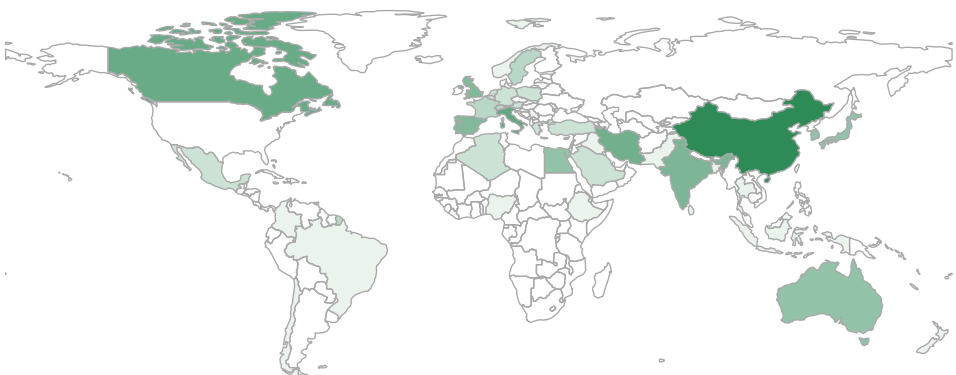


Figure 1.2: Location frequency distribution of academic affiliations for publications relevant to the research field.

The keyword clustering technique employing Kmeans was employed to characterize the article themes objectively [27]. This method capitalized on the capabilities of unsupervised machine learning to identify four distinct clusters of research topics. These clusters encompassed areas of optimization and design, sustainability and life cycle assessment, multi-criteria decision-making, and a fourth category that included experimental tests, case studies, and material characterization, among other subjects.

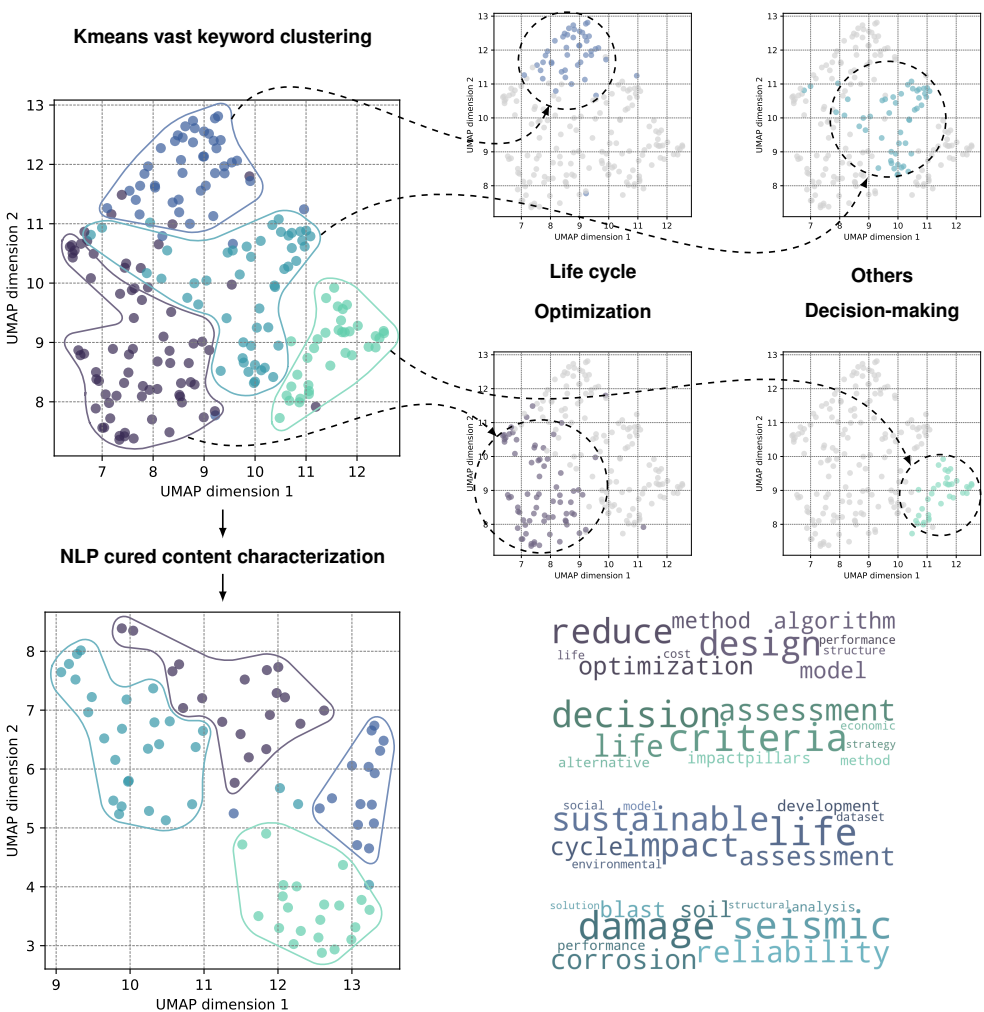


Figure 1.3: Thematic analysis UMAP visualization for the K-means and NLP clustering results.

After examining the initial clustering results, an advanced clustering technique utilizing a custom natural language processing (NLP) model was adopted to delve into the research papers' contents. The four initial clusters related to the previously mentioned themes were further characterized [28]. This refinement was achieved by employing a specialized BERT-based model tailored to exclude standard terms and accurately emphasize the appearance of features relevant to each research topic [29]. The Kmeans and NLP clustering results are presented in Figure 1.3, with the most relevant terms to each cluster being displayed. The uniform manifold approximation and projection (UMAP) dimensionality reduction algorithm was used to generate the two-dimensional illustration [30].

The subsequent phase in delineating the research gap involved the in-depth review of the papers on optimization, sustainability, and decision-making techniques applied to the road infrastructure. The studies discussed in the forthcoming paragraphs were pinpointed as most closely aligned with the doctoral topic through this examination. A discernible trend emerged, highlighting the adoption of optimization techniques, life cycle evaluations, and decision-making techniques as strategies to improve the structural design process. Nonetheless, it was noted that only a limited number of studies have specifically targeted the structural typology that this PhD thesis concentrates on, with previous research focusing primarily on the cast-in-place typology.

Prior studies integrated single-objective optimization and multi-objective optimization methods to enhance the design of such as retaining walls [31]–[33] or building structures [34]–[36]. In light of the pivotal role of transportation infrastructure in promoting sustainable development as delineated in Section 1.1.2 significant focus has been directed toward structures common in road networks, including reinforced concrete bridges [37]–[42], composite bridges [43]–[45], and piers [46]–[48]. This effort to refine structural design via optimization techniques constitutes a globally recognized research area dedicated to improving the sustainability of structural engineering. Moreover, the swift progress in artificial intelligence (AI) and the emergence of new, highly effective optimization algorithms present promising avenues for elevating traditional structural design practices.

Within the research field, the predominant objective has been the minimization of the economic cost. This focus on more efficient resource use directly reduces environmental impacts. The effort to minimize the overall cost of any structure inherently decreases material consumption, with research indicating a direct correlation between reductions in CO₂ emissions and final cost savings [38]. Nonetheless, exclusive emphasis on economic factors fails to provide a comprehensive perspective on structural design, particularly when aiming for sustainable infrastructure development [49].

Multi-objective strategies refine the approach by enabling the optimization process to minimize or maximize multiple objective functions simultaneously. This strategy facilitates the creation of structural designs that are both economically viable and sustainable by balancing the minimization of environmental or social impacts with economic considerations. Objectives such as associated CO₂ emissions or embodied energy are direct metrics for assessing the environmental ramifications of the materials utilized in a specific structural design [35], [37]. Furthermore, objectives focusing on reliability or constructability shed light on the social ramifications of the design [50]–[52]. Considering multiple objectives conforms to a broader perspective and provides a deeper insight into sustainability within structural engineering, highlighting the interplay between environmental, social, and economic dimensions [53].

Nevertheless, concentrating exclusively on diminishing the end-view impacts of a structural design fails to comprehensively determine whether the optimized structural solution genuinely improves life cycle sustainability. Therefore, it is essential to implement life cycle evaluation methodologies that integrate environmental and social factors into the design and optimization process for enhancing sustainability in transportation infrastructure structures.

There is a discernible shift towards quantifying the life cycle impacts of construction materials and designs [54]. Studies increasingly focus on life cycle sustainability across structural solutions, including retaining walls and buildings [16], [40]. Additionally, mirroring the trajectory observed in optimization research, several investigations concentrate on structures fundamental to transportation infrastructure, such as decks, reinforced concrete, and composite bridges [55]–[57].

There is a marked trend towards emphasizing environmental sustainability, with findings underscoring the importance of incorporating the CO₂ capture capability of concrete into the life cycle model of structures [58], [59]. This inclusion offers a more holistic view of environmental sustainability, spotlighting the positive facets of using a material traditionally viewed as polluting. Although less frequently examined, a number of researchers highlight the significance of considering the social dimension of sustainability to achieve a comprehensive approach [60], [61].

The recent research collectively indicates a move towards integrating sustainability more comprehensively and cohesively in structural design practices. This shift focuses on diminishing environmental impacts and enhancing the social and economic viability of structural projects [26], [62]. This trend marks a significant commitment to sustainable development, highlighting the importance of embedding extensive sustainability considerations at the early stages of structural design and optimization. Furthermore, it underscores a strategic approach to ensure that structural endeavours are developed with a balanced consideration of long-term sustainability impacts.

Incorporating the multifaceted aspects of sustainability into transportation infrastructure projects adds complexity to an already challenging decision-making process. Prior studies have aimed at introducing and assessing frameworks to facilitate more informed decisions within sustainable transportation infrastructure development. Employing decision-making techniques to evaluate and prioritize optimal structural designs represents a pragmatic approach that could significantly improve engineering decision-making practices. Nonetheless, the inherent complexity of these decision-making algorithms, along with their operational variances due to different algorithmic frameworks and scoring methodologies, may render choosing an appropriate decision-making technique a multi-criteria problem. This issue highlights the need for a meticulous evaluation of these techniques to ascertain their suitability and effectiveness in guiding sustainable infrastructure development.

Past applications of decision-making techniques to bridge structures facing harsh environmental conditions, composite bridge structures, and pedestrian bridge projects underscore the advantages of employing decision-making methodologies for fostering sustainable structural design within transportation infrastructure development [63]–[65]. These methods also show considerable prospects for building projects or infrastructure development management [66], [67], demonstrating their efficacy in facilitating more informed decisions. Furthermore, when considering these methodologies, decisions are grounded in an objective and systematic evaluation of diverse inputs to the decision-making process. This capability is crucial for achieving a holistic approach to structural design, where integrating the various dimensions of sustainability from the early stages presents a sophisticated decision-making challenge involving several criteria.

This PhD research is dedicated to advancing sustainable road transportation infrastructure, focusing on precast modular solutions suitable for reinforced concrete frame structural typologies within road networks. Prior studies by Perea et al. [68], [69], and Carbonell et al. [70], [71], yielded promising outcomes in employing single-objective optimization methods to refine the structural designs of reinforced concrete precast frames (RCCPF), specifically reducing economic costs and material usage. However, despite these advancements, there remains an unexplored prospect in evaluating road frame alternatives leveraging advanced algorithms capable of addressing multiple objectives simultaneously. Moreover, there is a notable void in the existing academic literature concerning this structural typology, with no further advancements in areas related to design optimization, life cycle sustainability, or decision-making strategies [72]–[76]. The positive outcomes of preliminary research into cast-in-place alternatives, combined with the absence of studies on precast modular alternatives, underscores a pressing demand for extended investigation in this area of research.

In addressing this gap, past research shows a discernible trend towards a more comprehensive approach to structural design across various typologies pertinent to transportation infrastructure. However, the focus on road frames has been notably sparse, with the few existing studies focusing on cast-in-place typologies. This gap in the existing knowledge, lack of ongoing development, and the potential for innovation within this field are the primary motivations for the research undertaken in this PhD thesis, which aims to contribute to and evolve the understanding and application of sustainable structural solutions.

Within this context, this PhD dissertation presents a comprehensive effort to broaden existing knowledge and develop an efficient structural design framework to enhance the life cycle sustainability of reinforced concrete precast hinged frames (RCPHF), also referred to as reinforced concrete precast modular frames (RCPMF) throughout this thesis. A novel design framework introduced and evaluated in this thesis effectively integrates novel single and multi-objective optimization algorithms, environmental and social life cycle assessments, and decision-making strategies to incorporate life cycle sustainability considerations from the inception of transportation infrastructure projects. The research targets a critical gap by applying this framework to RCPMF, expanding the current understanding of precast modular road frame structures' performance across pressing sustainability dimensions. Furthermore, it validates a comprehensive approach for better-informed, data-driven engineering efforts within sustainable transportation infrastructure development.

1.2 Research Objectives

This PhD dissertation introduces an innovative, holistic methodology for designing and evaluating highly efficient modular precast reinforced concrete structures common to road transportation infrastructure. The design framework integrates local search strategies, hybrid heuristics, and custom state-of-the-art evolutionary and genetic algorithms for the single objective optimization (SOO) and multi-objective optimization (MOO) of RCPMF designs. This research combines these optimization strategies with life cycle assessments (LCA) to balance environmental and social efficiency within economic constraints. The framework addresses the complex multi-criteria decision-making (MCDM) challenge in evaluating the high-efficiency designs by employing a range of decision-making strategies such as multiple additive weighting, outranking, distance-based, and compromise-ranking, enhanced by an entropy theory-based method for the objective weighting of criteria. This dissertation outlines a novel design framework that comprehensively targets the inherently complex challenge of integrating, objectively characterizing, evaluating and balancing life cycle sustainability considerations within transportation infrastructure development. Within

the research scope per the constraints and specific conditions elucidated throughout this dissertation, the successful application of this framework to RCPMF design underscores its validity and utility as a significant research and engineering strategy applicable to a broad spectrum of real-world engineering challenges.

At the core of this thesis are the following research questions focused on the potential benefits for life cycle sustainability offered by implementing the novel design framework for RCPMF as a highly efficient alternative to conventional cast-in-place options.

RQ1. How effective are trajectory-based, local search and hybrid metaheuristics in generating non-traditional sustainable RCPMF designs under cost-minimization constraints?

RQ2. Do the cost-optimized RCPMF conform to a viable alternative to cast-in-place solutions in terms of environmental and social life cycle impacts?

RQ3. How does the precast modular nature of RCPMF influence the generation and distribution of environmental and social life cycle ramifications?

RQ4. Can the concurrent minimization of economic, environmental, and social factors affect the RCPMF optimization outcomes?

RQ5. How do evolutionary and genetic optimization algorithms perform across different decision-making strategies within a robust design framework integrating MOO and MCDM for sustainable RCPMF?

The completion of the following research objectives was established as critical to generating the knowledge necessary for assessing the research questions in this dissertation:

1. Develop an optimization framework for applying local search and hybrid metaheuristics targeting RCPMF efficiency through single-objective cost-minimization.
2. Assess the capacity of multiple local search and hybrid optimization strategies to produce sustainable RCPMF designs within the SOO framework.
3. Construct comprehensive life cycle parametric models for modular and traditional cast-in-place solutions with varying characteristics to assess their environmental and social midpoint and endpoint life cycle results.
4. Conduct a data-driven parametric comparative analysis to delineate the environmental and social life cycle implications of cost-optimized RCPMF versus conventional cast-in-place structures.

5. Design a framework integrating MOO algorithms and MCDM techniques to create and objectively assess RCPMF designs that simultaneously target the minimization of economic, ELCA and SLCA life cycle objectives.
6. Apply the integrated design framework to a RCPMF and evaluate the performance of state-of-the-art evolutionary and genetic optimization algorithms across decision-making strategies coupled with entropy criteria weighting.

The findings in this PhD dissertation, stemming from fulfilling the previously mentioned research objectives, describe the concerted efforts to develop, introduce, and apply a holistic structural design framework. The efforts, focused on integrating optimization techniques, life cycle evaluation, and decision-making strategies, aim to enhance the development of sustainable transportation infrastructure through a more informed and efficient approach.

1.3 Methodology

The research methodology employed in this PhD thesis synthesizes cutting-edge optimization and decision-making techniques with integrated life cycle modelling, all aimed at systematically producing and assessing sustainable precast modular designs. This approach unfolds sequentially for a cohesive narrative targeting an enhanced understanding of sustainability within transportation infrastructure construction projects involving RCPMF.

At the core of this methodology lies developing a sophisticated Python optimization model. The mathematical model progressively evolves, integrating advanced meta-heuristic techniques, an array of design variables, objective functions, and additional constraints. Leveraging non-linear Finite Element Method (FEM) calculations, the model adeptly generates optimal designs that comply with existing regulatory standards under set calculation hypotheses.

The initial stage focuses on minimizing the final cost of a standard RCPMF structural configuration using trajectory-based algorithms. This stage is dedicated to producing cost-effective designs while integrating methods to assess key environmental sustainability metrics, such as CO₂ emissions and embedded energy. This unique integration facilitates exploring the connection between cost minimization and environmental impact reduction, emphasizing material efficiency. The study evaluates the performance of simulated annealing (SA), threshold accepting (TA), and old bachelor's acceptance (OBA) metaheuristics, algorithms renowned for their efficient navigation through the solution space and their criteria for accepting sub-optimal solutions to avert premature local optima convergence.

Population-based metaheuristic optimization algorithms present significant benefits for addressing complex optimization challenges. Despite the potential increase in computational demands, these algorithms are effectively hybridized with trajectory-based techniques, demonstrating strong performance in earlier phases of the research. Integrating a mutation operator (MO) improves these algorithms' exploration ability, enabling a more comprehensive examination of the solution space via hybrid simulated annealing (SAMO), hybrid threshold accepting (TAMO), and hybrid old bachelor's acceptance (OBAMO) strategies.

Enhancing the optimization model involves parameterizing the design and analysis according to critical features of the RCPMF. This advancement facilitates the parametric generative design of diverse structural configurations. The subsequent phases of the research incorporated the parametric generative design with fine-tuned hybrid metaheuristic techniques, targeting the single objective economic minimization of several RCPMF configurations while assessing environmental key performance indicators (KPI). The results were integral for developing regression-based predictive models as practical tools for estimating costs in optimal RCPMF design. Incorporating these linear and quadratic expressions into the generative process, a wide array of parameters including economic, geometric, resource, and environmental factors can be estimated during the design phase of precast modular structures.

In the following stage, social considerations are incorporated into evaluating cost-minimized, previously generated designs. This integration signifies a foundational step toward addressing the three pillars of sustainability. A thorough RCPMF life cycle model is developed using the OpenLCA application programming interface (API), an open-source life cycle modelling tool. This model incorporates environmental data from the Ecoinvent and BEDEC databases with social damage metrics through the PSILCA database, employing soca v2. In compliance with ISO 14040:2006, the model comprehensively delineates inputs and outputs across the structure's life cycle phases, meticulously tracking the impact of each material and process used. The practical application of this model in a SLCA case study of a previously assessed cost-optimized RCPMF design provides a detailed examination of the social impact of various processes and materials, leveraging the social impact weighting (SWIM) life cycle impact assessment (LCIA) method to quantify both their absolute and relative contributions to social damage endpoint categories.

The LCA model is refined through a thorough data quality assessment, incorporating uncertainty based on the dataset's reliability, completeness, and geographical, temporal, and technical representativeness, employing the pedigree matrix method. This comprehensive process significantly enhances the model's accuracy and reliability. Moreover, this refinement enables Monte Carlo simulation for result generation,

offering a robust approach to managing uncertainty in the subsequent stages of the research.

The advanced LCA model is utilized to conduct a comprehensive comparative sustainability assessment between cost-optimized RCCPF and RCPMF configurations. This stage merges previous methodologies and analytical tools to comprehensively compare the ELCA and SLCA outcomes for both modular and traditional cast-in-place road frame solutions. The life cycle metrics of precast and cast-in-place options are objectively measured to pinpoint the most environmentally and socially sustainable designs and identify targeted strategies for potential impact reductions. A tailored life cycle model is constructed for RCCPF, complementing the modular counterpart. The models are parameterized and employed to examine the environmental and social life cycle implications across 25 structural designs with varying horizontal spans and earth cover depths. The study employs the ReCiPe LCIA method for ELCA midpoint and endpoint and the SWIM LCIA method for SLCA endpoint results. Building upon the results of the previous research stages, this multifaceted approach to transportation infrastructure development targeting road frames yields a holistic evaluation of the sustainability of each cost-optimized structural solution.

In the previous stages, the optimization efforts focused on the SOO of the structure's economic cost. Environmental and social ramifications of the cost-optimized RCPMF designs were then evaluated through ELCA and SLCA. The relative and absolute impact contributions of processes and stages across the structure's life cycle were analyzed. Correlation analyses underscored the connection between the cost-minimization of RCPMF designs and the enhanced efficiency in natural resource use. The outcomes of the SOO presented lower environmental impacts when contrasted with comparable RCCPF configurations.

Upgrading the optimization model to deploy advanced evolutionary and genetic algorithms suitable for MOO involves tailoring the Python software to the object-oriented programming (OOP) principles common to most open-source optimization libraries. Additionally, the mixed integer programming (MIP) characteristic of the RCPMF challenge requires specialized crossover, polynomial mutation, and solution vector repair operators to discretize these algorithms. Evaluating the economic, environmental, and social dimensions involves incorporating the RCPMF life cycle, previously computed through OpenLCA, into the mathematical model. The ELCA and SLCA endpoint results are implemented via multiple modules developed to compute these outcomes as objective functions during the MOO process. These modules are designed to inform the optimization algorithms dynamically, influencing the optimization process. The integrated design framework developed throughout this research aims to promote better-informed and objective decision-making within sustainable transportation infrastructure development. The specific application to the RCPMF prob-

lem incorporated modules for applying several decision-making techniques, which are deployed within the Python model to address the MCDM challenges associated with optimized RCPMF designs.

After comprehensively advancing the optimization model to consider multiple life cycle objective functions concurrently, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) from the Pymoo library is selected to validate the optimization model's effectiveness and to explore the influence of simultaneously addressing the three sustainability pillars on the life cycle ramifications of optimized RCPMF. Custom simulated binary crossover (SBX) and polynomial mutation (PM) operators are integrated into the MOO algorithm. Additionally, statistical-based, proximity-based, and random repair operators are developed and implemented, resulting in a tailored NSGA-II algorithm designed to navigate the complex optimization landscape of the RCPMF problem. Two distinct decision-making techniques are employed to assess the MCDM problem concerning the non-dominated solutions derived from the MOO process.

The simple additive weighting (SAW) and the *faire un choix adéquat* (FUCA) are implemented. The SAW is a straightforward, widely employed technique for decision-making involving structural sustainability. The study considers the FUCA, less explored in structural decision-making contexts, as a potential combined or individual deployment technique for the RCPMF problem. An entropy theory-based method for objective and systematic criteria weighting enables a direct juxtaposition of SAW and FUCA techniques. This comparative analysis aims to detect convergences or divergences in scoring and ranking outcomes, thereby expanding the array of MCDM techniques for structural engineering problems.

This PhD research's concluding stage scrutinizes the efficacy of three cutting-edge evolutionary and genetic optimization algorithms across five decision-making strategies, all underpinned by entropy criteria weighting. The NSGA-II, Non-dominated Sorting Genetic Algorithm-III (NSGA-III) and Reference Vector Evolutionary Algorithm (RVEA) MOO algorithms are deployed within the integrated design framework to generate non-dominated solutions that concurrently minimize economic costs, along with ELCA and SLCA endpoint results. The evaluation concentrates on the algorithms' capability to produce solutions, measuring their performance against the three sustainability criteria. The MCDM challenge is further explored using five distinct decision-making methods: SAW, FUCA, technique for order of preference by similarity to ideal solution (TOPSIS), preference ranking organization method for enrichment evaluation (PROMETHEE), and "visekriterijumska optimizacija i kompromisno resenje" (VIKOR). This exhaustive approach deepens into the robustness and capabilities of the practical framework integrating MOO and MCDM for sustainable RCPMF.

Each stage of this PhD thesis unfolds progressively for a detailed effort to advance the application of innovative techniques and strategies to improve the sustainability of precast modular structures within transportation infrastructure. The methodological approach outlined in this section merges optimization research with practical validation, highlighting the significance and feasibility of novel integrated design frameworks in addressing the complex and diverse challenges of sustainable construction.

1.4 Dissertation Structure

This thesis is structured into ten chapters. The first chapter serves as an introduction. Chapters 2 through 8 elaborate on the core academic publications resulting from disseminating the thesis research. Notably, Chapters 3 and 5 feature the author's translations of the original articles that were published in Spanish. Each chapter, portraying a peer-reviewed academic work, includes a cover page with essential information about the journal of publication formatted cohesively to align with the dissertation's standards. Chapter 9 merges the results for a cohesive discussion of the findings, and Chapter 10 concludes the thesis, reflecting on the author's current research endeavours and outlining potential future investigations.

Chapter 1 contextualizes the research within the broader sustainable transportation infrastructure construction framework, presents the thesis's research questions, details its objectives, and delineates the thorough methodology employed in detail.

Chapter 2 presents the cost-minimization of a standard RCPMF layout utilizing the SA, TA, and OBA local search algorithms. The study assesses the performance of these algorithms and the characteristics of the cost-optimized RCPMF designs, exploring the relationship between economic SOO, efficient resource use, and environmental KPIs.

Chapter 3 elaborates on incorporating population-based features into local search optimization algorithms to enhance their exploratory capabilities. The chapter evaluates the SAMO, TAMO, and OBAMO hybrid metaheuristics, detailing their tuning processes via a design of experiments (DoE). It then identifies and applies the most effective algorithm to a cost-minimization case study of a RCPMF, utilizing an upgraded optimization model incorporating additional design variables.

Chapter 4 further leverages the hybrid metaheuristics to generate 225 cost-optimized RCPMFs for a detailed parametric comparative study encompassing twenty-five road frame structural layouts. The analysis examines the economic performance, environmental KPIs and material utilization and elaborates regression-based predictive tools for accurately estimating sustainability metrics in RCPMF design.

Chapter 5 presents an RCPMF life cycle model and develops an SLCA for assessing the social implications of the cost-optimized road frame outlined in Chapter 3. This study brings the social dimension into the investigation, advancing the research towards a holistic RCPMF evaluation within sustainable transportation infrastructure design.

Chapter 6 fully integrates the economic, environmental, and social pillars by conducting a comparative parametric analysis of cost-optimized RCCPF and RCPMF designs. The analysis considers ELCA and SLCA midpoint and endpoint results from 50 cost-optimized road frames, informed by the predictive regression models introduced in Chapter 4 and insights from Perea et al. [69].

Chapter 7 demonstrates the integration of economic, environmental, and social facets into the RCPMF optimization and decision-making framework. A custom NSGA-II algorithm is deployed within an extensively upgraded MOO optimization model for the concurrent minimization of cost, ELCA and LCA. The MCDM concerning the non-dominated optimal solutions is analyzed via an entropy theory-based approach for criteria weighting combined with the SAW and FUCA decision-making techniques.

Chapter 8 evaluates the performance of the NSGA-II, NSGA-III, and RVEA algorithms within the MOO and MCDM framework established in Chapter 7. The research broadens the scope of MCDM to encompass the SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR decision-making algorithms. This analysis concentrates on the robustness and functional capacity of the integrated framework combining MOO and MCDM approaches for enhanced RCPMF sustainability.

Chapter 9 serves as the nexus where the research findings discussed throughout the previous chapters of this dissertation are cohesively discussed and examined. The outcomes are synthesized and connected to the research questions and objectives outlined in Chapter 1.

Chapter 10 completes the dissertation with the general and case-specific findings of the research, underlining their relevance and implications within sustainable transportation infrastructure construction. Additionally, it offers prospective pathways for future research motivated by this thesis, emphasizing the author's ongoing and future research endeavours.

Figure 1.4 depicts the structure of the PhD research, mapping the progression and interconnections among the chapters within the dissertation through a clear visual guide to the thematic flow and structural composition.

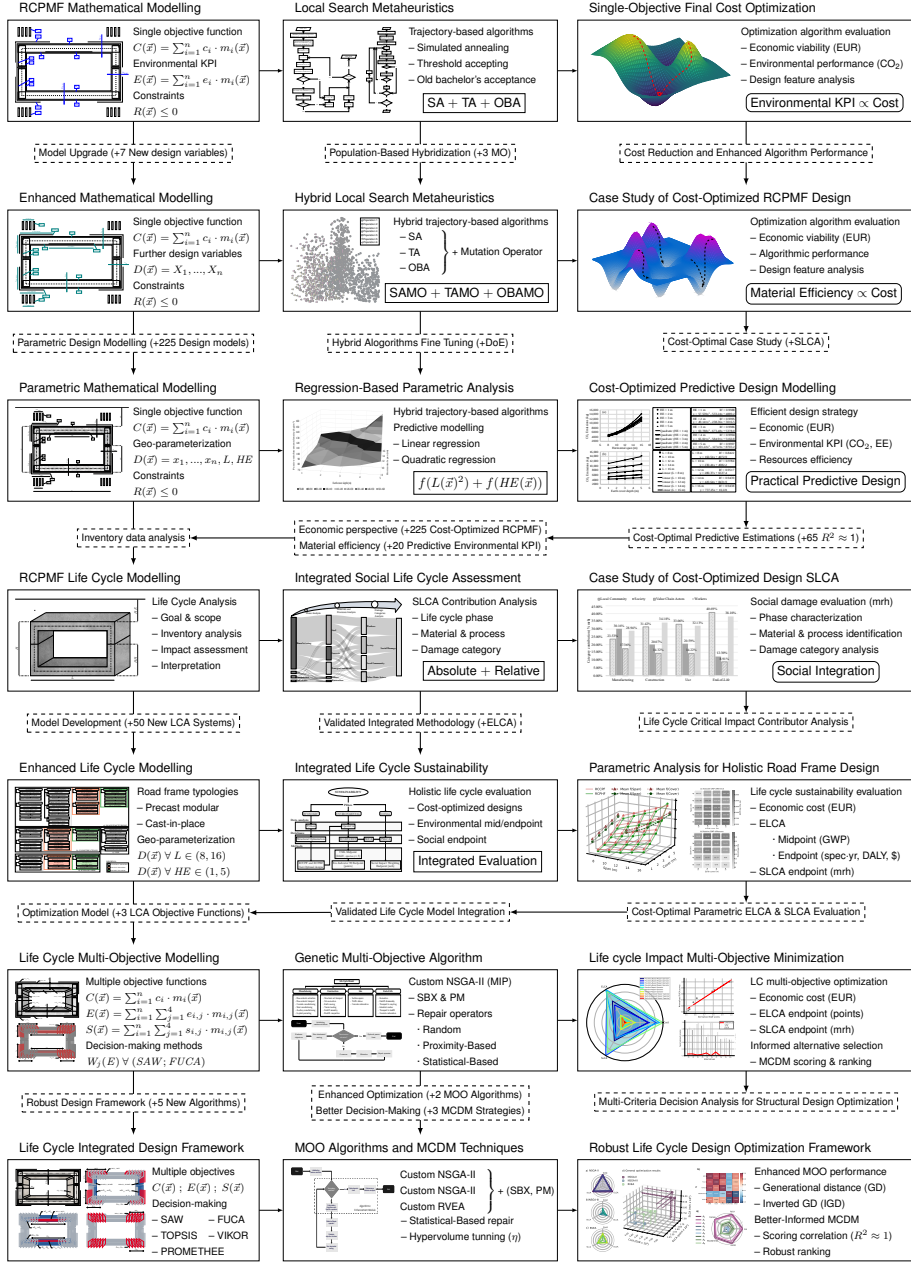


Figure 1.4: Visual representation of the dissertation's structure.

Chapter 2

Optimal design of sustainable reinforced concrete precast hinged frames

Authors:	A. Ruiz-Vélez, J. Alcalá, and V. Yepes		
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Abstract

Sustainable development requires improvements in the use of natural resources. The main objective of the present study was to optimize the use of materials in the construction of reinforced concrete precast hinged frames. Proprietary software was developed in the Python programming language. This allowed the structure's calculation, verification and optimization through the application of metaheuristic techniques. The final cost is a direct representation of the use of materials. Thus, three algorithms were applied to solve the economic optimization of the frame. By applying simulated annealing, threshold accepting and old bachelor's acceptance algorithms, sustainable, non-traditional designs were achieved. These make optimal use of natural resources while maintaining a highly restricted final cost. In order to evaluate the environmental impact improvement, the carbon-dioxide-associated emissions were studied and compared with a reference cast-in-place reinforced concrete frame. The results showed designs with reduced upper slab and lateral wall depth and dense passive reinforcement. These were able to reduce up to 24% of the final cost of the structure as well as over 30% of the associated emissions.

Keywords: reinforced concrete; precast; hinged frame; metaheuristic; optimization; sustainability

2.1 Introduction

The continuous improvement and widespread dissemination of knowledge about environmental issues raise awareness in a global population that seeks more sustainable development [20], [77]. The growth and evolution of societies are directly related to their infrastructure. Thus, the construction, maintenance and demolition of the structures that support a country's economic and social practices are activities intrinsic to its development [43]. The characteristic consumption of large quantities of materials places construction as one of the industries that produce more greenhouse gas emissions, generating around 5% of the total CO₂ emitted yearly [78]. Concrete is currently the most widely used material in construction. Therefore, a significant portion of the emissions is derived from its use [40], [79], [80].

In this context, it is feasible to affirm that construction is an activity inherent to human development. However, the intrinsic need for these related activities should not justify an inefficient use of natural resources. Hence, in the last decades, there has been a clear trend towards reducing the use and improving the characteristics of the materials necessary for constructing the structures surrounding us [81]–[83]. Using sustainable materials in conjunction with recycled materials allows direct reductions

in the associated CO₂ emissions [15], [17], [58]. However, the real-world application of these ways of improvement is limited by the need to develop comprehensive experimental studies that establish conditions of use and appropriate practical recommendations [84]. Thus, the experimental nature of these studies means that the implementation period of these solutions is considerably affected.

Considering the aforementioned limitations, several studies have focused on optimizing the structural design process [34], [85]–[87]. An improvement in the design can lead to immediate improvements in the social and environmental impact associated with its construction [88]. Traditionally, the design process has been very much linked to the engineer's theoretical knowledge, technical skills and previous experience [32]. This methodology starts with the complete definition of the different structural sections, which comprehends materials selection and the establishment of passive reinforcement configurations. Once defined, compliance with the limit states stipulated in the applicable code is verified. If the current structure does not comply, the type or quantity of materials is modified for further verification. This process is repeated on a trial-and-error basis until a final design is selected. Although this practice allows for achieving structurally safe designs, it does not comprehend the consideration of optimal material usage.

Interest in designing sustainable structures, together with the improvement of the computational tools currently available, has led to the development of a series of new design methodologies. Consisting of the application of metaheuristic techniques in the design of structures, these methodologies result in new designs. These, in addition to complying with the relevant limit states, manage to minimize or maximize a series of previously established factors such as economic cost, associated CO₂ emissions or the energy consumed in the construction of the designed structure [43]. These techniques have been highly improved during the last decade, mainly due to the simplicity of the algorithms and their high adaptability, in addition to the ability to avoid convergence to a local optimum. Due to the importance of improving the design process and the positive characteristics of the aforementioned methodologies, several studies have applied heuristic and metaheuristic optimization to design concrete structures, such as prestressed bridges [37], retaining walls [32], [33], [89], bridge piers [46] and building structures [35], [53]. The results establish a direct relationship between the final cost of the structure and the CO₂ emissions associated with its construction. The optimization of precast girder bridges carried out by Yepes et al. [38] concludes that a reduction of EUR 1 in the final cost of the bridge equals the avoidance of emitting 1.74 kg of CO₂.

The use of the reinforced concrete precast hinged frames (RCPHF), considered in the present study, is widely extended in transportation infrastructures. Mainly applied as a solution for the crossing of traffic lanes with the main road, these prefabricated

and reinforced concrete cast-in-place frames (RCCPF) typically cover spans between 3 and 20 m [90]. The RCPHF is a specific type of bridge structure that is particularly suitable when there is a low-bearing strength terrain or when the location happens to be a flood zone, something that could lead to a higher scour risk. The structure comprises three distinct parts, the top slab, the lateral walls and the bottom slab. The traditional design establishes the top and bottom slab depth between 1/10 and 1/15 of the span. In the case of the sidewalls, depth is established between 1/12 of the span and the depth considered for the slabs. In practice, the precast structural assembly is separated into two sets, allowing its transport from the prefabrication plant to its final site. Thus, the design of this structural typology is mainly determined by four factors: the horizontal span (L), the required height (H), the earth cover (HE), and the height of the hinge (HH). Figure 2.1 shows a graphic representation of the structural typology considered in this context.

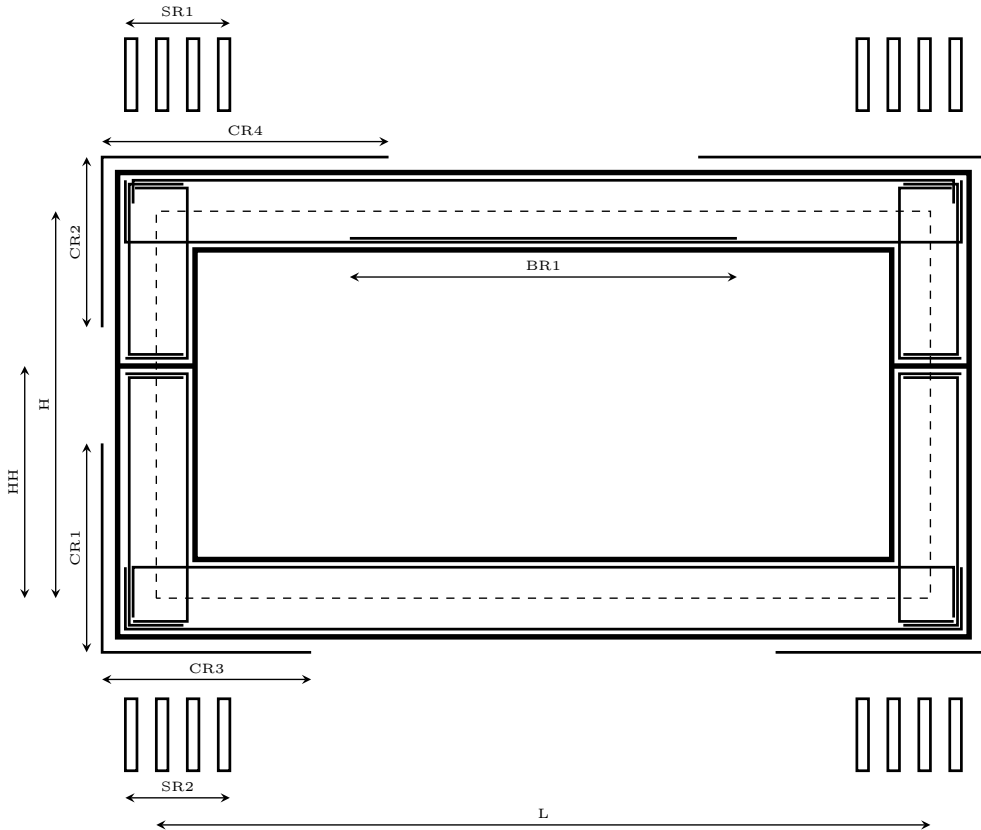


Figure 2.1: Parameters of the RCPHF considered in the optimization problem.

The design optimization of RCCPF with similar characteristics obtains high-quality results [69], [70]. However, there happens to be a lack of further development in the study of RCPHF applying current methodologies. The modular nature of precast structures, in conjunction with the greater quality and continuity of the prefabricated products when compared to cast-in-place structures, supports the relevance of studying the RCPHF as a better solution for transportation infrastructures [25], [47], [91]. In this context, the present study aims to optimize materials used to fabricate the RCPHF by applying three metaheuristic algorithms. In addition, a comparison between the optimized RCPHF and a reference RCCPF is carried out. The applied methodology consists of the initial development of proprietary software for stress calculation, structural and limits compliance verification and subsequent optimization through the application of heuristic algorithms. Once developed, the software is used to study the economic optimization of the RCPHF by applying simulated annealing, threshold accepting and old bachelor's acceptance algorithms. By doing so, the present study solves the lack of existing development, bettering the current knowledge and obtaining a series of practical recommendations applicable to the design of RCPHF. By comparing the precast and cast-in-place options, the study provides a comprehensive overview of the characteristics of each typology and the environmental impact associated with each. In addition, the software developed improves the application of heuristic techniques, allowing the further study of other relevant typologies of the study field while maintaining reasonable computational costs.

2.2 Optimization Problem and Computational Model Definition

The combinatorial optimization problem developed in the present study consists of the economic optimization of RCPHF. Generally, an optimization problem aims to minimize the value of a specific objective function while satisfying a series of previously established constraints [12]. In this context, the present optimization considers the final cost of the frame, calculated according to Equation (2.1), as the objective function of the problem. The evaluation consists of the direct calculation of the product of each material's unit cost c_i multiplied by the quantity used of each of the materials m_i . In addition, based on the aforementioned need to design structures that incur lower environmental impact, the CO₂ emissions associated with each design are evaluated by means of Equation (2.2). In this equation, similarly to the final cost, total CO₂ emissions are calculated as the product of the emissions associated with each material e_i multiplied by the quantity used of each of those materials m_i . The values considered both in the evaluation of the objective function and the calculation of the associated CO₂ emissions are summarized in Table 2.1. These were obtained from the Construction Technology Institute of Catalonia by the BEDEC database [92]. The RCPHF design is subject to compliance with the requirements established by the

standard regulations [93]–[95]. These, added to a series of technical considerations necessary for the complete verification of the RCPHF, are expressed in general terms through Equation (2.3).

$$C(\vec{x}) = \sum_{i=1}^n c_i \cdot m_i(\vec{x}) \quad (2.1)$$

$$E(\vec{x}) = \sum_{i=1}^n e_i \cdot m_i(\vec{x}) \quad (2.2)$$

$$R(\vec{x}) \leq 0 \quad (2.3)$$

Table 2.1: Unit cost and associated CO₂ emissions values [92].

Material	Unit	Cost (€)	Emissions (CO ₂ kg)
C25/30	m ³	88.86	256.66
C30/37	m ³	97.80	277.72
C35/45	m ³	101.83	278.04
C40/50	m ³	104.83	278.04
B 400 S	kg	1.40	0.70
B 500 S	kg	1.42	0.70

Once the general principles of the considered optimization problem have been detailed, the next step is the complete definition of the problem. This consists of considering, modelling and correctly defining the RCPHF parameters, variables and constraints. The parameters are magnitudes whose values are fixed throughout the optimization process. Constituted by known information, the value of the parameters is not subject to optimization. In conjunction with the parameters, the variables allow the complete definition of the considered structure. The set formed by the different values that the variables can adopt throughout the optimization process is the so-called solution space of the problem. Finally, the set of parameters and variables that define the design must comply with a series of constraints. As stated previously, these must ensure that the optimal design represents reality, meets the structural requirements and verifies the standard limit states [93], [94]. The following sections are dedicated to the description and complete definition of each component for the considered optimization problem.

2.2.1 Parameters

Starting with the parameters considered, it is relevant to reiterate that in conjunction with the variables these must provide all the information required to define the designed structure completely. Thus, the parameters considered in the present study must define the geometric characteristics of the frame, the acting actions and safety coefficients, ambient conditions and any other characteristic whose definition is necessary for the structural calculation and verification process.

There are three main geometrical parameters, consisting of the horizontal free span (L), the vertical free height (H), and the height at which the hinge is located (HH). In addition, following the standard process, the calculation is made per linear meter. Thus, all of the sections are one meter thick. In relation to the passive reinforcement of the structure, a series of parameters must be defined in order to establish the arrangement of the shear reinforcement ($SR1 - 2$), as well as the lengths of the corner reinforcement ($CR1 - 4$) and the negative bending reinforcement in the upper slab of the RCPHF ($BR1$). Due to the symmetrical nature of the structure, it is possible to completely define the passive reinforcement design by parameterizing one of its halves. Then, the other half is defined by considering the equivalent values. The complete set of parameters mentioned above, together with the designation established for each, is represented in Figure 2.1.

Additionally, it is necessary to establish various parameters related to the acting loads. One of the most determining considerations in the design of the considered structural typology is the depth of the earth cover above the RCPHF (HE). In this context, the first of the following parameters to define corresponds to this magnitude, and the value considered is 1.5 m. In addition, it is necessary to establish the specific weight of reinforced concrete and earth backfill, a material for which it is also necessary to define the ballast coefficient and the internal friction angle. Several parameters related to the standard regulations are also necessary. In the present study, the standard forms the regulatory basis for the acting loads, the environmental exposure directly related to the passive reinforcement cover and the load combination factor and material partial safety coefficients [93]–[95]. The global set of parameters and the values established for the optimization are presented in Table 2.2.

Adequately representing reality is complex. Thus, the mathematical modelling of the design process of RCPHF is an intrinsically complicated task. In this context, it is relevant to mention that during the modelling process of the problem it is necessary to make several hypotheses regarding the described parameters. First, based on the prefabricated nature, added to the consideration that sufficient expansion joints are present, it is possible to disregard the rheological effects and thermal actions. Furthermore, the magnitude of the foundation's differential settlement is also disre-

garded. It is also considered that the frame's location is a non-seismic zone, so the possible effect of the seismic actions can be neglected within the scope of the present study. Finally, common-use Spanish recommendations are considered to assess the overload associated with the Marston Effect and a heavy vehicle load [90], [95].

Table 2.2: Main parameters considered in the RCPHF optimization.

Geometrical parameters			
Free height	(m)	H	5
Horizontal span	(m)	L	10
Hinge height	(m)	HH	3
Earth cover	(m)	HE	1.50
Lower corner reinforcement length	(m)	$CR1$	2
	(m)	$CR3$	2
Upper corner reinforcement length	(m)	$CR2$	1.50
	(m)	$CR4$	3
Upper slab shear reinforcement length	(m)	$SR1$	3
Lower slab shear reinforcement length	(m)	$SR2$	2
Upper slab flexural reinforcement length	(m)	$BR1$	5
Loading parameters			
Earth specific weight	(kN/m ³)	γ_E	20
Reinforced concrete specific weight	(kN/m ³)	γ_C	25
Earth internal friction angle	(°)	IF	30
Coefficient of active earth pressure		K_A	0.33
Coefficient of resting earth pressure		K_R	0.50
Heavy traffic vehicle load	(kN/m ³)	TL	150
Heavy traffic vehicle load length	(m)	TLL	1.20
Uniform overload	(kN/m ³)	UO	10
Ballast coefficient	(MN/m ³)	B_E	10
Economic and emissions parameters			
Unit costs	(€)	c_i	Table 2.1
Associated emissions	(CO ₂ kg)	c_i	Table 2.1
Exposure and legislative parameters			
Exposure class		XC2	
Standard regulations		CEN [93], [94] / MFOM [95]	
Code considerations		MFOM [90]	

2.2.2 Variables

Once the parameters are detailed, this section focuses on defining the variables. A total of 31 design variables are considered in the economic optimization of the RCPHF. These include three geometrical variables that define the depth of the upper slab (D_{US}), the bottom slab (D_{LS}) and the lateral walls (D_{LW}). Two variables relate to the concrete and passive reinforcement material grades, and a set composed of the remaining 26 variables relates to the passive reinforcement configuration. This set, represented in Figure 2.2, allows the complete definition of the passive reinforcement design corresponding to the diameter and number of bars of the longitudinal reinforcement and the diameter and branch spacing of the shear reinforcement of the structure.

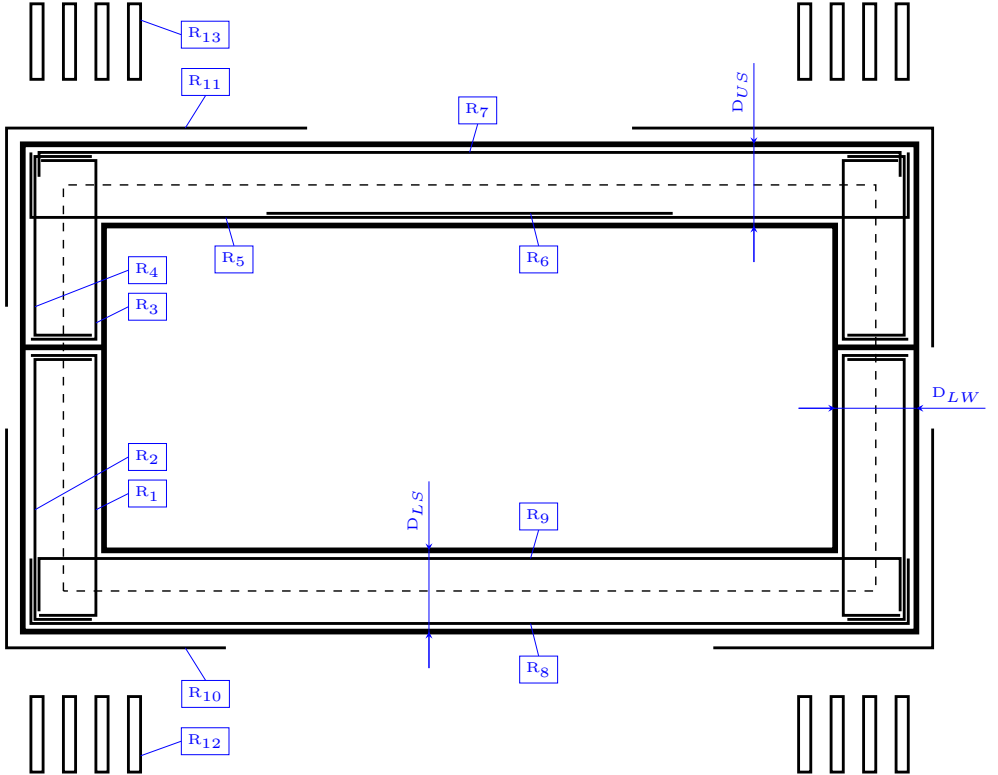


Figure 2.2: Set of variables considered in the RCPHF optimization problem.

Table 2.3: Variables considered in the optimization problem.

Geometrical variables			Num. values	Range values
Upper slab depth	(m)	D_{US}	41	0.40 to 1.20
Lower slab depth	(m)	D_{LS}	41	0.40 to 1.20
Lateral walls depth	(m)	D_{LW}	41	0.40 to 1.20
Materials variables				
Concrete grade	(MPa)	C	4	25 to 40
Steel grade	(MPa)	S	2	400 or 500
Passive reinforcement variables				
Flexural reinforcement R_1	(mm)	ϕ_{R_1}	6	10 to 32
	(bars)	n_{R_1}	9	4 to 12
Flexural reinforcement R_2	(mm)	ϕ_{R_2}	6	10 to 32
	(bars)	n_{R_2}	9	4 to 12
Flexural reinforcement R_3	(mm)	ϕ_{R_3}	6	10 to 32
	(bars)	n_{R_3}	9	4 to 12
Flexural reinforcement R_4	(mm)	ϕ_{R_4}	6	10 to 32
	(bars)	n_{R_4}	9	4 to 12
Flexural reinforcement R_5	(mm)	ϕ_{R_5}	6	10 to 32
	(bars)	n_{R_5}	9	4 to 12
Flexural reinforcement R_6	(mm)	ϕ_{R_6}	6	10 to 32
	(bars)	n_{R_6}	10	3 to 12
Flexural reinforcement R_7	(mm)	ϕ_{R_7}	6	10 to 32
	(bars)	n_{R_7}	9	4 to 12
Flexural reinforcement R_8	(mm)	ϕ_{R_8}	6	10 to 32
	(bars)	n_{R_8}	9	4 to 12
Flexural reinforcement R_9	(mm)	ϕ_{R_9}	6	10 to 32
	(bars)	n_{R_9}	9	4 to 12
Flexural reinforcement R_{10}	(mm)	$\phi_{R_{10}}$	6	10 to 32
	(bars)	$n_{R_{10}}$	10	3 to 12
Flexural reinforcement R_{11}	(mm)	$\phi_{R_{11}}$	6	10 to 32
	(bars)	$n_{R_{11}}$	10	3 to 12
Shear reinforcement R_{12}	(mm)	$\phi_{R_{12}}$	7	8 to 32
	(m)	$s_{R_{12}}$	7	0.10 to 0.40
Shear reinforcement R_{13}	(mm)	$\phi_{R_{13}}$	7	8 to 32
	(m)	$s_{R_{13}}$	7	0.10 to 0.40

It is relevant to note that each of the optimization variables is discretized. The variables corresponding to the width of the slabs and lateral walls can adopt values ev-

ery two centimetres within the stipulated range. In addition, the shear reinforcement branches can take spacing values every five centimetres within the limit values.

The diameter of the passive reinforcement can vary along the standard's values between 10 and 35 mm, and the number of bars can be any integer within the defined range. In this context, the set of variables considered, together with the number of values they can adopt during the optimization process of the frame and the limit values established, are listed in Table 2.3.

2.2.3 Constraints

As mentioned in Section 2.2, the structure object of the optimization process must comply with a series of constraints represented by Equation (2.3). In the case of the RCPHF, the considerations to be taken into account are those established by the regulations [93], [94]. In addition, the Spanish recommendations were considered [90], [95]. The constraints can be broadly classified into two separate groups. The first corresponds to the Ultimate Limit States (ULS), and the second one to the Service Limit States (SLS). The ULS are constraints that must ensure the structural resistance and integrity of the frame when it is under stress incurred by the acting loads. The SLS are responsible for ensuring the correct serviceability of the structure during its service life. A step prior to the verification of the ULS and SLS compliance is the calculation of the RCPHF stress and displacements. A two-dimensional model of the frame has been considered for the linear elastic analysis of the structure.

Employing the traditional design process, the passive reinforcement is initially defined so that the flexural ULS are verified. Then, the cracking SLS compliance is checked, and the shear reinforcement is sized to verify the shear ULS without modifying the defined flexural reinforcement. This procedure leads to structural designs that comply with the standard and are structurally sound. However, these do not make optimal use of the required materials. In this context, the proposed combinatorial optimization does not contemplate the frame's passive reinforcement design under traditional criteria. This raises considerations such as eliminating or significantly reducing shear reinforcement to be replaced by localized increases in flexural reinforcement. Such considerations can lead to non-traditional designs with reduced costs and lower environmental impact in terms of associated CO₂ emissions, something relevant to the sustainability considerations presented in Section 2.1.

In the present study, the initial verification consists of the compliance of the shear ULS by comparison with the compression and tensile exhaustion limit values. This process also includes calculating the tensile stress increase in the flexural reinforcement derived from the shear stress. This increase is then considered by applying the

proportional offset to the bending moment law, appropriately increasing the magnitude of the bending moment in each affected section. The next step consists of the verification of the flexural ULS. In order to do so, the calculation of the interaction diagram of each of the study sections is carried out. After doing so, it is verified that the point defined by the acting axial force and bending moment is located within this diagram. Once the flexural ULS is verified, the cracking SLS is checked by calculating the crack opening and comparing it with the maximum standard value for the environmental conditions. Next, the deformed state of the structure is checked by limiting the maximum displacement in the central section of the upper slab to 1/250 times the horizontal span. In addition, compliance with the minimum amounts of longitudinal and shear reinforcement is verified, as well as the reinforcement for cracking control. Due to the consideration of a two-dimensional analysis, which does not allow the study of the transversal stresses, the transversal reinforcement is calculated as a result of the longitudinal design, complying with the minimum standard values.

The verification process is carried out by means of the developed software, which considers a model consisting of 40 members and nodes. The stresses of the RCPHF are calculated, and then the geometric and constraints are checked. After the verification, the software provides results regarding the material measurements, final cost, associated CO₂ emissions and a series of structural verification coefficients. These represent the relation between the stress associated with the acting loads (A_s) and the resistant limit of the structure (R_s), which corresponds to Equation (2.4).

$$\frac{A_s}{R_s} \geq 1 \quad (2.4)$$

If all the verification coefficients are greater or equal to one, the RCPHF verifies the required ULS, SLS, minimum and maximum reinforcement amounts and the necessary geometrical checks.

2.2.4 Computational Model

The developed software obtains the deflections and internal stresses of the structure by applying the displacement method. This method consists of the solution of the matrix Equation (2.5).

$$|\mathbf{F}| = [\mathbf{K}] \cdot |\mathbf{U}| + |\mathbf{F}_0| \quad (2.5)$$

The procedure starts with the complete definition of the structure's stiffness matrix $\mathbf{K}$. This is obtained by assembling each member's stiffness matrices according to their

position in the model, considering the member's characteristics at both end nodes. The term $\mathbf{F}_0$ represents the perfect embedding forces vector, while $\mathbf{U}$ corresponds to the structure's displacements vector. The product of the stiffness matrix and the displacement vector, subsequently adding the perfect embedding forces vector, allows obtaining the structure's internal forces vector $\mathbf{F}$.

The internal stress vector is calculated for each of the RCPHF load cases. Afterwards, based on the linear elastic hypothesis, it is possible to apply the superposition principle. This way, the load stresses are combined to obtain the complete set of design stress envelopes.

2.3 Methodology

The three metaheuristic techniques applied to solve the optimization problem are simulated annealing, threshold accepting and old bachelor's acceptance. These are algorithms with relatively simplistic operating principles that allow the resolution of complex combinatorial optimization problems. While obtaining high-quality solutions, these techniques cannot ensure convergence to the global optimum of the considered problem.

Based on the local search principle, the algorithms start from a randomly generated initial solution to which a previously established movement is applied to generate a new solution within the neighbourhood of the current one. The value of the objective function is evaluated and compared with the current one. In case of improvement, when compared to the current solution, the new solution is accepted directly. However, the interesting feature of the three techniques applied in the present study is the ability to accept solutions that worsen the current one. This is performed according to an established criterion specific to each metaheuristic algorithm. This criterion can be probabilistic, as in the case of simulated annealing, or deterministic, as in the case of threshold accepting and old bachelor's acceptance algorithms. This way, premature convergence to low-quality optima can be avoided, allowing the algorithm to explore the solution space thoroughly.

In the present study, due to the number of design variables and the set of values that each of them can adopt during the optimization process, the solution space has a dimension of $2.1 \cdot 10^{28}$. The magnitude of this solution space makes it feasible to state that a complete exploration does not conform to a possible way to improve the design of the considered structural typology. In this context, thanks to the aforementioned ability to converge to high-quality optimums while maintaining adequate computational costs, metaheuristic algorithms are an excellent tool for solving combinatorial optimization problems with similar characteristics [34].

2.3.1 Simulated Annealing Algorithm

Turning to the details of the algorithms applied, the first is simulated annealing, SA henceforth. First proposed by Kirkpatrick et al. [96], the SA algorithm operates based on the physical modifications at a microstructural level that the materials undergo during the thermal annealing process. In this process, the materials are subjected to a high initial temperature and then cooled slowly at a cooling coefficient rate. In the beginning, the material presents configurations with high internal energy. However, during the cooling, the microstructure undergoes a series of modifications in search of the fundamental state, a stable crystallization state with the lowest internal energy associated. Thus, during the cooling, the material passes through crystallization states with decreasing internal energies. This process is governed by the Boltzmann energetic Equation (2.6).

$$e^{-(\Delta E/T)} \quad (2.6)$$

In this equation, ΔE is the energy increment of the new configuration, and T is the temperature at that time of the process. In this context, the SA algorithm resembles each of the combinatorial optimization problem's feasible solutions with the different crystallization states of the material. Thus, the value of the objective function for each of these solutions is equated to the internal energy associated with that particular crystallization state.

The algorithm's operation, represented in the flowchart corresponding to Figure 2.3, parts from a randomly generated initial feasible solution S_0 for which the objective function, $f(S_0)$, is evaluated. A new solution, S_1 , is then generated by applying a movement, and its objective function value, $f(S_1)$, is then evaluated. This movement consists in varying the magnitude of a certain number of the variables defining the current solution. Those solutions that present a lower cost than the current one are accepted directly. In the case of presenting a cost that involves a worsening of the current solutions, new solutions are accepted when the Boltzmann equation presents a value greater than a randomly generated value between 0 and 1. After this, the feasibility of the new solutions is evaluated by verifying compliance with the imposed constraints. If a feasible solution is found, the new solution, S_1 , becomes the current solution, S_0 . This process is repeated at a constant temperature for a specific number of iterations, denoted as Markov's chain. After the completion of Markov's chain, the temperature of the problem is geometrically reduced by applying the cooling coefficient k .

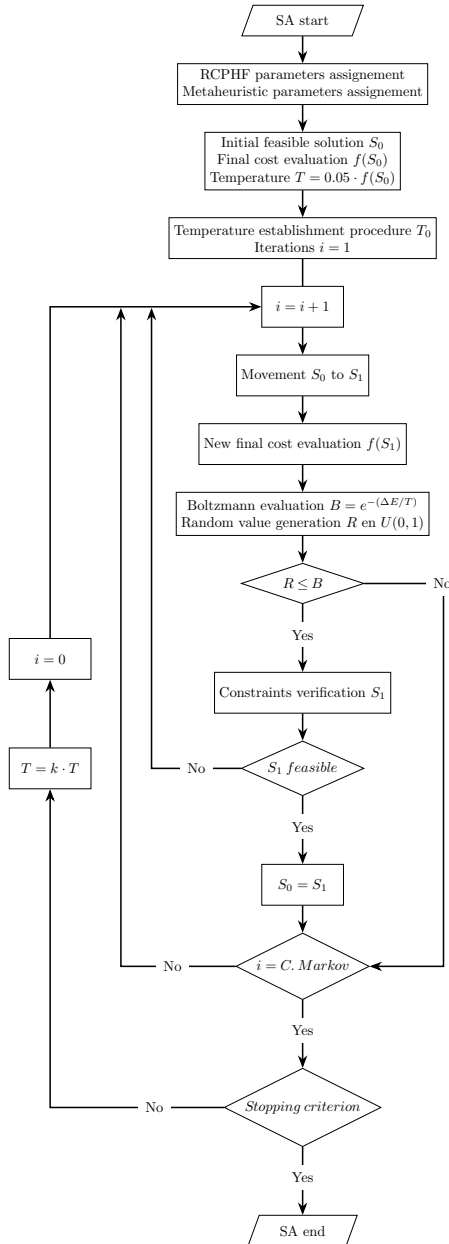


Figure 2.3: Flowchart of the simulated annealing (SA) process.

The algorithm's evolution and exploration of the solution space are highly conditioned by the correct establishment of the complete set of parameters that define it. In the case of the initial temperature, the approach proposed in Medina [97] is considered since it has proved to function in a correct manner in previous studies of similar characteristics [32], [33]. The optimization process finishes once the temperature of the problem is equivalent to a small percentage of the initial temperature or when, during a certain number of consecutive Markov chains, a new solution that improves the current one is not found.

The quality of the results obtained by applying the SA algorithm in the resolution of the combinatorial optimization problems of similar characteristics to the one considered in the present study directly depends on the correct calibration and definition of the metaheuristic parameters [37]. Thus, in order to achieve adequate performance, nine different metaheuristics are developed. These result from combining Markov chains between 500 and 5000 iterations and cooling coefficients between 0.80 and 0.95. Based on the results obtained in studies with similar characteristics, a maximum number of five Markov chains in which the new solutions do not improve the current ones is established as a stopping criterion. In addition, a minimum temperature equivalent to 5% of the initial temperature of the problem is set as a termination criterion.

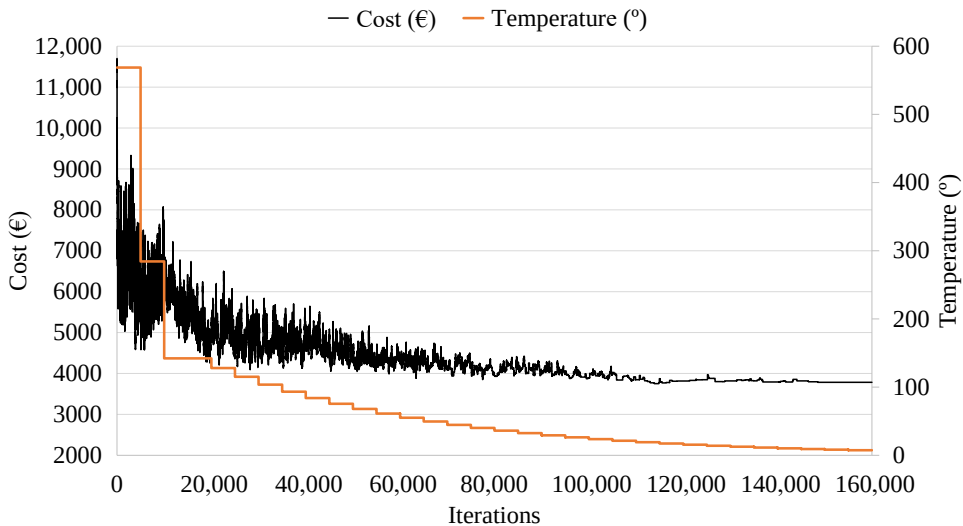


Figure 2.4: Simulated annealing trajectory for the cost and temperature as a function of iterations.

Figure 2.4 represents the RCPHF cost evolution for a generic execution of the developed SA algorithm. It shows the process of setting the initial temperature, the exploration of the solution space, as well as the intensification phase, where the algorithm studies the high-quality optimum towards which it has converged.

2.3.2 Threshold Accepting Algorithm

The threshold acceptance algorithm, TA henceforth, is the second of the metaheuristics applied in resolving the problem. Developed by Dueck and Scheuer [98] as an alternative to the SA, the TA presents a similar operation to the one described for SA. The TA algorithm starts with a randomly generated initial feasible solution S_0 for which the value of the objective function is evaluated. After this, a new solution is generated by applying a move, and the value of the objective function $f(S_1)$ is evaluated. If it presents a lower cost, it is directly accepted. Otherwise, the new solution is accepted if the cost increase, when compared to the current one, is smaller than a certain threshold. The feasibility of the new solution is then evaluated and accepted as the current solution if the imposed set of constraints is verified. This process is repeated for the same threshold for a given number of iterations called chain, after which the threshold is geometrically reduced at a rate of the threshold reduction coefficient [12], [99]. It can be noted that the SA and TA algorithms operation is quite similar, differing in the fact that the acceptance criterion of the SA is probabilistic, while the TA is deterministic. The detailed operation of the developed TA can be seen in the flowchart presented in Figure 2.5.

Similar to the SA algorithm, nine different metaheuristics are created, combining chain lengths between 500 and 5000 iterations and threshold reduction coefficients between 0.8 and 0.95. In addition, stop and termination criteria analogous to those detailed for the SA algorithm are established. Figure 2.6 shows a generic cost evolution for the programmed TA algorithm. This clearly distinguishes the initial threshold setting phase, followed by the exploration phase, where the algorithm evaluates RCHPC designs with fundamentally different characteristics thanks to the fact that its capacity to accept solutions that worsen the current one is relatively high at that time. Finally, the intensification phase is initiated towards a high-quality optimum.

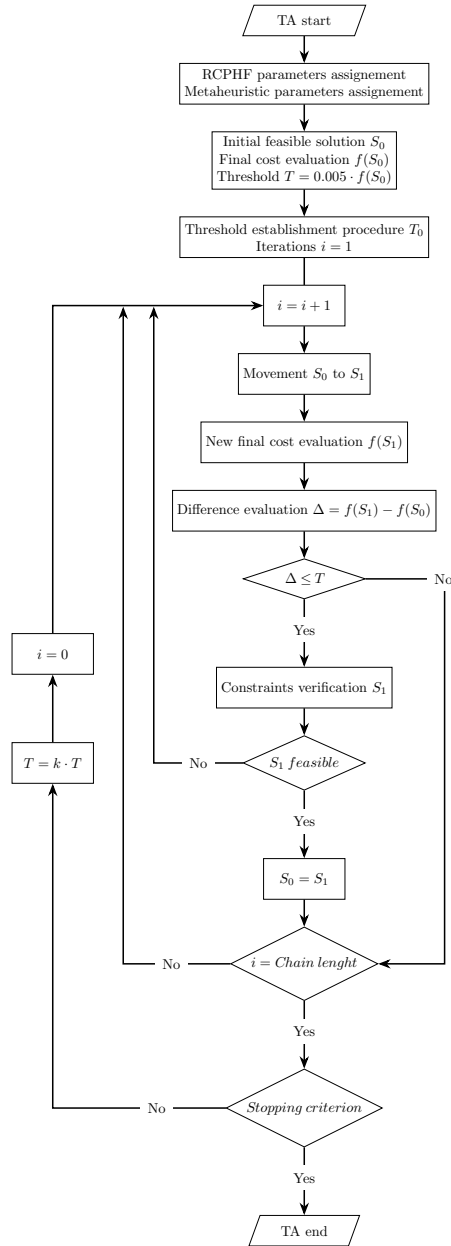


Figure 2.5: Flowchart of the threshold accepting (TA) process.

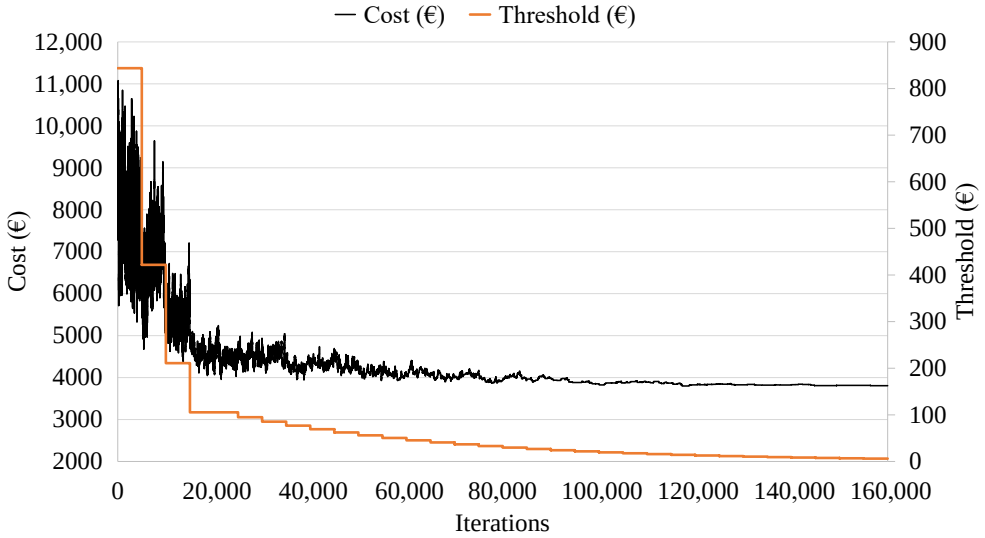


Figure 2.6: Threshold accepting trajectory for the cost and temperature as a function of iterations.

2.3.3 Old Bachelor's Acceptance Algorithm

The third and last of the metaheuristic techniques applied in the present study is the so-called old bachelor's acceptance algorithm, hereafter referred to as OBA. The OBA is a modified version of the TA algorithm described in Section 2.3.2. Instead of starting with a relatively high initial threshold that geometrically decreases over time, Hu et al. [100] proposed a modified algorithm which starts with a null threshold that then decreases or increases according to the acceptance or rejection of new solutions [101]. This quality allows the OBA algorithm to interweave exploration and intensification phases, which can be particularly interesting in problems of specific characteristics. In this context, the operation of the programmed OBA can be seen in Figure 2.7. The algorithm starts with a randomly generated initial feasible solution S_0 for which the value of the objective function is evaluated $f(S_0)$. Then, a new solution is generated by applying a move, and its objective function $f(S_1)$ is evaluated and compared with the current one. If the new solution improves the current solution or worsens it by a magnitude below the threshold at that time, the new solution is accepted and proceeds to be verified. It is accepted as the current solution if it is a feasible solution. Otherwise, it is rejected. In case the new solution is of better quality than the previous one, the OBA algorithm considers that the current region of the solution space can contain a good quality optimum. Thus, it is interesting to start an intensification phase, which is achieved by reducing the threshold at the rate of a pre-set variation factor $\Delta_{(-)}$. This factor is applied each time the new solution

is better than the previous one. On the other hand, if the new solution worsens the current one, the OBA considers that the current region of the space solution does not present particularly interesting qualities. Therefore, the algorithm must explore in order to find an optimum solution. In order to initiate the exploration phase, the threshold is increased at the variation factor rate $\Delta_{(+)}$. Unlike the described SA and TA algorithms, the OBA does not have a control parameter that decreases over time. Thus, the stopping criterion limits the process's duration by setting a maximum number of iterations (M).

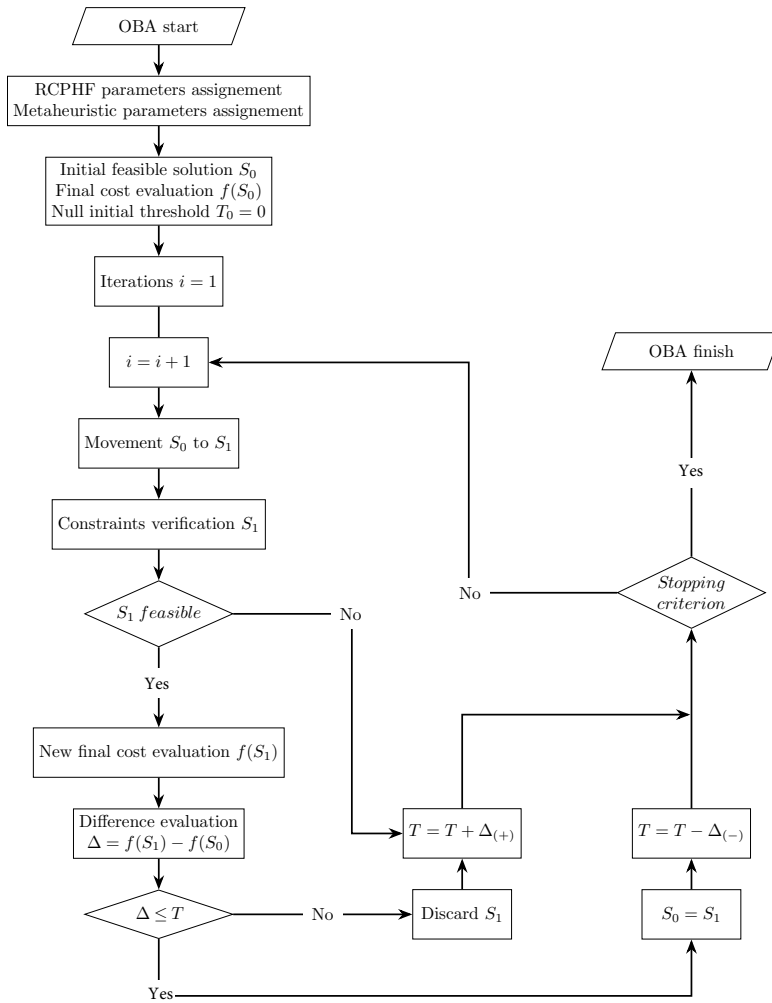


Figure 2.7: Flowchart of the old bachelor's acceptance (OBA) process.

2.4 Results

Section 2.2 provided a comprehensive overview of the combinatorial optimization problem posed in the present study. This includes the complete definition of the parameters, variables, constraints and objective function of the problem. In addition, Section 2.3 described the operation of the three metaheuristic techniques applied in order to solve it. This section presents the results obtained for the economic optimization of the RCPHF. These are referred to as the final cost of the frame, considered as the objective function of the optimization problem, as well as the associated CO₂ emissions.

2.4.1 SA Results

The SA algorithm, described in the previous section, starts with an initial feasible solution that it randomly generated. In addition, it requires the definition of the metaheuristic parameters, such as initial temperature, length of Markov's chain, cooling coefficient and stop or termination criterion. Following the process mentioned in Section 2.3.1 [97], an arbitrary temperature equivalent to five per cent of the final cost of the initial solution is set. Then, a Markov chain is run at that temperature, and the acceptance rate of worse solutions using the Boltzmann function is evaluated. If the said rate is below a specific lower limit, the algorithm is "cold". It presents no exploration capability, which is solved by doubling the temperature and repeating the process.

On the other hand, if the acceptance rate exceeds an upper limit, the SA algorithm is too "hot", which can lead to the loss of interesting solution qualities. To overcome this, the temperature is halved, and another Markov chain is run. This initial temperature-setting process is repeated until the acceptance rate is between 20% and 40%, at which point the initial temperature of the problem is fixed. Nine heuristics are used with Markov chain lengths of 500, 1000 and 5000 iterations and cooling coefficients of 0.80, 0.90 and 0.95. Two stopping criteria are established, the first is to terminate the process when the temperature reaches 5% of the initial temperature. Furthermore, the second is to terminate if, after five consecutive Markov chains, no solution of higher quality than the current one has been generated.

Table 2.4 presents the costs and associated CO₂ emissions and average and minimum values, obtained by each of the applied SA algorithms. In addition, the specific parameters of each of the metaheuristics are detailed.

The minimum values obtained by each of the nine metaheuristics are represented in Figure 2.8 as a function of the computation cost. The best result regarding the final

Table 2.4: Algorithm parameters in addition to the minimum and mean final cost and associated CO₂ emissions results obtained.

SA algorithm	Markov's chain	Temperature coefficient	Iterations	Minimum cost (€)	Mean cost (€)	Minimum CO ₂ (kg)	Mean CO ₂ (kg)
SA1	500	0.80	8158	3821.57	4003.31	5831.25	6200.67
SA2	500	0.90	15,451	3755.27	3828.82	5274.81	5596.65
SA3	500	0.95	26,497	3713.99	3804.87	5463.01	5611.49
SA4	1000	0.80	15,338	3709.59	3837.97	5316.74	5667.25
SA5	1000	0.90	31,686	3761.14	3825.08	5320.67	5660.71
SA 6	1000	0.95	46,246	3708.99	3810.27	5314.10	5725.23
SA7	5000	0.80	84,257	3691.30	3787.28	5241.13	5455.81
SA8	5000	0.90	138,728	3707.36	3769.21	5458.70	5585.77
SA9	5000	0.95	266,363	3683.84	3749.43	5311.64	5569.85
TA algorithm	Chain	Threshold coefficient	Iterations	Minimum cost (€)	Mean cost (€)	Minimum CO ₂ (kg)	Mean CO ₂ (kg)
TA1	500	0.80	7416	3805.03	3984.38	5663.23	6080.31
TA2	500	0.90	14,517	3675.73	3873.48	5268.30	5747.97
TA3	500	0.95	25,376	3719.86	3797.42	5366.11	5665.19
TA4	1000	0.80	17,857	3759.21	3854.84	5437.94	5776.78
TA5	1000	0.90	27,859	3766.73	3819.90	5476.89	5732.29
TA6	1000	0.95	27,913	3705.83	3771.47	5290.85	5672.44
TA7	5000	0.80	79,219	3682.57	3741.59	5290.80	5586.77
TA8	5000	0.90	146,111	3697.23	3762.97	5292.91	5648.35
TA9	5000	0.95	253,145	3678.59	3711.77	5372.34	5488.02
OBA algorithm	Iteration limit		Iterations	Minimum cost (€)	Mean cost (€)	Minimum CO ₂ (kg)	Mean CO ₂ (kg)
OBA	500,000		48,195	3804.83	3855.26	5714.00	5637.64
OBA1	500,000		32,028	3909.94	-	5430.45	-
OBA2	500,000		48,195	3804.82	-	5714.00	-
OBA3	500,000		49,409	3808.72	-	5785.66	-
OBA4	500,000		41,295	3847.44	-	5472.21	-
OBA5	500,000		48,878	3819.64	-	5551.71	-
OBA6	500,000		15,698	3874.68	-	6000.80	-
OBA7	500,000		13,336	3830.57	-	5927.97	-
OBA8	500,000		14,118	3866.86	-	5522.67	-
OBA9	500,000		47,809	3934.59	-	5333.26	-

cost of the RCPHF was obtained by applying the metaheuristic SA9. With a Markov chain length of 5000 iterations and a cooling coefficient of 0.95, this SA algorithm provides a feasible optimal solution with a final cost of EUR 3863.84 per linear meter. Generally, it can be noted that the SA algorithms with longer chain lengths manage to reach the best quality solutions. However, it is interesting to assess to what extent the computational cost associated with such lengths compensates for reductions in the final cost that may not be sufficiently large.

Concerning the associated emissions, the optimal frame generates roughly 5.3 tons of CO₂ that are emitted to the atmosphere as a result of its manufacture. With 5.24 tons of CO₂, the RCPHF design obtained with the SA7 algorithm presents slightly lower emissions. Both this and the aforementioned design use C25/30 concrete and B 500 S steel. The main difference is that the SA7 design presents denser

reinforcement while using smaller concrete amounts compared to the SA9 design with the lowest final cost. As stated in Section 2.1, this is somewhat to be expected since most of the associated CO₂ emissions originate in cement fabrication.

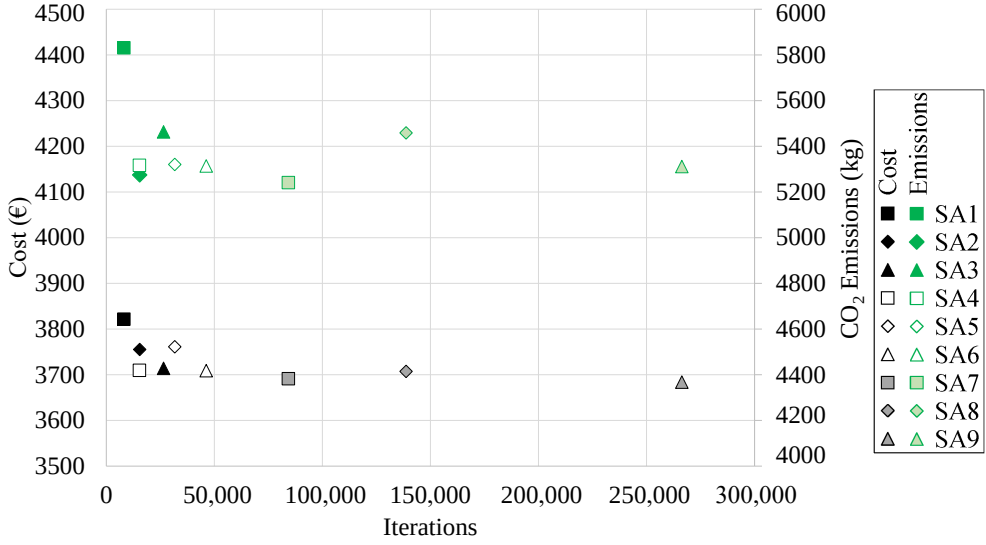


Figure 2.8: Minimum final cost and associated CO₂ emissions obtained by the SA algorithm.

2.4.2 TA Results

Moving on to the results obtained by applying the second metaheuristic technique, the same procedure as the one described for the SA is considered in the definition of the initial threshold of the TA algorithm. Using the method proposed in [97], an arbitrary threshold equivalent to 0.5% of the final cost of the randomly generated initial feasible solution S_0 is set. Once the initial threshold is set, the TA runs a chain, and the acceptance rate by threshold comparison is evaluated. If the rate is lower than 20%, the algorithm will not be able to accept solutions that worsen the current one, which can lead to premature convergence to a low-quality local optimum. In order to avoid this, the threshold is doubled and the process restarted. On the other hand, in case the acceptance rate is above 40%, the TA algorithm will accept solutions much worse than the current one. This is something that could mean the loss of interesting qualities of a solution that conforms to a high-quality optimum. To avoid this, the threshold is halved, and a new chain is run. As in the SA algorithm, this process is repeated until the acceptance rate sits between 20% and 40%, the moment at which the algorithm starts the optimization process. Nine

different algorithms are developed combining chain lengths of 500, 1000 and 5000 iterations and threshold reduction coefficients of 0.80, 0.90 and 0.95. A stopping criterion is set when the threshold reaches 5% of the initial threshold. A termination criterion is set in case new solutions fail to improve the current one in five consecutive chains.

Table 2.4 shows the minimum and average final cost and CO₂ associated emissions values obtained by applying each of the TA algorithms in the economic optimization of the RCPHF. In addition, each of the heuristic parameters that configure the algorithms is detailed. The minimum cost values as a function of the computation cost are shown in Figure 2.9.

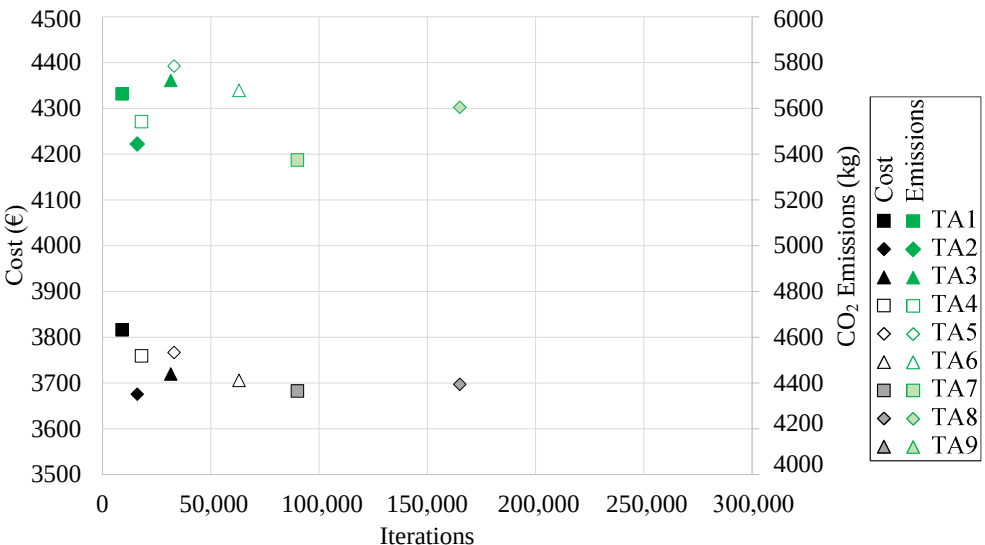


Figure 2.9: Minimum final cost and associated CO₂ emissions obtained by the TA algorithm.

The RCPHF with the lowest final cost was obtained by employing the TA2 algorithm. This is particularly interesting as said TA algorithm presents a chain length of 500 iterations, locating it in the lower bound of the chain length values. The optimum frame has a final cost of EUR 3675.73 and results in the emission of 5268 kg of CO₂ into the atmosphere. In this case, the RCPHF with the lowest final cost also happens to be the one that incurs the most negligible CO₂ emissions. This shows that in most cases minimal cost matches with the lowest CO₂ associated emission values.

It is of particular relevance to note that with an associated computational cost considerably higher than the TA2 algorithm the TA9 metaheuristic manages to achieve a slightly higher final cost design. This, together with other observations concerning

the performance of each of the designed algorithms and the particular characteristics of the optimal RCPHF are detailed in the discussion of the results.

2.4.3 OBA Results

This section focuses on the results obtained through the third and last of the metaheuristic techniques applied in the economic optimization of the RCPHF. As stated in Section 2.3.3, the OBA algorithm starts with a randomly generated initial feasible solution and an initial threshold equivalent to zero. After this, depending on the acceptance or rejection of new solutions, the threshold varies at the rate of the variation coefficients. In the case of acceptance, the threshold is decreased by $\Delta_{(-)}$, and in the case of rejection, the threshold is increased by $\Delta_{(+)}$. The initial implementation of the OBA algorithm considered a single magnitude equivalent to five monetary units for both of the variation coefficients. However, initial runs of the OBA algorithm showed an apparent lack of convergence to good quality optima. An initial study of the process noted that this was a direct consequence of the high exploration capability of the algorithm since the threshold increased excessively when a new solution was rejected. This negatively affected the OBA's capability to initiate appropriate intensification phases. In order to overcome this lack of convergence, differentiated values for the variation coefficients $\Delta_{(-)}$ and $\Delta_{(+)}$ were considered, maintaining the EUR 5 coefficient $\Delta_{(-)}$ while limiting the $\Delta_{(+)}$ to one-fifth of its previous value. This modification in the metaheuristic's parameters manages to sufficiently limit the exploration capability of the OBA algorithm, allowing it to enter prolonged intensification phases and study high-quality solutions.

Once tuned, considering a termination criterion of 500,000 iterations, the OBA algorithm is applied nine different times, obtaining the results presented in Table 2.4. These results encompass the minimum and average final cost and associated CO₂ emission values obtained by applying each of the nine OBA algorithms. In this context, Figure 2.10 shows the evolution of the final cost obtained by each OBA algorithm as a function of the computational cost associated with obtaining each of these optimal RCPHF designs.

The optimum RCPHF presents a final cost of EUR 3804.83 per linear meter, incurring 5.7 tons of CO₂ emission into the atmosphere. The optimal design reached by the OBA algorithm presents a slightly higher final cost than those obtained by the SA and TA algorithms. Although the OBA design might indeed be able to improve traditional designs used for the considered structural typology, it is interesting to evaluate which of the metaheuristics applied achieves the best results. This, together with other considerations, is detailed in the following section.

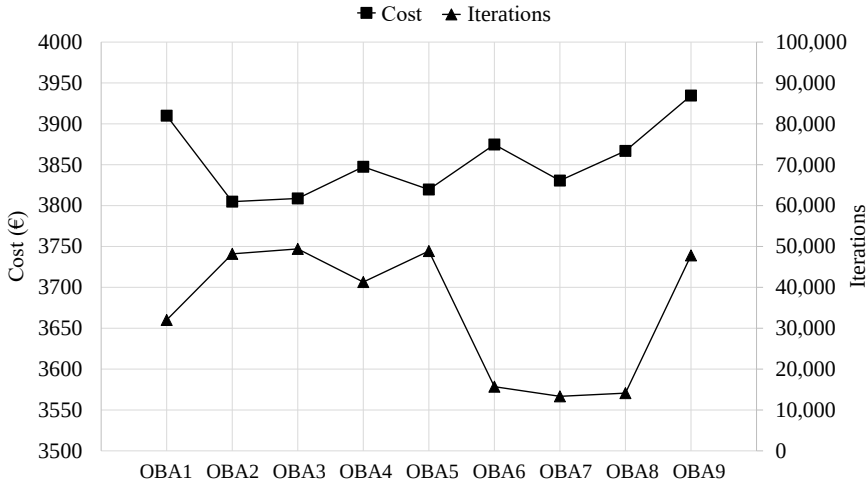


Figure 2.10: Minimum final cost and associated computational cost for each of the OBA algorithm runs.

2.5 Discussion

This section discusses the results obtained by applying each of the three metaheuristic techniques described in Section 2.3 to the combinatorial optimization problem detailed in Section 2.2. Thus, Table 2.5 summarises the final costs and associated CO₂ emissions obtained as a result of the RCPHF economic optimization developed in the present study. In addition, some of the most relevant characteristics of the RCPHF, such as the upper slab and lateral wall depths and the upper slab flexural reinforcement area are presented.

Considering the unit costs shown in Table 2.1, a reference RCCPF with the same horizontal span, height and earth cover as the RCPHF considered in the present study presents a final cost of EUR 4867.4 per linear meter [69], [92]. This means that the algorithms applied in solving the economic optimization achieve reductions of 24.32% in the case of the SA, 24.49% in the TA algorithm and 21.75% by applying the OBA algorithm. In addition, the cast-in-place frame would incur the emission of 7608.97 kg of CO₂ to the atmosphere, a considerably higher value when compared with the proposed modular structure.

As stated in Section 2.1, the main fundament behind the economic optimization of the RCPHF is the fact that the final cost is a direct representation of the use of materials. Thus, it also provides a comprehensive representation of the associated CO₂ emissions. In this context, reducing EUR 1 in the final cost of the RCPHF using

Table 2.5: Summary of the reference and the SA, TA and OBA algorithms results.

		Reference	SA	TA	OBA
Final cost	(€)	4867.64	3683.84	3675.73	3804.83
Associated CO ₂ emissions	(kg)	7608.97	5311.64	5268.30	5714.00
Upper slab depth	(m)	0.75	0.82	0.82	0.86
Lateral walls depth	(m)	0.44	0.40	0.40	0.46
Upper slab flexural reinforcement	(mm ²)	4785.50	2827.43	2827.43	2412.74
Final cost reduction	(%)	-	24.32	24.49	21.75
Associated CO ₂ emissions reduction	(%)	-	30.19	30.76	24.90

the SA algorithm allows for avoiding the emission of 1.94 kg of CO₂. This corresponds with the avoidance of a 1.96 kg CO₂ per euro reduction for the TA and 1.72 CO₂ kg per euro in the case of the OBA algorithm. This is in line with values presented in studies of similar characteristics [32].

Regarding the characteristics of the frames, the RCPHF designs present upper slabs of slightly greater depth when compared to the reference RCCPF. This solves the localized reduction of the flexural reinforcement of the upper slab, an area which is considerably more significant in the traditional cast-in-place design. In the case of the designs obtained by the TA and SA algorithms, the lateral walls are four centimetres slimmer than the cast-in-place reference. However, in the case of the OBA algorithm, the lateral walls present slightly greater depth, being two centimetres greater than the cast-in-place reference frame and a notable six centimetres greater than the TA and SA results.

It is particularly relevant to evaluate the performance of the applied metaheuristic techniques. In this context, it is especially interesting to understand that each of the algorithms cannot be evaluated by considering only the final cost of the optimal framework achieved via its application in the resolution of the economic optimization. Thus, given the nature of the metaheuristic techniques, it is especially interesting to evaluate the computational cost associated with obtaining each of these optimal solutions. As stated before, algorithms with longer chains seem to achieve better solutions for the SA algorithm, something similar happening with the TA, even though the minimum cost is achieved using the shorter chain length. However, it is crucial to understand whether the increase in computational cost associated with the higher bounds of such parameters is compensated by the difference in cost compared to other optimal solutions with much lower computational costs. In this context, Figure 2.11 represents the Pareto front of the combinatorial optimization problem. This corresponds to the union of each of the algorithms that conform to a Pareto optimum when considering the RCPHF final cost and the associated computational cost. In

order to be considered so, the algorithm must provide a solution with a restrained final cost while maintaining adequate computational cost. In this context, it can be noted that part of the SA algorithms sit close to the front. However, it is highly conditioned by the TA2 algorithm due to the fact that it obtains a high-quality solution with quite a low computational cost. On the other hand, the OBA algorithm sits considerably far from the area of interest because, considering the computational cost, it does not achieve optimums of sufficient quality that justify its application when compared with the SA or TA algorithms.

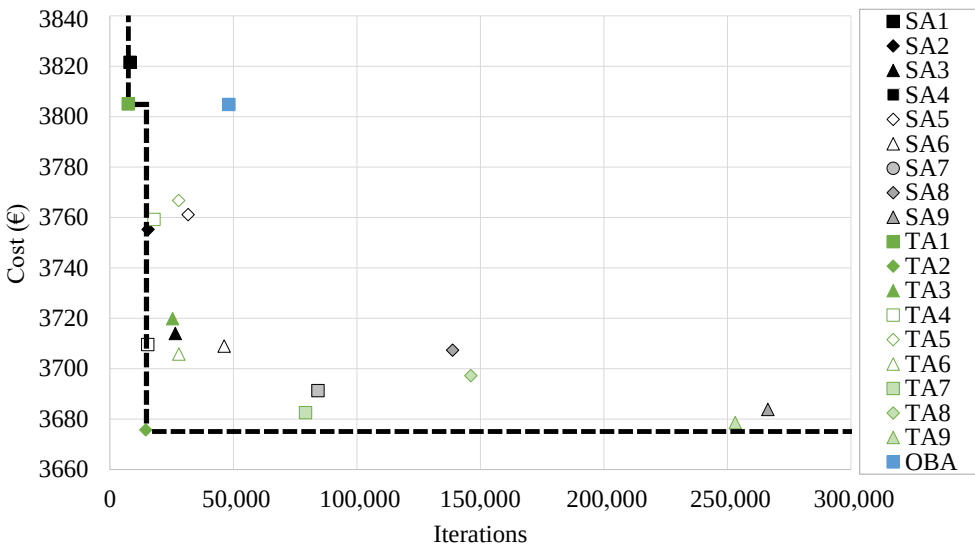


Figure 2.11: Pareto's front of the results obtained by the three metaheuristic techniques.

The optimal RCPHF obtained by applying the metaheuristic algorithms present several common characteristics. In this context, Table 2.6 contains the value of each of the different design variables of the optimal frames. It can be noted that the set of optimal RCPHF is characterized by slender sections of reduced depth with a dense passive reinforcement distribution. With reinforcement densities of 91 kg/m^3 in the case of the SA algorithm result, 89.12 kg/m^3 for the TA and 86.01 kg/m^3 in the case of the OBA. Some optimal designs present localized reductions in shear reinforcement, a lack solved by local increases in flexural reinforcement. The passive reinforcement density of the OBA algorithm result is slightly lower than those obtained by applying the rest of the considered metaheuristics. This reduction in the general passive reinforcement of the RCPHF is solved by increasing the upper slab and lateral wall depth. This results in using 6.75% and 5.68% more concrete when compared to the optimal RCPHF obtained by the SA and TA algorithms, respectively.

Table 2.6: Characteristics of the optimum RCPHF obtained by each metaheuristic technique.

Geometrical variables			SA	TA	OBA
Upper slab depth	(m)	D_{US}	0.82	0.82	0.86
Lower slab depth	(m)	D_{LS}	0.40	0.42	0.46
Lateral walls depth	(m)	D_{LW}	0.40	0.40	0.46
Materials variables			SA	TA	OBA
Concrete grade	(MPa)	C	25	25	25
Steel grade	(MPa)	S	500	500	500
Passive reinforcement variables			SA	TA	OBA
Flexural reinforcement R_1	(mm)	ϕ_{R_1}	16	12	16
	(bars)	n_{R_1}	7	12	6
Flexural reinforcement R_2	(mm)	ϕ_{R_2}	12	10	16
	(bars)	n_{R_2}	7	10	4
Flexural reinforcement R_3	(mm)	ϕ_{R_3}	10	10	12
	(bars)	n_{R_3}	8	8	7
Flexural reinforcement R_4	(mm)	ϕ_{R_4}	16	16	20
	(bars)	n_{R_4}	7	7	4
Flexural reinforcement R_5	(mm)	ϕ_{R_5}	20	20	25
	(bars)	n_{R_5}	9	9	6
Flexural reinforcement R_6	(mm)	ϕ_{R_6}	20	20	16
	(bars)	n_{R_6}	9	9	12
Flexural reinforcement R_7	(mm)	ϕ_{R_7}	12	16	12
	(bars)	n_{R_7}	11	6	7
Flexural reinforcement R_8	(mm)	ϕ_{R_8}	20	20	16
	(bars)	n_{R_8}	5	5	8
Flexural reinforcement R_9	(mm)	ϕ_{R_9}	10	10	10
	(bars)	n_{R_9}	4	4	5
Flexural reinforcement R_{10}	(mm)	$\phi_{R_{10}}$	12	12	12
	(bars)	$n_{R_{10}}$	8	8	7
Flexural reinforcement R_{11}	(mm)	$\phi_{R_{11}}$	10	10	12
	(bars)	$n_{R_{11}}$	4	4	7
Shear reinforcement R_{12}	(mm)	$\phi_{R_{12}}$	32	20	32
	(m)	$s_{R_{12}}$	0.35	0.15	0.40
Shear reinforcement R_{13}	(mm)	$\phi_{R_{13}}$	10	10	8
	(m)	$s_{R_{13}}$	0.35	0.35	0.40

2.6 Conclusions

In the present study, three metaheuristic techniques were applied to solve the final cost optimization of reinforced concrete hinged precast frames. The study's main objective is to improve and extend the current knowledge on this structural typology as a substitute for the traditional cast-in-place reinforced concrete frames. This is achieved by evaluating the CO₂ emissions associated with the optimal designs obtained under restrictive budgets. In this context, the authors consider it appropriate to draw the following conclusions:

- The TA and SA algorithms generate designs with very similar characteristics, achieving the lowest costs and associated CO₂ emissions. Reductions of EUR 1 in the final cost for a reference cast-in-place frame are equivalent to the avoidance of emitting 1.94, 1.96 and 1.72 kg of CO₂ in the case of SA, TA and OBA algorithms, respectively;
- Optimizing the final cost of a precast structure conforms to a suitable methodology aiming to reduce the use of materials. Thus, economic optimization allows the reduction of associated CO₂ emissions. Economic interest drives the industry, making this an especially interesting approach to optimal design;
- Optimal RCPHF designs present thin sections with reduced depths compared to traditional designs. This is solved with particularly dense passive reinforcement designs, which reach up to 91 kg/m³, 89.12 kg/m³ and 86.01 kg/m³ for the SA, TA and OBA algorithms, respectively;
- The optimal design with the lowest final cost obtained by the OBA algorithm presents a slightly lower passive reinforcement density than those obtained by applying the SA and TA. Upper slab and lateral wall sections with greater depths compensate for these reductions. Consequently, the final cost of the frame and the associated CO₂ emissions are higher than other optimal designs;
- The reduction in the use of materials from restricting the RCPHF final cost results in designs with lower self-weight. This also reduces the associated loads, limiting the structural requirements, which allows optimal use of the concrete and steel;
- The SA and TA algorithms found optimal design solutions where the values of the lateral walls and bottom slab take the minimum bound of the established range which may denote interest in slender designs. This is limited by the constructability conditions imposed. However, the study of this event is an avenue for improvement that will be considered in subsequent studies;

- The prefabrication of the considered structural typology conforms to a way of improvement in the use of natural resources when compared to the cast-in-place alternative. A complete study of the Life Cycle Assessment (LCA) of both structures and a parametric study conforms to a line of research under current development.

Chapter 3

Reinforced concrete precast hinged frames optimization through hybrid simulated annealing

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Abstract

Reinforced concrete precast hinged frames are commonly used in transportation infrastructure. Advances in optimization techniques lead to improvements in the traditional structural design process. These allow for minimizing factors such as the final cost of the structure. The present study developed the economic optimization of a reinforced concrete precast hinged frame. In order to do so, the hybrid metaheuristic technique of simulated annealing with a mutation operator was applied. The algorithm parameters were tuned utilizing a factorial Design of Experiments. This procedure allowed the algorithm to show excellent performance. Once tuned, the hybrid metaheuristic was applied, achieving designs with reduced final costs. Finally, a series of main characteristics are mentioned. The designs present reduced depths and considerably dense passive reinforcement designs. The results position the precast structure as an interesting alternative to similar cast-in-place structures.

Keywords: hinged frame; precast; reinforced concrete; optimization; hybrid metaheuristic

3.1 Introduction

The development of a nation is intricately linked to its infrastructure capacity for facilitating and keeping pace with its progress. Therefore, the construction, maintenance, and eventual decommissioning of the infrastructure in our immediate environment are essential for sustaining the progress of human socioeconomic activities [55]. Within this framework, reinforced concrete precast hinged frames (RCPHF) emerge as a prominent structural solution commonly utilized in transportation infrastructure. These structures play a crucial role in facilitating road crossings and drainage systems, thus establishing them as among the most prevalent structural typologies within the extensive web of road networks [70].

The continued advancement of optimization techniques, driven by the ever-increasing capability of computational tools available to the average technician, opens up new possibilities for contemplating alternative design processes that may result in superior outcomes [102], [103]. Structural design has traditionally parted from delineating a preliminary set of sectional characteristics. This initial draft of the structure is then checked for compliance. In cases where one or multiple sections incur non-compliance, either material grades or quantities are adjusted accordingly. While this approach yields structurally safe designs that meet standards' requirements, the final design remains significantly influenced by the technicians' ability, prior experience and technical expertise [104].

Utilizing exact techniques proves less effective in addressing most challenges encountered in structural design. This limitation primarily stems from the fact that, although these methods ensure the attainment of the global optimum solution, the computational costs grow exponentially as the number of considered factors increases [37], [105]. Structural design is inherently intricate, involving the generation of convoluted models encompassing many variables. The systematic acquisition of results for such a complex process poses a considerable challenge. In response to this challenge, utilizing metaheuristic techniques arises as a pragmatic solution, achieving high-quality optimal solutions while satisfying computational cost constraints [12], [36], [43]. These techniques frame the structural design as a combinatorial optimization problem resolved through metaheuristic algorithms. Consequently, they produce unconventional designs that, in addition to fulfilling the structural requisites, minimize a specific objective function [62], [89].

Optimizing various reinforced concrete structures, including prestressed decks [40]–[42], bridge piles [46], [106], and buttress walls [32], [107], has yielded significant results. Applying algorithms rooted in descent-based principles allows for substantial reductions in the overall construction costs of these structures. The cost reductions are directly derived from a more efficient utilization of materials. Furthermore, population-based algorithms exhibit several advantageous characteristics for tackling similar challenges [106], [108]. Combining both techniques allows for retaining the advantageous characteristics of descent-based search algorithms while accommodating the inherent positive variability associated with population-based algorithms [109], [110].

The present study focuses on the economic optimization of a reinforced concrete precast hinged frame (RCPHF) using a hybrid simulated annealing algorithm enhanced by incorporating a mutation operator. Economics is the primary driving force in the precast industry, and the ultimate cost of a structure directly reflects the materials employed in its construction. Consequently, pursuing cost minimization for the structure is a valid avenue for improvement. Proprietary software is developed to achieve this goal. The software is responsible for performing structural calculations, verifying ultimate limit states (ULS) and serviceability limit states (SLS), and subsequent optimization through the hybrid simulated annealing metaheuristic. The parameters defining this hybrid metaheuristic are calibrated through a fractional factorial design of experiments. Applying this technique in resolving combinatorial optimization challenges enables the generation of designs characterized by highly constrained costs that optimize material utilization to a significant extent.

3.2 Optimization Problem

The study poses the generation of RCPHF designs as a combinatorial optimization problem. The objective of minimizing the final cost of the structure is then the primary focus. The final cost is determined using Equation (3.1), wherein c_i represents the unit cost of each material and m_i represents the quantity of material used. The unit costs, presented in Table 3.1, are sourced from the BEDEC database of the Fundació Institut de Tecnologia de la Construcció de Catalunya [92]. Each design is subject to constraints to ensure the computational model accurately reflects real-world conditions. Furthermore, multiple checks are performed to verify that the design complies with the requirements established in current regulations [90], [93]–[95]. The complete set of constraints is generically expressed through Equation (3.2).

$$C(\vec{x}) = \sum_{i=1}^n c_i \cdot m_i(\vec{x}) \quad (3.1)$$

$$R(\vec{x}) \leq 0 \quad (3.2)$$

Table 3.1: Material grade and unit cost optimization values [92].

Material	Grade	Unit	Cost (€)
Concrete	C25/30	m ³	88.86
Concrete	C30/37	m ³	97.80
Concrete	C35/45	m ³	101.83
Concrete	C40/50	m ³	104.83
Steel	B 400 S	kg	1.40
Steel	B 500 S	kg	1.42

Beyond the objective function and the constraints, a combinatorial optimization problem necessitates the inclusion of parameters and variables. The information associated with these two components is essential for comprehensively defining the RCPHF design. Parameters consist of previously known data with values that remain constant throughout the optimization process. These may pertain to particular geometric properties of the structure, applied loads, or any other information essential for structural analysis and verification. Conversely, variables represent values subject to optimization through the hybrid simulated annealing algorithm. The variable magnitudes are the primary focus of design generation during optimization.

RCPHFs possess various geometric characteristics that exert significant influence over their design. The span (L) is a critical factor to consider, and in the context of

its intended application as a road crossing solution, a span length of ten meters is employed in this study. Another pivotal determinant is the clearance height of the frame (H), which is set at five meters within the scope of the current optimization. Furthermore, due to the modular nature of RCPHF, the hinge height (HR) is an adjustable parameter. For this study, it is presumed that the hinge height is 3/5 of the lateral wall's height, which equates to three meters measured from the central line of the lower slab. Lastly, the frame's burial depth (PE) is fixed at one and a half meters.

In conjunction with the geometric parameters, defining the attributes of the backfill soil and several essential values is required to ascertain the applied loads. Furthermore, specific environmental conditions and control levels are specified to determine the passive reinforcement nominal depth. The comprehensive list of parameters under consideration and their values utilized in the optimization process can be referenced in Table 3.2.

Table 3.2: Parameters considered for economic optimization.

Description		Parameter	Value
Free height	(m)	H	5
Horizontal span	(m)	L	10
Hinge height	(m)	HR	3
Earth cover	(m)	PE	1.50
Reinforced concrete specific weight	(kN/m ³)	γ_{HA}	25
Earth specific weight	(kN/m ³)	γ_{TR}	20
Earth internal friction angle	(°)	α	30
Uniform overload	(kN/m ³)	SU_{IAP}	10
Heavy traffic vehicle load	(kN/m ³)	CP_{IAP}	150
Concrete resistance reduction coefficient		γ_C	1.50
Steel resistance reduction coefficient		γ_A	1.15
Execution control level		NCE	Normal
Exposure class		CE	XC2

The final facet of the combinatorial optimization problem comprises the variables that, in conjunction with the parameters mentioned above, enable the comprehensive delineation of each RCPHF design. The optimization model encompasses 38 variables, encompassing geometric attributes, material grades, and details related to passive reinforcement design.

In reality, some of the variables are continuous. In the mathematical model, aligning them with the discrete nature of the combinatorial optimization process under con-

sideration is necessary. Thus, to appropriately represent these values, it becomes imperative to discretize them within the underlying optimization framework.

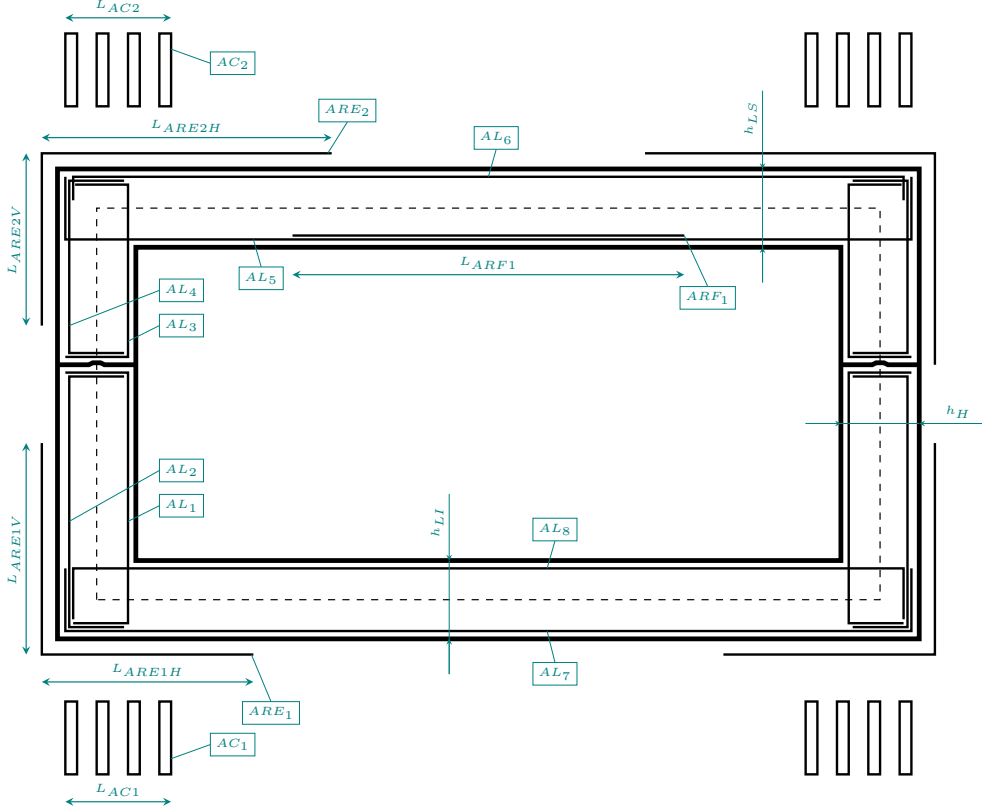


Figure 3.1: Set of variables considered in the economic optimization.

Three of the variables pertain to the depths of the upper slab (h_{LS}), the bottom slab (h_{LI}), and the lateral walls (h_H). Two additional variables correspond to the grades of concrete and passive reinforcement steel. The remaining 33 variables intricately define the passive reinforcement design. This comprehensive set of variables encapsulates the diameter and number of longitudinal reinforcement bars and the diameter and spacing between the shear reinforcement branches.

Table 3.3: Design variables and corresponding value ranges.

Description		Variable	Value range
Lower slab depth	(m)	h_{LI}	0.30 to 1.20
Upper slab depth	(m)	h_{LS}	0.30 to 1.20
Lateral walls depth	(m)	h_H	0.30 to 1.20
Concrete grade	(MPa)	C	25 to 40
Steel grade	(MPa)	A	400 or 500
Flexural reinforcement AL_1	(mm)	ϕ_{AL_1}	10 to 32
	(bars)	n_{AL_1}	4 to 12
Flexural reinforcement AL_2	(mm)	ϕ_{AL_2}	10 to 32
	(bars)	n_{AL_2}	4 to 12
Flexural reinforcement AL_3	(mm)	ϕ_{AL_3}	10 to 32
	(bars)	n_{AL_3}	4 to 12
Flexural reinforcement AL_4	(mm)	ϕ_{AL_4}	10 to 32
	(bars)	n_{AL_4}	4 to 12
Flexural reinforcement AL_5	(mm)	ϕ_{AL_5}	10 to 32
	(bars)	n_{AL_5}	4 to 12
Flexural reinforcement AL_6	(mm)	ϕ_{AL_6}	10 to 32
	(bars)	n_{AL_6}	4 to 12
Flexural reinforcement AL_7	(mm)	ϕ_{AL_7}	10 to 32
	(bars)	n_{AL_7}	4 to 12
Flexural reinforcement AL_8	(mm)	ϕ_{AL_8}	10 to 32
	(bars)	n_{AL_8}	4 to 12
Flexural reinforcement ARF_1	(mm)	ϕ_{ARF_1}	10 to 32
	(bars)	n_{ARF_1}	4 to 12
Flexural reinforcement ARE_1	(mm)	ϕ_{ARE_1}	10 to 32
	(bars)	n_{ARE_1}	4 to 12
Flexural reinforcement ARE_2	(mm)	ϕ_{ARE_2}	10 to 32
	(bars)	n_{ARE_2}	4 to 12
Shear reinforcement AC_1	(m)	S_{AC_1}	0.10 to 0.40
	(mm)	ϕ_{AC_1}	8 to 32
Shear reinforcement AC_2	(m)	S_{AC_2}	0.10 to 0.40
	(mm)	ϕ_{AC_2}	8 to 32

The variables related to the depths of the slab and lateral walls have been discretized to assume values at two-centimetre intervals within their designated range. The variables governing the separation between shear reinforcement branches can be altered at five-centimetre intervals. Similarly, the variables associated with corner re-

inforcement, upper slab bending reinforcement, and additional shear reinforcement positioning allow value increments every two centimetres. These considerations are crucial in facilitating the practical application of the hybrid metaheuristic. Furthermore, each variable's comprehensive range of values accommodated contributes to maintaining the problem's alignment with real-world design requirements. The variables under consideration are visually depicted in Figure 3.1, while their identifications and permissible value ranges throughout the optimization process are detailed in Table 3.3.

The length of the corner reinforcement, the negative bending reinforcement in the upper slab, and the span in which shear reinforcement is placed are defined by the variables presented in Table 3.4.

Table 3.4: Passive reinforcement design variables and corresponding value ranges.

Description		Variable	Value range
ARF_1 reinforcement effective length	(m)	L_{ARF_1}	3 to 10
ARE_1 reinforcement horizontal length	(m)	L_{ARE_1H}	1.50 to 5
ARE_1 reinforcement vertical length	(m)	L_{ARE_1V}	1 to 3
ARE_2 reinforcement horizontal length	(m)	L_{ARE_2H}	1.50 to 5
ARE_2 reinforcement vertical length	(m)	L_{ARE_2V}	1 to 2
AC_1 reinforcement disposition length	(m)	L_{AC_1}	1 to 5
AC_2 reinforcement disposition length	(m)	L_{AC_2}	1.50 to 5

3.3 Methodology

The optimization of the final cost for RCPHF was adeptly approached using a hybrid simulated annealing algorithm. The performance of this algorithm pivots crucially on the precise calibration of its integral parameters. To achieve optimal algorithmic performance, these parameters underwent a meticulous fine-tuning process utilizing a fractional factorial design of experiments. This section provides an in-depth exploration of the calibration process, elucidating the efficacy of the hybrid simulated annealing algorithm in addressing the distinct challenges posed by the specific optimization problem under study.

3.3.1 Hybrid Simulated Annealing Algorithm

The hybrid simulated annealing algorithm is founded in the simulated annealing metaheuristic initially conceived for designing electrical circuits by Kirkpatrick et al. [96]. The technique strategically evaluates multiple solutions for the optimization problem during the optimization process. To generate new solutions and evaluate current ones, it draws parallels between them and the crystallization states through which materials navigate during thermal annealing. In this context, the value of the objective function is thoughtfully juxtaposed with the internal energy unique to each crystallization state. The algorithm's progress is intricately linked to the temperature (T) parameter, a critical process control feature. Over time, the temperature is reduced geometrically by applying a cooling coefficient (k). This procedure effectively steers the algorithm through its optimization course.

Commencing with an initial solution, S_0 , generated randomly, the hybrid simulated annealing algorithm generates a new solution, S_1 . Each solution is generated by implementing specific modifications, known as movement, to the current solution variables. The solution generation process is further enhanced by introducing random mutations into the new solution, thereby injecting diversity into the optimization process while ensuring a focused exploration of significant areas within the solution space. The algorithm then evaluates the final cost of this new solution, $f(S_1)$, and compares it to the current cost, $f(S_0)$. Should the new solution prove to be more cost-effective than the existing one, it is promptly adopted.

Moreover, the algorithm is equipped to accept less advantageous solutions strategically by directly comparing the outcome of the Glauber expression [111], as delineated in equation (3.3), with a random value in the 0 to 1 range. This iterative process is conducted at a consistent temperature for a predetermined set of iterations, known as the Markov chain. For this study, the initial temperature value is determined using the method outlined by Medina [97].

$$P = \frac{1}{1 + e^{\frac{\Delta E}{T}}} \quad (3.3)$$

The Glauber function determines the probability of accepting solutions that worsen the current one based on the worsening degree (ΔE), considering both the cost difference and current temperature. As the optimization progresses, the intrinsic nature of this function systematically reduces the chances of adopting inferior solutions. This aspect forms the basis for distinguishing three distinct phases within the optimization process. Initially, there is the temperature determination stage, succeeded by an exploratory phase where the algorithm navigates the solution space in pursuit

of promising optima. Upon encountering a region rich in high-quality optima, the intensification phase commences. In this final stage, the algorithm meticulously examines subtle variations of the leading solution. These three phases can be identified in Figure 3.2, representing the final cost and temperature evolution for the RCPHF optimization.

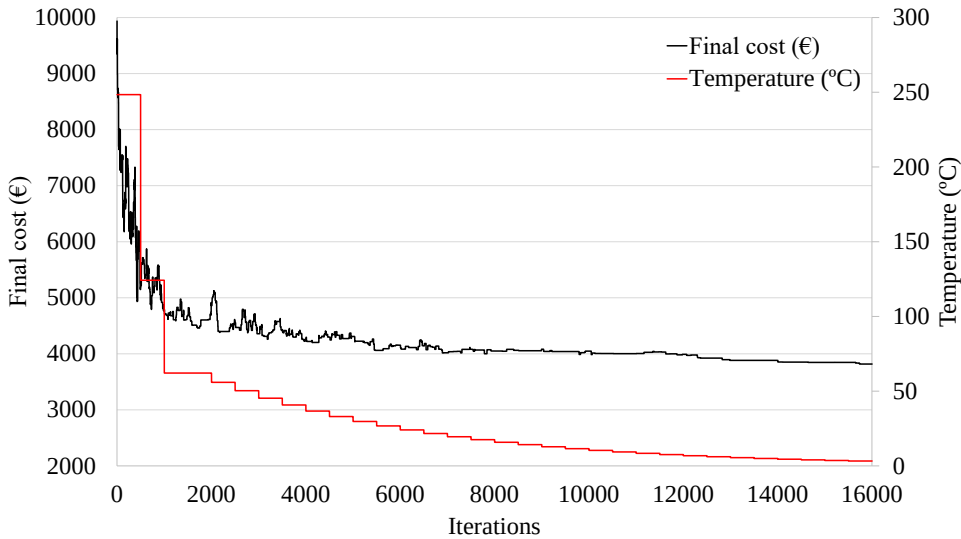


Figure 3.2: Hybrid simulated annealing optimization cost and temperature evolution.

Hybridizing the metaheuristic with the mutation operator significantly enriches the generation of new solutions [112]. The random mutations are a strategic variability inducer, amplifying the algorithm's exploratory capacity. The optimization concludes when a specific termination criterion is met, or the temperature has descended to a minimal fraction of its initial value. As a dual control mechanism, these conditions ensure a comprehensive yet bounded optimization process.

3.3.2 Algorithm Calibration Procedure

The functioning of the hybrid simulated annealing algorithm is contingent on five parameters. Precisely calibrating these parameters influences the quality of the result. To this end, a fractional factorial design of experiments was conducted [26], [41]. This study methodically evaluates each parameter's impact and collective interplay. Ensuring a systematic assessment of their influences allows for identifying the com-

bination that yields optimal performance and leads to the best-performing algorithmic configuration.

The first of the hybrid simulated annealing parameters is the Markov chain length (LCM), which denotes the number of iterations performed at a consistent temperature. Upon completing a Markov chain, the algorithm's temperature is adjusted downward in alignment with the cooling coefficient (k), the second crucial parameter of this metaheuristic. The algorithm's hybridization is characterized by the mutation operator, defined by the standard deviation (DE) and the number of variables it influences (NV). Additionally, an essential parameter linked to the stopping criterion (CP) is set, corresponding to the count of Markov chains where a new solution does not surpass the existing one in terms of improvement. The process also includes a termination criterion, activated when the temperature falls to five percent of its initial value.

In the context of the five parameters outlined, a fractional factorial $2^{(k-1)}$ design of experiments study was implemented. This approach entailed executing tests to explore diverse combinations of factor levels, thereby enabling a thorough evaluation of the algorithm's response to changes in these levels [113]. The information regarding the levels attributed to each parameter of the hybrid metaheuristic is presented in Table 3.5.

Table 3.5: Factor levels for the algorithm calibration design of experiments.

Parameter	Factor	Level (–)	Level (+)
Markov chain length	LCM	500	1000
Cooling coefficient	CE	0.80	0.90
Stopping criterion	CP	1	5
Variable number	NV	1	5
Standard deviation	DE	0.10	0.30

Table 3.6 presents the factor level combinations, average cost, and computational expense incurred in deriving each optimal design. Notably, the most cost-effective result is achieved with configuration number fourteen. This specific setup involves an LCM of 1000 iterations, a CE of 0.90, a CP of a single chain, and a mutation operator that impacts five NV with an DE of 0.10.

Nonetheless, assessing the hybrid metaheuristic performance cannot be exclusively based on the average final cost. Considering the computational cost associated with deriving these solutions is equally imperative.

Table 3.6: Results for the algorithm calibration design of experiments.

	<i>LCM</i>	<i>DE</i>	<i>NV</i>	<i>CE</i>	<i>CP</i>	Cost (€)	Iterations	% cost min	% iter. min
1	—	—	—	—	+	4901.39	10,469	0.3291	0.3506
2	+	—	—	—	—	4006.37	19,605	0.0864	0.6566
3	—	+	—	—	—	3934.28	10,425	0.0668	0.3491
4	+	+	—	—	+	4040.64	21,967	0.0957	0.7357
5	—	—	+	—	—	3934.27	7754	0.0668	0.2597
6	+	—	+	—	+	3921.62	17,895	0.0634	0.5993
7	—	+	+	—	+	3705.26	6350	0.0047	0.2127
8	+	+	+	—	—	4431.17	19,517	0.2016	0.6536
9	—	—	—	+	—	4006.37	17,998	0.0864	0.6027
10	+	—	—	+	+	3695.61	36,901	0.0021	1.2358
11	—	+	—	+	+	5859.99	18,799	0.5890	0.6296
12	+	+	—	+	—	4408.33	35,907	0.1954	1.2025
13	—	—	+	+	+	3689.62	14,554	0.0005	0.4874
14	+	—	+	+	—	3687.79	29,860	0.0000	1.0000
15	—	+	+	+	—	3817.06	15,737	0.0351	0.5270
16	+	+	+	+	+	3985.73	28,681	0.0808	0.9605
Minimum final cost (€)									3687.79

The seventh configuration achieves a final cost that, while slightly higher than the minimum, incurs a computational cost that is 4.7 times lower. Given the robust performance of this configuration, the hybrid simulated annealing approach is calibrated to an *LCM* of 500 iterations, a *CE* of 0.80, a *CP* of 5 chains, and a mutation operator defined by a *DE* of 0.30 and impacting 1 *NV*.

The analysis of the design of experiments results reveals that the selection of factor levels and the specific correlations subsequently identified among them have a considerable impact on the final cost realized in the optimization process.

3.4 Economic Optimization Results

This section is dedicated to presenting and analyzing the RCPHF economic optimization results. Once tuned, twenty iterations of the hybrid simulated annealing were conducted to guarantee statistical representativeness. Figure 3.3 illustrates the progression of the minimum and computational costs linked to the optimum design achieved after each optimization. Table 3.7 thoroughly records these values, encompassing the final cost, each associated computational expense and the deviations from the minimum value.

Table 3.7: Results for the economic optimization.

	Cost (€)	Iterations	% cost min	% iter. min
1	4408.38	8179	0.2077	0.4109
2	3752.28	7703	0.0280	0.3288
3	3959.54	8424	0.0848	0.4532
4	3740.44	7731	0.0247	0.3336
5	3650.13	5797	0.0000	0.0000
6	4992.39	10,506	0.3677	0.8123
7	3926.76	8554	0.0758	0.4756
8	4181.66	7150	0.1456	0.2334
9	4225.32	8458	0.1576	0.4590
10	4637.70	7495	0.2706	0.2929
11	4057.37	10,460	0.1116	0.8044
12	4319.87	6094	0.1835	0.0512
13	3682.73	8407	0.0009	0.4502
14	3713.67	8404	0.0174	0.4497
15	4197.53	6485	0.1500	0.1187
16	3849.91	9210	0.0547	0.5888
17	3896.73	9281	0.0676	0.6010
18	3693.33	8406	0.0118	0.4501
19	4012.22	8937	0.0992	0.5417
20	3890.25	8446	0.0658	0.4570
Minimum final cost			(€)	3650.13

The fifth iteration attained the lowest cost, with the RCPHF registering a final cost of EUR 3650.13. The hybrid simulated annealing achieved more cost-effective designs than those typically associated with traditional in situ execution [110], demonstrating effective performance in producing results under tight economic constraints.

Table 3.8 details the design features of the optimal RCPHF. This design incorporates 18.03 m³ of concrete with a characteristic strength of 25 MPa, and its passive reinforcement comprises 1442.07 kg of type B 500 S steel. The optimal designs generated through hybrid simulated annealing generally exhibit reduced section depths.

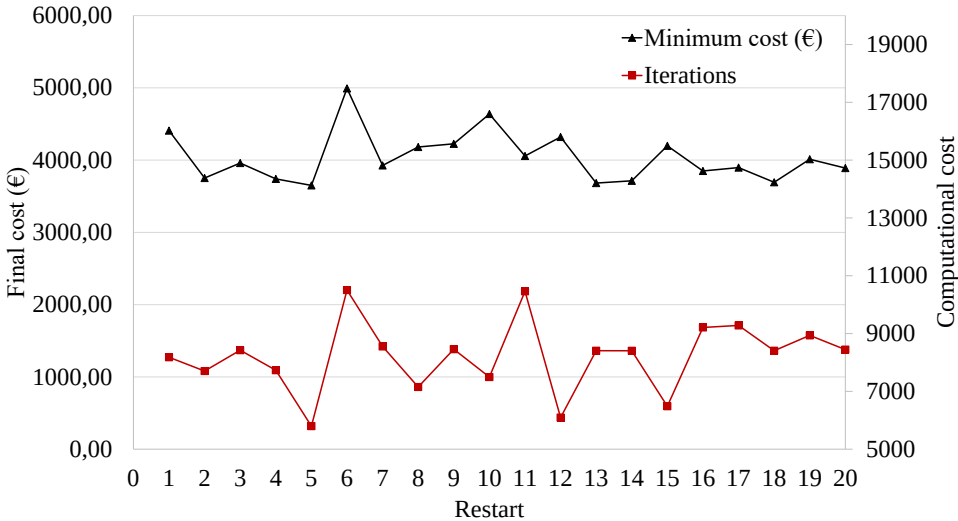


Figure 3.3: Final economic and computational cost evolution for each algorithmic restart.

In conventional designs, the ratios of section depth to horizontal span for slabs typically vary between 1/10 and 1/15, with lateral walls adhering to a range between 1/12 and the slab's depth. In contrast, optimal precast designs display significantly lower ratios, precisely 0.048 for the bottom slab and 0.046 for the lateral walls. The optimal designs employ a high-density reinforcement approach to offset the reduced structural capacity of these diminished section depths. In the most cost-effective RCPHF design, the passive reinforcement density reaches 79.97 kg/m³.

The designs incorporate additional negative bending reinforcement in the upper slab, with an average effective length of 6.95 m. In specific models, the corner bending reinforcement is characterized by localized increases. This modification facilitates a leaner shear reinforcement setup relative to traditional in-situ designs. These strategic changes effectively reduce overall material consumption, consequently lowering the final cost of the structure.

Table 3.8: Main characteristics of the cost-optimum RCPHF design.

Description		Variable	Value
Lower slab depth	(m)	h_{LI}	0.48
Upper slab depth	(m)	h_{LS}	0.84
Lateral walls depth	(m)	h_H	0.46
Concrete grade	(MPa)	C	25
Steel grade	(MPa)	A	500
Flexural reinforcement AL_1	(cm ²)	A_{AL_1}	15.71
Flexural reinforcement AL_2	(cm ²)	A_{AL_2}	6.79
Flexural reinforcement AL_3	(cm ²)	A_{AL_3}	12.44
Flexural reinforcement AL_4	(cm ²)	A_{AL_4}	9.42
Flexural reinforcement AL_5	(cm ²)	A_{AL_5}	15.71
Flexural reinforcement AL_6	(cm ²)	A_{AL_6}	4.52
Flexural reinforcement AL_7	(cm ²)	A_{AL_7}	15.71
Flexural reinforcement AL_8	(cm ²)	A_{AL_8}	4.71
Flexural reinforcement ARF_1	(cm ²)	A_{ARF_1}	40.21
Flexural reinforcement ARE_1	(cm ²)	A_{ARE_1}	5.50
Flexural reinforcement ARE_2	(cm ²)	A_{ARE_2}	11.31
Shear reinforcement AC_1	(m)	S_{AC_1}	0.30
	(mm)	ϕ_{AC_1}	12
Shear reinforcement AC_2	(m)	S_{AC_2}	0.15
	(mm)	ϕ_{AC_2}	20
ARF_1 reinforcement effective length	(m)	L_{ARF_1}	6.42
ARE_1 reinforcement horizontal length	(m)	L_{ARE_1H}	4.26
ARE_1 reinforcement vertical length	(m)	L_{ARE_1V}	2.30
ARE_2 reinforcement horizontal length	(m)	L_{ARE_2H}	4.06
ARE_2 reinforcement vertical length	(m)	L_{ARE_2V}	1.10
AC_1 reinforcement disposition length	(m)	L_{AC_1}	1.38
AC_2 reinforcement disposition length	(m)	L_{AC_2}	3.47

3.5 Conclusions

The research undertakes the economic optimization of a reinforced concrete precast hinged frame, achieving cost-effective designs through the application of a hybrid simulated annealing metaheuristic complemented by a mutation operator. Based on the results obtained, the following conclusions may be drawn.

The use of hybrid metaheuristics marks a significant advancement in the design process of RCPHF. By balancing optimal material usage with manageable computational demands, these techniques enable the creation of efficient designs. The calibration of their defining parameters is crucial, as the quality of the outcomes is directly tied to their configuration. In this case, with its specific configuration, the hybrid simulated annealing demonstrates superior final cost efficiency and computational expenditure results.

Integrating mutation operators in metaheuristics based on neighbourhood search, as in simulated annealing, endows these techniques with robust exploratory capabilities. This enhancement makes them particularly suitable for addressing combinatorial optimization challenges akin to the problem posed in this study.

The study's optimal structure designs exhibit slender sections with reduced depths compared to traditional designs, compensated by highly dense reinforcement strategies, approaching 80 kg/m² in the highest quality optima. Specific designs also show a strategic reduction in shear reinforcement, offset by localized increases in longitudinal flexural reinforcement.

Improving the design process through hybrid metaheuristics generally leads to attractive designs that allow responsible technicians to evaluate designs with less common characteristics. This avoids the intrinsic predisposition in the traditional design process to create structures highly conditioned by existing designs. Additionally, minimizing a specific objective function allows for the optimal use of materials, something especially interesting from an economic and environmental point of view.

Employing hybrid metaheuristics leads to innovative and less conventional designs, enabling technicians to consider alternatives to traditional structures. This approach minimizes the reliance on existing designs and ensures more effective material utilization, with notable economic and environmental benefits.

As a final remark, improving the use of material resources and subsequently reducing economic costs is beneficial for any structural typologies. However, while in-situ frames can gain from the techniques outlined in this study, these advantages are expected to be more pronounced in serially manufactured structures. Consequently, optimizing material usage in precast frames and reducing their environmental, social, and economic impacts emerges as a research domain of substantial significance.

Chapter 4

A parametric study of optimum road modular hinged frames by hybrid metaheuristics

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Abstract

This paper addresses a study of cost-optimal road modular hinged frames. The performance of three hybrid metaheuristics is assessed through a fractional factorial design of experiments. The results allow for selecting and calibrating the hybrid simulated annealing to solve the combinatorial optimization problem. By varying the horizontal span from 8 to 16 meters and the earth cover from 1 to 5 meters, 25 different structural configurations are studied. The calibrated methodology is applied to obtain nine different frames with optimal costs for each configuration. The study of the economic, environmental and geometrical characteristics of the 225 optimum structures allows for the development of a regression analysis. With R^2 correlation coefficients close to the unit, the expressions form a valuable tool for calculating the final cost, associated emissions, embodied energy and particular geometric characteristics. The optimum structures present slender and densely reinforced designs. In addition, some structures show considerable reductions in the shear reinforcement, something solved by localized increases in longitudinal reinforcement.

Keywords: reinforced concrete; modular; hinged frame; hybrid metaheuristic; param

4.1 Introduction

There is a growing general interest in caring for the environment. Widespread awareness of the consequences of pollution promotes sustainable alternatives over traditional ones [16], [77], [114]. In this context, construction is one of the most contributing industries to global pollution. Currently, in addition to fulfilling their service, infrastructures must incur the lowest possible environmental impact [50], [91], [115].

However, improving the structural design process is a challenging task [116]–[118]. A large number of discrete variables must be considered. Therefore, systematizing the obtaining of designs is very complicated. This complexity leads to the traditional design process depending on the responsible technician [32]. Based on existing structures, the structural engineer defines an initial design. It is then checked, and the grade or quantity of materials is modified if it does not meet structural requirements. This process is repeated, achieving a safe structure that, on the other hand, does not make optimal use of the materials. One way of improvement consists of approaching the design process of reinforced concrete structure as a combinatorial optimization problem [70], [85]–[88]. Its solution results in obtaining non-traditional designs that, in addition to verifying the structural requirements, make optimum use of materials.

The techniques applied to solve combinatorial optimization problems can be divided into two main groups: exact techniques and approximate or metaheuristic tech-

niques. The former achieve the best possible result and are suitable for problems with a limited number of variables [119], [120]. The latter allow for the study of more complex problems, obtaining high-quality results. This characteristic generates a general interest in applying approximate techniques to solve structural problem designs [49], [116], [121], [122].

These approximate methods make use of a variety of metaheuristic algorithms based on different working principles. This allows the conditioned exploration of the solution space with a certain degree of randomness. The techniques considered in the present study can be framed within the so-called hybrid metaheuristics. Based on the simulated annealing (SA), threshold accepting (TA) and old bachelor's acceptance (OBA) algorithms, these integrate a mutation operator (MO) specific to genetic algorithms (GA). The SA, TA and OBA algorithms classify as local search algorithms. Starting with a feasible solution, these obtain and evaluate new solutions similar to the current one through a series of rules. In contrast to these, GAs search for optimal solutions by selection, crossover and mutation of populations of feasible solutions. Hybridizing both typologies allows for high-quality results in optimizing structures such as composite bridges [39], [49], retaining walls [40], [88], [89], [123] or pre-stressed box girder bridges [37], [39].

In this context, the present work develops a parametric study of road modular hinged frames (RMHF). Reinforced concrete frames are a very common structural typology in transport infrastructure. With spans ranging between three and twenty meters, these structures are applicable as a solution for road crossings. Previous work focused on studying cast-in-place road frames (CPRF) [69]. However, the analysis of the related literature allows for identifying a lack of development in the study of RMHF. Based on the quality and consistent characteristics of prefabrication, the present study solves the lack of current development and improves the general knowledge about optimal RMHF. In this way, the precast typology, considered an alternative to the cast-in-place structures, is proposed.

The RMHF comprises two sets, which facilitate transport to the construction site. The two sets present three main structural components, the upper and lower slabs and the lateral walls. Traditionally, the slab's thickness is established between 1/15 and 1/10 of the span. The lateral walls' thickness ranges between 1/12 of the vertical span and the particular slab thickness. Four main geometric characteristics define the RMHFs: the clear height (H), the horizontal span (L), the height of the hinge (HH) and the earth cover above the structure (HE). Figure 4.1 represents the detailed RMHF design.

The study considers spans ranging between 8 and 16 m and earth cover depths between 1 and 5 m. The study of the optimal designs allows for determining the in-

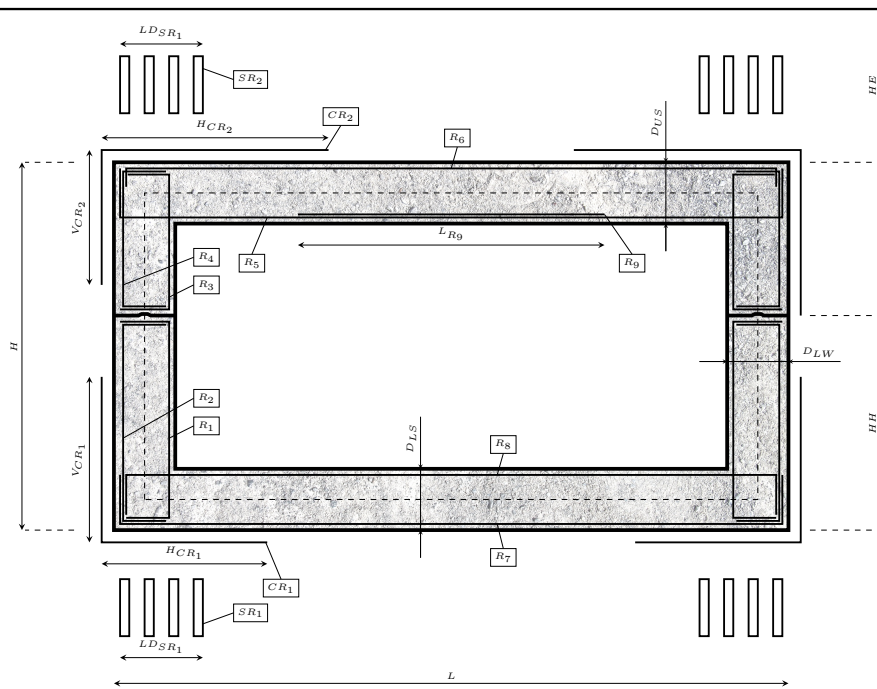


Figure 4.1: Set of variables of the RMHF considered in the optimization problem.

fluence of the characteristics that define them and developing a regression analysis. In addition, the comparison with the cast-in-place alternative allows for establishing a series of improvements derived from the prefabrication of this structural typology.

This way, the study develops a factorial design of experiments (DoE) in order to evaluate the performance of three hybrid metaheuristics: simulated annealing with mutation operator (SAMO), threshold accepting with mutation operator (TAMO) and old bachelor's acceptance with mutation operator (OBAMO). Analysing the results allows for calibrating the parameters that define the algorithms and the subsequent selection of the best-performing technique [113]. Once selected, the hybrid metaheuristic is applied to obtain optimal RMHF. Obtaining optimal designs requires the establishment of an objective function. The economic cost of a structure is a direct representation of the use of materials. Thus, the final cost of RMHFs is optimized for 25 different horizontal span and earth cover combinations. Nine designs are optimized for each configuration, obtaining a total of 225 environmentally efficient designs under highly restrictive budgets.

4.2 Optimization Problem

This section details the combinatorial optimization problem proposed. This comprehends the complete definition of the variables, parameters, constraints and objective function [12]. The problem posed consists of minimizing the use of materials in the construction of RMHFs. The structure's final cost $C(\vec{x})$, calculated by means of Equation (4.1), was considered the objective function. Its calculation is direct, consisting of the multiplication of the unit price of each material c_i and the quantity used $m_i(\vec{x})$. In addition, to analyse the optimal designs' environmental impact, the associated CO₂ emissions $AE(\vec{x})$ and embodied energy $EE(\vec{x})$ were evaluated through Equations (4.2) and (4.3). Similar to the objective function, emissions are obtained as a factor of each material's quantity $m_i(\vec{x})$, the unitary emissions ae_i and unitary embodied energy ee_i , respectively. The designs must comply with a series of constraints $R(\vec{x})$ detailed in Section 4.2.3. The compliance of the optimal designs with the constraints is generally expressed through Equation (4.4).

$$C(\vec{x}) = \sum_{i=1}^n c_i \cdot m_i(\vec{x}) \quad (4.1)$$

$$AE(\vec{x}) = \sum_{i=1}^n ae_i \cdot m_i(\vec{x}) \quad (4.2)$$

$$EE(\vec{x}) = \sum_{i=1}^n ee_i \cdot m_i(\vec{x}) \quad (4.3)$$

$$R(\vec{x}) \leq 0 \quad (4.4)$$

Table 4.1: Unit cost, associated CO₂ emission and embodied energy values for each material [92].

Unit	Material	Unit cost (EUR)	Emissions (CO ₂ kg)	Energy (kWh)
m ³	C25/30 Concrete	88.86	256.66	402.44
m ³	C30/37 Concrete	97.80	277.72	428.29
m ³	C35/45 Concrete	101.83	278.04	429.95
m ³	C40/50 Concrete	104.83	278.04	429.95
kg	B 400 S	1.40	0.70	3.38
kg	B 500 S	1.42	0.70	3.38

The set of unit cost c_i , unitary associated CO₂ emissions ae_i and embodied energy ee_i for each of the materials can be consulted in Table 4.1. These values were obtained from the Construction Technology Institute of Catalonia by the BE-DEC database [92].

4.2.1 Variables

A total of 38 variables defined each RMHF design solution, establishing the geometry, grade of materials and passive reinforcement design. The value of the variables represented in Figure 4.1 was subjected to optimization within the ranges presented in Table 4.2. Meanwhile, parameters were established previously and remained constant during the optimization process. The influence of the main geometrical parameters was the subject of a parametric study shown in Section 4.4.

Table 4.2: Variables considered in the optimization problem.

Geometrical variables			Num. values	Range values
Upper slab depth	(m)	D_{US}	46	0.30 to 1.20
Lower slab depth	(m)	D_{LS}	41	0.40 to 1.20
Lateral walls depth	(m)	D_{LW}	46	0.30 to 1.20
Materials variables				
Concrete grade	(MPa)	C	4	25, 30, 35 or 40
Steel grade	(MPa)	S	2	400 or 500
Passive reinforcement variables				
Flexural reinforcement R_1	(mm)	ϕ_{R_1}	6	10 to 32
	(bars)	n_{R_1}	9	4 to 12
Flexural reinforcement R_2	(mm)	ϕ_{R_2}	6	10 to 32
	(bars)	n_{R_2}	9	4 to 12
Flexural reinforcement R_3	(mm)	ϕ_{R_3}	6	10 to 32
	(bars)	n_{R_3}	9	4 to 12
Flexural reinforcement R_4	(mm)	ϕ_{R_4}	6	10 to 32
	(bars)	n_{R_4}	9	4 to 12
Flexural reinforcement R_5	(mm)	ϕ_{R_5}	6	10 to 32
	(bars)	n_{R_5}	9	4 to 12
Flexural reinforcement R_6	(mm)	ϕ_{R_6}	6	10 to 32
	(bars)	n_{R_6}	10	3 to 12
Flexural reinforcement R_7	(mm)	ϕ_{R_7}	6	10 to 32
	(bars)	n_{R_7}	9	4 to 12
Flexural reinforcement R_8	(mm)	ϕ_{R_8}	6	10 to 32
	(bars)	n_{R_8}	9	4 to 12

Table 4.2: Cont.

Passive reinforcement variables				
Flexural reinforcement R_9	(mm)	ϕ_{R_9}	6	10 to 32
	(bars)	n_{R_9}	9	4 to 12
	(m)	L_{R_9}	151 to 451	3 to $0.75 \cdot L$
Corner reinforcement CR_1	(mm)	ϕ_{CR_1}	6	10 to 32
	(bars)	n_{CR_1}	10	3 to 12
	(m)	H_{CR_1}	76 to 226	1.5 to $0.375 \cdot L$
	(m)	V_{CR_1}	76	1 to 2.5
Corner reinforcement CR_2	(mm)	ϕ_{CR_2}	6	10 to 32
	(bars)	n_{CR_2}	10	3 to 12
	(m)	H_{CR_2}	101 to 251	1 to $0.375 \cdot L$
	(m)	V_{CR_2}	26	1 to 1.5
Shear reinforcement SR_1	(mm)	ϕ_{SR_1}	7	8 to 32
	(m)	s_{SR_1}	7	0.10 to 0.40
	(m)	LD_{SR_1}	76 to 226	1.5 to $0.375 \cdot L$
Shear reinforcement SR_2	(mm)	ϕ_{SR_2}	7	8 to 32
	(m)	s_{SR_2}	7	0.10 to 0.40
	(m)	LD_{SR_2}	101 to 251	1 to $0.375 \cdot L$

Prior to solving the problem, all variables were discretized. This way, the variables could take a given number of values within the range stipulated for each. The geometric variables adopted thicknesses every two centimetres within limits. The separation between shear reinforcement branches was established every five centimetres within the stipulated range. Normalized reinforcement diameters between 10 and 35 millimetres were considered. Moreover, the number of bars was set to any integer lower or equal to the maximum value established.

Due to the number of variables and values each was allowed to take, the problem's solution space presents a dimension of $9.87 \cdot 10^{43}$. This large magnitude states that a complete study of the solution space is not feasible. Thus, the application of the techniques described in Section 4.3 is particularly interesting. The calibration and selection of the hybrid metaheuristic allow for obtaining high-quality results while maintaining adequate computational costs.

4.2.2 Parameters

There are several determining factors in the design of RMHF. The first of these is the vertical span (H). Based on common characteristics of this typology, a vertical span of five meters was established. The second factor is the height of the hinge (HH), whose position relative to the lower slab was set at 3/5 of the vertical span. The remaining two parameters were the subject of the parametric study. The variation of their magnitude gave rise to optimum designs whose study allowed a regression analysis. The first one is related to the horizontal span (L). RMHFs functioning as a solution for road crossings bridge spans ranging from 8 to 16 m. Therefore, RMHFs were optimized in which L adopted 8, 10, 12, 14 and 16 m. This type of buried structure is usually located in up to 12 m deep embankments. Considering the established H , the study adopted earth cover depths of 1, 2, 3, 4 and 5 m for a medium quality soil. The set of parameters and all those necessary for the calculation and verification of the RMHF can be consulted in Table 4.3.

Loads associated with heavy vehicles and Marston's effect were considered according to the Spanish regulation recommendations [90], [95]. The remaining loads, actions and associated conditions were taken from current applicable regulations [93], [94]. As a completely buried structure, temperature variations occur slowly and homogeneously throughout the surrounding earth's mass. Following the current standard's recommendations [90], [93], it is feasible to consider that no loads are derived from temperature gradients. Thus, the thermal effects were disregarded. In addition, since prefabricated structures undergo intensive control in the manufacturing and curing process, the rheological effects were neglected. Finally, a generic location was established within a non-seismic zone, so consideration of the associated actions was not necessary.

4.2.3 Constraints

As stated in Section 4.2, the optimal RMHF design is subject to several constraints. These ensured adequate representation of the reality and the resulting structure meeting the structural requirements of current regulations [93], [94]. The constraints applied are divided into Ultimate Limit States (ULS) and Service Limit States (SLS). ULS ensure structural integrity, while SLS ensure adequate service life. Prior to verification, it is necessary to calculate the structure's internal stresses. This was achieved by applying the displacement method to the two-dimensional model under the linear elastic analysis hypothesis.

Once the internal stresses were known, the shear ULS was checked. This consisted of comparing the acting shear stress with the standard's exhaustion limit values stipu-

Table 4.3: Main parameters considered in the RMHF optimization.

Geometrical parameters			
Free height	(m)	H	5
Horizontal span	(m)	L	8 to 16
Hinge height	(m)	HH	$(3/5) \cdot H$
Earth cover	(m)	HE	1 to 5
Loading parameters			
Earth specific weight	(kN/m ³)	γ_E	20
Reinforced concrete specific weight	(kN/m ³)	γ_C	25
Earth internal friction angle	(°)	IF	30
Active earth pressure coefficient		K_A	0.33
Resting earth pressure coefficient		K_R	0.50
Heavy traffic vehicle load	(kN/m ³)	TL	150
Heavy traffic vehicle load lenght	(m)	TLL	1.20
Uniform overload	(kN/m ³)	UO	10
Ballast coefficient	(MN/m ³)	B_E	10
Economic and sustainability parameters			
Unit costs	(EUR)	c_i	Table 4.1
Unit CO ₂ emissions	(CO ₂ kg)	ae_i	Table 4.1
Unit embodied energy	(kWh)	ee_i	Table 4.1
Exposure related parameters			
Exposure class			XC2
Legislative related parameters			
Standard regulations		CEN [93], [94]/MFOM [95]	
Code considerations		MFOM [90]	

lated. In addition, the stress increase in the tensile reinforcement associated with the shear stress was calculated. If the structure complied with the shear ULS, the tensile increment was applied, and the normal stresses ULS were checked. This consisted of verifying that the axial stress and bending moment are located within the interaction diagram of each section. After this, the deflection ULS was checked, limiting the displacement of the upper slab to 1/250 times the frame span. Subsequently, compliance with the fatigue ULS was ensured.

Within the second group of constraints, the cracking SLS was checked. In order to do so, the crack opening was obtained and compared with the standard's limit value. In

addition, the maximum and minimum passive reinforcement and crack control reinforcement amounts were also checked. Constructibility was reviewed by calculating the spacing between bars. Finally, the transversal reinforcement was obtained directly from the flexural passive reinforcement design.

The developed software allowed verifying the ULS and SLS according to the described process. The result of the verification process was a series of coefficients generally expressed by Equation (4.5). Associated with the ULS and SLS verification, these resulted from the relation between each section's acting (A_s) and resistant (R_s) stresses.

$$\frac{A_s}{R_s} \geq 1 \quad (4.5)$$

4.3 Proposed Hybrid Metaheuristic Strategies

This section details each of the hybrid metaheuristics considered in the study. A DoE, detailed in Section 4.3.4 was carried out to calibrate and select the best-performing technique. Once selected, it was applied to obtain the optimal design analysed in the parametric study presented in Section 4.4. Initially, the SAMO, TAMO and OBAMO hybrid metaheuristics were considered. The following sections detail the functioning of each.

4.3.1 Hybrid Simulated Annealing

The SAMO algorithm was the first of the three techniques considered. The basis of the technique is the SA, proposed by Kirkpatrick et al. [96] for electrical circuit design. The SAMO's novelty consists of adding a mutation operator to the SA. For specific problems, this hybridization results in considerable improvements in the exploration capability of the algorithm [89], [116], [119].

The algorithm bases its operation on the thermal annealing process. The annealing is applied to certain materials to modify their mechanical characteristics. These changes are achieved thanks to the microstructural modifications during the thermal annealing. The temperature is the controlling parameter of the process. Initially, it has a high value, which is gradually reduced by applying the cooling coefficient. During this period, the material adopts different crystallization states with lowering energy levels. The SA equates each feasible solution to the problem with a physical crystallization state. Consequently, the objective function is equivalent to the internal energy associated with each state.

The SAMO generates and evaluates the cost of an initial random solution. Then generates a new solution by applying a movement, which is affected by the mutation operator. The newly generated solution is evaluated and directly accepted if it costs less. If the new cost worsens, it is accepted if the probability P obtained through Boltzmann energetic expression, Equation (4.6), is greater than a random value in the 0 to 1 range. The acceptance probability P depends on the difference between the current and new objective function values ΔE and the current temperature T [96]. This process is repeated at the same temperature for a predetermined number of iterations called the Markov chain. When a chain is finished, the temperature decreases geometrically at the rate of the cooling coefficient. The temperature reduction progressively limits the SAMO's ability to accept solutions worse than the current one.

$$P = e^{-(\Delta E/T)} \quad (4.6)$$

The optimization process ends when one of two criteria is met. The stop criterion establishes the maximum number of chains in which a bettering solution is not found. On the other hand, the termination criterion dictates a minimum percentage of the initial temperature of the problem. The initial temperature setting is carried out as proposed in Medina [97]. Correctly calibrating this parameter is essential in order to obtain high-quality results [37], [124].

Five parameters define the SAMO, three of which are specific to the SA algorithm. The Markov chain length (MCL), the cooling coefficient (CC) and the stopping criterion (SC). The remaining two determine the standard deviation (SD) and the number of variables (VN) affected by the mutation operator. The values considered for the DoE are detailed in Section 4.3.4.

4.3.2 Hybrid Threshold Accepting

The second alternative assessed in the study was the TAMO. This technique is based on the TA, which Dueck and Scheuer [98] developed as an improvement for the SA. The TA and the SA differ in the acceptance criterion for worsening solutions. As described in Section 4.3.1, the SA has a probabilistic criterion. On the other hand, the TA accepts worse solutions by directly comparing the cost difference and a threshold.

The initial threshold is established analogously to the SA [97]. It is then geometrically reduced at the rate of the reduction coefficient. Limiting the ability to accept worse solutions as the optimization develops. Like the SAMO, five parameters define the TAMO. The chain length (CL), the reduction coefficient (RC) and the stopping

criterion (SC) are specific to the TA. The remaining two are the mutation operator's standard deviation (SD) and the number of affected variables (VN). Similar to the SAMO, the process finishes when either the SC or the termination criterion are met.

4.3.3 Hybrid Old Bachelor's Acceptance

The third technique studied was the OBAMO. Consisting of a modification of the OBA proposed by Hu et al. [100], it works similarly to the TAMO. The main difference is that the threshold does not start from a high initial value and then decreases over time. In the OBAMO, the initial threshold is zero. Then, it increases or decreases depending on the rejection or acceptance of new solutions. The criterion of acceptance of worsening solutions is deterministic. As in the TAMO, worsening solutions are accepted if the cost increase is lower than the threshold at that time.

In this context, the OBAMO is also defined by five parameters. Two establish the standard deviation (SD) and the number of variables (VN) affected by the mutation operator. Two of the remaining are related to the threshold increase (IC) and decrease (DC) coefficients. These are applied each time a solution is rejected or accepted, respectively. Unlike the algorithms described in Sections 4.3.1 and 4.3.2, the OBAMO does not have a control parameter that decreases in time. Therefore, the fifth parameter is the termination criterion (TC), equivalent to the algorithm's maximum number of iterations.

4.3.4 Design of Experiments

The hybrid metaheuristic parameters' calibration directly impacts the optimization results' quality. Each technique's performance varies depending on the studied optimization problem. Thus, selecting the best-suited algorithm for the considered problem is crucial. In addition, it is essential to appropriately calibrate the metaheuristic parameters. In this context, the DoE detailed in this section allowed the selection and application of the technique with the best performance.

The study developed a $2^{(n-1)}$ fractional factorial DoE for each hybrid metaheuristics. Two levels were established for each parameter, corresponding with the values presented in Table 4.4. A total of five parameters define the three techniques, so 16 combinations of each parameter's level need to be considered. In order for the results to be statistically representative, each of the configurations is run five times. Therefore, the influence of each of the parameters of the hybrid metaheuristics can be addressed. Table 4.5 presents the mean results of the DoE for each configuration.

Table 4.4: Metaheuristic parameter bounds considered in the DoE.

SAMO	P1	P2	P3	P4	P5
Parameter	<i>MCL</i>	<i>SD</i>	<i>VN</i>	<i>CC</i>	<i>SC</i>
Lower bound (–)	1000	0.1	1	0.8	1
Upper bound (+)	5000	0.3	5	0.9	5
TAMO	P1	P2	P3	P4	P5
Parameter	<i>CL</i>	<i>SD</i>	<i>VN</i>	<i>RC</i>	<i>SC</i>
Lower bound (–)	1000	0.1	1	0.8	1
Upper bound (+)	5000	0.3	5	0.9	5
OBAMO	P1	P2	P3	P4	P5
Parameter	<i>TC</i>	<i>SD</i>	<i>VN</i>	<i>IC</i>	<i>DC</i>
Lower bound (–)	10,000	0.1	1	1	1
Upper bound (+)	50,000	0.3	5	5	5

Table 4.5: DoE mean minimum cost results and associated computational cost for each configuration.

SAMO									TAMO			OBAMO		
P1	P2	P3	P4	P5	Cost (EUR)	Iter.	% Min.		Cost (EUR)	Iter.	% Min.	Cost (EUR)	Iter.	% Min.
–	–	–	–	+	3722.99	11,472	0.0067		4484.78	7790	0.2127	4266.87	5621	0.1538
+	–	–	–	–	3700.97	56,759	0.0008		4206.81	28,405	0.1376	3935.18	15,901	0.0641
–	+	–	–	–	3809.90	10,551	0.0302		4005.26	6823	0.0831	3939.44	6688	0.0653
+	+	–	–	+	3723.28	44,999	0.0068		3933.48	19,124	0.0636	4108.21	30,886	0.1109
–	–	+	–	–	3893.24	13,428	0.0528		3844.05	14,008	0.0395	4131.20	6607	0.1171
+	–	+	–	+	3764.81	75,442	0.0180		3764.61	64,237	0.0180	4420.60	31,150	0.1954
–	+	+	–	+	3854.21	14,101	0.0422		3917.74	12,470	0.0594	4470.99	3043	0.2090
+	+	+	–	–	3787.60	76,644	0.0242		3764.19	62,072	0.0179	3978.78	23,037	0.0759
–	–	–	+	–	3759.89	32,726	0.0167		3900.58	20,817	0.0548	4233.84	5175	0.1449
+	–	–	+	+	3735.80	137,994	0.0102		3990.50	61,719	0.0791	3808.35	30,193	0.0298
–	+	–	+	+	3745.25	38,517	0.0127		3953.74	22,026	0.0691	3878.68	7326	0.0488
+	+	–	+	–	3717.33	135,874	0.0052		4376.86	41,030	0.1835	4103.01	28,609	0.1095
–	–	+	+	+	3810.35	53,194	0.0304		3759.25	53,703	0.0165	4135.06	8395	0.1182
+	–	+	+	–	3740.23	254,796	0.0114		3711.42	227,138	0.0036	3788.71	30,451	0.0245
–	+	+	+	–	3808.14	52,211	0.0298		3755.12	52,050	0.0154	4188.70	4486	0.1327
+	+	+	+	+	3730.33	266,381	0.0087		3698.10	258,351	0.0000	3838.12	43,960	0.0379

The algorithm's performance does not depend solely on the final result quality. Thus, in addition to analysing the lowest costs, the computational cost associated with obtaining each optimal RMHF was addressed. The analysis of the DoE results allows for identifying the SAMO as the best performing technique for its application to solving the problem posed. Furthermore, considering the associated computational cost, the algorithm was calibrated so that the *MCL* was 10,000 iterations, with *CC* of 0.8 and *SC* of 5 chains without improvement. In addition, the mutation operator was

defined by an SD of 0.1 and affected a VN of 5. In general, as Figure 4.2 shows, longer chain lengths achieve better results.

However, the computational cost increases rapidly. In this context, the calibration achieved an optimum RMHF whose cost differed only 0.006% from the general optimum. However, the computational cost is 4.95 times lower. Moreover, with a means standard deviation of 0.597%, the algorithm is a robust tool for solving the problem. The algorithm was applied in order to obtain optimum RMHF analysed in the parametric study detailed in Section 4.4.

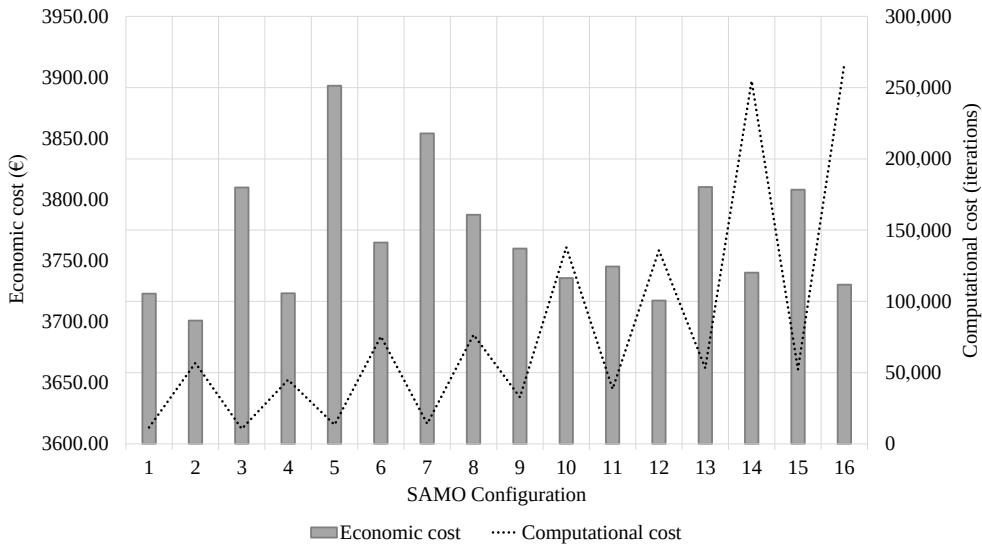


Figure 4.2: DoE results for the SAMO hybrid metaheuristic.

4.4 Results of the Parametric Study and Regression Analysis

The present work carried out the parametric study of optimal RMHF obtained by applying the SAMO hybrid metaheuristic described in Section 4.3.1 to the combinatorial optimization problem described in Section 4.2. Five horizontal spans of 8, 10, 12, 14 and 16 m were considered. In addition, five earth cover depths of 1, 2, 3, 4 and 5 m were considered. The combination of both parameters allowed the study of 25 different RMHF configurations. The calibrated SAMO was applied, and nine optimal structures were obtained for each configuration. The analysis of a total of 225 optimal RMHF allowed the study of the main economic, geometrical and design characteristics.

Furthermore, the regression analysis was carried out, obtaining good fitting results. The expressions obtained allow for structural techniques to calculate certain approximations prior to RMHF design. This section focuses on the presentation and discussion of the results obtained.

4.4.1 Final Cost Analysis

Figure 4.3 represents the mean minimum final cost of the optimum RMHF as a function of the span. The results showed a clear quadratic relation in all cases. Increasing the size of the RMHF causes the loads associated with self-weight and soil fill to increase linearly. Consequently, the shear and bending moments vary linearly and quadratically, respectively. In addition, deflections vary at a two-quadratic rate. Together, these variations make it necessary to increase the amount of resistant material in the RMHF.

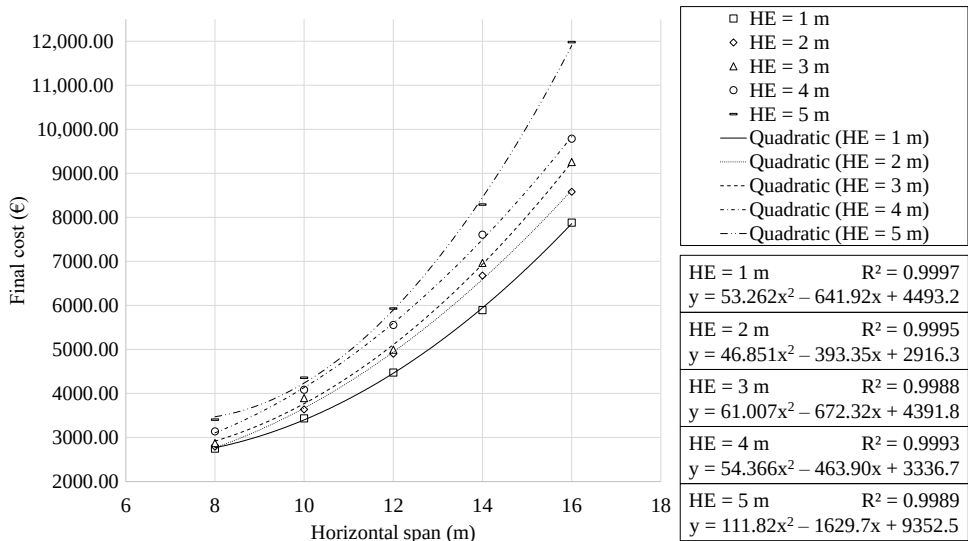


Figure 4.3: Cost of the RMHF as function of the horizontal span, for each earth cover depth.

The final cost of the structure is a direct representation of the use of materials. The results allowed associating the variation in the final cost to two reasons. The first is the intrinsic need to use more material to build a larger structure. The second is that the structure needs to resist stresses of greater magnitude. The first reason justified a linear increase in the final cost. The study of the second allowed establishing the increase in shear and bending moment stresses as the direct cause behind the

quadratic relation identified in the regression analysis. With an R^2 regression coefficient between 0.9988 and 0.9997, the expressions obtained are an adequate tool for the final cost approximation of the RMHF. It is relevant to highlight that when the earth cover above the structure is five meters, the final cost increases 1.44 times when the span increases from 14 to 16 m. This factor is, to some extent, more significant than other earth cover cases, varying between 1.28 and 1.33 for 1 and 4 m, respectively.

Figure 4.4 shows the mean minimum cost as a function of earth cover depth. The regression analysis showed a linear relation. With slightly lower correlation coefficients, the expressions obtained represent the final cost as a function of the earth cover depth. The analysis of the results allowed for associating the linear relation to the linear increase or decrease in the axial forces of the RMHF when varying the earth cover. Increasing the earth cover by one meter results in final cost increases between 5.73% and 10.49% for the 8 and 16 m frames, respectively. This corresponds to an increasing slope of the regression trendlines as the earth cover increases.

Furthermore, the analysis of the results allowed identifying that increments in the larger span range relate to more significant increases in the final cost. In Figure 4.3, this is represented by faster growth of the cost curve. Whereas in Figure 4.4, it corresponds to an increasing separation between the straight trend lines.

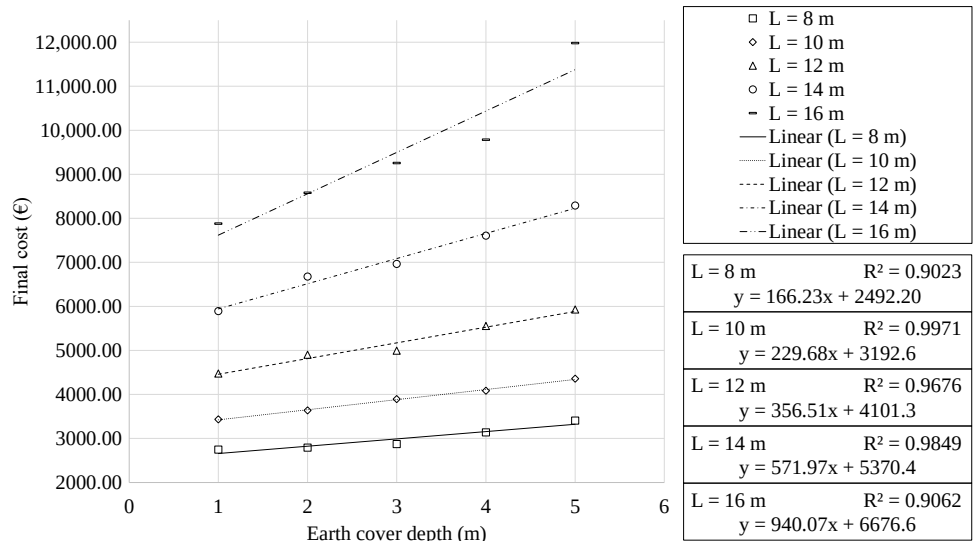


Figure 4.4: Cost of the RMHF as function of the earth cover, for each horizontal span.

4.4.2 Sustainability Analysis

This section focuses on the results related to the associated CO₂ emissions and embodied energy of the optimum RMHF.

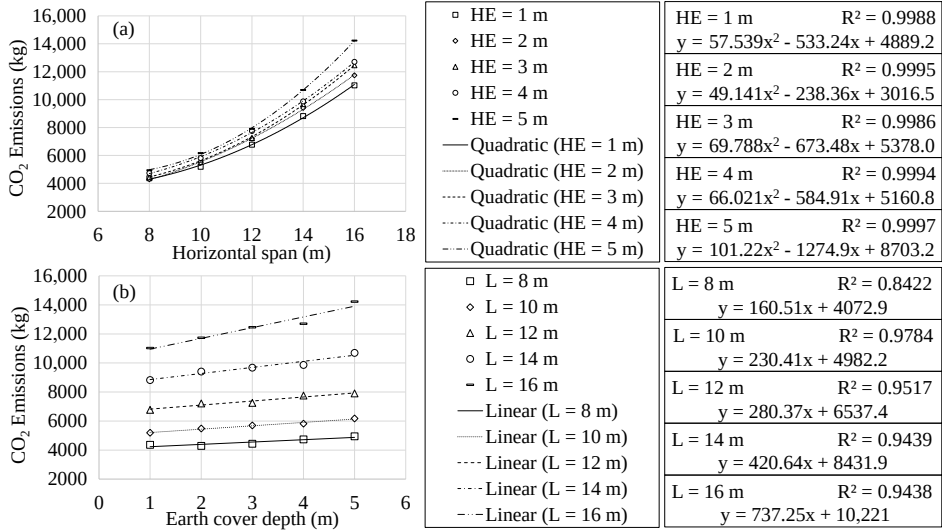


Figure 4.5: Associated CO₂ emissions analysis as a function of: a) horizontal span; b) earth cover.

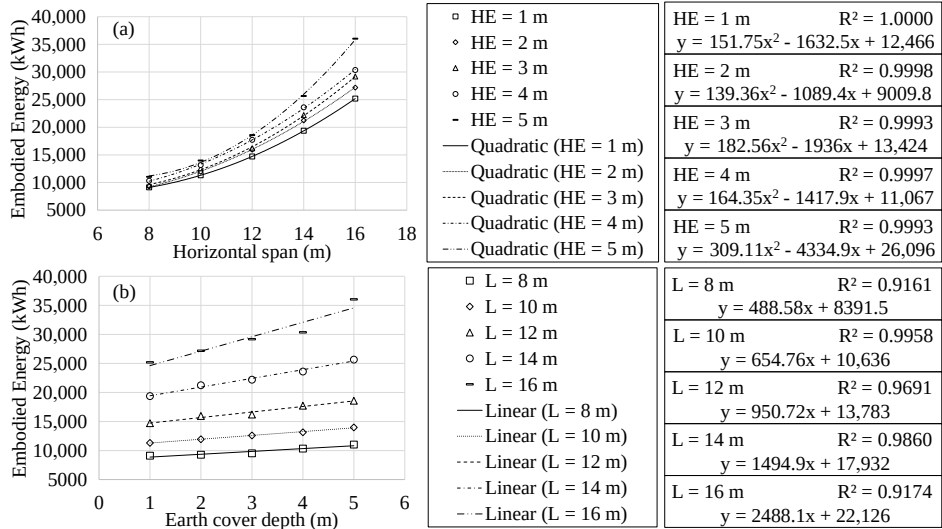


Figure 4.6: Embodied energy analysis as a function of: a) horizontal span; b) earth cover.

The regression analysis allowed identifying similar characteristics to those mentioned for the final cost in section ref. In both cases, there is a quadratic relationship with the span. In addition to a linear relation to the earth cover depth.

The present work considered associated CO₂ emissions and embodied energy as impact measuring tools associated with the optimal RMHF obtained. However, these were not considered objective functions. Thus, the particularized study of the characteristics of optimal frames as a function of such variables is beyond the scope of the study. Figures 4.5 and 4.6 show the results obtained in the regression analysis. With R^2 correlation coefficients close to one, the expressions form rough impact measuring tools for the design of RMHFs.

4.4.3 Geometrical Characteristics Analysis

This section continues with the results of the study. In this context, the relevant geometric characteristics of the optimal RMHFs were analysed. Figures 4.7 and 4.8 show the top slab depth and mid-span reinforcement area as a function of the horizontal span. The regression analysis showed a clear linear relationship between the upper slab depth and horizontal span. The results present a similar trend to those obtained in previous studies of similar structures [69], [70]. The optimization problem posed does not condition the design of passive reinforcement with traditional considerations. The individualized study of specific variables resulted in expressions with correlation coefficients somewhat lower but still representative. This is somewhat to be expected when studying particular variables. Unlike the final cost or sustainability indicators, the precise analysis of a single variable makes the consequences of the discretization process relatively more noticeable.

For an earth cover of one meter, the upper slab depth and horizontal span ratio vary between 10.05 and 9.92 for horizontal spans of 8 and 16 m, respectively. For structures buried at five meters deep, this ratio varies between 15.76 and 15.40 for the same cases. The expressions result of the regression analysis allowed for calculating a mean variation factor of 1.47 as the span increased from 8 to 16 m.

The reinforcement area in the mid-span section of the upper slab showed a clear linear relationship with the horizontal span of the RMHF. The passive reinforcement area increases with an average factor of 2.82 as the span varies from 8 to 16 m.

It is of particular interest to note that the RMHF configuration buried at one meter presents a behaviour that differs from the one presented by the rest of the depths. This characteristic behaviour is seen when studying Figures 4.7 and 4.8.

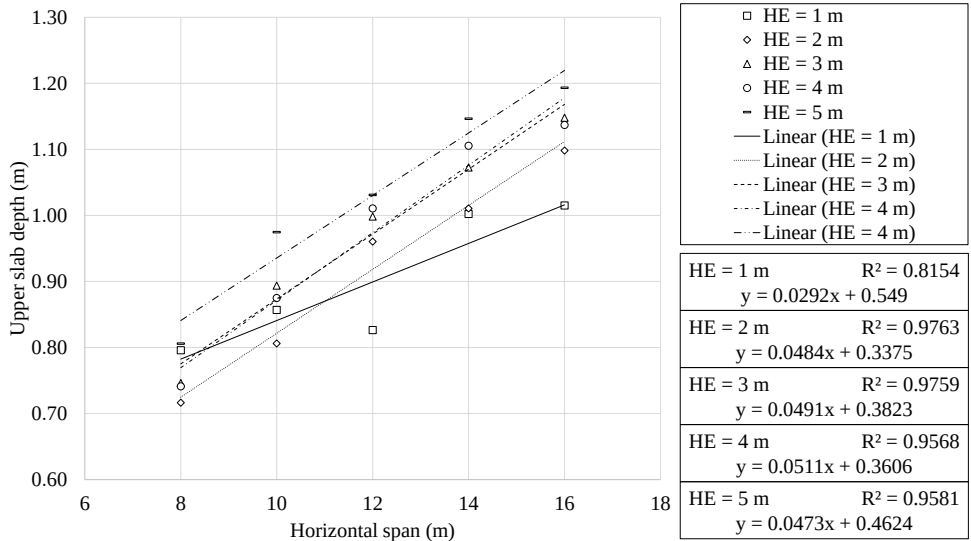


Figure 4.7: Upper slab depth as a function of the horizontal span.

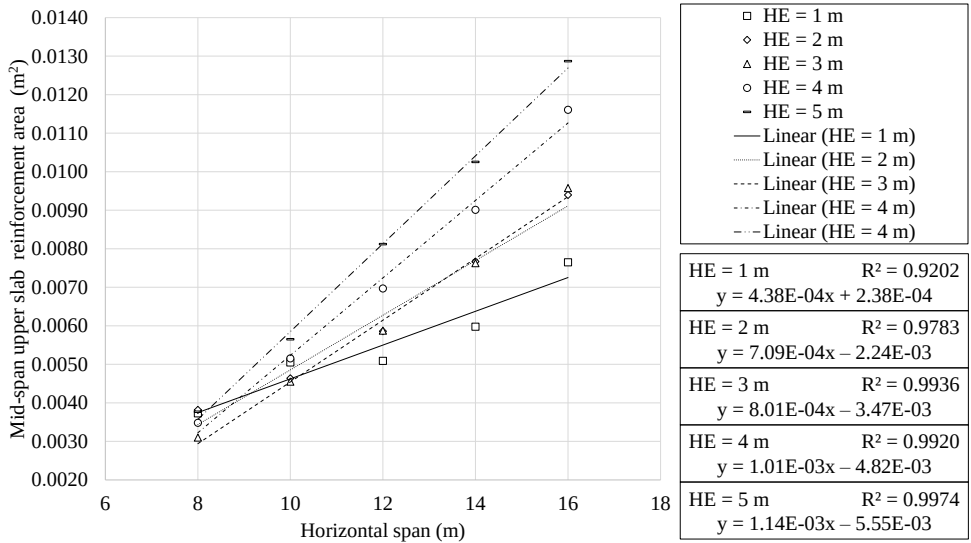


Figure 4.8: Upper slab mid span reinforcement area as a function of horizontal span.

In both figures, it can be seen that the slope of the line corresponding to 1 m of burial depth is less pronounced than the others. An in-depth analysis of the designs

corresponding to this configuration allows us to identify the frames with 8 and 10 m of horizontal span responsible for this behaviour. These configurations showed upper slabs with greater depths and higher flexural reinforcement. Such characteristics result from RMHF designs whose shear reinforcement showed considerable reductions. The problem posed made use of combinatorial optimization to obtain the designs. Thus, there is no predisposition for the traditional design. Therefore, the reduction in shear reinforcement in the one-meter deep, 8 and 10 m horizontal span RMHF was solved with localized increases of flexural reinforcement and greater depth sections.

Generally, the designs presented lower slab average depths values of 57.18% of the upper slab depth. Therefore, on average, the upper slab depth is 1.75 greater than the lower slab. In the case of the lateral walls, the optimum RMHFs presented reduced depths. On average, the lateral wall depth equalled 47% of that of the upper slab. The identified ratios provide an initial approximation in the design of the structural typology. However, the proposed reinforcement design depends on a substantial set of variables. Thus, the scope of the study makes a particularized analysis of each of them unfeasible. The results presented are a functional tool to be considered by structural technicians with pertinent technical backgrounds.

4.4.4 Materials Analysis

Section 4.4.3 highlighted the main geometric characteristics that were identified. This section focuses on the analysis of the materials used in the building of the optimum RMHFs. Figures 4.9 and 4.10 show the volume of concrete required as a function of the span and the earth cover depth. Concrete usage showed a quadratic relationship with the horizontal span. Meanwhile, the analysis of the results indicated a linear relationship with the earth cover depth. The regression analysis allowed for obtaining expressions with R^2 correlation coefficients very close to unity. In all cases, the expressions where concrete volume is expressed as a function of the horizontal span perform an approximation of greater quality when compared to those where the concrete volume is a function of the earth cover.

A total of 212 out of the 225 optimal frames studied make use of concrete grade C25/30. The use of higher grade concrete leads to more slender designs. However, the fact that 94.22% of the optimal RMHF designs used the lowest grade within the possible options shows that using a higher grade is not the most economical solution. In this context, the expressions obtained in the regression analysis are a useful tool for calculating the C25/30 grade concrete usage. Based on the results presented in Table 4.1, it was observed that the increase of 1 m in the earth cover leads to an increase of EUR 40.20 and 114.07 per linear meter in the 8 and 16 m span frames,

respectively. Furthermore, as a consequence, 182.06 and 516.61 additional kWh are required for the aforementioned spans. This leads to an additional 116.11 and 329.47 kg of CO₂ emitted into the atmosphere.

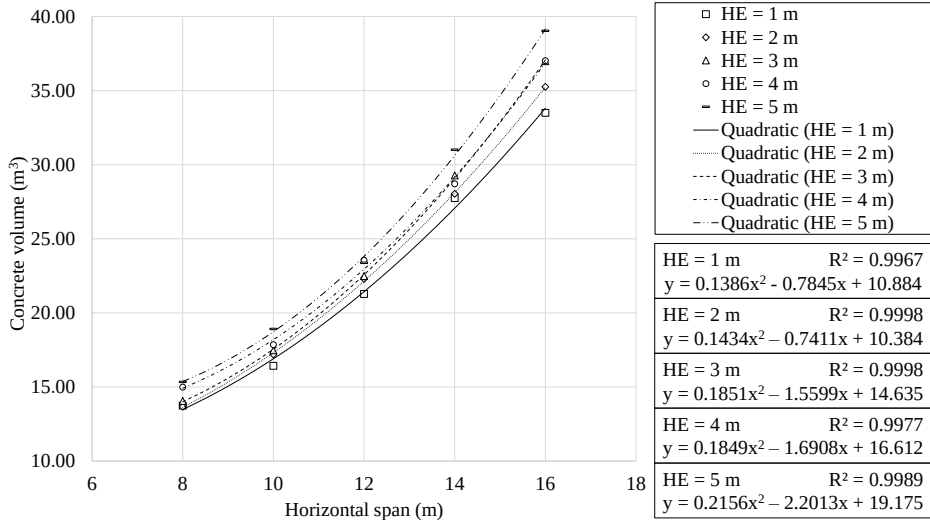


Figure 4.9: Concrete volume as function of horizontal span, for each earth cover depth.

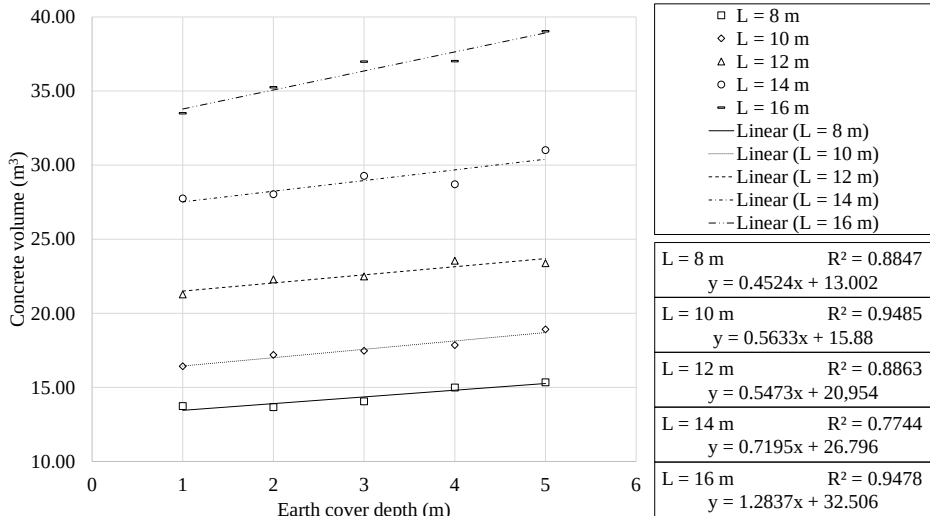


Figure 4.10: Concrete volume as function of earth cover depth, for each horizontal span.

The analysis of the amount of steel used for passive reinforcement is presented in Figures 4.11 and 4.12.

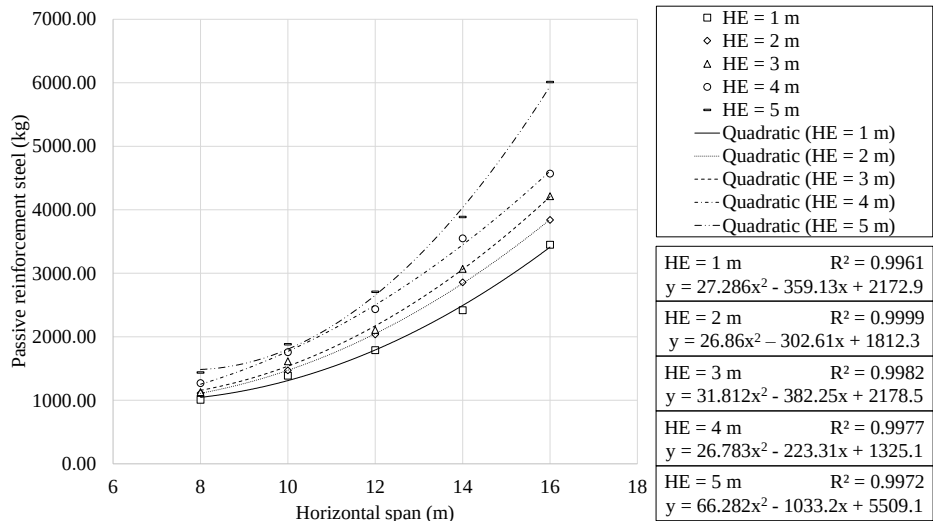


Figure 4.11: Passive reinforcement steel as function of horizontal span, for each earth cover depth.

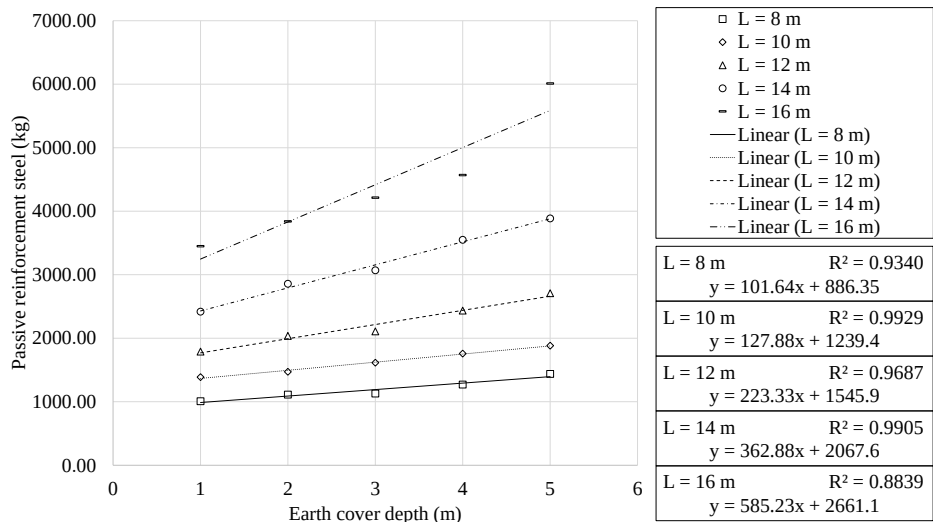


Figure 4.12: Passive reinforcement steel as function of earth cover depth, for each horizontal span.

Similar to the behaviour highlighted for concrete volume, quadratic and linear relationships are observed with the span and earth cover, respectively. Furthermore, the results showed a clear trend towards using a specific steel grade. This led to 91.11% of the optimal RMHFs using B500S steel for the passive reinforcement. The regression analysis obtained expressions with R^2 correlation coefficients close to one. A one meter increase in the earth cover leads to an increase in steel use of 101.64 and 585.23 kg for the 8 and 16 m span RMHFs, respectively. As stated in Section 4.1, the final cost of the structure is a direct representation of the use of materials. Thus, the higher usage of steel mentioned above, leads to an increase in the final cost of EUR 144.32 and 831.02 per linear meter, respectively. Similar to that mentioned for concrete use, the increase in steel necessary is also related to higher energy consumption and CO_2 emissions.

The passive reinforcement design of the RMHFs studied depends on a large number of variables. The scope of the study allows for considering the most relevant characteristics. Thus, Section 4.4.3 described results relating to the passive reinforcement area in the mid-section of the upper slab. In addition, another relevant result regarding the passive reinforcement design is the overall reinforcement density of the structure. In this context, Figure 4.13 shows the passive reinforcement density distribution surface as a function of the horizontal span and earth cover depth.

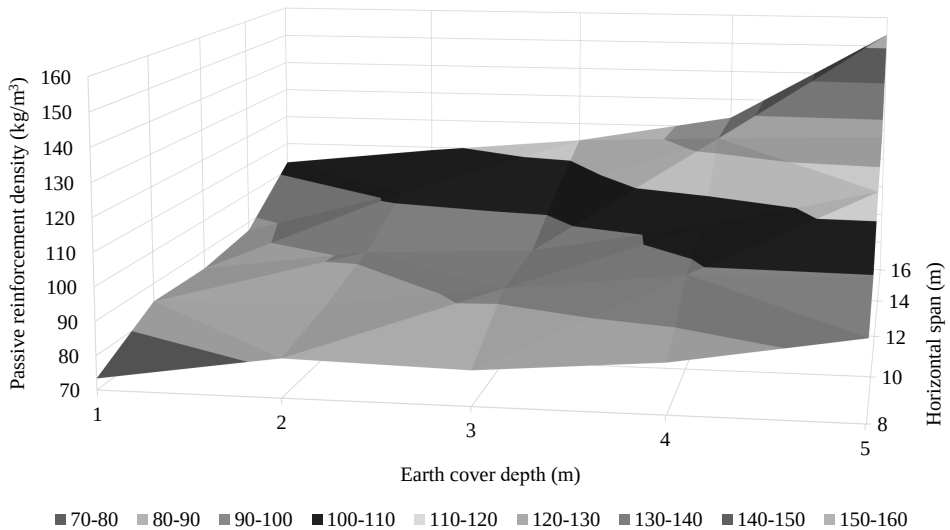


Figure 4.13: Reinforcement density distribution surface for the optimum RMHFs configurations studied.

The optimum RMHFs presented quite dense passive reinforcement designs when compared with similar structural solutions [32], [69], [70]. With densities ranging from 73.34 to 153.99 kg/m³. The increase from 8 to 16 m span led to an average increase of 1.45 in the passive reinforcement density. In addition, the study identified the influence of the earth's cover depth. Similarly to the case above, the increase in earth cover depth factors the reinforcement density by 1.35.

4.5 Conclusions

The present work examined the parametric study of optimal RMHFs. For this purpose, the study approached the structure's design as the combinatorial optimization problem described in Section 4.2. The use of three hybrid metaheuristic algorithms was considered for solving the problem. A fractional factorial DoE was carried out, the results of which placed the SAMO as the most suitable technique. In addition, the analysis of the DoE results allowed calibration of its parameters to obtain the best possible performance. The metaheuristic techniques and the DoE were detailed in Section 4.3.

Considering spans between 8 and 16 m and earth cover depths from 1 to 5 m, the study analysed 25 different RMHF configurations. The SAMO was applied to obtain nine optimal RMHFs for each configuration. The economic optimization allowed the analysis of 225 RMHF designs. By studying the main characteristics, a regression analysis was developed. The analysis obtained representative expressions with R^2 regression coefficients close to one. In view of the results presented in Section 4.4, the authors consider it appropriate to note the following conclusions:

- The hybridization of local search-based algorithms with GA mutation operators gives rise to hybrid metaheuristics. These techniques are applicable in automating the optimal design of precast structures. The SAMO presents the best performance in solving the problem posed. The calibrated method has Markov chain lengths of 10,000 iterations, a cooling coefficient of 0.8 and a stopping criterion of 5 chains without improvement. In addition, the mutation operator affects one variable with a standard deviation of 0.1.
- The cost and environmental impact meters present an excellent fitting quadratic relationship when studied as a function of the horizontal span. This relationship is linear when considered a function of the earth cover depth. The expressions obtained are representative and form a valuable tool for the approximate calculation of the final cost, the associated CO₂ emissions and the embodied energy of RMHFs.

- The RMHF design depends on a large number of variables. The study of each particular variable lands out of the scope of the present work. However, optimal structures present reduced depths with dense reinforcement designs. This density increases with both span and earth cover depth. In addition, the mid-span upper slab reinforcement area shows quadratic and linear relationships with the span and burial depth, respectively.
- Previous designs do not condition the structures conceived using the proposed methodology. Thus, any configuration that verifies the requirements is considered a feasible solution. In this context, the 8 and 10 m span RMHF buried one meter deep presented specific characteristics that differ from the general. With considerable reductions in shear reinforcement, these structures have upper slabs with greater depth and mid-span reinforcement areas.

Chapter 5

Social perspective on an optimized modular frame: Integrated life cycle analysis

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Abstract

The social perspective is a crucial aspect of constructing sustainable infrastructures. This study assesses the social life cycle analysis of an economically optimized precast reinforced concrete articulated frame. The manufacturing stage is identified as the most influential in the structure's social impact by analyzing the phased contribution to the overall social damage. Furthermore, it is confirmed that the modular structure exhibits notably minimal impact during the construction and end-of-life stages. The analysis of the most significant materials and processes indicates that passive reinforcing steel is primarily responsible for the social damage of the structure. While the contribution of concrete and transportation is comparatively lower, it remains relevant across the four categories of damage examined. These findings underscore the significance of considering social aspects in transportation infrastructure development and offer valuable insights for decision-makers and stakeholders.

Keywords: hinged frame; precast; life cycle analysis; optimization; social sustainability

5.1 Introduction

Developing and maintaining robust transportation infrastructure is crucial for national development [60]. A well-connected road network transcends economic utility, connecting people and facilitating the distribution of goods across communities. [56], [125]. Construction projects have predominantly focused on technical and economic considerations [32], [55]. However, assessing the social ramifications of structural solutions is imperative to guarantee that the industry's expansion fosters equality and social well-being in line with the tenets of sustainability [57], [104].

Transportation planning and decision-making generally prioritize economic feasibility and environmental impact [62], [126]. However, knowledge improvements derived from academic activity have promoted the recognition of these projects' effects on the social fabric of communities [103], [127]. This paradigm shift towards a more holistic approach is further bolstered by the growing adoption of governmental initiatives like Agenda 2030 [3]. As a result, there is growing consensus within the industry that disregarding the social implications of a construction project overlooks a fundamental pillar of sustainability. Such omission limits our understanding of the potential benefits or impacts construction may have on individuals, local communities, or society as a whole [13], [40].

This study aims to broaden the understanding of social sustainability metrics for reinforced concrete precast hinged frames (RCPHF), a prevalent structural solution in

Spain's transportation network. Ruiz-Vélez et al. [128] previously tackled the economic optimization of this structural type by conceptualizing the structural design as a combinatorial optimization problem and resolving it through a hybrid simulated annealing algorithm enhanced with a mutation operator [129]. Further research has focused on parameterizing environmental sustainability metrics for comparable structures, elucidating the environmental impacts associated with such structural typology [130]. Consequently, this study investigates the social implications of these optimally designed structures, cultivating an all-encompassing perspective on the sustainability of RCPHF [37].

Within this framework, the complete life cycle of the optimal RCPHF is modelled, focusing on the Social Life Cycle Assessment (SLCA) results to understand and quantify the social ramifications of the optimal precast structural design. Harm categories concerning the local community, broader society, value chain actors, and workers are examined through the Life Cycle Assessment (LCA) endpoint results [61]. This approach provides a comprehensive overview of the social performance of RCPHF designed under highly restrictive economic constraints, identifying the key areas and opportunities for significant improvements [40], [106]. The research further evaluates how distinct life cycle phases contribute to the overall social impact of the structure via comparative analysis [26], [131]. Moreover, the life cycle model's contribution tree is analyzed to identify the LCA's most influential processes and materials [21]. The results of these assessments provide a robust basis for formulating targeted strategies and interventions to enhance the social sustainability of future projects involving RCPHF.

This research contributes to advancing the growing trend of evaluating the social impacts of transport infrastructure. The findings underscore the importance of adopting a more balanced and socially sustainable approach in developing transport infrastructure, highlighting the need for holistic considerations in such projects. The conclusions are relevant to decision-making processes for policymakers, infrastructure developers, and stakeholders.

5.2 Methodology

The study employed the open-source software OpenLCA to develop and compute the LCA model [132]. Essential data for the social damage evaluation was sourced from PSILCA using the SOCA v2 database, a resource extensively endorsed in academia [133]. The social impact was analyzed using the Social Impact Weighting Method (MISP), effectively condensing 55 social impact categories into four more encompassing harm categories [16]. In adherence to existing European regulations, the

study followed a four-stage process: defining the objectives and scope of the study, conducting the model's inventory analysis, assessing the social impact, and interpreting the results [134], [135]. This section elaborates on each of these four critical stages.

5.2.1 Goal and Scope Definition

This study aimed at elucidating the social sustainability of the optimal RCPHF presented in Ruiz-Vélez et al. [129]. This goal entailed fulfilling three secondary objectives: analyzing the contribution of each life cycle phase to the overall RCPHF's social impact, evaluating the impact of primary processes and materials, and characterizing the LCA endpoint damage categories.

Modelling the life cycle of a road infrastructure component is inherently complex, constrained by available information, computational costs, and the necessary assumptions for its definition. The study introduced the model depicted in Figure 5.1 to address these challenges.

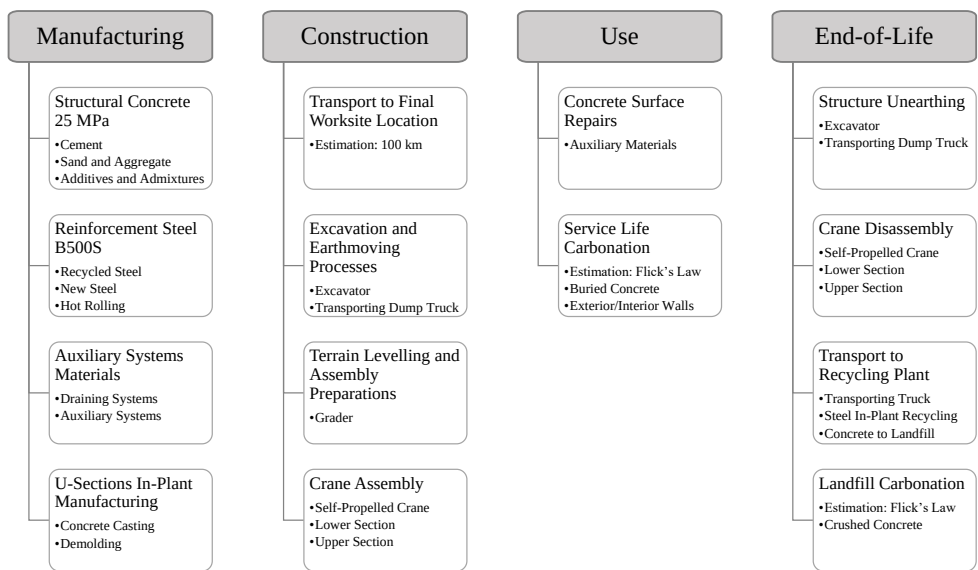


Figure 5.1: Optimal RCPHF life cycle model.

The life cycle of the optimal RCPHF encompasses four distinct stages: manufacturing, construction, usage, and end-of-life. The manufacturing phase covers all processes, from the extraction of raw materials to the production of ready-to-use

components. The case study included the manufacturing and transporting of structural concrete, steel for passive reinforcement, materials for auxiliary systems, and the in-plant serial prefabrication of the precast U-sections constituting the RCPHF.

The construction phase begins with transporting all necessary products and machinery to the site. The construction of RCPHF comprises straightforward processes such as excavating the area where the structure will be placed, levelling the ground and setting up the auxiliary drainage systems. Subsequently, a crane lifts and positions the pieces, assembling the structure that is then secured and checked.

Upon completing the construction phase, the structure enters a standard service life of 100 years. During this period, road frames are susceptible to damage like water seepage or carbonation. Aimed at representatively estimating these subjects, the study modelled surface repairs on the internal faces of the structure. Additionally, Fick's law was considered for simulating the in-service carbonation process of RCPHF, as expressed in Equation (5.1) [13].

$$Fixed\ CO_2 = 0.383 \cdot \frac{k_1 \cdot t^{0.5}}{1000} \cdot A \cdot C \cdot k \quad (5.1)$$

Calculating carbon dioxide mass fixed through concrete carbonation relies on several factors. Equation (5.1) evaluates the CO_2 kg as a function of a carbonation constant (k_1), the RCPHF lifespan in years (t), the surface area exposed to the carbonation process (A), the cement content (C) and the clinker percentage (k). The dosing for the optimal RCPHF's structural concrete is listed in Table 5.1. Different carbonation constants were applied to the external and internal faces of the walls and the crushed concrete [59].

Table 5.1: RCPHF structural concrete dosing.

Material		Quantity
Concrete	(kg/m ³)	305.00
Sand	(kg/m ³)	735.00
Aggregate	(kg/m ³)	1110.00
Superplasticizer	(kg/m ³)	0.31
Water	(kg/m ³)	202.50

Ultimately, the end-of-life stage commences once the RCPHF service life is completed. This final phase evaluates the processes necessary for dismantling the RCPHF and the subsequent recycling of its materials. Furthermore, this phase includes the complete carbonation of the structural concrete once crushed and de-

posited in the landfill. The linear meter was selected as the functional unit for calculation, a decision matching standards stipulations [90], [93]–[95]. Accurately characterizing and modelling the four stages above was crucial in deriving comprehensive and representative results.

5.2.2 Inventory Analysis

The inventory analysis involved gathering comprehensive data on the materials and resources utilized across the entire life cycle of the optimal RCPHF. Obtaining detailed information regarding the necessary material resources was efficiently achieved by referencing the optimal design characteristics outlined in Ruiz-Vélez et al. [129]. In line with this approach, Table 5.2 in the study delineates the quantities of materials and processes considered.

Table 5.2: Optimal RCPHF material and process quantities.

Material or process		Quantity
Structural concrete HA-25	(m ³)	18.03
Passive reinforcement steel B 500 S	(kg)	1442.07
Backfill soil	(m ³)	101.83
Levelling sand	(kg)	1620.50
Material transport to site	(km)	100.00
Service life concrete carbonation	(CO ₂ kg)	124.14
Site preparation excavation	(m ³)	5.12
Site decommissioning excavation	(m ³)	57.06
Steel transport to recycling plant	(km)	50.00
Concrete crushing	(t)	44.87
Concrete transport to landfill	(km)	10.00
Crushed concrete carbonation	(CO ₂ kg)	1508.80

5.2.3 Impact Assessment

The social impact assessment in any SLCA hinges on the methodology used for calculating the impact. This study employed the MISP to determine the social impacts incurred by a linear meter of optimal RCPHF during its life cycle. MISP computes the parameters inputted in the RCPHF life cycle model, evaluating social impact results across 55 diverse midpoint impact categories. These categories confine very specific aspects, are quantified in diverse units, and exhibit different magnitudes, making their collective analysis intricate and challenging for obtaining a concise understanding of the structure's social sustainability.

The advantage of the MISP methodology lies in its capacity to process these 55 impact categories and consolidate them into four comprehensive damage categories: local community, broad society, value chain actors, and workers. All damage categories are measured in medium risk per hour (mrh). Quantifying the four categories in the same unit resolves issues related to magnitude disparities. This uniformity simplifies the analysis and comparison, ultimately facilitating a clearer and more representative depiction of social damage throughout the life cycle of the optimal RCPHF.

The study introduced a methodology for an all-encompassing analysis and evaluation of the SLCA final results, exemplified by the Sankey diagram in Figure 5.2. The contribution of each life cycle phase to the total social damage was analyzed, incorporating both absolute values and percentage contributions. This analysis was instrumental in pinpointing the phases contributing most significantly to social damage, thereby guiding the focus of mitigation strategies to the most impactful stages.

Afterwards, an in-depth analysis of the main processes was conducted, focusing on their cumulative and relative contributions to social damage. Additionally, the contributions of each material were evaluated to pinpoint the most impactful ones. Gaining insight into these critical contributors is essential for effectively designing and managing projects involving RCPHFs.

The phase-by-phase, process, and material analyses provided essential data to evaluate the damage categories comprehensively. This approach offers a thorough perspective on the social sustainability of the optimal RCPHF. Utilizing databases with up-to-date, high-quality data and applying a widely recognized impact assessment methodology enables accurate quantification and characterization of the social damage incurred throughout the life cycle of the structural solution under study.

5.2.4 Result Interpretation

The results are meticulously analyzed in the final stage of the four-step process outlined by the standards concerning the LCA of reinforced concrete structures. Proper interpretation of these results hinges on adequately comprehending the damage categories under study.

The local community category addresses the social effects on communities near the RCPHF location. It quantifies the well-being and quality of life improvements or detriments for the adjacent population, factoring in elements like noise pollution and alterations to the local landscape. This category is particularly crucial in infrastructure projects where minimizing negative impacts, especially during construction, is essential to foster positive community relations and support sustainable regional development.

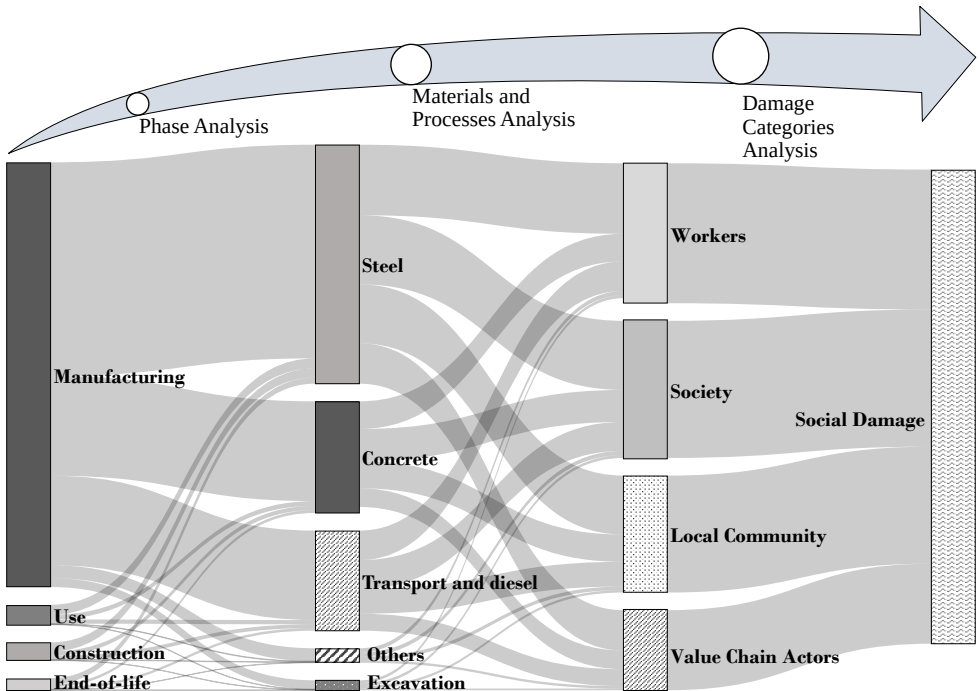


Figure 5.2: Integrated approach to RCPHF social impact evaluation.

The society category encapsulates the broader societal impact of constructing and operating road infrastructure. By assessing aspects such as accessibility, regional economic growth, or traffic flow, this category evaluates communities' overall well-being and economic development. As transportation infrastructure facilitates connections and supports the routine functioning of industrial and commercial activities, it is vital to quantify and incorporate the social impact of structures into decision-making for a sustainability-aligned approach.

The third damage category evaluates the social impact on parties involved in constructing the RCPHF, including suppliers, contractors, and material manufacturers. By scrutinizing sustainable and ethical practices in the life cycle processes of the precast structure, the value chain actors category plays a significant role in fostering social responsibility in the construction sector. Ensuring fair practices and equitable treatment among involved parties is pivotal for the long-term sustainability of the construction industry, further highlighting the relevance of this category for ensuring a socially responsible transport infrastructure development.

The fourth and final category, damage to workers, concentrates on the social impact on individuals directly engaged in the structure's construction. From engineers to workers, this category assesses aspects like occupational health and safety, work schedules and workload, fair wages, and professional development opportunities, aiming to evaluate and develop tools to promote and safeguard workers' rights.

5.3 Social Life Cycle Analysis Results

The comprehensive methodology employed in this study facilitated the acquisition of detailed results regarding the contributions of each life cycle phase, as well as the main materials and processes involved. This approach yielded a sound understanding of the extent of each of the four damage categories. Consequently, this section is dedicated to presenting and discussing the key findings.

5.3.1 Life Cycle Phases

The study parted from assessing the contributions of each of the four life cycle phases across the four damage categories. In this regard, Table 5.3 delineates each phase's absolute and relative contributions to the various damage categories depicted in Figures 5.3 and 5.4, respectively.

The manufacturing phase emerged as the most substantial contributor in all categories, with its absolute influence ranging from 85.27% in the local community category to 93.25% in societal damage. This significant role of the manufacturing phase in shaping the overall social damage of the RCPHF can be primarily attributed to the raw material extraction processes and their direct repercussions. Furthermore, in-plant manufacturing of precast modular structures, like the precast sections constituting the final structural assembly under study, inherently entails resource and energy-intensive processes. Therefore, results that showcase a manufacturing stage that highly conditions the overall SLCA outcomes align with RCPHF's precast core.

Table 5.3: Phase contribution analysis results for each social damage category.

	Local community		Society		Value chain actors		Workers	
	(mrh)	(%)	(mrh)	(%)	(mrh)	(%)	(mrh)	(%)
Manufacturing	1.28E+06	85.27	1.65E+06	93.25	9.47E+05	91.86	1.58E+06	87.68
Construction	7.35E+04	4.88	4.70E+04	2.66	3.35E+04	3.25	8.00E+04	4.44
Use	8.52E+04	5.66	5.31E+04	3.01	3.66E+04	3.55	8.28E+04	4.60
End-of-life	6.31E+04	4.19	1.91E+04	1.08	1.38E+04	1.34	5.91E+04	3.28

The construction phase contributed 4.44% to the workers social damage. Generally, the construction contributions to social damage are significantly lower than those of the manufacturing phase. However, these remain relevant to the comprehensive social impact analysis throughout the RCPHF life cycle. The construction stage involves localized disruptions, such as road closures and concentrated pollution due to construction machinery. Subsequently, this stage most notably affects the local community category, with an impact measured at $7.35\text{E}+04$ mrh, accounting for 4.88% of the total impact in this category. Conversely, the broader perspective encapsulated in the society damage category minimizes the perceived local impact, with a considerably lower damage value of $4.70\text{E}+04$ mrh, compared to the more pronounced effects on the local community.

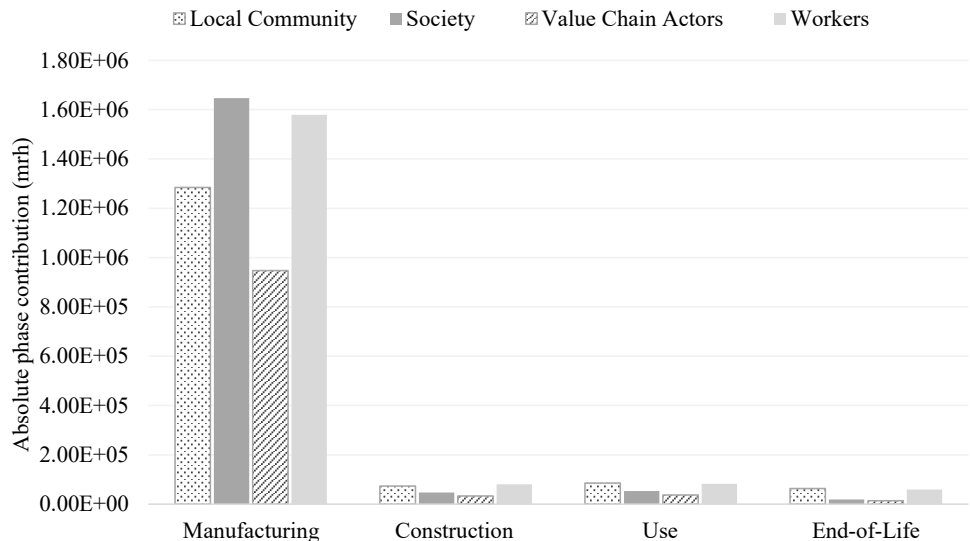


Figure 5.3: Absolute contribution to each social damage category for each life cycle phase.

The use and end-of-life phases show relatively lower contributions to all damage categories. The contribution rates are between 1.08% and 4.19% for the use phase, ranging from 1.39% to 4.19% for the end-of-life phase. These stages encompass the utilization of the structure, its routine maintenance, and all dismantling processes. These conclude with the transport for disposal and subsequent landfill carbonation of the crushed concrete and the transport of the passive reinforcement steel to the recycling plant. While asserting that the social benefits provided by the optimal RCPHF significantly offset the impacts associated with these particular phases, their contri-

butions should not be overlooked, as they still entail social implications affecting all damage categories.

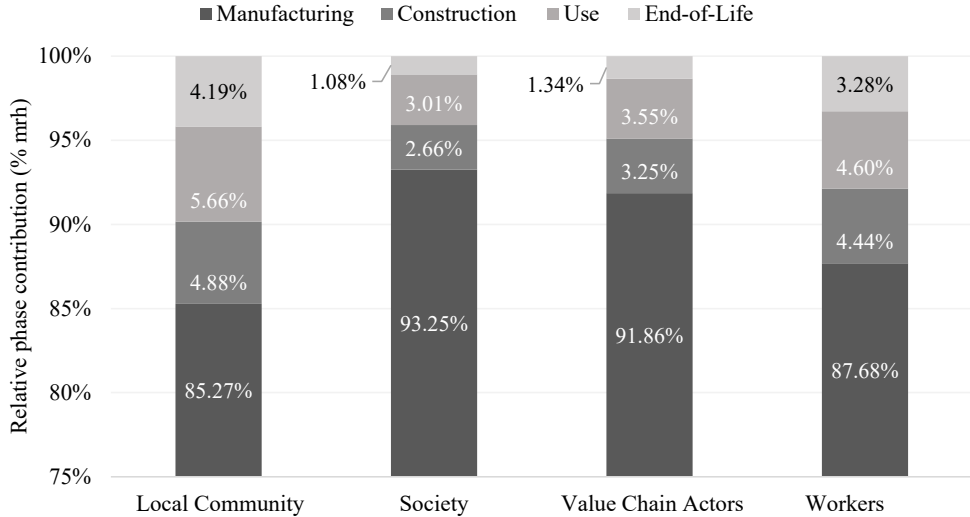


Figure 5.4: Relative contribution to each social damage category total for each life cycle phase.

The findings offer insightful data on the impacts exerted by the RCPHF during each stage of its life cycle. To gain further insight, the study analyzed each phase's contribution to the total social damage and calculated the proportional impact on each damage category. The results of this in-depth analysis, detailed in Table 5.4, are visually represented in the comparative graphs illustrated in Figures 5.5 and 5.6.

Table 5.4: Total damage contribution analysis for each phase and social damage category.

	Phase contribution to total		Local community	Society	Value chain actors	Workers
	(mrh)	(%)	(%)	(%)	(%)	(%)
Manufacturing	5.46E+06	89.40	23.53	30.16	17.36	28.94
Construction	2.34E+05	3.83	31.42	20.07	14.32	34.18
Use	2.58E+05	4.22	33.06	20.59	14.22	32.13
End-of-life	1.55E+05	2.54	40.69	12.30	8.91	38.10
Total	6.10E+06	100.00	24.67	28.92	16.90	29.51

The analysis revealed that the manufacturing phase is responsible for a substantial 89.40% of the total social damage throughout the life cycle of the optimal RCPHF, translating to 5.46E+06 mrh. The social damage showcases an uneven distribution

across society and the value chain actors, enduring 30.16% of this phase's damage and 17.36% as the most and least affected categories, respectively. On the other hand, the local community and workers experience a closer impact distribution, at 25.53% and 28.94%, respectively.

The construction phase contributes 3.83% of the total social damage. While less substantial than the previous phase, this impact is still relevant since it translates to $2.34\text{E}+05$ mrh of social harm among the four damage categories. The value chain actors are less affected, bearing 14.32% of the damage during construction. However, the processes intrinsic to preparing the work site and assembling the structure transfer 31.42% to the local community. The construction process explicitly targets the workers, a category that bears 34.18% of the phase's total social damage. The results suggest that the construction phase predominantly affects the stakeholders directly involved in the RCPHF construction site, with comparatively less severe influence on the remaining value chain actors.

The damage distribution trend identified during the construction phase analysis becomes even more pronounced in the use phase, displaying a marked polarization towards groups primarily encompassing local stakeholders. The local community experiences significant impacts, accounting for 33.06% of the total social damage of $2.58\text{E}+05$ mrh incurred during this phase. This substantial impact primarily arises from the nature of the preventive maintenance activities considered in the LCA model, which include temporary road closures at the RCPHF site, leading to disruptions in local traffic. Workers involved in the project also face considerable social damage, receiving 32.13% of the phase's total impact. However, the broader societal harm category indicates that the benefits of utilizing RCPHF considerably mitigate the negative aspects of its operational processes, highlighting a nuanced balance in the social impacts during this stage.

In the end-of-life stage, the social damage is relatively minor, constituting only 2.54% of the overall impact, equivalent to $1.55\text{E}+05$ mrh. This stage continues the pattern of polarized impact distribution, with the local community and workers predominantly bearing 40.69% and 38.10% of the social damage, respectively. This distribution is directly attributable to the specific activities involved in dismantling, which tend to cause local traffic disruptions and environmental contamination, primarily affecting these two groups.

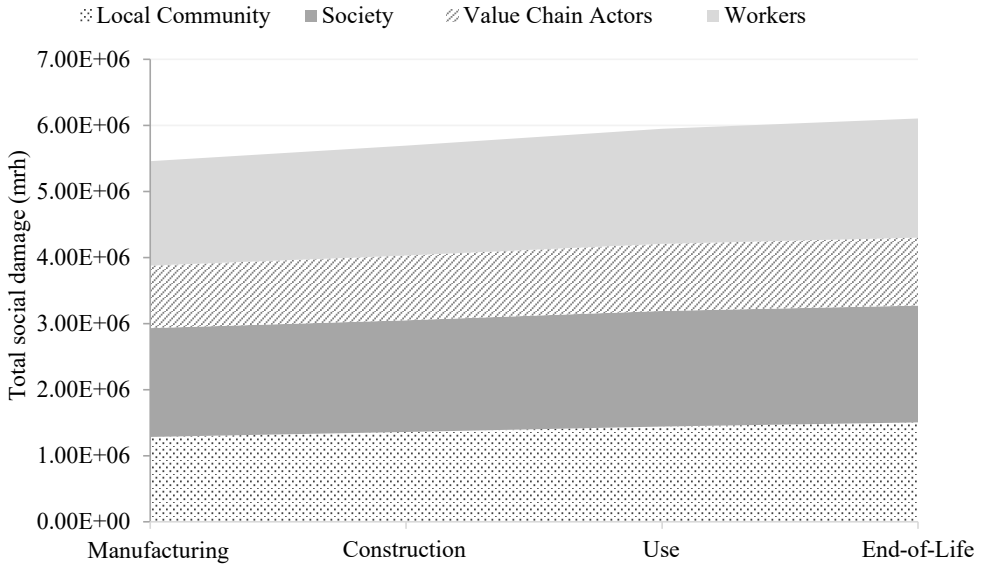


Figure 5.5: Social damage evolution for each phase of the RCPHF's life cycle.

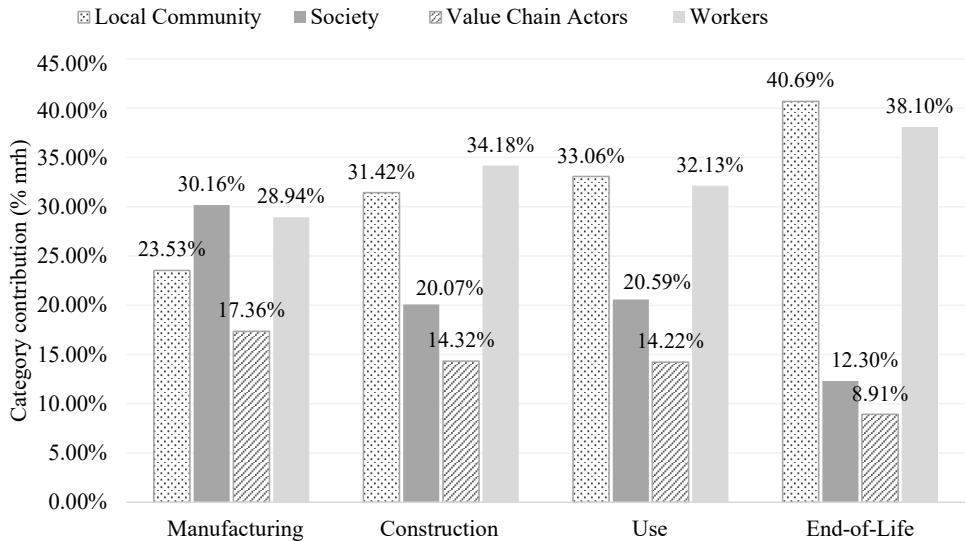


Figure 5.6: Relative contribution of each damage category to total social damage, for each phase of the RCPHF's life cycle.

The comprehensive analysis of phase contributions highlights that the manufacturing phase of the RCPHF is the most significant in terms of social impact. This phase's contributions far exceed those of other stages, underscoring the substantial impact inherent in the prefabrication of the modular structure. In contrast, the straightforward nature of the RCPHF's construction process results in a considerably lower social impact during this phase, with the most significant effects felt by the local community and the workers involved. A relevant trend is identified: as the RCPHF progresses through its life cycle stages, a substantial polarization of social damage seems to occur, increasingly concentrating the social damage on the local community and workers. This observation emphasizes the critical need to thoroughly consider the implications for these groups in planning and implementing infrastructure projects involving RCPHFs.

5.3.2 Processes and Materials

The comprehensive analysis in Section 5.3.1 provided critical insights into the phase contributions to social damage. The next phase of the research focused on evaluating the impacts of key materials and processes throughout the RCPHF's life cycle on each social damage category and their cumulative effects. This comprehensive approach involved a detailed assessment of the major contributors' absolute and relative impacts. The findings are systematically presented in Table 5.5, which outlines the absolute damage and the proportional contributions of materials and processes across each damage category. These results are visually represented in Figures 5.7 and 5.8.

Table 5.5: Material and process contribution analysis results for each social damage category.

	Local community		Society		Value chain actors		Workers	
	(mrh)	(%)	(mrh)	(%)	(mrh)	(%)	(mrh)	(%)
Concrete	4.08E+05	27.10	5.07E+05	28.73	1.67E+04	1.62	4.93E+05	27.39
Excavation	7.05E+04	4.68	0.00E+00	0.00	0.00E+00	0.00	5.71E+04	3.17
Steel	8.17E+05	54.21	1.18E+06	67.01	0.00E+00	0.00	1.08E+06	59.79
Transport/Diesel	1.79E+05	11.91	5.79E+04	3.28	9.13E+05	88.54	1.38E+05	7.67
Others	3.16E+04	2.10	1.73E+04	0.98	1.01E+05	9.84	3.58E+04	1.99

The SLCA model developed is a complex system comprising tens of thousands of inner flows, charting materials and processes through the RCPHF's life cycle and computing them into multiple metrics that culminate in social impacts and damages. Given the model's extensive and intricate nature, the investigation focused on concrete, excavation and earthmoving processes, steel, and the transportation or diesel consumption in machinery as the primary contributors to social damage. The combined social damage from other materials or processes was aggregated into a single

group for analysis. Notably, some materials contributed marginally to specific categories, deemed negligible by the model's precision and thus considered null.

Passive reinforcing steel emerged as the top contributor to social damage across several categories. Its life cycle processes in the RCPHF significantly impacted $8.17\text{E}+05$, $1.18\text{E}+06$ and $1.08\text{E}+06$ mrh to local communities, society, and workers, with relative contributions of 54.21%, 67.01%, and 59.79%, respectively. The energy-intensive production of steel, coupled with the extensive mineral extraction required, leads to noise pollution near mining and processing sites and poses various risks to value chain actors and workers. This material accounts for over half of the RCPHF's social damage, suggesting that refining the processes associated with steel production and subsequent usage could be a well-performing targeted approach to enhancing the sustainability of this structural typology.

Structural concrete's impact followed, with social damage impacts between 27.10% and 28.73% in categories affecting local communities, society, and workers, with $4.70\text{E}+05$ mrh on average. These three categories account for 98.93% of the total social damage yielded by the set of processes inherent to the life cycle of the 25 MPa structural concrete used to cast the optimal modular frame.

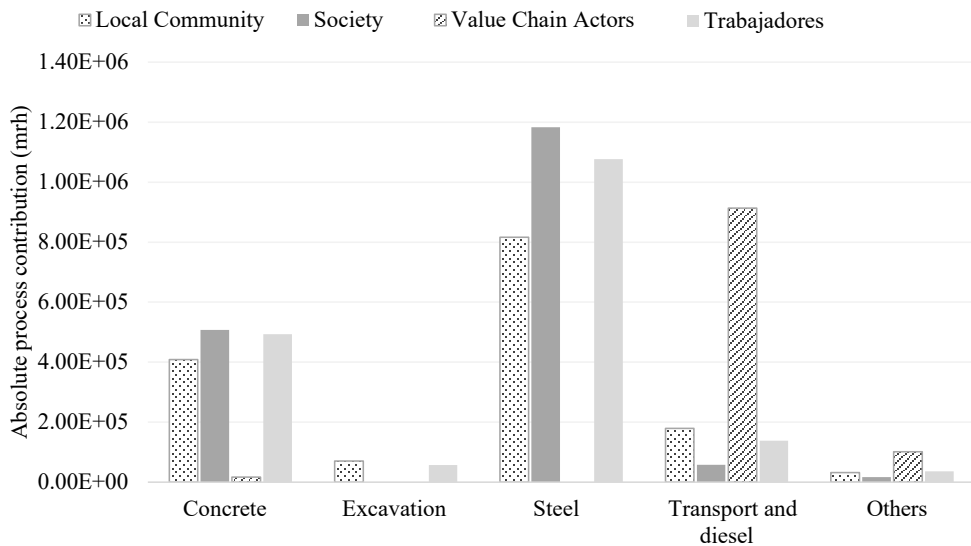


Figure 5.7: Absolute contribution to each social damage category for the main materials and processes.

Concrete directly benefits the local communities where the RCPHF's are built by improving the road network. Upstream, producing said concrete also provides local benefits such as generating and sustaining jobs, which are the basis of livelihood for workers in multiple industries. However, concrete production is a polluting process with profound social implications, mainly affecting the workers producing the clinker necessary for manufacturing cement. The results derived from the SLCA model align with these realities, reflecting the significant impact of concrete usage.

All transportation operations and diesel consumption in self-propelled machinery form the third major group. The optimal RCPHF's life cycle encompasses various transportation activities, from raw material extraction to waste disposal, with the SLCA model accounting for the different transportation weights and size requirements. The consumption of diesel by construction machinery like cranes is also factored in. These activities contribute an average of $3.22E+05$ mrh across the damage categories, representing 27.85% of the total impact.

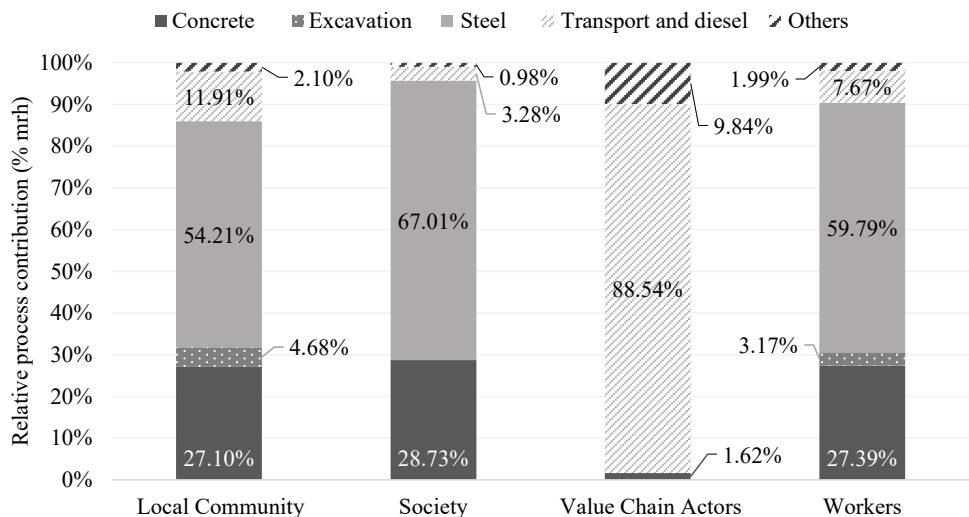


Figure 5.8: Relative contribution to each social damage category total for the main materials and processes.

Further analysis allowed for identifying a distribution trend that significantly differs from the abovementioned behaviour. While steel and concrete induce minor damage, transport and diesel consumption predominantly affects value chain actors. This category bore 88.54% of the social damage associated with these processes, underlining the serious risks faced by industry professionals engaged in special load

transportation and heavy machinery operations. A competitive environment where the lack of adequate training setups and inadequate safety measures education lead to fatal accidents explains this behaviour in damage distribution.

Table 5.6: Total damage contribution analysis for each material or process and social damage category.

	Material or process contribution to total		Local community	Society	Value chain actors	Workers
	(mrh)	(%)	(%)	(%)	(%)	(%)
Excavation	1.28E+05	2.09	55.23	0.00	0.00	44.77
Steel	3.08E+06	50.40	26.54	38.45	0.00	35.01
Transport/Diesel	1.29E+06	21.11	13.92	4.49	70.87	10.72
Others	1.86E+05	3.05	16.99	9.29	54.49	19.24
Total	6.10E+06	100.00	24.67	28.92	16.90	29.51

The remaining groups correspond with the excavation operations and the amalgamation of the remaining, less impacting processes and materials. The results on how each process and material contributes to the individual damage categories show-cased relevant trends. Additionally, the specific behaviours in damage distribution fit the reality after the SLCA model, further confirming the representativeness of the results.

Subsequent analysis delved into the total social damage attributable to each process and material throughout the RCPHF's life cycle. Table 5.7 summarizes these findings, illustrated in Figures 5.9 and 5.10.

Steel emerged as the dominant contributor to total social damage, responsible for over half of it. Society bore the brunt, receiving 38.45% of the damage incurred during steel's life cycle. Workers and the local community were also significantly affected, receiving 35.01% and 26.54% of the total 3.08E+06 mrh attributed to steel's passive reinforcement.

Concrete followed, accounting for 23.35% of the total social damage, equating to approximately 1.43E+06 mrh. The damage was evenly distributed among local communities, society, and workers, each receiving 28.64%, 35.58%, and 34.61%, while the remaining 1.17% impacted value chain participants in the precast modular structure concrete's life cycle.

Transportation operations and machinery diesel consumption accounted for 21.11%, contributing slightly less than concrete to the total social damage. Consistent with previous observations, value chain participants were the most affected, bearing 70.87% of the 1.29E+06 mrh attributed to these processes.

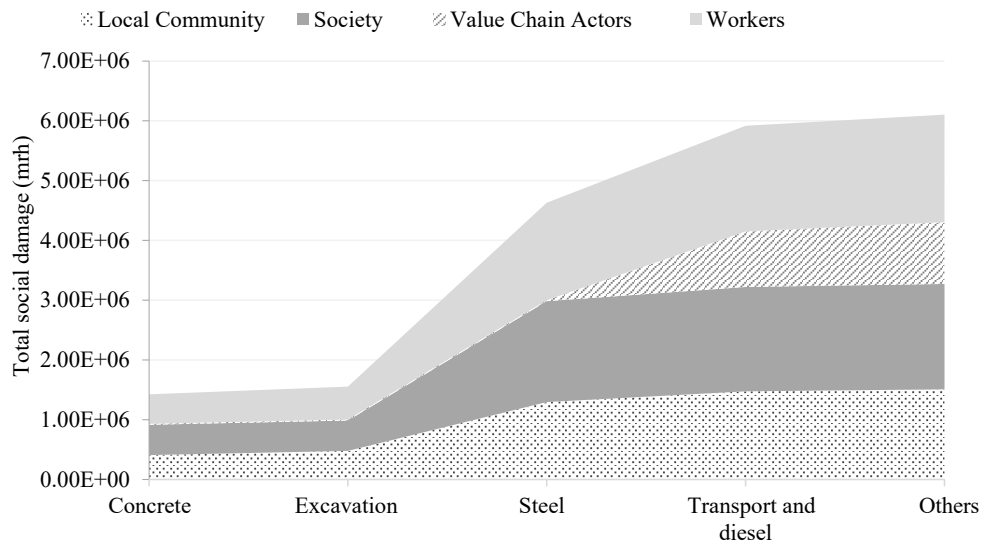


Figure 5.9: Social damage evolution for the main material and process of the RCPHF's life cycle.

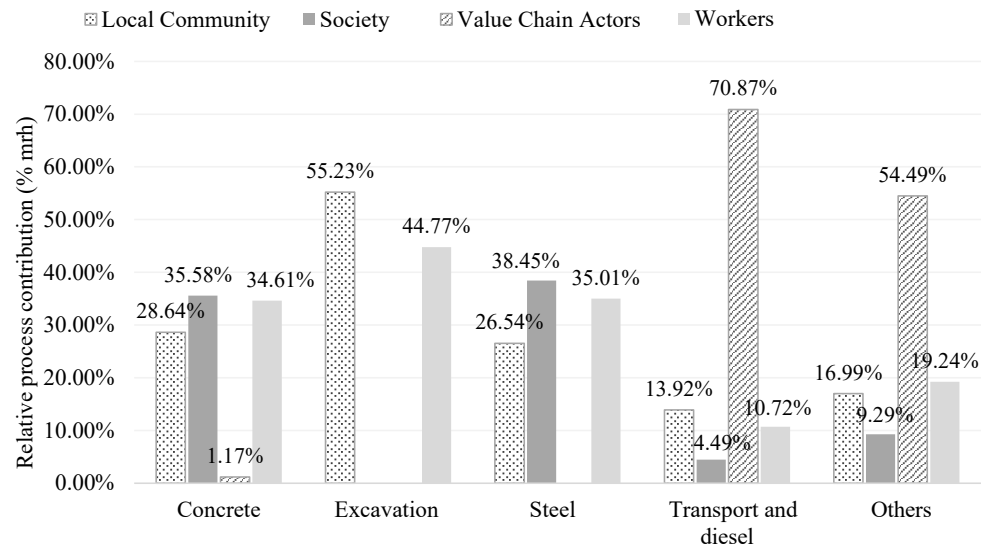


Figure 5.10: Relative contribution of each damage category to total social damage, for the main materials and processes of the RCPHF's life cycle.

Site excavation prior to the RCPHF's assembly and the earthmoving necessary during its decommissioning contribute 2.09% of the total social damage. These activities mainly impacted local communities and workers. The workers are exposed to direct occupational risks directly associated with the normal development of these activities, while the community experiences localized negative environmental impacts. The remaining 3.05% of the total social damage is attributed to the multiple, less impacting processes and materials.

In summary, the meticulous examination of the results on the absolute and relative contribution of the materials and processes provided a nuanced understanding of the sustainability of the optimal RCPHF from a social standpoint.

5.3.3 Damage Categories

In light of the findings detailed in Section 5.3.1 and Section 5.3.2, the analysis culminated in a comprehensive evaluation of the overall contributions. This approach involved a focused analysis of the aggregate values and, more critically, the individual contributions of each category to the total social damage incurred. Table 5.7 outlines each social damage category's absolute and proportional contributions in the SLCA of the optimal RCPHF. This global assessment underscores the nuanced interplay of different factors contributing to social damage, offering a holistic perspective on the sustainability impacts of the optimal RCPHF.

Table 5.7: Total damage category contribution analysis summary.

		Local community	Society	Value chain actors	Workers	Total
Absolute	(mrh)	1.51E+06	1.77E+06	1.03E+06	1.80E+06	6.10E+06
Relative	(%)	24.67	28.92	16.90	29.51	100.00

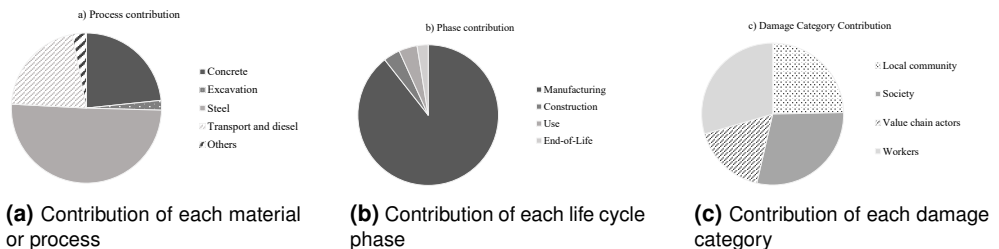


Figure 5.11: Contribution to total social damage where: a) Contribution of each material or process; b) Contribution of each life cycle phase; and c) Contribution of each damage category.

Figure 5.11a displays the contribution of each process to the overall social damage, offering a clear and concise visualization. This figure distinctly highlights the considerable contribution of steel, notably higher than the contributions of concrete and transportation, which are comparatively lower and almost equal in their impact.

Figure 5.11b illustrates the contribution of each life cycle phase to the total social damage. This representation delineates the pronounced disparity between the construction phase's contribution and the other phases of the RCPHF life cycle. The detailed analysis provided in this section has thoroughly explored these results, uncovering pertinent trends in the distribution of social damage across different phases for each damage category.

Figure 5.11c provides a visual breakdown of the contributions made by each damage category to the overall social damage incurred during the entire life cycle of the optimal RCPHF. The life cycle results in a total of $6.10\text{E}+06$ mrh in social damage, with the most substantial impact being on workers, who endure 29.51% of this total. Following are the impacts on the local society and community, bearing 28.92% and 24.67% of the social damage, respectively. Meanwhile, value chain actors experience a more minor yet significant portion of the social damage, accounting for 16.90% of it, which equates to approximately $1.03\text{E}+06$ mrh.

5.4 Conclusions

This research offers an extensive evaluation of the sustainability of an RCPHF, achieved by analyzing the social life cycle of a structure optimized for economic efficiency. The study involved developing a complex life cycle model, gathering essential data, and computing social impacts to ascertain the social damage attributable to the life cycle of the modular structure in focus. The analysis of the results was segmented into phase-wise contributions. Additionally, it assessed the contributions of primary processes and materials to the social damage across different SLCA damage categories. A holistic view of social damage was then realized by examining the cumulative contributions. Collectively, these efforts have yielded insightful and well-defined results that depict a comprehensive picture of the cost-optimal RCPHF's social sustainability. In light of these findings, and based on the specific hypotheses applied to this case study, the authors are poised to present a set of particularly relevant conclusions.

The manufacturing phase of RCPHF stands out as the most significant contributor to all evaluated categories of social harm throughout its life cycle. This trend aligns with the reality behind the processes required for prefabricating the structure's sections in the precast factory setting. Addressing and reducing social harm during this manu-

facturing phase emerges as a critical area for enhancement. Therefore, any initiative to diminish the social damage associated with modular frames should primarily target this manufacturing stage. However, paying attention to potential improvements in subsequent phases of the structure's life cycle is equally important, ensuring a comprehensive approach to social sustainability.

The construction phase of the RCPHF embodies a relatively lower impact, primarily due to its straightforward construction process involving crane-assisted assembly at the final worksite. This phase's social damage prominently affects the local community, attributable to factors like traffic disruptions, alterations in the local landscape, and noise pollution, all of which are endured by residents near the RCPHF building site. The minimal impact generated during this stage poses modular precast frames as an especially interesting structural solution in areas where such social disturbances could be particularly impactful. Therefore, the findings from this phase of the study provide valuable insights for informed decision-making in the planning of road infrastructure projects, underscoring the importance of considering local community impacts in construction methodologies.

Steel is the material that contributes the most to social damage during the life cycle of RCPHF, being responsible for more than half of the total social impact. Together, concrete and transportation contribute practically the same as steel for reinforcement. This is a consequence of the intensive processes inherent to the life cycle of passive reinforcement steel, highlighting the importance of mitigating the damage associated with using this material.

Steel is the most damaging material throughout the RCPHF's life cycle, accounting for over half of the social damage. In comparison, 18.03 m³ of HA-25 concrete and all transportation operations collectively contribute a magnitude similar to the 1442.07 kg of B 500 S comprising the passive reinforcement of the cost-optimal RCPHF. This significant impact of steel is attributed to its life cycle's labour and resource-intensive processes, particularly when manufactured for passive reinforcement applications. The substantial social damage linked to steel use underscores the critical need for strategies aimed at mitigating these impacts. Such strategies would not only enhance the sustainability of the construction process but also significantly reduce the overall social footprint of RCPHF projects.

Total social damage from the RCPHF's life cycle mainly impacts the local community, broader society, and workers. Collectively, these groups bear a significant portion of the total social harm. In contrast, the value chain actors experience relatively lighter effects, predominantly from transportation activities and diesel usage. This trend underscores the necessity of mitigating risks associated with road transport and the operation of heavy machinery. Effectively addressing these risks can lead to a sub-

stantial reduction in social harm, particularly for those involved in the logistic and operational aspects of the construction process. This insight is vital for enhancing safety measures and adopting more sustainable practices in the construction industry, especially in the transport and machinery operation stages.

The research findings emphasize the imperative to develop and apply specific strategies aimed at enhancing the manufacturing stage and the utilization of steel in the construction of RCPHF. The economic optimization of this modular precast solution has led to a significant reduction in concrete use, resulting in designs that feature notably dense passive reinforcement. This attribute likely plays a role in the substantial social damage linked to steel use across the frame's life cycle. The study reveals a marked distribution of social harm affecting local communities and workers during different phases of the RCPHF's lifecycle. These insights provide a thorough perspective on the structure's social sustainability, making them an asset for decision-making in infrastructure projects incorporating RCPHF. Thus, the study emerges as an essential tool for decision-making in planning such projects, enhancing and informing the sustainability aspect of these structures.

Chapter 6

Holistic road frame sustainability: Comparative life cycle assessment of cost-optimized structures

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Abstract

The sustainable development of the construction industry necessitates a comprehensive assessment of its economic, environmental, and social dimensions. This study focuses on road frames, a critical component of transportation infrastructure. Environmental and Social Life Cycle Assessments (E-LCA and S-LCA) were conducted for two reinforced concrete typologies: cast-in-place and precast hinged frames. OpenLCA software and data from Ecoinvent 3.7.1, BEDEC, SOCA v2, and PSILCA databases were utilized to create the LCA model, employing the ReCiPe 2008 (H) and Social Impact Weighting methodologies to calculate midpoint and endpoint environmental and social results. Fifty cost-optimal structures were analyzed across twenty-five horizontal span and burial depth configurations to determine the most sustainable alternative and evaluate the influence of span and earth cover on road frames' sustainability. The research established clear relationships between span, earth cover, and sustainability metrics. The phase contribution analysis highlighted precast hinged frames' construction and end-of-life phases as less environmentally impactful than cast-in-place frames. The findings demonstrate that the precast structures exhibit superior environmental performance, particularly for larger spans, while the most substantial percentage reductions in environmental impact occur in shorter spans with shallower burial depths. In contrast, the S-LCA results reveal that precast structures are more socially sustainable for shorter spans, whereas the cast-in-place frames excel for spans exceeding 12 m. Overall, the precast alternative emerges as the most sustainable choice for spans ranging from 8 to 12 m, with earth cover depths of 1 to 5 m. However, careful consideration is necessary to evaluate the environmental benefits versus social consequences for road frames with spans above 14 m.

Keywords: life cycle assessment; road frame; concrete; social; environmental; sustainability

6.1 Introduction

A significant portion of the scientific community is committed to evaluating and raising awareness about the impacts of human socio-economic activities. Environmental challenges such as climate change, natural resource depletion, and the energy crisis have been extensively researched. Furthermore, contemporary events such as the pandemic and armed conflicts have heightened public concern and emphasized the need for transformative change. In response to these challenges, the Sustainable Development Goals (SDGs) were established to promote sustainable practices that preserve the ability of future generations to meet their needs [136]. With 17 objec-

tives outlined in Agenda 2030, the SDGs encourage sustainable initiatives and practices across all sectors, calling for the engagement of government institutions and companies [3]. The legislative framework for sustainability is dynamic and evolving, with tools such as Environmental Product Declarations (EPDs) and Environmental, Social, and Governance (ESG) reports playing a crucial role in increasing transparency and accountability in sustainability practices across industries [137], [138]. To effectively develop and communicate these tools, it is crucial to have a precise understanding of the impact of products, processes and services [139], [140].

Construction is fundamental to human socio-economic activities, contributing to developing and improving living standards in every country [116]. However, the construction industry is also known for its intensive use of natural resources and generation of waste, making it one of the least sustainable industries [54]. In fact, the production of construction materials accounted for 9% of global anthropogenic emissions last year [8]. Concrete, the most widely used material in construction, is projected to remain the dominant choice in the coming years. The production of cement, a key component of concrete, alone emitted 2.3 Gt of CO₂ into the atmosphere last year [141], [142]. Urgent action is necessary to transition the construction industry towards more sustainable practices that minimize its negative environmental impact. While the environmental impact of construction practices is widely studied, it is equally important to consider the social and economic aspects to address sustainable growth in the construction sector comprehensively. Therefore, a holistic analysis considering all three pillars of sustainability is crucial.

Two main research areas are dedicated to enhancing the sustainability of concrete structures. The first area focuses on developing “green concrete” by incorporating less polluting materials or utilizing by-products in the cement mixture [14], [143]. This approach has significant scalability potential once the industry embraces it. However, the widespread adoption of innovative materials requires extensive research and establishing a supportive legislative framework [14]. The second research area focuses on improving structural designs, which can lead to immediate reductions in resource consumption. This approach poses the structural design process as a combinatorial optimization problem [21], [37], which is then solved using metaheuristic techniques to generate highly efficient non-traditional designs within economic constraints. The industry can directly benefit from design guidelines based on the analysis of optimal designs [130].

Previous studies focused on optimizing structural solutions for transportation infrastructure. Furthermore, the results on box girder bridges [45], [51], composite bridges [16], [144], and reinforced concrete frames [128], highlight the relationship between final cost and environmental impact indicators. Further examining the environmental and social impacts of these cost-optimal structures provides a comprehensive un-

derstanding of the three pillars of sustainability. The Life Cycle Assessment (LCA) objectively evaluates the impacts associated with a structural typology to conduct such sustainability analyses.

Reinforced concrete frames are widely employed structural solutions for road crossings, with two primary typologies: cast-in-place frames (RCCPF) and precast hinged frames (RCPHF). Perea et al. [69] conducted a parametric study using simulated annealing (SA) to optimize the final cost of RCCPF, focusing on geometry and material utilization. Furthermore, Ruiz-Vélez et al. [130] employed a hybrid simulated annealing (SAMO) approach to analyze the geometry, material utilization, and relevant environmental impact indicators for cost-optimized RCPHF. The results provide practical recommendations for the optimal design of 25 standard configurations of RCCPF and RCPHF, considering spans ranging from 8 to 16 meters and earth cover depths from 1 to 5 meters.

Properly selecting road frame typologies plays a crucial role in improving a structural solution's overall life cycle sustainability. This paper conducts a comparative parametric assessment of the environmental and social sustainability of 50 cost-optimal RCCPF and RCPHF using an LCA methodology adhering to current standards [134], [135]. By focusing on cost-optimal designs, the study aims to determine which alternative, cast-in-place or precast, is more sustainable for each of the 25 configurations. By focusing on cost-optimal designs, the study aims to determine which alternative, cast-in-place or precast, is more sustainable for each of the 25 configurations. This approach ensures that the study comprehensively addresses the three pillars of sustainability: environmental, social, and economic. Furthermore, the comprehensive analysis of the entire set of structures, considering social and environmental LCA, enables a deeper understanding of the most impactful phases for each structure, accounting for the distinct nature of processes involved in cast-in-place and precast structures.

6.2 Materials and Methods

This study comprehensively evaluated the environmental and social impact of the optimal road frames throughout their entire life cycle using the Life Cycle Assessment (LCA) methodology. The research adhered to international standards ISO 14040:2006 and ISO 14044:2006, which provide guidelines for conducting LCA analyses [134], [135]. The LCA process consisted of four distinct phases: goal and scope definition, inventory analysis, impact assessment, and interpretation of the results. The importance of evaluating the three pillars of sustainability, namely environmental, social, and economic aspects, was emphasized in section 6.1. The study

approached this through two types of assessments of cost-optimal designs: an Environmental Life Cycle Analysis (E-LCA) and a Social Life Cycle Analysis (S-LCA). These analyses capture the complete set of sustainability dimensions, enabling us to comprehensively understand optimal road frames' environmental and social impacts.

The E-LCA was conducted using the ReCiPe 2008 Life Cycle Impact Assessment (LCIA) methodology, a widely recognized approach for assessing environmental impacts [145]. The Ecoinvent v3.7.1 and BEDEC databases were used to obtain comprehensive and reliable information on the environmental parameters associated with the analyzed structures [92], [146]. For the assessment of social impacts, the S-LCA information was sourced from PSILCA through the SOCA v2 database and evaluated using the LCIA social impact weighting method [40], [56], [133]. This procedure allowed for a comprehensive evaluation of the social impacts, considering factors beyond the environmental dimension.

The open-source software OpenLCA was used for LCA modelling and computation, as the scientific community widely employs it for conducting life cycle analyses of complex systems such as road frames [147]. By adhering to international standards, collecting data from reputable sources, and utilizing open-source software, the present study ensured a rigorous and reliable assessment of the environmental and social impacts associated with the life cycle of optimal road frames.

6.2.1 Goal and Scope Definition

The primary objective of this study is to enhance the understanding of the life cycle impacts of cost-optimal road frames through a comprehensive comparative parametric analysis of the social and environmental consequences of RCCPF and RCPHF. The study models and analyzes the E-LCA and S-LCA of 50 cost-optimized structures to achieve this objective. These assessments encompass 25 configurations with varying spans (8, 10, 12, 14, or 16 meters) and earth cover depths (1, 2, 3, 4, or 5 meters), comprehensively exploring standard design layouts. By quantifying the impacts through a numerical score, the study identifies the most sustainable alternative in each scenario and highlights the critical phases within the life cycle of each structure that significantly contribute to the overall impact. Notably, precast structures demonstrate improved quality and uniformity compared to cast-in-place alternatives [148], and their modular design contributes to reduced environmental impacts during construction and decommissioning. Therefore, a thorough comparison of the impacts associated with each life cycle stage of RCCPF and RCPHF is essential to understand their environmental and social performance comprehensively.

Road Frame Type Selection

Reinforced concrete road frames are vastly adopted as a structural solution for facilitating the crossing of secondary roads with main roads in transportation infrastructure. These road frames typically feature spans ranging from 8 to 16 meters and are constructed with embankments that can reach depths of up to 10 meters while maintaining clearing heights of approximately 5 meters. They prove particularly well-suited for areas characterized by low-bearing capacity soils, especially in flood-prone zones where the risk of scouring is prevalent. These inherent characteristics render reinforced concrete road frames highly suitable for ensuring the stability and integrity of road crossings, particularly in challenging soil conditions.

The road frame structures commonly employed in transportation infrastructure are predominantly rectangular and can be classified into two main typologies: closed and open frames. Closed frames consist of a single structural set constructed with cast-in-place reinforced concrete, while open frames are formed by assembling two U-shaped pieces to form the complete structure. Open frames offer the advantage of precast prefabrication, making them more convenient for transportation and construction purposes. RCCPFs have traditionally been widely utilized as road frame structures. However, with recent advancements in prefabrication technology, RCPHF have emerged as an increasingly appealing alternative, primarily due to their promising economic and environmental performance [128].

The present study examines cost-optimal RCCPF and RCPHF, considering their specific design parameters. For RCCPFs, the design is primarily influenced by the span (L), height (H), and burial depth (HE). In contrast, RCPHF designs require additional consideration of the height of the hinged union (HH). Figure 6.1 visually represents the structural typologies and their key characteristics.

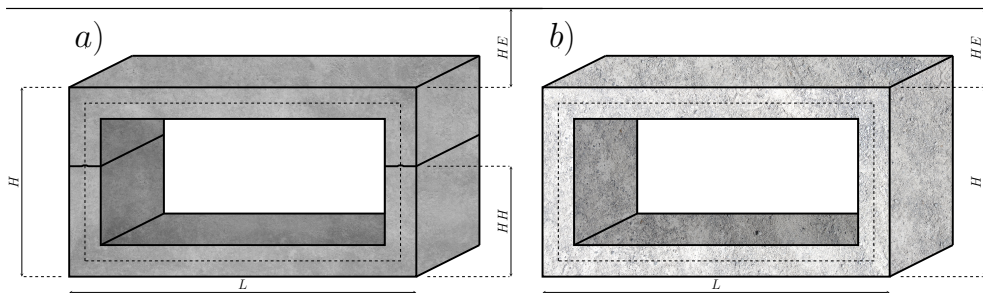


Figure 6.1: Road frame types and key parameters where: a) precast hinged frame (RCPHF) and b) cast-in-place reinforced concrete frame (RCCPF).

Phases of the Analysis

The life cycle of road frames encompasses multiple stages, beginning from the design phase and extending throughout their entire service life. In order to conduct a comprehensive analysis of the impact associated with road frames, the LCA approach breaks down the life cycle into four distinct phases: manufacturing, construction, use, and end-of-life.

The manufacturing phase of road frames entails the acquisition of construction materials, starting from the extraction of raw materials and encompassing the subsequent manufacturing processes involved in producing the final products. On the other hand, the construction phase focuses on transporting these materials to the construction site and the actual assembly and construction of the road frames.

During the use phase, which extends throughout the standard 100 years of service life of road frames, the structures are subject to regular operation and maintenance activities to ensure their optimal functionality. This phase also considers the carbonation of concrete, which has implications for the overall environmental performance of the road frames.

Finally, the end-of-life phase involves activities associated with the dismantling, demolition, and disposal of the road frames. This phase encompasses the transportation of passive reinforcement steel to recycling facilities and adequately disposing of crushed concrete in a landfill where it carbonates completely.

By examining each life cycle phase, the LCA methodology enables a comprehensive assessment of the impact associated with road frames throughout their entire life cycle.

Functional Unit

Diverse factors contribute to the cost-optimized design of RCCPFs and RCPHF [128]. Nevertheless, determining the functional unit for this study is straightforward. Consistent with prevailing standards, road frame structure design, stress calculation, and compliance verification are conducted per linear meter [93], [95]. Consequently, the LCA analysis in this study considers the linear meter as the functional unit for assessing the environmental and social impact of both RCCPF and RCPHF road frames.

6.2.2 Inventory Analysis

Inventory analysis is a crucial component of LCA as it aims to identify and quantify the inputs involved in producing a process, product, or service. This study's inventory analysis captures the resource consumption, energy usage, and labour requirements of constructing one linear meter of RCCPF and RCPHF. This detailed information is the foundation for evaluating the environmental and social impacts of the cost-optimal structures throughout their life cycle. By accurately conducting the inventory analysis, this research provides an objective and comprehensive assessment of the environmental and social impact of the road frames.

Software

The current research utilized two databases for conducting the E-LCA. The Ecoinvent 3.7.1 database, renowned for its current and validated information on the environmental impact of various processes, was employed as a primary resource [146], [149]. For processes not covered by Ecoinvent 3.7.1, the BEDEC database from the Construction Technology Institute of Catalonia was utilized to ensure comprehensive modelling [92]. In addition, the S-LCA analysis drew upon the SOCA v2 database [133], which integrates information from the PSILCA social database to accurately attribute social impacts to each process modelled in the E-LCA.

The E-LCA analysis utilized the ReCiPe 2008 LCIA methodology to assess the environmental impact, while the S-LCA analysis employed the weighted social impact methodology to evaluate the social implications. To model the LCA of RCCPF and RCPHF structures, the open-source software OpenLCA by GreenDelta was utilized. This software is widely recognized and adopted in the scientific community for conducting E-LCA and S-LCA studies across various structural typologies [147].

The E-LCA and S-LCA findings provide a comprehensive understanding of the specific environmental and social impacts associated with the life cycles of the structures, as they encompass a wide range of impact categories. These impact categories are further grouped into broader damage categories, allowing for a holistic assessment of the overall consequences of the life cycle. Detailed information on these impact and damage categories can be found in section 6.2.3.

The study adopts a midpoint approach to analyze the impact categories relevant to E-LCA. Additionally, a comprehensive endpoint analysis is conducted for both E-LCA and S-LCA, focusing on the results of the damage categories. This enables a direct comparison of the impacts between different RCCPF and RCPHF configurations. Table 6.1 summarizes the databases, methodologies, and approaches utilized in the

E-LCA and S-LCA. It serves as a concise overview of the key components considered in the analyses, facilitating a better understanding of the study's methodology and framework.

Table 6.1: Data and software utilized for the LCA.

	Database	LCIA	Approach	Software
E-LCA	Ecoinvent 3.7.1 and BEDEC	ReCiPe 2008	CML Eco-Indicator 99	Midpoint Endpoint
S-LCA	PSILCA through SOCA v2	Weighted Social Impact	Endpoint	OpenLCA

Uncertainty

The utilization of databases in the LCA model introduces inherent uncertainties, mainly influenced by the data's location and time frame. Certain databases may lack specific information directly relevant to the geographic and temporal scope of the study. The present study complements the Ecoinvent 3.7.1 database with the BEDEC national database aiming to enhance the accuracy and completeness of the data utilized. In addition, the study incorporates a pedigree matrix that assigns an uncertainty value to each process within the life cycle model [132]. This matrix considers data reliability, completeness, and the study's geographical, temporal, and technical correlation. The study quantifies the uncertainty associated with each process by evaluating these five factors. Process-specific and basic uncertainty are considered in the calculation to determine the overall uncertainty of the life cycle model. This approach ensures that the study acknowledges and addresses the intrinsic uncertainties present in the LCA analysis.

Road Frame Design

The study evaluated 50 cost-optimal road frames, focusing on 25 configurations tailored for road crossings. The road frames featured horizontal spans ranging from 8 to 16 meters in two-meter increments and earth cover depths ranging from 1 to 5 meters in one-meter increments. The optimal designs of RCCPF and RCPHF share common characteristics regarding the grade of construction materials used [69], [130], enabling a direct and accurate comparison of their environmental and social impacts. However, there are variations in the required quantities of these materials and differences in fabrication, construction, and assembly processes between RCCPF and RCPHF [128]. Through a comprehensive evaluation of all 25 configura-

tions, the study deeply assesses each road frame typology's distinct advantages and benefits.

The cost-optimal designs feature 25 MPa structural concrete and employ B500S grade steel for passive reinforcement. The structural concrete grade is dosed with 275 kg/m³ of cement (95% clinker), 165 l/m³ of water, 1035 kg/m³ of aggregate, and 1155 kg/m³ of sand. Opting for higher-grade concrete would significantly increase cement consumption, resulting in a more unfavourable environmental impact. Moreover, it would lead to cost overruns. Therefore, the cost-optimal designs utilize 25 MPa concrete, the minimum grade permitted by standards, ensuring reduced economic expenses.

Table 6.2 presents the primary materials required to construct one linear meter of RCCPF. It displays the values corresponding to designs buried at 1 and 5 meters depth for each horizontal span. In addition to these common materials, each linear meter of RCCPF requires the use of between 11.00 and 13.22 m² of drainage geotextile, 0.80 to 1.60 m³ of blinding concrete, and 61.77 to 172.38 m² of formwork.

Table 6.2: Materials necessary for constructing a linear meter of RCCPF based on span.

Span (m)	Concrete (m ³)	Steel (kg)	Drain filler (m ³)	Backfill (m ³)
8	12.91 - 20.24	1223.84 - 2046.48	15.58 - 16.58	13.00 - 72.37
10	17.26 - 25.38	1556.60 - 3055.06	16.39 - 17.68	15.11 - 83.12
12	23.73 - 34.07	2034.13 - 4182.33	17.21 - 18.81	17.23 - 93.87
14	31.10 - 44.10	2641.34 - 5535.33	18.05 - 19.97	19.34 - 104.62
16	40.49 - 55.84	3313.89 - 7267.24	18.91 - 21.17	21.45 - 115.37

In the context of RCPHF, Table 6.3 presents the main materials necessary for constructing one linear meter. RCPHF's precast nature eliminates the need for blinding concrete or formwork. However, they still require a comparable quantity of geotextile, ranging from 11.59 to 12.39 m². Additionally, the construction process involves the utilization of 0.80 to 1.60 m³ of levelling sand. and precasting metal molds with a capacity of 13.74 to 39.03 m³.

Table 6.3: Materials necessary for constructing a linear meter of RCPHF based on span.

Span (m)	Concrete (m ³)	Steel (kg)	Drain filler (m ³)	Backfill (m ³)
8	13.74 - 15.34	1007.73 - 1437.58	16.61 - 17.04	13.20 - 72.69
10	16.43 - 18.91	1387.77 - 1883.18	17.04 - 17.87	15.24 - 83.25
12	21.27 - 23.38	1790.27 - 2708.04	17.14 - 18.16	17.22 - 93.44
14	27.75 - 31.01	2418.60 - 3886.80	18.01 - 18.74	19.33 - 103.82
16	33.50 - 39.03	3449.74 - 6011.35	18.08 - 18.98	21.34 - 113.98

Life Cycle Model Description

The road frame's life cycle encompasses the four phases outlined in Section 6.2.1. Figure 6.2 provides an overview of the primary processes associated with each phase, as incorporated in the life cycle model. The study leverages the processes in the Ecoinvent database to construct a comprehensive and representative E-LCA model. In cases where specific processes, such as those related to construction machinery, are not covered in the Ecoinvent database, the BEDEC database is employed to model equivalent impact processes. This approach enables the development of a comprehensive and representative model. Furthermore, as discussed in section 6.2.2, it allows the conduction of an S-LCA analysis using SOCA v2.

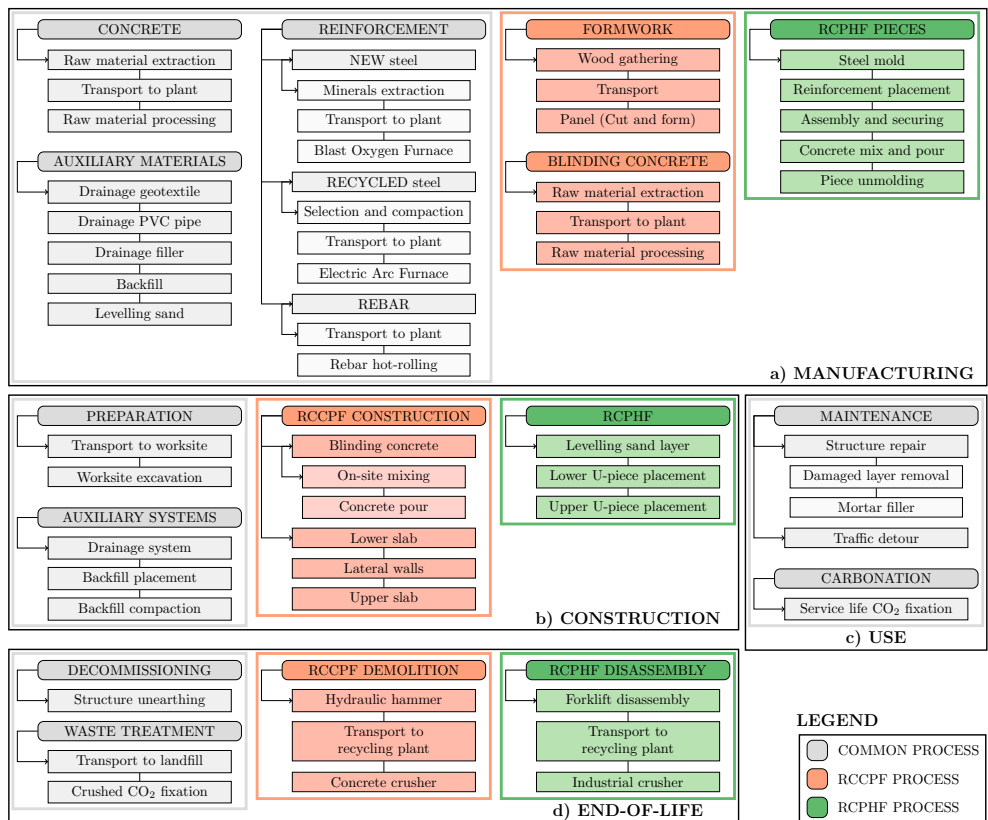


Figure 6.2: Road frame life cycle model where: a) Manufacturing; b) Construction; c) Use; and d) End-of-Life.

The manufacturing phase encompasses the entire process of producing the final construction materials, starting from the extraction of raw materials to manufacturing the ready-to-use components. As outlined in section 6.2.2, the structural materials utilized in constructing the cost-optimal RCCPFs and RCPHF s consist of grade 25 MPa concrete and B500S steel. Concrete production entails several steps, including excavating raw minerals, transportation to a processing facility, and various processing activities such as crushing, grinding, and mixing.

The passive reinforcement rebars in the road frames combine new and recycled steel, requiring separate production processes. The manufacturing of new steel involves the excavation of raw minerals, their transportation to the processing plant, and melting through a blast oxygen furnace (BOF). On the other hand, recycled steel starts with selecting and separating scrap metal, which is then compacted and transported to a processing plant, where it is melted using an electric arc furnace (EAF). The resulting products from both processes are transported to a final processing plant and hot rolled to form the final reinforcement rebars used in the road frames. Besides concrete and steel, additional materials are needed to construct the road frames, such as a drainage system consisting of geotextile, drain filler, PVC pipes, and the backfill soil in the embankment areas closest to the frame. The life cycle model considers all upstream processes involved in producing these auxiliary materials.

The manufacturing processes discussed thus far apply to both RCCPFs and RCPHF s. However, it is crucial to consider the specific procedures involved in producing the materials unique to each typology. In the case of RCCPFs, the manufacturing of plywood formwork is necessary. This fabrication involves sourcing, transporting, cutting and shaping wood into the final panels. The study assumes the formwork panels can be disassembled and reused up to 15 times, thus minimizing waste and enhancing sustainability. Additionally, RCCPFs require a blinding concrete base. Therefore, all the requisite steps in producing a 20 MPa concrete mix with a soft consistency are considered.

On the contrary, RCPHF s follow a prefabrication process. These components are manufactured at a precast plant, where wet concrete is poured into steel molds. The molds used in the process have a lifespan ranging from 100 to 200 uses, depending on production rates and maintenance. An average of 150 uses were considered in this study. The impact associated with the manufacturing and usage of these molds is quantified based on the size of the precast pieces, as defined by the BEDEC database [92].

The in-plant manufacturing of RCPHF s commences with the manual placement of passive reinforcement within the molds, followed by assembly using cranes and se-

curing the components in their final positions by hand. The concrete is mixed and poured, ensuring a consistent distribution throughout the mold. Under controlled curing conditions, high-quality and uniform precast pieces are produced. Once the concrete has fully cured, the molds are removed, and each precast piece is stored at the precast plant until it is transported to the construction site for assembly into the road frame. The manufacturing of each RCPHF assumes a total crane usage time of 45 min.

The construction stage begins with transporting all necessary materials to the job site [134], [135]. Before commencing construction, site preparation involves excavating a volume equivalent to the thickness of the bottom slab, along with an additional 10 centimetres to accommodate the levelling materials. From this point onward, the construction processes for RCCPFs and RCPHFs significantly diverge.

RCCPF construction involves mixing and pouring a 10-centimeter layer of blinding concrete into the excavation site to achieve proper levelling and create a separation between the structural concrete of the lower slab and the ground. After the blinding concrete has fully cured, the preparation of formwork and passive reinforcement for the lower slab begins. The procedure includes placing the passive reinforcement for the lower slab and connecting supports to the lateral walls. Subsequently, concrete is mixed, poured, and left to harden. This process is repeated for the lateral walls and their connection to the upper slab, ensuring that the lower slab has adequately hardened to withstand nearby activities. Once the lateral walls have sufficiently hardened, the formwork and passive reinforcement for the upper slab are positioned. The construction process entails three concrete pours, culminating with the upper slab. The timber planks used in the formwork are carefully removed by hand to avoid damage and preserve them for future use.

The construction process for RCPHFs is relatively simple and involves the on-site assembly of the structure. The two U-shaped structural components are transported to the construction site. To ensure proper levelling, a 10-centimeter layer of sand is first placed. Subsequently, the lower component is lifted into position using a crane, which is also used for placing the upper component on top. The structure is considered fully assembled once the secure placement of both components has been verified.

After the completion of RCCPF construction or the assembly of RCPHFs, the subsequent phase involves a set of shared processes for both typologies. Buried structures are susceptible to rapid deterioration caused by environmental conditions. A layer of drainage geotextile is applied to the exterior surface of the lateral walls to counteract this. The geotextile facilitates the redirection of any moisture towards the lower portion of the lateral wall, where it is collected and subsequently drained through a

PVC pipe placed on a compacted sand base. Moreover, drainage filler is positioned near the lateral walls to prevent the accumulation and retention of moisture. Lastly, the construction process is finalized by placing and compacting the backfill material over the structure, ensuring proper stabilization and support.

Upon the completion of construction, road frames enter the use phase, which encompasses three distinct activities: energy consumption associated with the structure's utilization, maintenance tasks, and CO₂ fixation through concrete carbonation. Unlike building structures, RCCPFs and RCPHF s do not inherently require energy consumption for regular operation. The durability of concrete structures throughout their service life is greatly influenced by the conditions to which they are exposed and must be considered in optimal design. Thus, two preventive maintenance overhauls are scheduled during service life to ensure durability. These overhauls aim to maintain the structural integrity and functionality of the road frames. The impact of these maintenance overhauls is quantified in terms of diesel consumption required to redirect vehicles during the periods when the structure is under maintenance and temporarily inaccessible.

Over time, concrete's structural integrity gradually diminishes due to the carbonation. The CO₂ reacts with calcium hydroxide in highly humid environments, reducing the concrete's alkalinity. This process initiates surface deterioration that gradually progresses inward. If the carbonation reaches the reinforcing steel, it can result in oxidation and potential structural damage. On a positive note, the structure effectively captures and stores CO₂ within its composition.

Optimal designs for RCCPFs and RCPHF s consider the carbonation process and incorporate a nominal cover suitable to specific environmental conditions. The quantity of CO₂ fixed during the service life carbonation can be determined using Equation (6.1), corresponding with Fick's first law [54]. This formula calculates the amount of fixed CO₂ by considering various factors, including the carbonation constant (k_1), the structure's service life (t), the surface area affected by carbonation (A), the cement content per cubic meter of concrete (C), and the clinker content (k).

$$CO_2 \text{ (kg)} = 0.383 \cdot \frac{k_1 \left(\frac{\text{mm}}{\sqrt{\text{year}}} \right) \cdot \sqrt{t(\text{year})}}{1000} \cdot A(\text{m}^2) \cdot C \left(\frac{\text{kg}}{\text{m}^3} \right) \cdot k(\%) \quad (6.1)$$

Lagerblad et al. [59] establishes carbonation constants for various grades of structural concrete based on the surface exposure conditions. In the context of this study, the calculation of captured carbonation takes into account the specified dosage noted in section 6.2.2 and utilizes a carbonation constant value of 1.5 mm/year^{0.5} for the external faces of the frame and 2.5 mm/year^{0.5} for the internal faces.

Upon completing a 100-year service life, both RCCPFs and RCPHF s cease to deliver satisfactory performance and require replacement, marking the onset of the end-of-life phase. This final life cycle phase entails essential activities involving the demolition or decommissioning of the road frames and the appropriate disposal of waste and material recycling. These operations encompass the transportation of waste to the designated landfill, procedures for material recycling, and the carbonation-induced fixation of CO_2 within the remaining crushed concrete volume after it has been deposited in the landfill.

The RCCPF's life cycle's concluding stage commences with the structure's unearthing. Subsequently, the structure is demolished utilizing a hydraulic hammer, with an estimated time of around 20 minutes per cubic meter of concrete. Following the demolition, the reinforcing steel is separated using electromagnets for recycling, and the concrete debris is transported to the designated landfill using dump trucks. The life cycle analysis also incorporates the carbonation-induced fixation of CO_2 within the entire concrete volume once it has been deposited in the landfill.

For RCPHF s, the removal process is facilitated by their modular design. Once the excavation is completed, the structure is disassembled using forklift cranes, and the individual components are transported to a recycling plant for crushing. The reinforcing steel bars are separated and recycled, while the crushed concrete undergoes complete carbonation at the landfill. Efforts are underway to explore alternative applications for prefabricated structures beyond their service life. The geometric characteristics of RCPHF elements offer the potential for reuse in non-structural concrete constructions. However, examining these considerations and their impact on the life cycle is beyond the scope of the present research.

6.2.3 Impact Assessment

The goal of the impact assessment is to assess and quantify the outcomes of the inventory analysis. By employing a designated LCIA method, the data on consumed resources, energy, and labour are converted into environmental indicators. The process of transforming these data into environmental indicators helps to make the analysis and understanding of the environmental impact of the activities during the structure's life cycle more accessible. It is important to note that the LCIA method choice significantly impacts the assessment results.

As outlined in Section 6.2.2, different LCIA methodologies are employed to evaluate a product's environmental and social impacts. In the context of E-LCA, the ReCiPe methodology combines two distinct LCIA s: the CML midpoint methodology and the Eco-Indicator 99 endpoint methodology. The midpoint methodology allows for a de-

tailed assessment of impacts, utilizing specific impact categories and units of measurement. On the other hand, the endpoint methodology consolidates these impact categories into three overarching damage categories: human health, ecosystems, and resource availability. These categories are quantified using Disability Adjusted Life Years (DALY), species per year (species·yr), and U.S. dollars (\$). The hierarchical version (H) of the ReCiPe H/A person/year normalization set is used to compare the total impact in points directly.

By integrating these two widely utilized LCIA methodologies, ReCiPe enables comprehensive analyses and yields detailed and interpretable outcomes. The midpoint methodology generates results for 18 sustainability indicators, which can be intricate, challenging to interpret, and not directly comparable. The primary objective of this study is to evaluate the LCAs of two structural typologies to identify the most sustainable option and significant differences in impacts throughout each phase of their life cycle. In this context, a general overview of the midpoint approach is provided, specifically focusing on the Global Warming Potential (GWP) impact category. Subsequently, the study emphasizes the significance of the endpoint analysis, which provides a clear and intuitive understanding of the long-term consequences for a process, product, or service. By examining the three damage categories, the study identifies the most influential phases in each structure and outlines the optimal alternatives for each configuration.

On the other hand, the S-LCA is conducted using the Social Impacts Weighting Method LCIA. The study utilizes the SOCA v2 database to collect data on 55 midpoint social impact indicators. These indicators enable the endpoint estimation of the long-term consequences of the LCA in terms of medium-risk hours (mrh) for four key stakeholders: the local community, society, value chain actors, and workers. The evaluation of the long-term social implications of the structures is performed through the analysis of endpoint results, which provide a clear and comprehensible perspective.

Figure 6.3 summarizes the comprehensive analysis approach employed in the study, which encompasses examining the three pillars of sustainability.

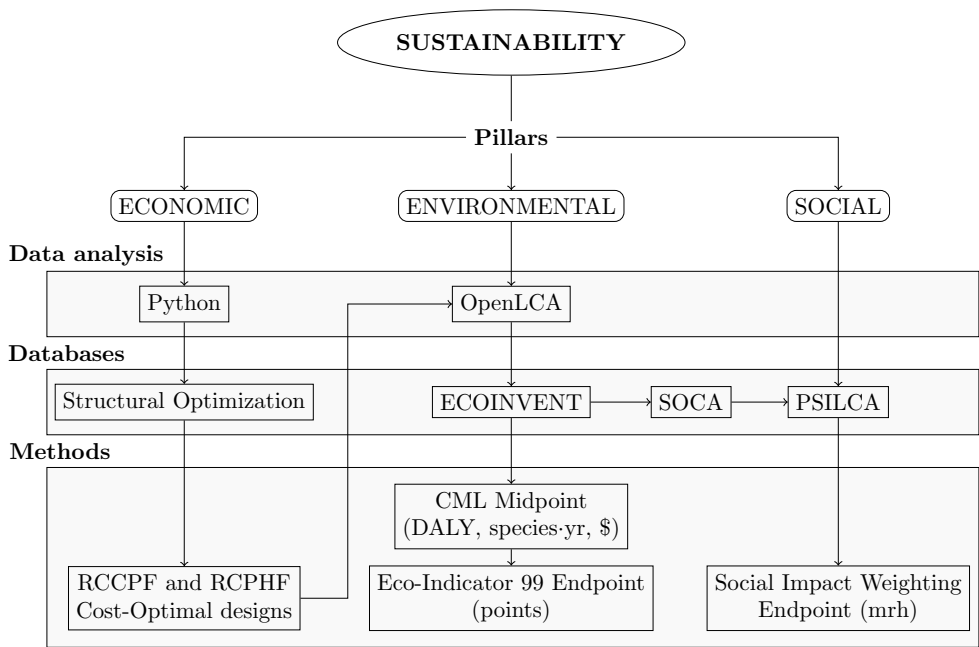


Figure 6.3: Integrated approach for evaluating the three pillars of sustainability.

6.2.4 Interpretation

Following the acquisition of results, the interpretation phase begins, tailored to the study's objectives and scope. In this study, the interpretation focuses on identifying the best alternative across sustainability pillars. Additionally, the analysis investigates and compares the most impactful phases for each alternative, highlighting similarities and differences between the structural typologies.

The research assesses the performance discrepancy between the RCCPF and RCPHF across various structural configurations. The results are quantified and expressed as an absolute or percentage difference in specific instances using a delta parameter. A positive delta value indicates that the RCPHF performs better than the cast-in-place road frame in that particular context. Conversely, a negative difference suggests that the RCCPF is the superior alternative for that specific configuration and metric.

6.3 Life Cycle Assessment Results

The study incorporates an uncertainty evaluation into the E-LCA analysis. A Monte Carlo simulation is employed with 1000 iterations to achieve this. This simulation generates a mean value and deviation, allowing a more comprehensive evaluation of the midpoint and endpoint results. In the case of S-LCA, the endpoint results are obtained directly through direct analysis, obtaining an absolute endpoint score.

6.3.1 Environmental Life Cycle Assessment

The LCIA method utilized in this study, ReCiPe 2008, allows for both midpoint and endpoint analyses. In section 6.3.1, a general overview of the midpoint results of the E-LCA is provided, while section 6.3.1 offers a detailed account of the endpoint results. The Monte Carlo analysis results are displayed in both sections, presenting a mean value and deviation for a comprehensive assessment.

Midpoint Approach

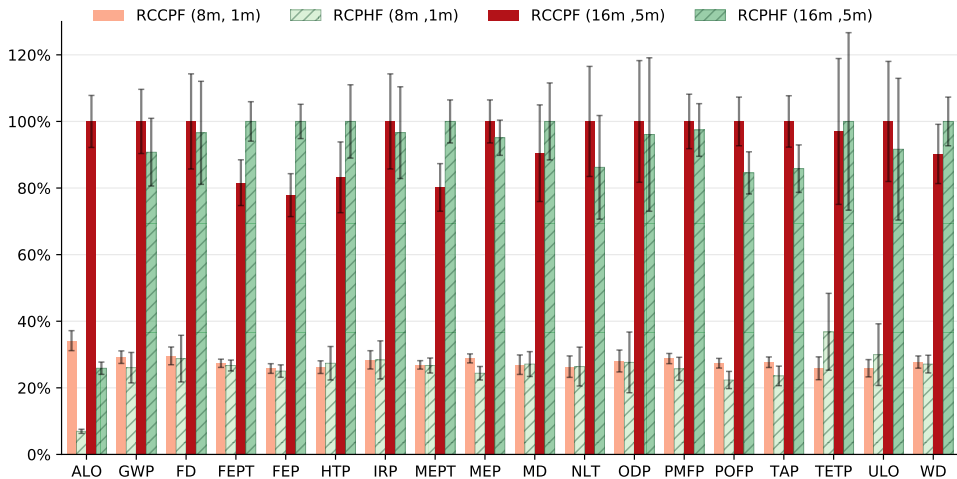
Analyzing the midpoint impact categories entails a complex process that requires a meticulous examination of specific indicators to ensure the reliability of the obtained information. However, conducting an in-depth analysis of all 18 indicators for each of the 50 optimal structures surpasses the scope of the study. Nonetheless, it is still valuable to establish the order of magnitude of the midpoint results. The most and least impactful configurations are selected by combining the lowest and highest light and burial depth values. Specifically, the study considers the configurations of 8 m of span buried at 1 m depth and 16 m of span buried at 5 m depth. These extreme configurations provide valuable insights into the potential range of impacts. Table 6.4 showcases the mean values and coefficients of variation for each impact category in both configurations, enabling an assessment of the relative magnitude and variability of the impact categories.

Considering the diverse units of measurement for each impact category, there are significant variations in magnitude among the results. The wide range of orders of magnitude for the impact categories can make visualizing the results challenging. Figure 6.4 compares each impact category relative to the structure with the highest impact to facilitate the visualization and understanding of the relative magnitudes.

The analysis reveals a consistent pattern where the RCPHF exhibits lower mean impacts than the RCCPF across most impact categories for both configurations. The superiority of the RCPHF over the RCCPF is particularly pronounced in the 8-meter

Table 6.4: Midpoint results for the least and most impacting configurations, for both typologies.

Impact Category	Acronym	Unit	Configuration (8m, 1m)				Configuration (16m, 5m)			
			RCCPF		RCPHF		RCCPF		RCPHF	
			Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)
Agricultural land occupation	ALO	m ² ·a	533.98	8.78	108.52	9.02	1562.59	7.81	404.48	7.14
Climate change	GWP	kg CO ₂ eq	6813.60	6.45	6077.43	17.57	23327.56	9.64	21174.01	11.20
Fossil depletion	FD	kg oil eq	1711.70	9.01	1664.02	24.37	5783.15	14.29	5585.55	16.02
Freshwater ecotoxicity	FEPT	kg 1,4-DB eq	144.91	4.53	141.36	6.14	432.17	8.42	529.53	5.93
Freshwater eutrophication	FEP	kg P eq	1.77	5.64	1.72	7.48	5.34	8.28	6.86	5.15
Human toxicity	HTP	kg 1,4-DB eq	1792.11	7.27	1872.31	18.38	5689.84	12.77	6837.35	11.01
Ionizing radiation	IRP	kg U235 eq	444.12	9.69	444.00	20.15	1563.84	14.28	1511.18	14.26
Marine ecotoxicity	MEPT	kg 1,4-DB eq	135.73	4.74	134.76	8.45	404.74	8.92	504.81	6.46
Marine eutrophication	MEP	kg N eq	1.70	4.69	1.44	8.33	5.91	6.46	5.62	5.56
Metal depletion	MD	kg Fe eq	0.96	10.86	0.97	13.75	3.22	16.04	3.56	11.56
Natural land transformation	NLT	m ²	2.40	12.23	2.40	22.14	9.10	16.53	7.85	18.05
Ozone depletion	ODP	kg CFC-11 eq	6.13E-04	11.72	6.04E-04	32.99	2.19E-03	18.27	1.99E-03	23.99
Particulate matter formation	PMFP	kg PM10 eq	15.76	5.32	14.08	13.46	54.75	8.18	53.35	8.12
Photochemical oxidant formation	POFP	kg NMVOC	36.74	5.31	29.97	11.57	134.11	7.31	113.39	7.49
Terrestrial acidification	TAP	kg SO ₂	26.33	5.72	22.42	12.48	95.09	7.72	81.61	8.31
Terrestrial ecotoxicity	TEPT	kg 1,4-DB eq	0.78	13.28	1.11	31.34	2.93	22.56	3.02	26.66
Urban land occupation	ULO	m ² ·a	303.56	10.05	351.46	30.94	1172.98	18.03	1075.21	23.22
Water depletion	WD	m ³	12613.27	6.62	12336.41	9.82	41027.47	9.86	45465.50	7.31

**Figure 6.4:** Midpoint results for the least and most impacting configurations, for each typology.

span configuration, buried at a depth of 1 meter. However, it is essential to note a few categories, namely HTP, FEPT, FEP, and MEPT, where RCPHF structures show higher impact values, highlighting the complexity of the midpoint environmental impact assessment. Additionally, the variability of the impacts indicates a higher inconsistency in specific impact categories for RCPHFs, especially ODP and TEPT, potentially affecting their environmental performance predictability.

Calculated in kg CO₂ eq, the GWP is a crucial impact category extensively evaluated in sustainability research [150], [151]. Figure 6.5 depicts the trend of GWP as a function of earth cover depth for each span, providing valuable insights into how different configurations impact each typology's GWP. Consistently across all examined structural configurations, RCPHFs exhibit lower GWP than RCCPFs, as evidenced by the mean GWP values and variation coefficients in Table 6.5.

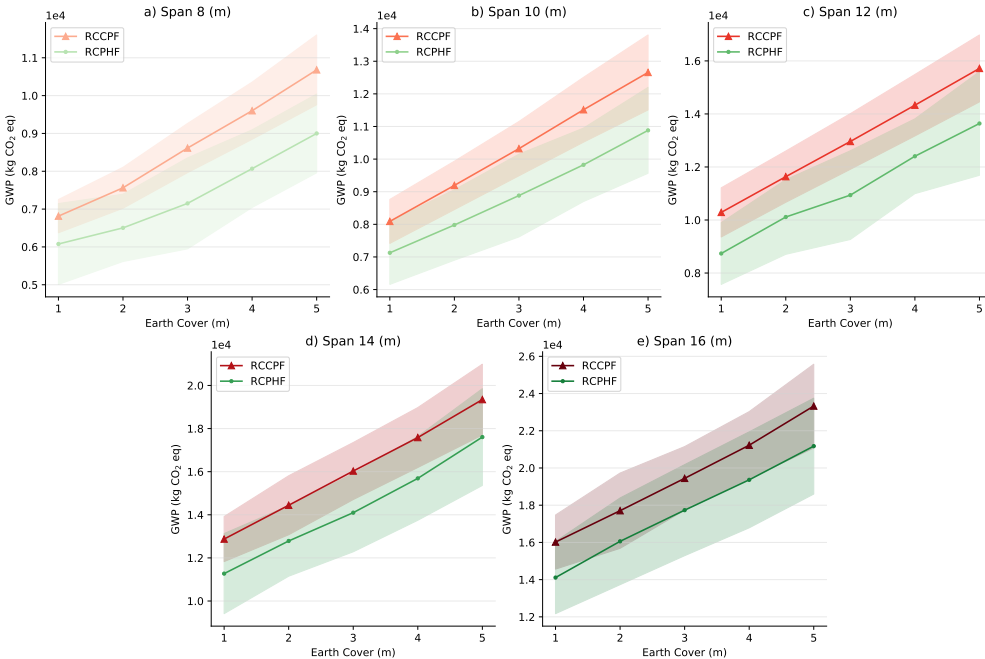


Figure 6.5: GWP comparison as a function of the earth cover, for each horizontal span.

Table 6.5: GWP results in kg CO₂ eq for each configuration, for both typologies.

		Horizontal span (m)									
		8		10		12		14		16	
Cover (m)	Type	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)
1	RCCPF	6813.60	6.45	8089.76	8.33	10286.57	9.01	12873.98	8.12	16019.15	9.08
1	RCPHF	6077.43	17.57	7126.50	13.58	8736.65	13.33	11271.48	16.48	14111.71	13.75
2	RCCPF	7562.72	7.15	9193.53	8.07	11634.28	8.31	14442.59	9.48	17704.36	11.43
2	RCPHF	6503.24	13.66	7979.63	13.54	10112.69	13.91	12785.71	12.79	16058.69	14.50
3	RCCPF	8613.37	7.55	10320.37	8.06	12961.39	8.09	16029.49	8.26	19442.74	8.78
3	RCPHF	7150.43	16.80	8881.92	14.28	10937.89	15.29	14098.05	12.87	17732.84	13.79
4	RCCPF	9600.06	7.87	11512.70	8.63	14329.06	8.09	17583.40	7.91	21222.88	8.51
4	RCPHF	8068.45	12.71	9824.40	11.46	12403.62	11.37	15689.27	12.39	19362.99	13.32
5	RCCPF	10680.58	8.64	12656.91	9.08	15716.45	8.03	19343.85	8.49	23327.56	9.64
5	RCPHF	8999.63	11.56	10881.06	12.10	13639.35	14.33	17605.34	12.75	21174.01	12.17

The sensitivity analysis reveals that horizontal span and burial depth significantly impact both typologies' GWP. Increasing the horizontal span by 2 meters within the considered range results in an average GWP increase of 22.74% for RCCPFs. Similarly, RCPHF experience an additional 24.55% gain in GWP, indicating a slightly higher sensitivity to span changes. Regarding burial depth, a 1-meter increase has a comparable influence on both typologies, leading to mean GWP increases of 11.10% for RCCPFs and 11.16% for RCPHF. Nevertheless, these values are noticeably lower than the increases associated with changes in span length, underscoring the greater influence of horizontal span on the overall GWP impact.

Overall, it can be concluded that RCPHFs provide a GWP improvement compared to RCCPFs. The most substantial gains are observed in the larger span and deeper burial depths configurations. However, it is crucial to note that the improvement ratio is inverse to the absolute GWP reduction. These findings underscore the importance of conducting a comprehensive analysis of the environmental impact of different life cycle phases and considering the variability within each configuration when selecting the most appropriate alternative.

After examining the behaviour of each typology under different spans and burial depths configurations, conducting a direct comparative analysis of the GWP between the two structures is especially relevant. The average absolute and percentage reduction in GWP achieved using the RCPHF precast alternative over the traditional RCCPF is presented in Figure 6.6. The absolute and percentual difference is showcased as heatmaps a and b, respectively.

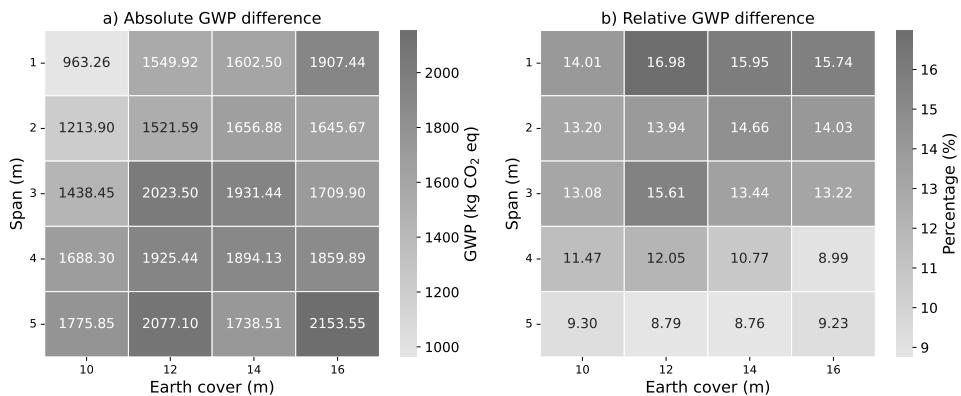


Figure 6.6: RCPHF GWP reduction respect to RCCPF as a function of the earth cover and horizontal span where: a) Absolute GWP difference; and b) Relative GWP difference.

The RCPHF consistently outperforms the RCCPF in every structural configuration examined. It is important to note that RCPHFs exhibit slightly higher variability than the cast-in-place alternative, which can be attributed to the distinct processes involved in the life cycle of each typology. Nevertheless, the absolute reduction in GWP increases with horizontal span and burial depth, ranging from 736.17 to 2153.55 kg CO₂ eq for the 8 m span configuration buried at 1 m and the 16 m span configuration buried at 5 m, respectively. In other words, the use of RCPHFs in larger spans and burial depths results in avoiding 9.23% of the associated kg of CO₂ emissions, a reduction that, when considering the structure's total GWP, yields a more significant improvement than the 10.80% reduction associated with the smaller structures.

Notably, the percentage reduction's behaviour entirely differs from the absolute improvements. The most substantial percentage reductions are observed in the 8 m span configurations, achieving a maximum reduction of 16.98% in the 3 m burial depth configuration. Conversely, the least noticeable but still positive improvements, with average differences of approximately 9%, are observed in the 16 m span configurations buried at depths of 4 and 5 m. Thus, while selecting the RCPHF for larger span configurations leads to more significant absolute reductions, it does not necessarily correspond to a better improvement ratio.

Identifying the most impactful phases for each configuration is essential due to the significant differences in the life cycle processes of RCCPFs and RCPHFs. Additionally, understanding the substantial influence of horizontal span on the total GWP highlights the relevance of developing a comprehensive assessment of each phase's contribution to the cumulative GWP. The mean percentage contributions of each life cycle phase were calculated for each road frame typology. It is important to note that these calculations were averaged across all burial depths ranging from 1 to 5 meters for each horizontal span. The results of this analysis are presented in Table 6.6. For a visual comparison, refer to Figure 6.7, which provides an overview of the mean contributions for structures with varying spans.

Table 6.6: Mean percentual midpoint GWP (kg CO₂ eq) contribution of each life cycle phase for each horizontal span, for both typologies.

Span (m)	Manufacturing		Construction		Use		End of Life	
	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF
8	78.17%	88.52%	23.24%	20.84%	4.43%	5.29%	-5.84%	-14.65%
10	80.72%	91.48%	23.61%	19.53%	3.55%	4.15%	-7.87%	-15.16%
12	83.62%	94.70%	22.98%	18.49%	2.68%	3.16%	-9.28%	-16.35%
14	85.74%	98.03%	22.33%	16.78%	2.04%	2.40%	-10.12%	-17.21%
16	87.77%	100.10%	21.95%	15.69%	1.58%	1.76%	-11.31%	-17.55%

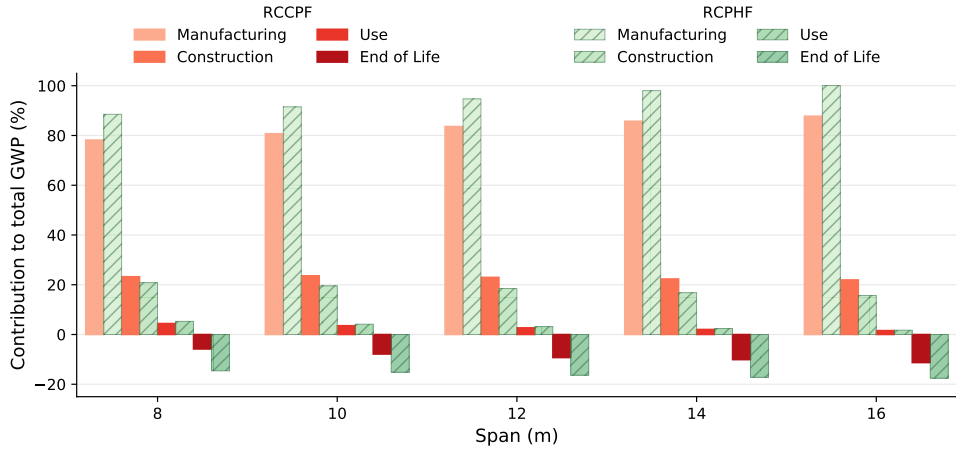


Figure 6.7: Comparative contribution of each stage to the total GWP by horizontal span.

Examining the effects of increasing the span from 8 to 16 meters reveals notable variations in each life cycle phase's contribution to the total GWP. For RCCPFs, the increase in horizontal span leads to a higher contribution from the manufacturing phase, which grows from 78.17% to 87.78%. This occurrence can be attributed to the need for more concrete, a carbon-intensive material, in the construction of larger structures. Although the increased span entails more substantial excavation and on-site concrete mixing and pouring, all other processes remain stable, resulting in a slight reduction from 23.24% to 21.95% in the percentual contribution of the construction phase. The maintenance tasks for RCCPFs remain consistent across different spans, but the increase in concrete volume results in a substantial increase in the amount of CO₂ fixed through carbonation during the service life. As a result, the contribution of the use phase decreases from 4.43% to 1.58%. Additionally, the increased span leads to a higher amount of CO₂ to be fixed by the crushed concrete in the landfill, causing the contribution of the final phase to decrease from -5.84% to -11.31%. These results highlight how increasing the span of RCCPFs results in a polarization of GWP contribution, with a significant flow towards the manufacturing phase.

In the case of RCPHF, the high contribution of the manufacturing phase inherent its prefabricated nature increases from 88.52% to 100.10% with the span. This occurrence can be attributed to the in-plant fabrication process, which becomes more influential as the size of the structure increases. On the other hand, the contribution of the construction phase decreases from 20.84% to 15.69%. The assembly process

for RCPHF remains relatively consistent regardless of the structure's size, so the associated increase in total GWP is much smaller than in the manufacturing phase. The use phase follows a similar trend as in the RCCPF case, reducing its contribution from -5.29% to -1.76% for RCPHF. The simplicity of the RCPHF dismantling process and the higher volume of carbonated concrete in the landfill improve the end-of-life phase impact from -16.65% to -17.55% for RCPHF.

RCPHF shows a lower percentual contribution in the construction and decommissioning phase. This difference is even more significant when considering the lower total GWP associated with each configuration. These characteristics emphasize the importance of considering the complete life cycle of road frames to deepen their sustainability, identify avenues for improvement by understanding the relevance of each phase, and make better decisions in their use.

Endpoint Approach

The endpoint approach combines the impact categories discussed in section 6.3.1, resulting in three damage categories: ecosystems (species·yr), human health (DALY) and resources (\$). By consolidating the impacts into damage categories, the study facilitates a more comprehensive and concise assessment of the environmental and social implications associated with the road frames. This method allows for a clearer understanding of the overall impact and enables a more focused analysis of the critical areas of concern regarding environmental and social sustainability.

Table 6.7: Ecosystems-total (species-year) comparison as a function of the earth cover, for each horizontal span.

Cover (m)	Type	Horizontal span (m)									
		8		10		12		14		16	
		Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)
1	RCCPF	7.69E-05	6.49	9.20E-05	7.47	1.17E-04	7.83	1.47E-04	9.87	1.81E-04	8.18
1	RCPHF	6.47E-05	16.98	7.83E-05	15.09	9.75E-05	17.19	1.23E-04	19.62	1.56E-04	21.78
2	RCCPF	8.59E-05	7.41	1.04E-04	8.38	1.32E-04	8.85	1.65E-04	9.99	2.01E-04	9.18
2	RCPHF	7.06E-05	12.77	8.67E-05	14.98	1.11E-04	15.70	1.40E-04	14.16	1.73E-04	13.28
3	RCCPF	9.64E-05	7.93	1.17E-04	8.88	1.47E-04	8.04	1.82E-04	8.61	2.21E-04	8.64
3	RCPHF	7.78E-05	13.52	9.67E-05	13.60	1.19E-04	13.37	1.54E-04	14.36	1.93E-04	14.03
4	RCCPF	1.08E-04	7.77	1.29E-04	8.91	1.62E-04	8.72	1.99E-04	8.55	2.42E-04	8.63
4	RCPHF	8.75E-05	12.38	1.06E-04	13.16	1.35E-04	12.72	1.70E-04	14.06	2.09E-04	12.93
5	RCCPF	1.20E-04	8.37	1.42E-04	9.03	1.61E-04	8.09	2.19E-04	9.78	2.64E-04	9.39
5	RCPHF	9.82E-05	12.83	1.17E-04	12.21	1.47E-04	12.55	1.89E-04	11.89	2.47E-04	10.94

In this context, the next step is to directly compare the average results of each damage category for each configuration. Table 6.7 showcases the ecosystems damage results. The overall findings indicate that RCPHF continues to appear as the more sustainable choice. To quantify the benefit derived from selecting RCPHF over RC-

CPF, a delta parameter representing the species-yr percentage reduction is established for each configuration. Figure 6.8, a combined bar and line chart, illustrates the total comparative impact in the ecosystem damage category for each configuration and the delta parameter.

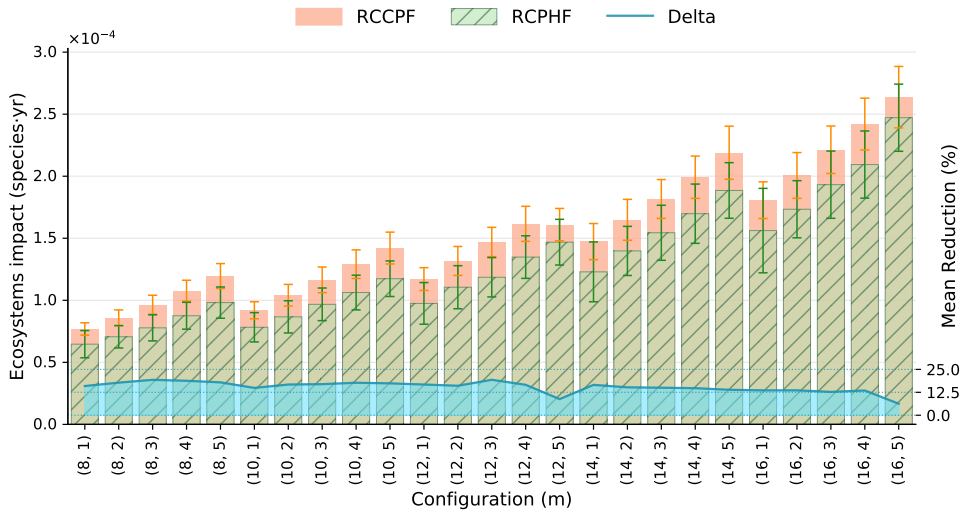


Figure 6.8: Ecosystems-total (species·yr) impact comparison for each configuration.

RCPHF consistently demonstrate a lower impact across all configurations, resulting in an average cut of $2.2485 \cdot 10^{-05}$ species·year, equivalent to a mean reduction of 15.44%. The delta values range from 6.28% to 19.33%, indicating significant improvements compared to RCCPFs. These results highlight the precast solution's ability to incur a lower environmental impact, firmly establishing RCPHF as the superior alternative for mitigating ecosystem damage in road frame construction projects.

Notably, RCCPFs generally exhibit lower variability. While this observation may be relevant when both solutions bear similar impacts, the substantial improvements achieved by RCPHF over RCCPFs render this factor inconclusive and non-decisive when selecting the best-performing alternative.

Both typologies exhibit a quadratic relationship between ecosystem damage and span, indicating that the ecosystem damage increases nonlinearly with the span. Additionally, there is a clear linear relationship between ecosystem damage and earth cover depth, suggesting that as the burial depth varies, the ecosystem damage changes proportionally. These findings align with the results reported by Ruiz-Vélez

et al. [130], who identified a quadratic relationship between saved span and raw material consumption, as well as a linear relationship between earth cover depth and raw material consumption. These consistent trends highlight the importance of examining the influence of horizontal span and land cover on the potential reductions in ecosystem damage that RCPHF's can offer in the context of road frames.

The absolute reductions relate to horizontal span through behaviour in which two main patterns can be identified. The first demonstrates a linear trend, where the mean reduction continuously increases from $1.76 \cdot 10^{-05}$ to $2.20 \cdot 10^{-05}$ species/yr during the transition from 8 to 12 meters. The second section exhibits a higher increase rate, with the mean reduction rising from $2.20 \cdot 10^{-05}$ to $2.73 \cdot 10^{-05}$ at the transition from 12 to 14 meters, followed by an even faster decrease to $2.58 \cdot 10^{-05}$ species/yr improvement for the 16-meter frames. A clear inverse linear trend with span is identified regarding the improvement ratio achieved by RCPHF's. This trend implies that the percentual reduction decreases proportionally from 18.05% to 11.65% as the horizontal span increases. These findings indicate that although larger road frames offer a more pronounced improvement than smaller structures, this progress is not matched by a proportionally more significant reduction in percentage terms.

The mean absolute improvement displays a linear relationship with earth cover depth. It gradually increases from $1.89 \cdot 10^{-05}$ to $2.64 \cdot 10^{-05}$ species/yr in the 1 to 4 m depth range and then rapidly decreases to a difference of $2.15 \cdot 10^{-05}$ species/yr for the frames buried at 5 m. In contrast, the percentual improvement remains relatively stable from 1 to 4 meters, ranging from 15.39% to 16.02%, before decreasing rapidly to 11.85% for the frames buried at 5 m. These results highlight that ecosystem damage is far more sensitive to span than burial depth variations.

Moving to human health damage, Table 6.8 provides the mean results and the variation coefficient for each configuration of both typologies. The total damage of each configuration is visualized in Figure 6.9 through a bar chart. In addition, the percentual improvement of RCPHF, represented by the delta parameter, is depicted as an overlaid line chart. Consistent with the previous findings, RCPHF's consistently exhibit lower impacts than RCCPF's, resulting in an average reduction of $2.63 \cdot 10^{-03}$ DALY, equivalent to 9.95% reductions, across 24 of the 25 configurations. However, an exception is observed in the case of 16 m span frames buried at 5 m depth. RCCPF appears to be the preferred alternative for this configuration, generating damage of $1.94 \cdot 10^{-03}$ DALY lower than the equivalent RCPHF, representing a 3.82% difference.

With a mean cv of 12.25%, RCPHF's exhibit a slightly higher variability than the 8.00% for RCCPF's. While this variability could be a relevant factor in cases where

both typologies have comparable impacts, the significant performance improvement achieved by the precast alternative renders this factor non-decisive.

Table 6.8: Human health-total (DALY) comparison as a function of the earth cover, for each horizontal span.

Cover (m)	Type	Horizontal span (m)									
		8		10		12		14		16	
		Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)
1	RCCPF	1.49E-02	6.16	1.78E-02	7.03	2.27E-02	7.38	2.86E-02	9.23	3.51E-02	7.70
1	RCPHF	1.31E-02	14.92	1.60E-02	13.15	1.99E-02	14.97	2.53E-02	17.00	3.24E-02	18.66
2	RCCPF	1.67E-02	6.97	2.02E-02	7.90	2.55E-02	8.30	3.20E-02	9.31	3.87E-02	8.57
2	RCPHF	1.45E-02	11.17	1.78E-02	12.99	2.28E-02	13.56	2.90E-02	12.14	3.62E-02	11.32
3	RCCPF	1.87E-02	7.48	2.26E-02	8.38	2.85E-02	7.60	3.51E-02	8.05	4.27E-02	8.04
3	RCPHF	1.59E-02	11.80	2.00E-02	11.72	2.45E-02	11.50	3.21E-02	12.29	4.05E-02	11.91
4	RCCPF	2.10E-02	7.30	2.51E-02	8.44	3.12E-02	8.18	3.85E-02	8.01	4.67E-02	8.09
4	RCPHF	1.80E-02	10.70	2.21E-02	11.33	2.81E-02	10.90	3.57E-02	11.91	4.41E-02	10.93
5	RCCPF	2.33E-02	7.87	2.76E-02	8.53	3.11E-02	7.58	4.23E-02	9.16	5.09E-02	8.80
5	RCPHF	2.03E-02	11.01	2.44E-02	10.51	3.08E-02	10.70	3.97E-02	10.06	5.28E-02	9.11

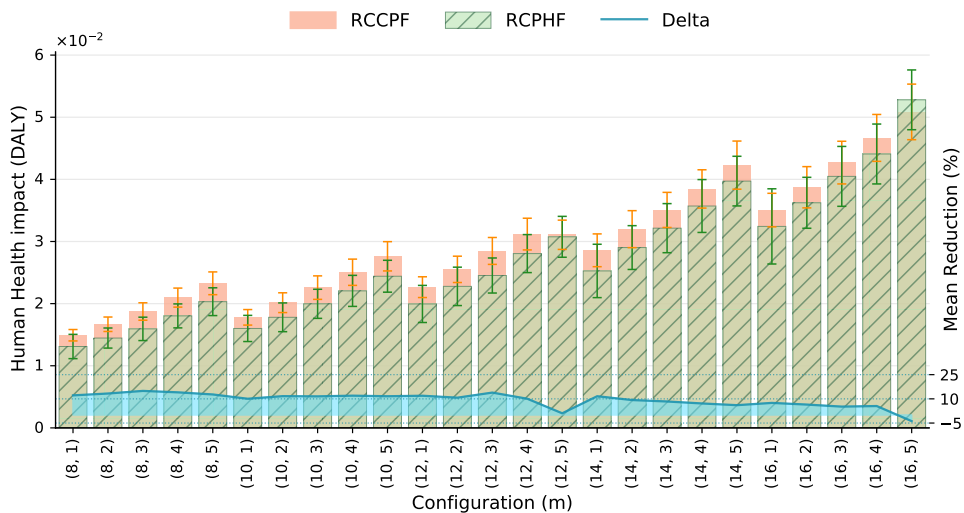


Figure 6.9: Human health-total (DALY) impact comparison for each configuration.

The absolute improvement attained by RCPHF stays relatively stable from 8 to 12 meters, varying between $2.55 \cdot 10^{-03}$ and $2.59 \cdot 10^{-03}$ DALY. This uniform linear trend is followed by a slight increase to $2.91 \cdot 10^{-03}$ DALY for the 12 m road frames and a substantial decrease to $1.60 \cdot 10^{-03}$ DALY for the 16 m structures. In terms of percentual improvement, there is an inverse linear relationship with the amount of span saved,

progressively decreasing from 13.47% to 3.73% for smaller and larger structures, respectively.

In terms of the relationship between absolute improvement and earth cover depth, there is a linear increase from $2.45 \cdot 10^{-03}$ to $2.90 \cdot 10^{-03}$ DALY in the transition from 1 to 3 m. The absolute mean difference stabilizes at this value and remains constant at $2.88 \cdot 10^{-03}$ DALY for structures buried at 4 m before decreasing significantly to $1.42 \cdot 10^{-03}$ DALY for road frames buried at 5 m. These absolute performance improvements correspond to an improvement ratio that linearly decreases with increasing burial depth, ranging from 13.47% to 4.07% for structures buried at 1 and 5 m, respectively.

The analysis of resource damage is presented in Table 6.9 and Figure 6.10. Consistent with the previous findings, RCPHFs generally result in lower resource damage for 23 out of the 25 road frame configurations. However, for the 12 and 16-meter configurations buried at 5 meters depth, RCCPFs demonstrate lower resource damage, deviating from the overall trend. These configurations show 1.37% and 4.50% reductions, resulting in 7.96 and 43.12 \$ decreases in mean damages, respectively. RCPHFs exhibit an average reduction of 32.03 \$ in resource damage for the remaining configurations, corresponding to an average improvement of 6.50% compared to the cast-in-place alternative.

Table 6.9: Resources-total (\$) comparison as a function of the earth cover, for each horizontal span.

Cover (m)	Type	Horizontal span (m)									
		8		10		12		14		16	
		Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)	Mean	cv (%)
1	RCCPF	283.48	9.05	334.74	10.77	427.10	11.43	537.05	14.53	655.00	12.08
1	RCPHF	263.81	22.35	318.85	19.94	398.22	22.71	501.74	26.01	640.95	28.74
2	RCCPF	311.84	10.32	377.89	12.00	478.76	12.91	600.69	14.65	729.39	13.49
2	RCPHF	285.67	16.77	349.65	19.77	448.53	20.73	568.86	18.64	704.75	17.55
3	RCCPF	348.68	11.19	422.69	12.36	532.68	11.46	659.52	12.38	805.08	12.61
3	RCPHF	313.43	17.49	389.43	17.49	477.19	17.34	626.67	18.95	783.83	18.39
4	RCCPF	387.77	10.58	466.45	12.44	584.97	12.46	721.28	12.27	881.52	12.48
4	RCPHF	351.07	15.50	426.04	17.03	541.06	16.48	685.90	18.43	846.37	17.01
5	RCCPF	428.50	11.17	512.17	12.50	580.93	11.22	791.42	14.11	957.56	13.50
5	RCPHF	392.80	16.15	469.33	15.32	588.89	16.30	757.79	15.37	1000.68	14.06

Like the previous damage categories results, RCPHFs exhibit a slightly higher resource variability with an average cv of 18.58%, compared to the RCCPFs with a 12.16% average. However, this variability difference does not influence the selection between the two typologies, given the precast alternative's substantial improvement in resource damage performance.

Analyzing the relationship between the average improvement achieved by RCPHF and the span allowed for identifying a clear linear trend within the 8 to 14 m range, with mean reductions ranging from 30.70 \$ to 33.80 \$. However, there is a significant reduction to 10.39 \$ for the 16 m structures. The percentual reduction follows a linear decline as the span increases, ranging from 8.72% for the 8 m road frames to a minimal 1.29% for the 16-meter structures.

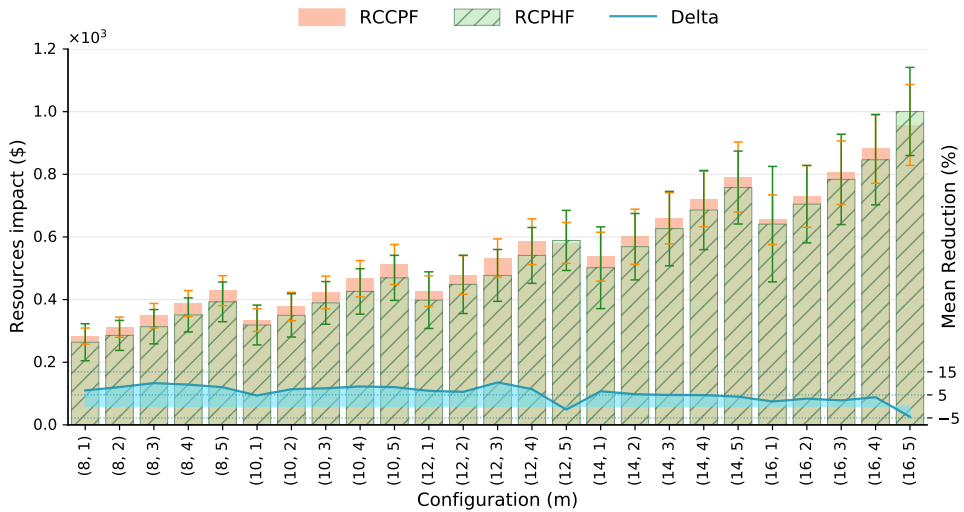


Figure 6.10: Resources-total (\$) comparison for each configuration.

The subsequent analytical step in the research involves assessing the average contribution of each life cycle phase to the damage categories. Table 6.10 compares the average contribution of each phase to the ecosystem damage based on the horizontal span for both typologies. These findings are visually depicted in Figure 6.11.

Table 6.10: Mean percentual endpoint Ecosystems-total (Species-yr) contribution of each life cycle phase for each horizontal span, for both typologies.

Span (m)	Manufacturing		Construction		Use		End-of-life	
	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF
8	79.83%	85.73%	18.59%	18.60%	4.33%	5.35%	-2.76%	-9.68%
10	81.76%	88.35%	18.82%	17.47%	3.52%	4.26%	-4.08%	-10.08%
12	83.86%	90.93%	18.43%	16.71%	2.71%	3.30%	-4.97%	-10.94%
14	85.40%	93.43%	18.04%	15.63%	2.11%	2.49%	-5.51%	-11.55%
16	86.84%	95.44%	17.79%	14.55%	1.67%	1.90%	-6.27%	-11.89%

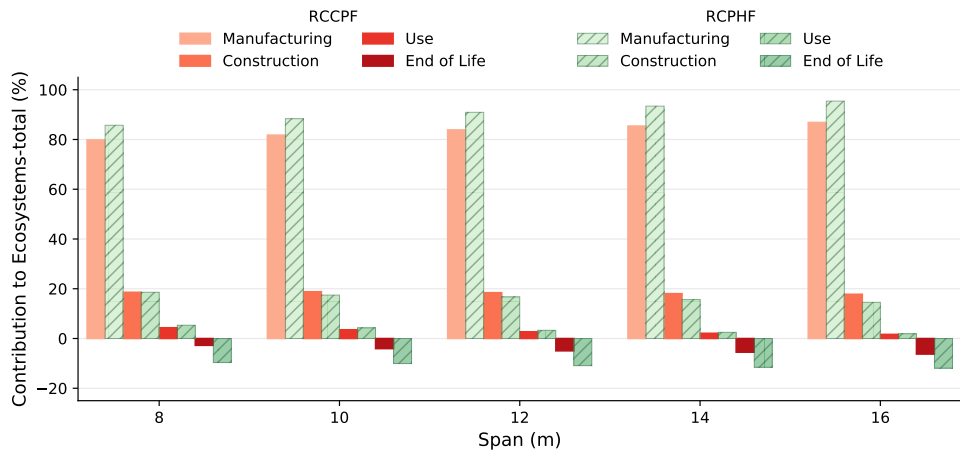


Figure 6.11: Comparative contribution of each stage to the Ecosystems-total by horizontal span.

The manufacturing phase has the most significant impact on ecosystem damage. RCPHFs exhibit an average contribution of 7.24% higher than RCCPFs, which can be attributed to the more intensive processes involved in their in-plant manufacturing. Moreover, the contribution of this initial phase increases linearly with the span saved, ranging from 79.83% to 86.84% for RCCPFs and from 85.73% to 95.44% for RCPHFs. The manufacturing phase contribution in RCPHFs increases more rapidly than RCCPFs, resulting in a more pronounced disparity as the span increases.

The specific processes associated with each typology's construction result in the precast solution incurring less absolute damage during this phase. Furthermore, the RCPHFs construction consistently contributes less to each structure's ecosystem damage. The analysis reveals that RCPHFs have an average contribution of 1.47% lower than RCCPFs. The RCCPFs maintain nearly constant contributions across all spans, ranging from 18.82% to 17.9%. In contrast, the RCPHFs exhibit a distinct behaviour in which the contribution of the construction phase decreases linearly from 18.60% to 14.55%. This disparity leads to a contribution difference varying from 0.01% to 3.24% for 8 and 16 m road frames, respectively.

The differences in the decommissioning process of the two typologies are significant. The simplicity of disassembling RCPHFs results in a much lower contribution during the end-of-life phase, leading to an average reduction of -6.11% in ecosystem damage compared to RCCPFs. Similar to the use phase, the size of the structures plays a paramount role in the end-of-life phase. Disassembling larger structures generates

more crushed concrete, which carbonates in landfills, resulting in the fixation of larger amounts of CO₂. The contribution of the end-of-life phase decreases from -2.76% to -6.27% for RCCPFs and from -9.68% to -11.89% for RCPHF as the span increases from 8 to 16 meters.

The human health results are presented in Table 6.11 and graphed in Figure 6.12. The analysis of phase contributions revealed similar trends to those described earlier. The manufacturing phase continues to be the primary contributor to total human health damage, with RCPHF showing contributions that, on average, are 10.85% higher than RCCPFs. The contribution of this first phase increases with the span, growing from 74.30% to 81.26% in RCCPFs and from 83.44% to 93.66% in RCPHF. Once again, the precast structure's contribution increase rate is higher, resulting in a more significant difference in larger structures.

Table 6.11: Mean percentual endpoint Human Health-total (DALY) contribution of each life cycle phase for each horizontal span, for both typologies.

Span (m)	Manufacturing		Construction		Use		End-of-life	
	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF
8	74.30%	83.44%	21.88%	19.26%	4.34%	5.05%	-0.51%	-7.75%
10	75.88%	86.14%	22.22%	17.95%	3.52%	4.01%	-1.62%	-8.10%
12	78.09%	88.83%	21.55%	16.93%	2.71%	3.10%	-2.35%	-8.86%
14	79.78%	91.50%	20.89%	15.54%	2.11%	2.34%	-2.78%	-9.38%
16	81.26%	93.66%	20.48%	14.21%	1.67%	1.77%	-3.40%	-9.63%

During the construction phase, RCPHF consistently exhibit contributions that are, on average, 4.63% lower than RCCPFs. The human health damage derived from cast-in-place construction processes is less influenced by the size of the structure, resulting in a stable contribution ranging between 20.48% and 22.22%. In contrast, the contributions of RCPHF during the construction phase decrease significantly from 19.26% to 14.21% as the span increases.

The contribution to human health damages associated with the use phase is very similar for both typologies displaying a slightly declining trend as the size of the structure increases. Regarding the end-of-life phase, the differences in the specific processes result in significantly better performance from RCPHF compared to RCCPFs. While the end-of-life phase of RCCPFs shows an improvement from a practically neutral -0.51% to a slightly more promising -3.40%, RCPHF achieve a more substantial reduction in human health damage ranging from -7.75% to -9.63%.

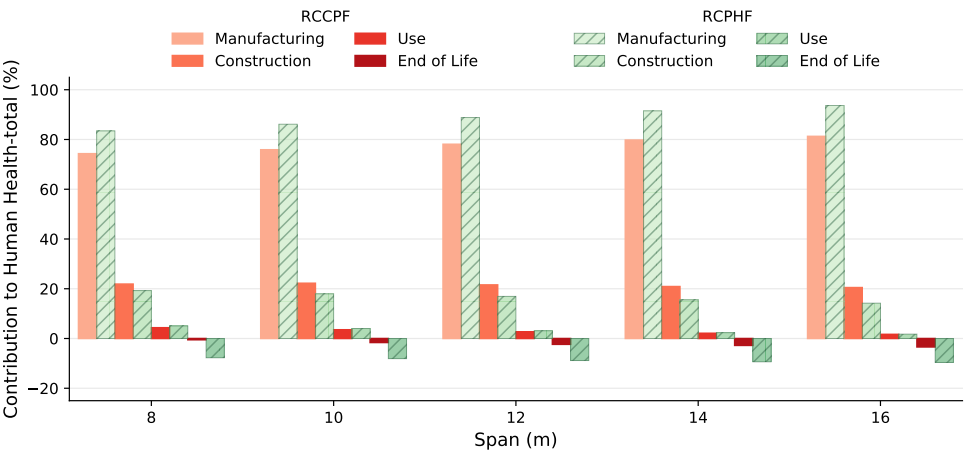


Figure 6.12: Comparative contribution of each stage to the Human Health-total by horizontal span.

As presented in Table 6.12 and Figure 6.13, the contribution of each phase to resource damage follows similar patterns to those observed in the previous damage categories. Although, to a lesser extent, the manufacturing phase remains the primary contributor, accounting for 59.63% to 62.53% of the total resource damage in RCCPFs and 64.61% to 74.56% in RCPHF. Once again, the precast structure demonstrate a contribution that averages 8.66% higher than the cast-in-place road frame.

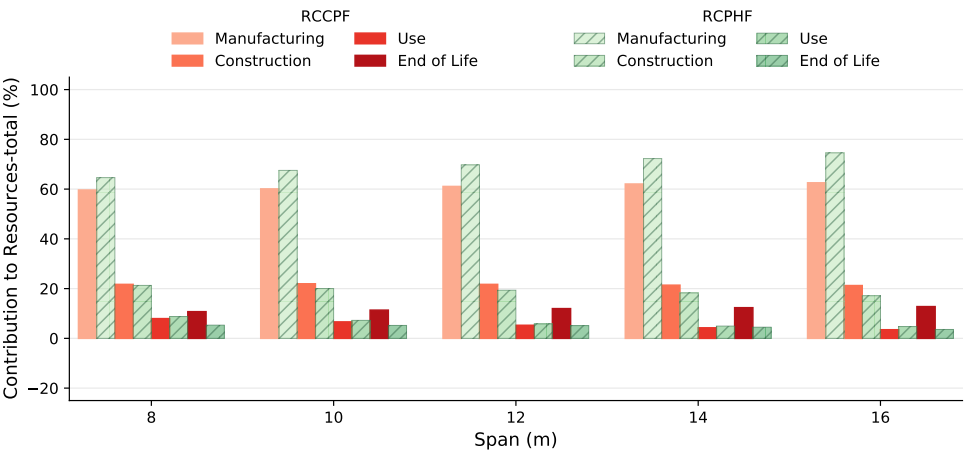


Figure 6.13: Comparative contribution of each stage to the Resources-total by horizontal span.

Table 6.12: Mean percentual endpoint Resources-total (\$) contribution of each life cycle phase for each horizontal span, for both typologies.

Span (m)	Manufacturing		Construction		Use		End-of-life	
	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF
8	59.63%	64.61%	21.70%	21.29%	7.94%	8.76%	10.73%	5.34%
10	60.08%	67.52%	21.94%	20.03%	6.62%	7.24%	11.35%	5.20%
12	61.07%	69.73%	21.70%	19.36%	5.26%	5.80%	11.96%	5.12%
14	62.05%	72.27%	21.38%	18.26%	4.24%	4.96%	12.33%	4.51%
16	62.53%	74.56%	21.23%	17.13%	3.47%	4.74%	12.77%	3.58%

Once again, the contribution of the construction phase in RCCPFs remains relatively unchanging, hovering around 21.50%. In contrast, the assembly method's simplicity in RCPHFs leads to a decrease in the contribution, ranging from a close 21.29% to 17.13%. Both typologies exhibit a similar trend in the use stage, with the contribution of this phase almost halving in both cases. It is worth noting that RCCPFs demonstrate a slightly lower contribution during this third phase.

The two road frame typologies under study exhibit fundamentally different end-of-life phase contribution behaviours. For RCCPFs, the contribution increases linearly from 10.73% in the 8 m frames to 12.77% in the 16 m road frames. Conversely, the contribution of RCPHFs decreases from a much lower 5.34% to 3.58% in the transition from the smaller to the larger span configurations.

Thus far, the results provide a comprehensive understanding of the E-LCA of the road frames under study. The final stage of the endpoint analysis involves aggregating all the data to derive a single score that quantifies the overall damage resulting from the product's life cycle. Figure 6.14 visually represents this information, displayed in Table 6.13 by depicting the scores for all 50 cost-optimal structures studied as a mesh graph, with the averages represented as line plots.

Table 6.13: Single score results of each configuration for both road frame typologies.

Cover (m)	Horizontal span (m)									
	8		10		12		14		16	
	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF
1	840.94	757.72	1001.62	893.73	1270.50	1106.45	1593.33	1410.48	1965.18	1791.40
2	933.03	813.96	1128.54	997.46	1425.12	1265.17	1776.30	1605.79	2172.62	2018.33
3	1046.38	888.15	1259.02	1108.62	1582.51	1366.16	1960.11	1772.54	2386.24	2242.47
4	1161.84	1006.15	1392.21	1224.69	1739.88	1550.25	2150.12	1964.96	2604.45	2428.90
5	1281.05	1122.33	1528.69	1354.09	1901.50	1695.00	2342.66	2191.04	2825.01	2913.71

The single scores analysis reveals a gradual increase from smaller-sized structures buried at 1 m to larger structures buried at the maximum considered depth. In 24

out of the 25 configurations, the precast alternative scores lower than the RCCPFs, except for the 16 m RCCPF buried at 5 m. As the size of the configurations increases, the absolute difference between the scores also increases, except for the structures buried at 5 m. The line graph of the averages provides further insights, highlighting the linear relationship between the environmental impact and the burial depth of the road frames. Additionally, it confirms the quadratic relationship with the span, which is directly related to the structural requirements and internal stresses experienced by this particular structural typology.

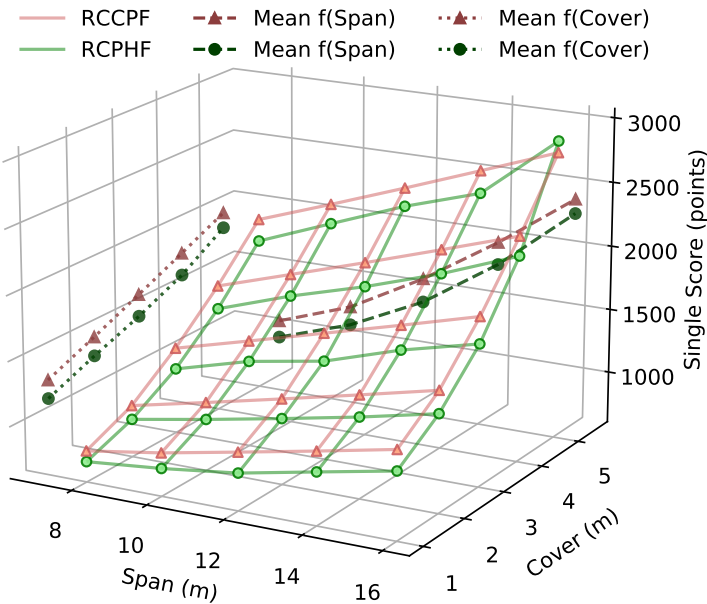


Figure 6.14: Endpoint single score impact points of each configuration for both typologies.

6.3.2 Social Life Cycle Assessment

This section focuses on evaluating the social performance of road frames throughout their life cycle, which is an essential aspect of the third pillar of sustainability. Analyzing the social impact of a product's life cycle is a complex yet crucial task for the construction industry to understand and address the effects caused by the structural solutions being discussed. In this context, Table 6.14 presents the results of the S-LCA endpoint analysis for the cost-optimal road frames. To enhance readability, a $\cdot 10^5$ reduction coefficient has been applied to all four social damage categories. As a result, the Local Community (LC), Society (S), Value Chain Actors (VCA), and Workers (W) results presented in the table are measured in $\text{mrh} \cdot 10^5$.

Table 6.14: S-LCA complete damage category results ($\text{mrh} \cdot 10^5$) of each configuration for both road frame typologies.

Cat.	Cover	Horizontal span (m)									
		8		10		12		14		16	
		RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF	RCCPF	RCPHF
LC	1 m	11.60	11.00	14.00	13.70	17.90	17.30	22.60	22.40	28.00	29.20
LC	2 m	12.70	12.00	15.30	14.90	19.50	19.40	24.60	25.30	29.50	32.40
LC	3 m	13.90	12.70	16.70	16.30	21.20	20.50	25.90	27.50	31.70	35.60
LC	4 m	15.10	14.20	18.10	17.70	22.20	23.10	27.80	30.30	33.90	38.10
LC	5 m	16.30	15.70	19.50	19.30	23.80	25.00	29.70	33.40	36.10	40.00
S	1 m	13.40	12.90	16.40	16.40	21.30	20.90	27.20	27.50	33.90	36.30
S	2 m	14.40	13.80	17.60	17.50	22.80	23.20	29.10	30.70	35.50	39.90
S	3 m	15.50	14.30	18.80	18.90	24.30	24.10	30.40	33.00	37.60	43.40
S	4 m	16.60	15.90	20.10	20.20	25.40	27.00	32.20	36.20	39.70	46.10
S	5 m	17.70	17.40	21.40	21.80	26.90	29.00	34.00	39.70	41.80	48.70
VCA	1 m	7.98	7.51	9.71	9.51	12.60	12.10	16.00	15.90	20.00	20.90
VCA	2 m	8.62	8.07	10.50	10.20	13.60	13.50	17.30	17.80	20.60	23.10
VCA	3 m	9.33	8.45	11.40	11.10	14.60	14.10	17.70	19.20	21.90	25.10
VCA	4 m	10.00	9.40	12.20	11.90	14.90	15.80	18.80	21.10	23.20	26.80
VCA	5 m	10.80	10.30	13.10	12.90	15.80	17.00	20.00	23.20	24.50	28.20
W	1 m	14.00	13.20	17.00	16.50	21.80	20.90	27.70	27.30	34.40	35.70
W	2 m	15.20	14.20	18.50	17.90	23.70	23.40	30.10	30.70	35.50	39.50
W	3 m	16.60	15.00	20.10	19.40	25.70	24.50	30.90	33.10	37.90	43.20
W	4 m	17.90	16.70	21.60	21.00	26.20	27.60	33.00	36.50	40.40	46.10
W	5 m	19.20	18.40	23.20	22.80	28.00	29.80	35.10	40.10	42.80	48.50

The preliminary assessment of the potential social impact on various stakeholders reveals significant deviations from the performance identified in the E-LCA analysis. Moreover, Figure 6.15 illustrates the averaged results for each span in both typologies, highlighting distinct trends that sharply contrast the patterns observed in the preceding sections. Interestingly, the life cycle of RCCPFs demonstrates lower social damage across diverse configurations, with an overall average social damage that is $4.16 \cdot 10^5$ mrh lower than that of RCPHFs. This difference corresponds to an overall improvement of 2.34%, positioning the in situ alternative as the superior choice from a social performance perspective. However, it is essential to note that the overall

average does not comprehensively portray the S-LCA outcomes, underscoring the need for further analysis of the endpoint results.

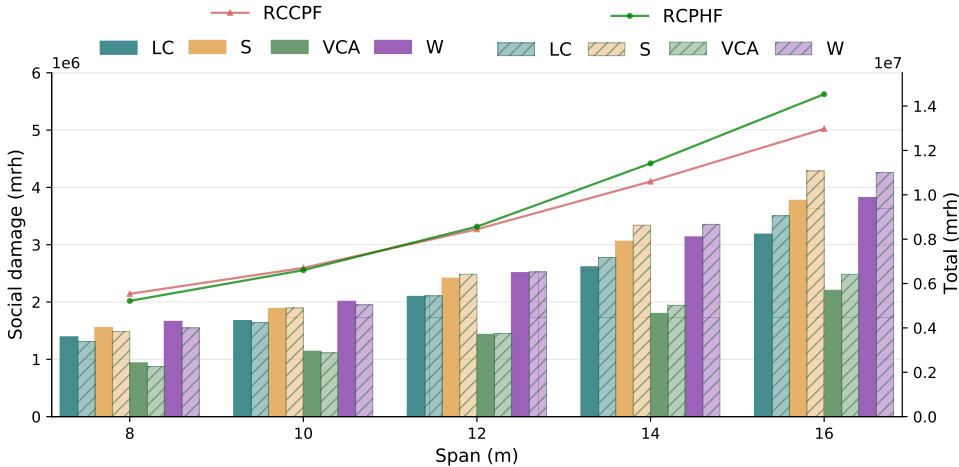


Figure 6.15: S-LCA endpoint damage comparison as a function of horizontal span.

In this context, the next step in the analysis is studying how the horizontal span influences the road frame's total social damage. RCCPFs and RCPHF exhibit a clear quadratic relationship between total damage and span, although the influence is slightly more pronounced in the precast structure. At 8 and 10 m spans, the precast road frames result in lower total damage than the equivalent RCCPF. With an average reduction of $3.18 \cdot 10^5$ mrh, RCPHF achieves better social performance, reducing 6.09% of the total damage attributed to their life cycle. However, the sensitivity of RCPHF to structure size becomes evident as larger spans are considered. Despite the lower damages detailed for smaller configurations, the differences in social damage become equalized at the 14 m span structures. Both typologies demonstrate comparable total social damage in this intermediate configuration, differing by only 1.38%. When analyzing the 14 and 16 m span configurations, RCCPFs perform significantly better than the precast alternative. These larger cast-in-place road frames exhibit significantly lower social damage, with reductions of $8.17 \cdot 10^5$ and $1.56 \cdot 10^5$ mrh compared to the equivalent RCPHF, representing reductions in social damage by 7.15% and 10.76%, respectively.

Based on the findings presented thus far, it is valuable to conduct a similar analysis to investigate the influence of burial depth on the social damage incurred throughout the life cycle of road frames. Figure 6.16 presents the averaged total social damage

across the range of considered spans for each burial depth, encompassing both RCCPF and RCPHF. Notably, a clear linear relationship between burial depth and social damage emerges. Furthermore, RCPHFs appear more influenced by the depth at which the structure is buried. For four out of the five burial depths examined, RCPHFs exhibit more significant mean social damage compared to RCCPFs. However, an exception arises for frames buried at 1 m, where RCPHFs outperform RCCPFs by a margin of 4158.70 mrh. In contrast, configurations buried at 2 m demonstrate lower social damage in the in-situ structure, with average reductions of $2.57 \cdot 10^5$, equivalent to a 3.01% decrease in social damage. This discrepancy grows progressively as burial depth increases, culminating in an $8.34 \cdot 10^5$ mrh difference for structures buried at 5 m, corresponding to a 7.71% reduction in social damage throughout their life cycle.

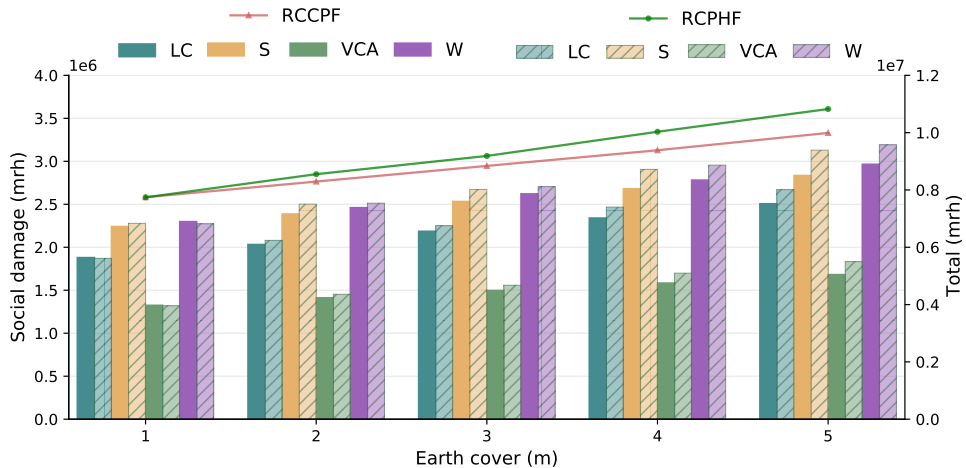


Figure 6.16: S-LCA endpoint damage comparison as a function of earth cover depth.

The study's primary objective is to determine the most socially sustainable alternative between the RCCPF and RCPHF typologies. Therefore, it is crucial to delve into the specific performance of each structural configuration under analysis. Figure 6.17 presents the difference in total social damage as a function of burial depth for each span. While the precast alternative was previously identified as the most environmentally sustainable solution, the endpoint results of the S-LCA presented in this section deviate from that trend. Illustrating the difference in damage between the RCCPF and RCPHF life cycles is a valuable comparative tool for decision-makers to consider as they aim to gather comprehensive information when selecting a road frame typology within the examined configurations.

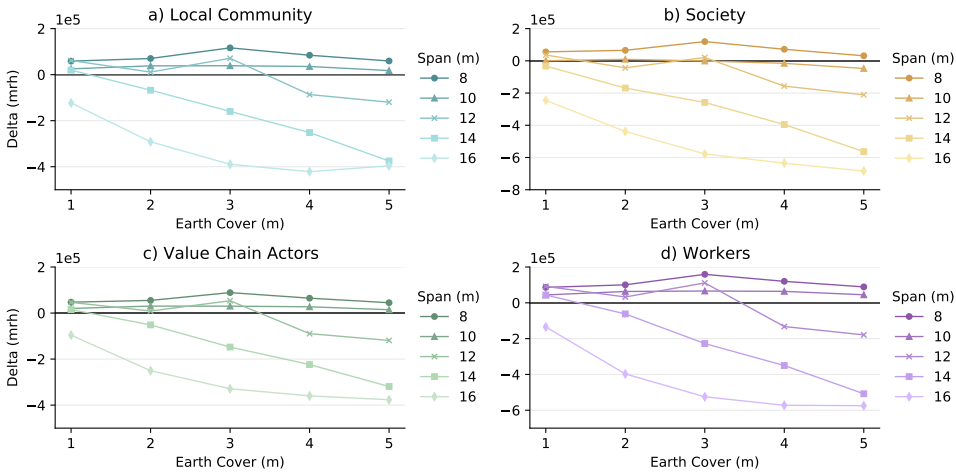


Figure 6.17: Social damage difference between RCCPF and RCPHF as a function of horizontal span, for all categories, where: a) Local Community; b) Society; c) Value Chain Actors; and d) Workers.

In this context, the first line plot illustrates the disparity in social damage inflicted on the local community, encompassing all impact factors directly affecting the community residing near the road frame's location. Notably, the precast alternative, RCPHF, demonstrates a significant advantage over the RCCPF for an 8 m span across all burial depths. RCPHF exhibits a substantial average difference of $7.78 \cdot 10^4$ mrh, equivalent to a 6.02% reduction in social damage. This improvement translates to absolute reductions ranging from $5.86 \cdot 10^4$ to $1.16 \cdot 10^5$ mrh, corresponding to a 3.79% to 9.17% decrease in overall damage inflicted on the local community.

A similar trend is observed for the 10 m structure, where the RCPHF continues to cause less social damage than the RCCPF. This disparity remains relatively stable, with an average reduction of $3.10 \cdot 10^4$ mrh, equivalent to 1.93%. So far, the precast structural solution demonstrates better social performance regarding damage inflicted on the local community. However, in line with the general behaviour identified in the endpoint S-LCA results discussed throughout this section, the 12 m structures no longer present a clear alternative that outperforms the other in terms of social damage.

In the case of a 1 m earth cover depth, the RCPHF outperforms RCCPF, resulting in a 3.54% reduction in damage to the local community. However, this advantage diminishes to a minimum of 0.57% at a cover depth of 2 m, where both typologies

incur similar damage levels. The decreasing trend is interrupted for the 12 m configurations buried at a depth of 3 m. In this scenario, RCPHF frames generate $7.10 \cdot 10^4$ mrh less damage than RCCPF, equivalent to a 3.46% improvement in local community impact. However, for equally sized frames buried at 4 or 5 m, the RCCPF achieves reductions of 9.06% and 12.64% compared to their RCPHF counterparts.

Moving to larger structures significantly affects the extent of social impact caused to the local community by RCPHF. Apart from the 1 m deep configuration, the RCCPF proves to be the better alternative for the 14 m span. The RCPHF results in $1.97 \cdot 10^4$ mrh less at the shallowest depth considered, equivalent to a 0.88% reduction. However, the difference gradually diminishes nearly linearly, leading to a substantial $3.75 \cdot 10^5$ reduction attained by the RCCPF buried 5 m deep. This absolute difference translates to a 5.02% decrease in the overall local community damage resulting from the life cycle of these road frames.

Regarding the 16 m designs, RCCPFs consistently outperform the precast option across all burial depths. The absolute difference in damage starts at $1.23 \cdot 10^5$ mrh for road frames buried at 1 meter and rapidly increases up to the 4 m structures, after which it stabilizes. This behaviour leads to substantial differences of $4.22 \cdot 10^5$ and $3.96 \cdot 10^5$ mrh, corresponding to reductions of 12.45% and 10.98% for the 4 and 5 m earth cover depths, respectively.

The society category encompasses a broader range of entities potentially affected by road frame construction and use. It is crucial to assess the social performance of both typologies from this perspective to ensure sustainable development. In line with this, the second line plot in Figure 6.17 reveals a similar performance difference to the one identified in the local community category.

RCPHF remains the more sustainable alternative for 8 m span structures, demonstrating improvements ranging from 2.00% to 9.41%. On average, the precast solution yields results of $6.87 \cdot 10^4$ mrh lower than RCCPF's. For the 10 m configurations, both structures incur practically equivalent damage. However, a similar pattern to the one observed in the local community category emerges for the 12 m structures. RCPHF results in lower social damage for structures buried at shallower depths, while RCCPF proves to be the more suitable alternative for those buried below 3 m deep.

RCCPF emerges as the sustainable choice for the 14 and 16 m spans, with a reduction of $3.24 \cdot 10^4$ mrh for the 14 m road frame buried at 1 m. Similar to the local community results, the difference increases linearly, reaching $5.64 \cdot 10^5$ mrh, a substantial average reduction of 10.30%. RCCPF also demonstrates significantly better performance in the 16 m configurations, with society damage that is, on average,

$5.16 \cdot 10^5$ mrh lower than the equivalent RCPHF. Overall, the cast-in-place solution showcases notable benefits, achieving reductions exceeding 8.76% in society damage.

Transitioning to the third S-LCA endpoint damage metric, the value chain actors category examines the impact on various stakeholders involved in the life cycle of road frames. This category evaluates factors such as working conditions and fair wages for individuals engaged in activities ranging from suppliers and contractors to manufacturers. Assessing road frame construction practices from this standpoint contributes to fostering an ethical and responsible construction industry, supporting the long-term sustainability of the infrastructure development sector.

Similarly to the analysis conducted on the local community and society, evaluating the value chain actors category reveals comparable trends. The RCPHF continues to demonstrate superior social sustainability for 8 and 10 m spans, with average reductions of $6.01 \cdot 10^4$ and $2.43 \cdot 10^4$ mrh compared to their RCCPF counterparts. These findings further underscore the social suitability of the RCPHF, yielding significant reductions of 8.88% compared to traditional on-site construction. It is viable to affirm that these benefits pose RCPHF as the preferred solution for shorter spans.

The 12 m span configurations analysis portrayed the RCCPF as the most damaging alternative up to a 3 m earth cover. However, it evolves into a more sustainable option for greater depths. As we transition to larger spans, RCCPF emerges as the preferable choice for minimizing damage to value chain actors. In the case of 14 m configurations, the difference between the two typologies demonstrates a linear decrease in favour of RCCPF. This trend indicates that although RCPHF performs better when buried at 1 m, RCCPFs achieve average improvements of $1.45 \cdot 10^5$ mrh, resulting in a notable 4.48% reduction in social damage. Lastly, for 16 m spans, the traditional alternative is the superior solution, with damage differences exceeding 2.84%. This choice helps prevent an average of $2.82 \cdot 10^5$ mrh damage to value chain actors.

The final category, workers damage, concentrates on individuals directly involved in the road frame's life cycle. By assessing impact factors such as occupational health and job stability, the workers damage category evaluates the well-being of the construction industry's workforce. Examining the performance of both typologies reveals a similar pattern to what was observed in the analysis of the local community, society, and value chain actors categories. In this context, RCPHF remains the socially sustainable alternative for a wide range of 8 and 10 m span structures and the 12 m road frames buried up to 3 m deep. In these cases, RCPHF achieves results up to $1.59 \cdot 10^5$ mrh below RCCPF, representing substantial reductions of 18.84% in favour of the precast structures.

On the other hand, RCCPFs exhibit lower workers damage in the remaining configurations. The results reveal a clear pattern where larger structures demonstrate more pronounced damage in the workers category for RCPHF. This trend, derived from the specific processes involved in each structure's life cycle, translates to average differences of $2.21 \cdot 10^5$ and $4.41 \cdot 10^5$ mrh for the 14 and 16 m structures, respectively. In contrast, RCCPFs achieve reductions in average damage of up to 17.64%, highlighting the superior social performance of cast-in-place road frames for spans exceeding 12 m.

The endpoint results of the S-LCA provide a polarized perspective where each alternative emerges as the socially sustainable choice for specific span and earth cover configurations. It is important to note that in cases where the precast alternative outperforms the traditional cast-in-place structure, the average improvement stands at 3.68%. While significant, the average improvement in cases where RCCPF is the superior alternative is much higher, reaching 9.10%. Moreover, RCCPFs demonstrate greater percentage reductions in social damage for longer spans, significantly impacting the absolute social damage difference between the two typologies for larger configurations.

6.4 Conclusions

This study conducted a comprehensive and detailed comparative assessment of the E-LCA and S-LCA of two reinforced concrete frame typologies. By evaluating 50 cost-optimal structures across 25 combinations of horizontal span and burial depth, the investigation acquired valuable insights into each typology's environmental and social sustainability. The E-LCA results considered complex midpoint impact categories, focusing on GWP. In contrast, the analysis of endpoint damage categories offered a comprehensive understanding of environmental damage. Additionally, a phase contribution analysis was performed to quantify the disparities in the life cycle impact of RCPHF and RCCPF, shedding light on the differences in their respective processes. The endpoint results from the S-LCA provided clear insights into the social sustainability of both road frame typologies. Furthermore, the study parameterized the influence of horizontal span and burial depth, revealing strong relationships between geometric design parameters and the environmental and social implications throughout the life cycle of road frames. Several conclusions may be drawn based on the assumptions and results of this specific case study.

- The geometric parameters of road frame design significantly impact these structures' environmental and social sustainability metrics. The E-LCA and S-LCA reveal a quadratic relationship between the span of road frames and their en-

vironmental and social impacts. This influence is particularly pronounced in precast structures, with impacts escalating rapidly for spans exceeding 12 m. Burial depth exhibits a linear relationship with sustainability metrics, comparably affecting both typologies.

- The overall analysis of the midpoint impact categories in the E-LCA reveals that RCPHF demonstrate a lower overall impact than RCCPFs. A detailed analysis of the GWP indicates that precast frames generally outperform their counterparts in terms of equivalent CO₂ emissions performance across most configurations. Significant improvement ratios in environmental impact are observed in structures with spans of 8 and 10 m, while the most substantial absolute reductions occur in configurations spanning above 12 m.
- The endpoint analysis in the E-LCA aligns with the trend observed in the midpoint analysis, indicating that the precast alternative is the most sustainable solution for most configurations. However, the percentage improvements in environmental impact decrease as the size of the structures increases. Ultimately, in the largest configuration, with a burial depth of 5 m, RCCPF demonstrates a lower environmental impact than RCPHF.
- The phase contribution analysis highlights a distinct polarization towards the manufacturing phase in RCPHF, with higher contributions than RCCPF. This disparity becomes more pronounced as the size of the structures increases. However, the prefabrication processes in the RCPHF life cycle result in reduced contributions to the overall impact in the construction and end-of-life phases compared to RCCPF.
- The S-LCA results do not indicate an overall superior alternative from a social perspective. The endpoint analysis reveals that RCPHF is the more socially sustainable option for spans up to 12 meters. However, there is a clear transition where RCCPF emerges as the more socially sustainable alternative for structures spanning 14 and 16 m, buried at depths ranging from 1 to 5 m.

The study contributes to a comprehensive understanding of road frame sustainability by assessing the most suitable alternative for multiple configurations. It also identifies the key phases that substantially contribute to environmental and social damage, providing valuable insights for targeted improvement efforts. The analysis, conducted on cost-optimized structural designs, ensures an objective assessment encompassing the three sustainability dimensions for RCPHF and RCCPF. The results have highlighted the need for further research to explore the underlying causes for the observed differences in environmental and social performance, presenting a relevant research prospect.

Chapter 7

Sustainable road infrastructure decision-making: Custom NSGA-II with repair operators for multi-objective optimization

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Abstract

The integration of sustainability principles into the structural design and decision-making processes for transportation infrastructure, particularly concerning reinforced concrete precast modular frames (RCPMF), is recognized as crucial for ensuring outcomes that are environmentally responsible, economically feasible, and socially beneficial. In this study, this challenge is addressed, with the significance of sustainable development in modern engineering practices being underscored. A novel approach, which is a combination of multi-objective optimization (MOO) with multi-criteria decision-making (MCDM) techniques, is proposed, tailored specifically for the design and selection of RCPMF. The effectiveness of three repair operators—random, statistical-based, and proximity-based—in optimizing economic, environmental, and social objectives is evaluated. Precise evaluation of objective functions is facilitated by a customized Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm, complemented by a detailed life cycle analysis (LCA). The utilization of simple additive weighting (SAW) and fair un choix adéquat (FUCA) methods for the scoring and ranking of the MOO solutions has revealed that notable excellence in meeting the RCPMF design requirements is exhibited by the statistical-based repair operator, which offers solutions with lower impacts across all dimensions and demonstrates minimal variability. MCDM techniques produced similar rankings, with slight score variations and a significant correlation of 0.9816, showcasing their consistent evaluation capacity despite distinct operational methodologies.

Keywords: multi-objective optimization; multi-criteria decision-making; modular structure; life cycle sustainability; NSGA-II; simple additive weighting; fair un choix adéquat

7.1 Introduction

Transport infrastructure plays a pivotal role in enhancing the quality of life and propelling global economic and social advancement. This importance is evidenced by the allocation of over 20% of the World Bank's loans to transportation infrastructure in recent years [152]. The construction industry, accounting for 9% of Europe's GDP, is on track to expand into a USD 14 trillion global industry by 2025 [153]. In light of this growth, fostering sustainable development in transportation infrastructure becomes imperative. This challenge requires integrating the three key pillars of sustainability—economic, environmental, and social—into transport infrastructure's design and operational strategies [1], [12], [154].

In contemporary structural engineering, it is critical to extend beyond adhering to technical standards by incorporating sustainability principles from the design stage. This holistic approach demands integrating complex criteria into the decision-making process of structural design [16], [155], [156]. Researchers have increasingly employed multi-objective optimization (MOO) techniques for concurrently considering multiple criteria, thus yielding balanced and optimal solutions in civil engineering [157].

Previous research focused on applying single-objective optimization (SOO) strategies to minimize the economic cost and embodied energy in transportation infrastructure solutions [158]. Recently, there has been a shift towards employing MOO in the design of various structural typologies, from reinforced concrete buildings to wind turbine foundations [159], [160]. Adopting MOO strategies marks a significant progression in harmonizing technical compliance with sustainability objectives within structural engineering [161].

Aligning MOO in structural design with contemporary industry trends, particularly the emphasis on integrating sustainability principles from the outset, significantly enhances the effectiveness of the multi-criteria decision-making (MCDM) process. Furthermore, it highlights its escalating relevance in modern structural engineering practices [162].

The intersection of secondary routes with primary roads presents a frequent challenge in transportation networks. Reinforced concrete road frames are a versatile solution to manage this issue. These road frames in transportation infrastructure have been predominantly constructed on-site as reinforced concrete cast-in-place frames (RCCPF). However, recent research exploring the reduction in economic costs through SOO of reinforced concrete precast modular frames (RCPMF) has identified precasting as a viable alternative for road networks [128]. Furthermore, environmental assessments focusing on factors such as CO₂ emissions and embodied energy indicated that RCPMF presents environmental benefits compared to RCCPF [130]. Conceiving a systematic method based on objective analysis for enhanced structural decision-making is a relevant research avenue [31]. This study introduces a MOO strategy utilizing the Non-dominated Sorting Genetic Algorithm II (NSGA-II) for the optimal design of RCPMF [163]. The NSGA-II algorithm is specifically adapted to minimize the final cost, environmental life cycle analysis (ELCA), and social life cycle analysis (SLCA) endpoint results [134]. Customized crossover and mutation operators are implemented into the NSGA-II algorithm to adapt the specific nature of NSGA-II to the mixed-integer programming (MIP) nature of the RCPMF problem. Furthermore, the study develops, implements, and evaluates the performance of three distinct repair operators. The optimal designs derived from the MOO process are subsequently examined and evaluated through two MCDM techniques: single additive weighting (SAW) and fair un choix adéquat (FUCA) [164].

Both methods employ an entropy theory-based criteria weighting computation for an objective and data-informed weighting process [165].

Integrating MCDM techniques with MOO methodologies capitalizes on the inherent strengths of both approaches. MOO enables the generation of optimal solution sets that consider the economic, environmental, and social dimensions of the RCPMF life cycle in a balanced manner. MCDM methodologies add a further dimension by providing a systematic framework for evaluating, scoring, and ranking these optimal solutions. As a result, the novel approach presented in this study effectively balances and evaluates economic feasibility with environmental and social impacts throughout the entire life cycle of the structure.

Merging MOO with MCDM presents unique challenges, especially when applied to complex engineering contexts, as detailed in this study. This integration requires a thorough understanding of the optimization objectives and the decision-making criteria. In this analysis, the MOO objectives are crafted carefully considering life cycle sustainability, derived from an exhaustive analysis of critical factors that influence sustainable infrastructure development, ensuring an unbiased representation of economic, environmental, and social factors. Moreover, the objectives are aligned with MCDM criteria to reflect stakeholder priorities accurately throughout the structure's life cycle. Harmonizing and weighting these criteria demands meticulous consideration of the diverse priorities underpinning sustainable development.

This research outlines a clear and methodical strategy to effectively facilitate the integration of MOO and MCDM, formulating a coherent framework for practical implementation. Three novel repair operators are introduced within the NSGA-II algorithm, designed to optimize the RCPMF while addressing the MIP challenges. These operators play a crucial role in refining solutions to ensure they meet constraints and enhance feasibility. Adjustments are made randomly by the first operator, facilitating exploration of new solution spaces. Modifications guided by proximity concepts are employed by the second operator, steering towards previously successful solutions. The third operator utilizes statistical methods, drawing on data patterns for solution improvements. The efficient exploration of the solution space is enabled and adherence to constraints is ensured, significantly enhancing the quality of the solutions and contributing to the sustainable and cost-effective design of infrastructure.

Section 7.2.2 of this paper elaborates on the customized version of the NSGA-II algorithm integrating tailored crossover and mutation operators. Sections 7.2.3 and 7.3.1 focus on introducing and evaluating the effectiveness of three distinct repair operators, emphasizing their performance in generating optimal solutions. The application of MOO to the RCPMF problem, detailed in Section 7.2.1, aims to broaden the existing knowledge and understanding of RCPMF design. The MCDM strategy, described

in Section 7.2.4, allows for a better-informed decision-making process, yielding the results evaluated in Section 7.3. The approach is designed to effectively balance economic feasibility with the environmental and social impacts throughout the entire structure life cycle.

7.2 Methods

This section provides a comprehensive overview of the RCPMF problem and delineates the NSGA-II algorithm as the selected MOO strategy. Furthermore, it delves into the entropy theory-based weighting method and the MCDM approaches, specifically delineating the SAW and FUCA techniques employed to assess the optimal solutions derived from the MOO process.

7.2.1 Optimization Problem Overview

MOO involves identifying a vector $\vec{X}$, comprising n variables, that minimizes k objective functions while adhering to m constraints. Equations (7.1) through (7.3) delineate the foundational structure for a generic MOO problem.

$$\vec{X} = x_1, x_2, \dots, x_n \quad (7.1)$$

$$\min(f_i(\vec{X})) = \min(f_1(\vec{X}), f_2(\vec{X}), \dots, f_k(\vec{X})) \quad (7.2)$$

$$g_m(\vec{X}) \leq 0 \quad (7.3)$$

The optimization problem of this research consists of the design of a RCPMF. The specified structure extends 10 m horizontally, has a height of 5 m, and is buried to a depth of 5 m. Sections 7.2.1 and 7.2.1 detail the variables, parameters, and constraints integral to the RCPMF problem. Adopting a comprehensive MOO approach, this study integrates the three pillars of sustainability: the economic cost of the structure, the ELCA endpoint single score, and the SLCA endpoint score. These elements, elaborated on in Section 7.2.1, are the objective functions earmarked for minimization.

Variables and Parameters

The RCPMF problem, illustrated in Figure 7.1, encompasses 41 design variables, broadening the scope beyond previous studies focused on the final cost minimization via SOO [130].

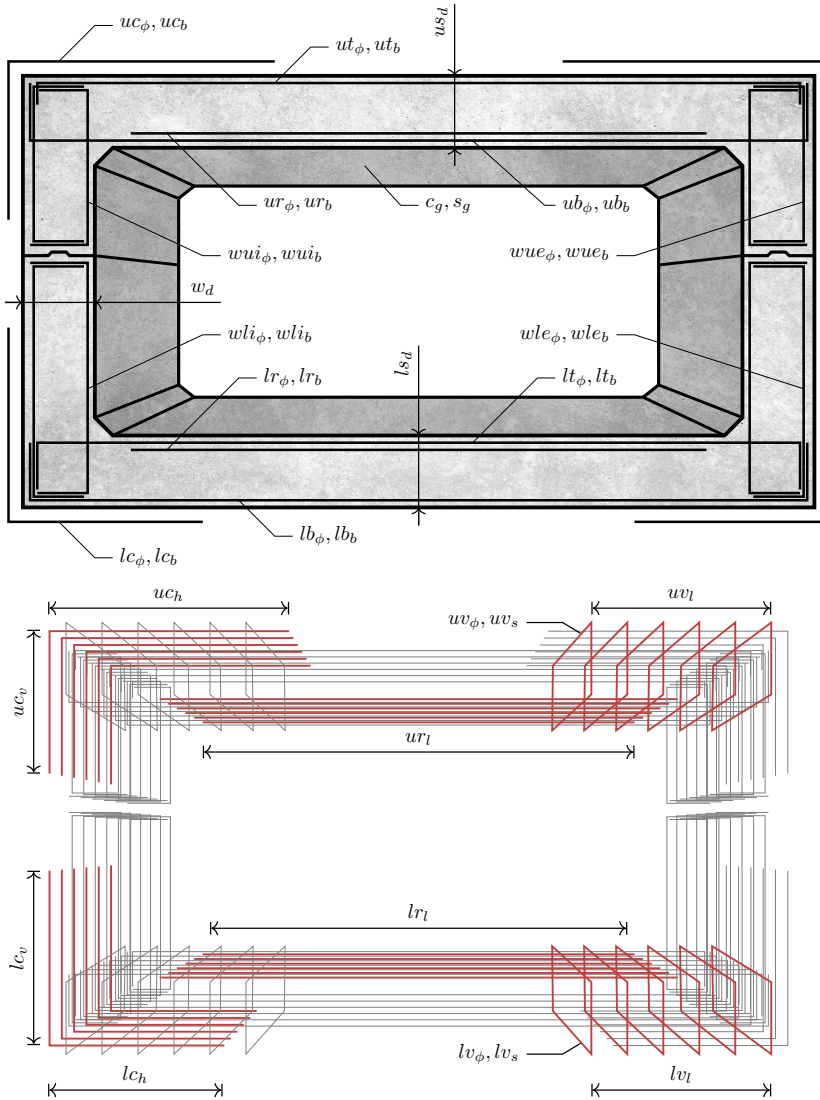


Figure 7.1: RCPMF optimization variables.

Among these variables, three relate to the geometry of the lateral walls and the upper and lower slabs (w_d, us_d, ls_d). Multiple variables are allocated to the configurations of passive reinforcement in all structural sections. This comprehensive set includes corner reinforcement ($uc_{\phi,b,h,v}, lc_{\phi,b,h,v}$) and bending reinforcement in the central sections of the top and bottom slabs ($ur_{\phi,b,l}, lr_{\phi,b,l}$). The remaining variables are critical in defining the positioning and configuration of shear reinforcement and determining structural concrete and steel material grades (c_g, s_g).

The MIP nature of the problem requires establishing upper and lower bounds for three distinct categories of variables: choice (discrete), integer, and real (continuous).

Each category undergoes unique processing during the optimization phase via custom-developed repair operators. These operators are designed explicitly for mutation, crossover, and repair functions within the NSGA-II optimization algorithm. Table 7.1 comprehensively details the set of optimization variables, categorizing them by type and specifying their respective upper and lower bounds.

Table 7.1: Optimization problem variables and boundaries.

Variable	Unit	Lower limit	Upper limit	Type
Section geometry				
us_d	m	0.60	1.60	continuous
ls_d	m	0.40	1.40	continuous
w_d	m	0.30	1.20	continuous
Base reinforcement				
ut_{ϕ}	mm	8, 10, 12, 16, 20, 25, 32		discrete
ut_b	bars	4	20	integer
ub_{ϕ}	mm	8, 10, 12, 16, 20, 25, 32		discrete
ub_b	bars	4	20	integer
lt_{ϕ}	mm	8, 10, 12, 16, 20, 25, 32		discrete
lt_b	bars	4	20	integer
lb_{ϕ}	mm	8, 10, 12, 16, 20, 25, 32		discrete
lb_b	bars	4	20	integer
wui_{ϕ}	mm	8, 10, 12, 16, 20, 25, 32		discrete
wui_b	bars	4	20	integer
wue_{ϕ}	mm	8, 10, 12, 16, 20, 25, 32		discrete
wue_b	bars	4	20	integer
wli_{ϕ}	mm	8, 10, 12, 16, 20, 25, 32		discrete
wli_b	bars	4	20	integer

Continued on next page

Table 7.1 – continued from previous page

Variable	Unit	Lower limit	Upper limit	Type
wle_ϕ	mm	8, 10, 12, 16, 20, 25, 32		discrete
wle_b	bars	4	20	integer
Corner and central reinforcement				
uc_ϕ	mm	8, 10, 12, 16, 20, 25, 32		discrete
uc_b	bars	4	20	integer
uc_h	m	1	5	continuous
uc_v	m	0.70	1.80	continuous
lc_ϕ	mm	8, 10, 12, 16, 20, 25, 32		discrete
lc_b	bars	4	20	integer
lc_h	m	1	5	continuous
lc_v	m	0.70	2.80	continuous
ur_ϕ	mm	8, 10, 12, 16, 20, 25, 32		discrete
ur_b	bars	4	20	integer
ur_l	m	5	9.50	continuous
lr_ϕ	mm	8, 10, 12, 16, 20, 25, 32		discrete
lr_b	bars	4	20	integer
lr_l	m	3	8	continuous
Shear reinforcement				
uv_ϕ	mm	10, 12, 16, 20, 25, 32		discrete
uv_s	m	0.1	0.4	continuous
uv_l	m	1.50	4.80	continuous
lv_ϕ	mm	10, 12, 16, 20, 25, 32		discrete
lv_s	m	0.1	0.4	continuous
lv_l	m	1.50	4.80	continuous
Material grade				
c_g	MPa	25, 30, 35, 40		discrete
s_g	MPa	400, 500		discrete

In addition to the optimization variables, the structural design problem encompasses a comprehensive set of parameters that remain constant throughout the optimization process. In conjunction with the previously delineated optimization variables, these parameters enable the complete characterization of the RCPMF design. The problem incorporates parameters relevant to the structure's geometry and those necessary for calculating structural loads. Moreover, it includes several parameters necessary for evaluating the objective functions. These encompass the economic cost

of materials and the environmental and social impacts, which are assessed over the structure's life cycle. Table 7.2 summarizes the main optimization parameters of the problem along with their specific values.

Table 7.2: Optimization problem parameters and specific values.

Parameter	Unit	Value
Structure geometry		
Vertical height	m	5
Horizontal span	m	10
Hinge height	m	3
Embankment depth	m	5
Section depth	m	1
Structural loads		
Terrain density	kN/m ³	20
Concrete density	kN/m ³	24
Steel density	kN/m ³	78.5
Terrain internal friction angle	°	30
Active earth pressure	–	0.33
Resting earth pressure	–	0.50
Heavy vehicle load	kN	150
Heavy vehicle length	m	1.20
Uniform overload	kN/m ²	10
Ballast coefficient	MN/m ³	10
Sustainability metrics		
Economic costs	EUR	Table 7.3
Environmental impact	point	Table 7.4
Social impact	mrh	Table 7.4
Verification parameters		
Standard regulations	CEN [93], [94]/MFOM [95]	
Applicable codes	MFOM [90]	

Constraints

The constraints of the RCPMF problem ensure the representativeness of the mathematical model. Structural solutions generated during the optimization process are required to conform to the ultimate limit states (ULS) and service limit states (SLS) as stipulated in the applicable regulations [93], [94]. Furthermore, the designs adhere to specific guidelines and recommendations for buried structures [90], [95].

The ULS ensure the structural integrity of all sections under diverse loading scenarios. Compliance with ULS involves a multi-step verification process [128]. Initially, it requires verifying sectional shear stress resistance [166], followed by assessing normal stresses via N-M interaction diagrams. This procedure includes accounting for the increase in bending moments due to shear interaction. Subsequent steps include confirming the fatigue resistance of the structure and evaluating additional geometrical and reinforcement design characteristics, which are closely linked to sectional properties.

The SLS criteria focus on maintaining the structure's aesthetic integrity by preventing the generation and propagation of cracks. Additionally, SLS involves the restriction of deformations. Thus, global structure deflections in the upper slab central sections are assessed to remain within predefined allowable limits [95].

Structural calculation and compliance verification are conducted using a mathematical model developed in Python 3 [167]. This approach incorporates global models for calculating sectional internal forces, utilizing a finite element analysis (FEA) methodology [168]. Additionally, local models for each structural section are computed and thoroughly evaluated to confirm compliance with the specified constraints [93], [94]. The NSGA-II optimization algorithm from the pymoo library is modified and utilized to solve the MOO [169]. During this process, the mathematical model generates a constraint vector adapted to its functional requirements for each solution.

Objective Functions

Three objective functions are established for an integrated approach to enhancing RCPMF sustainability performance. Equations (7.4), (7.6), and (7.7), evaluate the economic cost, the ELCA endpoint, and the SLCA endpoint of the structure life cycle, respectively. The Python numerical model integrates all necessary calculations for evaluating these objective functions and generates a vector representing specific values for each solution throughout the optimization process.

The final cost of the structure is determined by summing the products of the material unit costs, c_i , and the specific quantities of materials used, m_i . The unit values in this study, detailed in Table 7.3, were sourced from the BEDEC database [92].

$$C(\vec{X}) = \sum_{i=1}^n c_i \cdot m_i(\vec{X}) \quad (7.4)$$

Table 7.3: Unit cost values for each RCPMF material [170].

Material	Unit	Cost (EUR)
C25/30 concrete	m ³	112.85
C30/37 concrete	m ³	126.16
C35/45 concrete	m ³	129.32
C40/50 concrete	m ³	133.13
B400S steel	kg	1.79
B500S steel	kg	1.84

The life cycle of the RCPMF encompasses all processes from raw material extraction to the post-service life disposal of the structure's remains, while treating the life cycle assessment (LCA) calculation as a "black box" executed externally by OpenLCA 2.1 software is a feasible method [147], this study opts to develop a numerical model that utilizes the precomputed individual impacts of each process.

The life cycle model, depicted in Figure 7.2, adheres to the ISO 14040:2006 standard, including four stages: manufacture, construction, use, and end-of-life [134]. Table 7.4 details each process's unit environmental and social impacts. The data is sourced from the ecoinvent 3.7.1 and soca v2 databases [133], [149], [171] and evaluated employing the ReCiPe 2008 and SWIM life cycle impact assessment (LCIA) methods for environmental and social impacts, respectively, [145].

The manufacturing stage covers all processes, from the extraction of raw materials to the delivery of ready-to-use materials to the construction site. The construction phase includes site preparation, earth moving, transportation, assembling the structural components, covering the structure, and installing auxiliary systems. The use phase models routine minor repairs to the internal surface of the structure and the associated impact of traffic diversions due to these activities. Lastly, the end-of-life stage encompasses unearthing, dismantling the structure and transporting materials to recycling facilities and landfills.

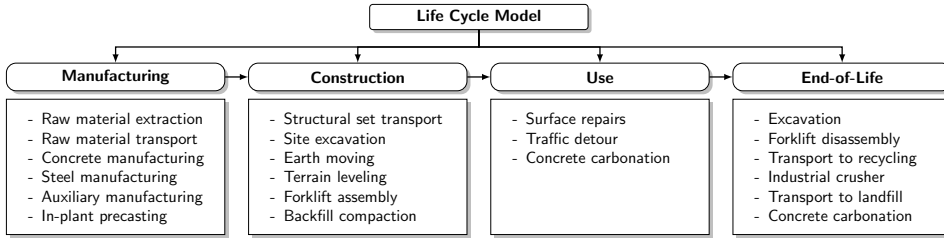


Figure 7.2: RCPMF life cycle model stages and processes.

Table 7.4: LCA processes and environmental and social unit impact values [133], [149], [171].

Process	Unit	$elca_i$ (point)	$slca_i$ (mrh)
concrete production 25MPa	m ³	2.037E+01	1.254E+05
concrete production 30MPa	m ³	2.631E+01	1.668E+05
concrete production 35MPa	m ³	2.478E+01	1.554E+05
concrete production 40MPa	m ³	2.585E+01	1.623E+05
steel production B400S	kg	2.417E-01	1.941E+03
steel production B500S	kg	2.538E-01	2.067E+03
clay production	kg	1.062E-03	8.475E+00
gravel production	kg	1.196E-03	2.617E+00
sand production	kg	1.718E-03	3.543E+00
transport, freight, lorry 16-32 ton	t·km	2.502E-02	4.116E+01
transport, freight, lorry 3.5-7.5 ton	t·km	7.755E-02	1.655E+02
transport, passenger, car	km	2.760E-04	1.417E-01
digger, operation	min	7.876E-02	8.825E+02
skid plate, operation	min	7.651E-02	8.657E+02
diesel, burned in building machine	MJ	1.361E-02	8.764E+00
carbon dioxide	kg	4.369E-02	0.000E+00
mortar production	kg	3.084E-02	1.415E+02
epoxy production	kg	8.399E-01	4.107E+03
rock crushing	kg	7.223E-05	8.304E-01

Concrete acts as a carbon-sequestering component. The carbon dioxide captured through the carbonation process during the structure's use and end-of-life stages is estimated using Fick's law, detailed in Equation (7.5). Here, t represents the 100-year service life of the structure, k the carbonation coefficient, A the area affected by carbonation, C the amount of cement, and K the clinker content. The optimization problem incorporates parameters such as the carbonation coefficients for the interior

and exterior walls, the quantity of cement, and the clinker content. The area affected by carbonation is calculated by integrating the geometric optimization variables of the RCPMF.

$$CO_2 (kg) = 0.383 \cdot \frac{k \left(\frac{mm}{\sqrt{year}} \right) \cdot \sqrt{t(year)}}{1000} \cdot A(m^2) \cdot C \left(\frac{kg}{m^3} \right) \cdot K(\%) \quad (7.5)$$

By integrating all the considerations above, the endpoint results for the ELCA and SLCA are computed as the cumulative sum of the products of the environmental impact factors, $elca_i$, or social impact factors, $slca_i$, and the quantity of the process m_i required throughout the j stages of the structure's life cycle.

$$ELCA(\vec{X}) = \sum_{i=1}^n \sum_{j=1}^4 elca_{i,j} \cdot m_{i,j}(\vec{X}) \quad (7.6)$$

$$SLCA(\vec{X}) = \sum_{i=1}^n \sum_{j=1}^4 slca_{i,j} \cdot m_{i,j}(\vec{X}) \quad (7.7)$$

7.2.2 Optimization Algorithm

This section aims to delineate the NSGA-II, [163], the MOO algorithm employed for optimizing the RCPMF structure. Initially, a comprehensive elucidation of the standard NSGA-II algorithm will be presented. Subsequently, the next section will introduce specialized repair operators tailored for addressing the unique challenges posed by the mixed-integer optimization problem, which amalgamates discrete, integer, and continuous variables. This dual-phase approach facilitates a profound understanding of the algorithm's core mechanics before delving into the customized modifications necessary for the specific optimization task at hand. Figure 7.3 presents a flowchart that encapsulates the algorithm's proposed framework, illustrating the integrated process introduced in our study.

NSGA-II is a methodical, iterative process leveraging a population-based approach. It draws upon the principles of natural selection and genetics to evolve solutions towards an optimal set of trade-offs, known as the Pareto front. Central to NSGA-II is its non-dominated sorting mechanism, which stratifies the population into various levels of Pareto fronts based on dominance criteria. A solution is deemed to dominate another if it is equally competent in all objectives and superior in at least one.

The foremost front comprises solutions not dominated by any others in the population, with subsequent fronts determined in a similar fashion.

Another critical element of NSGA-II is the crowding distance assignment. This metric gauges solution density within the objective space, ensuring diversity among solutions and averting premature convergence to localized Pareto front regions. It aids in maintaining a comprehensive spread of solutions across the entire range of trade-offs. Genetic operators in NSGA-II, namely selection, crossover, and mutation, play pivotal roles. Selection processes prefer solutions from lower Pareto fronts and those with greater crowding distances, promoting the caliber and diversity of solutions. Crossover and mutation introduce novel variations and traits into the population, encouraging a thorough exploration of the solution space.

The iterative nature of NSGA-II involves cultivating a new population (offspring) from the existing one via these genetic operators. The amalgamated population of parents and offspring is then subjected to non-dominated sorting and crowding distance evaluation. The top-tier solutions are cherry-picked to constitute the next generation, preserving a constant population size. The efficacy of NSGA-II is manifest in its adeptness at unearthing a diverse array of high-caliber trade-off solutions, rendering it apt for complex multi-objective quandaries. Its utility spans diverse domains, ranging from engineering design to resource management, where decisions necessitate juggling conflicting objectives.

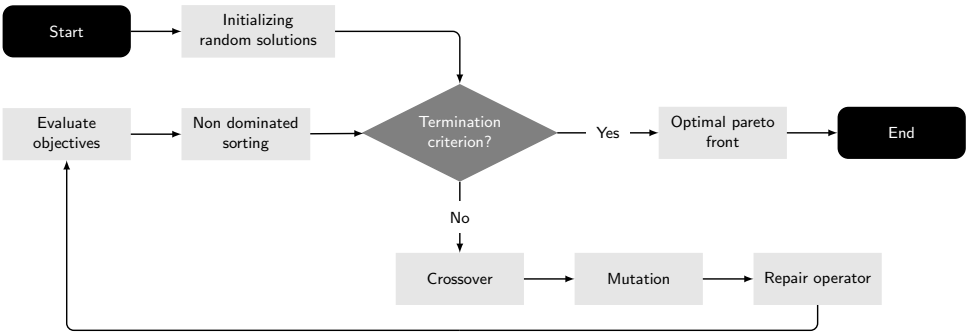


Figure 7.3: Flowchart of the proposed algorithm illustrating its step-by-step process.

In this particular study, additional configurations were implemented for crossover, mutation, and repair operators, which will be explicated in the following section

7.2.3 Solution Crossover, Mutation, and Repair Algorithms

In this study, the crossover operation was implemented using a Simulated Binary Crossover (SBX) operator, while mutations were introduced via a Polynomial Mutation (PM) operator. Additionally, three distinct repair operators were integrated: one based on proximity, another employing random modifications, and a third leveraging statistical concepts of mean and median for solution adjustments.

Simulated binary crossover (SBX): The SBX operator, a nuanced crossover technique, emulates the single-point crossover observed in binary strings, but is adapted for real-coded genetic algorithms. It excels in generating offspring solutions proximate to their parent solutions, thereby enabling a detailed search in the immediate solution space. The offspring distribution's breadth is modulated by a distribution index parameter, which determines the offspring's spread relative to their parents. A lower index promotes exploration by creating offspring further from the parent solutions, while a higher index encourages exploitation by generating offspring closer to the parent solutions.

Polynomial mutation (PM): The PM operator, designed for real-valued representations, introduces variability by subtly modifying a solution's variable values. Governed by a distribution index, this mutation process mirrors the bit-wise mutation in binary-coded genetic algorithms, yet it is specifically tailored for continuous variable contexts. PM plays a vital role in maintaining diversity within the population and averting premature convergence, particularly in scenarios involving continuous or real-valued parameters.

Proximity-based repair operator: The proximity-based repair operator is an approach designed to rectify solutions that do not adhere to the constraints of an optimization problem, Algorithm 1. This operator is particularly effective in contexts where solutions involve a mix of discrete, integer, and continuous variables. The core principle of this operator lies in its ability to adjust each variable of a solution by selecting values that are closest to the original, yet still within the permissible range defined by the problem's constraints.

Algorithm 1 Proximity-Based Repair Operator

```
1: Function Repair( $X$ )
2: Input:  $X$ 
3: Output:  $repaired\_X$ 
4:  $repaired\_X \leftarrow$  copy of  $X$ 
5: for each solution  $x$  in  $repaired\_X$  do
6:   for each variable index  $j$  in  $x$  do
7:      $var \leftarrow$  variable type at index  $j$ 
8:     if  $var$  is Choice then
9:        $x[j] \leftarrow$  value closest to  $x[j]$  in  $var.options$ 
10:    else if  $var$  is Integer then
11:       $x[j] \leftarrow$  round  $x[j]$  to nearest integer within  $var.bounds$ 
12:    else if  $var$  is Real then
13:       $x[j] \leftarrow$  clip  $x[j]$  within  $var.bounds$ 
14:    end if
15:  end for
16: end for
17: return  $repaired\_X$ 
```

For each variable in a solution, the operator evaluates its typewhether it is a choice (discrete), integer, or real (continuous). Based on the type, the operator performs the following actions:

- Choice variables: The operator selects the option from the predefined set that is closest to the current value of the variable.
- Integer variables: The operator rounds the variable to the nearest integer that falls within the defined bounds, ensuring that the solution remains feasible.
- Real variables: The operator clips the variable's value to ensure it lies within the allowable continuous range.

Statistical-based repair operator: The statistical-based repair operator, Algorithm 2, ingeniously integrates statistical measuresmean and medianwith a probabilistic approach to refine solutions in an optimization algorithm. This operator, in each iteration, processes every solution and employs a probability parameter α to determine the repair strategy. If the random number generated is less than α , the operator uses median for discrete variables (Choice and Integer) and mean for continuous

(Real) variables. The median is particularly beneficial for discrete variables, offering robustness against outliers and reflecting the most common values in the population. Conversely, the mean provides an average value for continuous variables, encapsulating the central tendency of the population.

Algorithm 2 Statistical-Based Repair Operator

```

1: Function StatisticalRepair( $X, \alpha$ )
2: Input:  $X, \alpha$ 
3: Output:  $repaired\_X$ 
4:  $repaired\_X \leftarrow$  copy of  $X$ 
5:  $means \leftarrow$  mean of  $X$  along axis 0
6:  $medians \leftarrow$  median of  $X$  along axis 0
7: for each solution  $x$  in  $repaired\_X$  do
8:   for each variable index  $j$  in  $x$  do
9:      $var \leftarrow$  variable type at index  $j$ 
10:    if random number  $< \alpha$  then
11:      if  $var$  is Choice or Integer then
12:         $choice \leftarrow medians[j]$ 
13:        if  $var$  is Choice then
14:           $x[j] \leftarrow$  closest value to  $choice$  in  $var.options$ 
15:        else
16:           $x[j] \leftarrow$  round  $choice$  to nearest integer within  $var.bounds$ 
17:        end if
18:      else if  $var$  is Real then
19:         $x[j] \leftarrow$  clip  $means[j]$  within  $var.bounds$ 
20:      end if
21:    else
22:      Apply standard repair based on variable type and bounds
23:    end if
24:  end for
25: end for
26: return  $repaired\_X$ 

```

Random repair operator: The random repair operator, Algorithm 3, is designed to introduce randomness into the solution repair process, which is essential for enhancing diversity in the solution space. It operates by iterating over each solution in the population and randomly assigning new values to the variables based on their type.

For choice variables, a random option is selected from the available choices. Integer variables are assigned a random integer within their bounds, and real variables receive a random value within their defined range. This randomness helps in exploring uncharted areas of the solution space, thereby preventing the algorithm from stagnating at local optima and encouraging a more thorough exploration.

Algorithm 3 Random Repair Operator

```
1: Function RandomRepair( $X$ )
2: Input:  $X$ 
3: Output:  $repaired\_X$ 
4:  $repaired\_X \leftarrow$  copy of  $X$ 
5: for each solution  $x$  in  $repaired\_X$  do
6:   for each variable index  $j$  in  $x$  do
7:      $var \leftarrow$  variable type at index  $j$ 
8:     if  $var$  is Choice then
9:        $x[j] \leftarrow$  random choice from  $var.options$ 
10:    else if  $var$  is Integer then
11:       $x[j] \leftarrow$  random integer within  $var.bounds$ 
12:    else if  $var$  is Real then
13:       $x[j] \leftarrow$  random real number within  $var.bounds$ 
14:    end if
15:  end for
16: end for
17: return  $repaired\_X$ 
```

7.2.4 Evaluation and Decision-Making Methods

The result of the MOO conducted in this study is a set of RCPMFs that balance the minimization of the objective functions. These solutions are evaluated by aggregating and comparing the influence of relevant structural characteristics on the economic cost, ELCA and SLCA scores for each repair operator. This analysis aims to identify common trends in the optimal solution set and derive directly applicable, improvement-oriented design approaches.

Decision-making within transportation infrastructure projects is fundamentally intricate. Influences outside the purview of this research, including local regulations and specific project mandates, frequently affect the identification of optimal solutions in civil engineering. This study provides a framework for integrating sustainability's mul-

tifaceted dimensions into the optimal structural design, aiming for a more informed decision-making process. This approach aligns well-defined MOO objectives with relevant criteria for MCDM. Despite the inherent complexity, integrating these aspects into a well-informed decision-making framework is essential for fostering the construction industry's long-term sustainability.

Utilizing MCDM techniques introduces several advantageous elements to complex engineering decision-making processes. Sustainable construction requires the equilibrium of intricate economic, environmental, and social criteria. The diverse stakeholders involved in the life cycle of an infrastructure project often have different criteria with conflicting and competing natures. Within this framework, harmonizing the criteria of the MCDM problem with the objectives of the MOO problem, as delineated in this study, offers a pathway to enhance the decision-making process in sustainable construction.

This research addresses a MCDM problem, represented by a decision matrix denoted as $X = r_{ij}$ consisting of n criteria and m alternatives $A_i = \{A_1, A_2, \dots, A_m\}$. The element r_{ij} of the decision matrix X provides insight into the performance of the alternative i concerning criterion j . Weighting the multiple criteria is a crucial step in resolving the MCDM problem. The research employs an entropy-based method to calculate the W_j criteria weights, [165].

The entropy-based weighting approach utilized in this research objectively calculates the weight of each criterion according to its variability among the alternatives. This methodology leverages the intrinsic uncertainty or randomness linked with entropy to eliminate subjectivity in the weighting process, with criteria deemed to offer more information to the decision-making process receiving higher weighting. Moreover, it fosters transparent and inclusive decision-making when applied to sustainability criteria.

The criteria weights are computed through a four-step process. The first step involves normalizing the decision matrix, as described in Equation (7.8), resulting in X' , the normalized decision matrix.

$$X' = r_{ij} \left\langle \sum_{i=1}^m r_{ij} \right\rangle^{-1} \quad (7.8)$$

In the second step, the entropy of each criterion E_j is calculated using Equation (7.9). A higher entropy value indicates greater variability across the i alternatives for criterion j . In this step is assumed that, if $r_{ij} = 0$, then the corresponding natural logarithm is null.

$$E_j = \frac{-1}{\ln\langle m \rangle} \left\langle \sum_{i=1}^m r_{ij} \cdot \ln\langle r_{ij} \rangle \right\rangle \quad (7.9)$$

The third step is dedicated to assessing the variation of each criterion through Equation (7.10). This evaluation yields the degree of divergence D_j for each criterion j .

$$D_j = 1 - E_j \quad (7.10)$$

Finally, the fourth step involves normalizing the D_j , as delineated in Equation (7.11), resulting in the final criteria weights W_j .

$$W_j = \frac{D_j}{\sum_{j=1}^n D_j} \quad (7.11)$$

The subsequent phase in the decision-making process involves applying an algorithm to address the MCDM problem. The research employed the SAW and FUCA algorithms to resolve the optimum selection problem.

Numerous researchers in the construction sector employ SAW for decision-making involving structural sustainability [172]. This approach, rooted in complexity-based classification, facilitates the evaluation of solutions through a well-established objective and transparent method. Implementing the SAW algorithm within this study involves three distinct steps. The process begins by calculating the normalized decision matrix X' .

The second step calculates the S_i scores for each alternative, employing Equation (7.12). The scores result from aggregating the weighted normalized performance of each alternative across all criteria.

$$S_i = \sum_{j=1}^n W_j \left\langle r_{ij} \left\langle \sum_{i=1}^m r_{ij} \right\rangle^{-1} \right\rangle \quad (7.12)$$

In the third and concluding step, the S_i values determine the ranking of the alternatives, providing a systematic framework for identifying the most sustainable options.

The second decision-making algorithm chosen to address the MCDM problem is the FUCA [164], while having an approach and algorithmic structure similar to the

SAW, this technique has operational differences that could lead to differing outcomes. A significant challenge in solving engineering MCDM problems lies in selecting suitable and effective techniques, which can evolve into a complex decision-making problem. The study conducts a comparative analysis within this framework between the established SAW method and the FUCA approach. This comparison aims to evaluate the feasibility and applicability of the FUCA technique in construction engineering decision-making, highlighting its potential advantages and differences in outcomes.

The FUCA algorithm is executed in three stages. In the first step, the solutions are ranked according to each criterion. The second step involves calculating the scores of the alternatives through Equation (7.13), where R_{ij} denotes the rank of m solutions across n criteria.

$$S_i = \sum_{j=1}^n W_j \cdot R_{ij} \quad (7.13)$$

The third and final step of the FUCA algorithm employed in this research is ranking the alternatives according to previously computed S_i values.

The criteria weighting procedure and the MCDM techniques outlined in this section provide a methodical strategy for managing complex engineering decision-making problems. This structured approach provides decision-makers with a framework for informed and transparent choices.

7.3 Results

In this section, the findings from a comprehensive quantitative analysis of different repair operators applied within a multi-objective optimization framework are presented. The performance evaluation of each repair operator, detailed in Section 7.3.1, highlights their impact on key objectives: economic cost, environmental life cycle analysis, and social life cycle analysis. Subsequently, Figure 7.4 utilizes violin charts for visualizing these operators' efficacy in minimizing the MOO objectives, where the statistical-based repair operator is shown to deliver the most consistent and effective performance across all metrics. These outcomes are further examined through normalized radar plots in Section 7.3.1, offering a visual comparison of the operators' effectiveness in achieving optimization goals. The subsequent subsections delve into multi-criteria decision analysis for structural design optimization, utilizing both tabulated results and graphical representations to elucidate the comparative performance of the repair operators and the optimization variables involved. This analyt-

ical approach facilitates a nuanced understanding of each operator's strengths and limitations in optimizing structural design parameters, setting the stage for informed decision-making in engineering applications.

7.3.1 Quantitative Analysis of Repair Operators

The tuning process for the crossover and mutation operators within the NSGA-II algorithm was conducted methodically in two phases, with the hypervolume metric serving as the primary evaluation criterion. In the initial exploratory phase, a range of η values 0.2, 0.5, and 0.9 were examined to assess their impact on offspring distribution relative to their parent solutions, applied to both the SBX and PM operators. Furthermore, the probabilities for these operators were explored across a spectrum of values 0.01, 0.1, 0.2, 0.3 to identify a broad scope of potential settings aimed at enhancing the optimization efforts. This stage sought to identify a preliminary configuration that could facilitate a balanced exploration and exploitation within the multi-objective optimization landscape.

Advancing to the second phase, a more focused exploitation strategy was employed, evaluating a tighter range of η values 0.45, 0.5, 0.55 to refine the distribution tightness of solutions. In parallel, the operator probabilities were adjusted to finer values 0.1, 0.08, 0.06, 0.04, 0.02 to optimize the frequency of generating new solutions. This phase was instrumental in determining the precise parameter settings that maximize the hypervolume metric, ensuring an optimal balance between Pareto front convergence and diversity maintenance within the solution population.

Throughout the tuning process, a proximity-based operator was utilized to systematically navigate the parameter space, enabling a comprehensive evaluation of the effectiveness of each parameter combination. This meticulous approach led to the identification of the optimal settings for the crossover and mutation operators: SBX with a probability of 0.1 and an η value of 0.5, and PM with a probability of 0.02 and an η value of 0.5. These configurations were deemed most effective in achieving an ideal balance between convergence to the Pareto front and sustaining diversity within the pool of solutions, as evidenced by the maximized hypervolume metric.

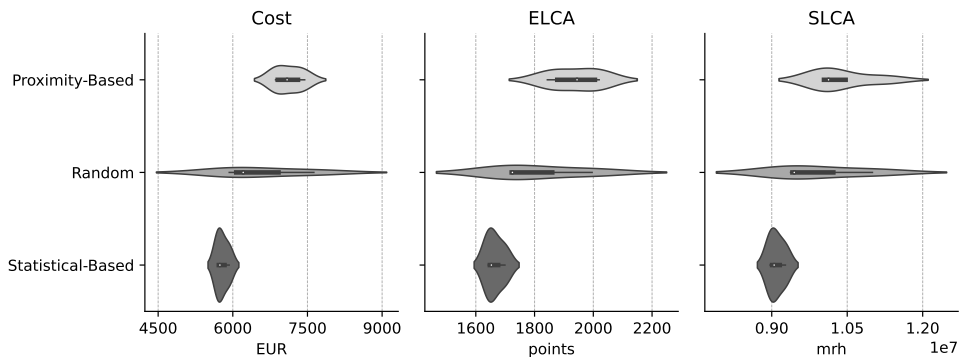
Table 7.5 presents a detailed quantitative analysis of the solutions generated by different repair operators in a multi-objective optimization problem context. The table elucidates each repair operator's performance across three key objectives: economic cost, ELCA, and SLCA.

Figure 7.4 presents the data from Table 7.5 using violin charts to visualize the performance of three distinct repair operators in minimizing the MOO objectives. The statistical-based repair operator demonstrates the most consistent performance, averaging

Table 7.5: Multi-objective optimization results for each repair operator.

Algorithm	Cost (EUR)	ELCA (point)	SLCA (mrh)
Proximity-Based Repair Operator	6859.12	1888.47	10,213,316.60
Proximity-Based Repair Operator	6916.66	1843.53	10,044,173.90
Proximity-Based Repair Operator	7265.14	2000.79	10,034,435.19
Proximity-Based Repair Operator	7444.46	2019.94	10,019,198.00
Random Repair Operator	5928.40	1719.59	9,374,328.45
Random Repair Operator	7628.83	1995.95	10,001,144.50
Random Repair Operator	6209.17	1724.68	9,042,720.41
Statistical-Based Repair Operator	5926.73	1642.59	9,047,905.18
Statistical-Based Repair Operator	5697.68	1699.12	9,271,219.62
Statistical-Based Repair Operator	5740.80	1653.04	8,967,342.29

EUR 5788.40, 1664.92 points, and 9.095×10^6 mrh, and exhibits minimal variability in all metrics. In contrast, the proximity-based repair operator displays the highest average values across all metrics, with slightly more significant variability. It underperforms the statistical-based repair operator by 23.03% in economic cost, 16.41% in ELCA, and 14.10% in SLCA. The random repair operator occupies a middle position, with moderate median scores but higher variability, peaking at 11.30% for economic cost.

**Figure 7.4:** Multi-objective optimization results for each objective function and repair operator.

The findings indicate that the statistical-based repair operator is more effective in minimizing the objectives of the MOO problem in this study. Exhibiting lower average values for all metrics and significantly less variability compared to the proximity-based

repair operator and the random repair operator, the statistical-based repair operator emerges as the most fitting algorithm for the specific features of the MOO problem at hand.

These results have been normalized for the direct comparison in Section 7.3.1. The proximity-based, random, and statistical-based repair operators are compared, providing insights into their respective effectiveness in minimizing each of the objectives.

Data Visualization using Normalized Radar Plots

In this research, we employed radar plots to visualize and compare the solutions proposed by various algorithms in a multi-objective minimization problem. The effectiveness of the algorithms is assessed based on three criteria: economic cost, ELCA, and SLCA. As these objectives possess varying units and scales, a normalization process was implemented to enable a fair and effective comparison between the solutions.

For normalization, we utilized a modified approach of the Min-Max technique, scaling the values for each objective such that the minimum value is not reduced to zero but to a higher predefined threshold (e.g., 0.5), and the maximum value to 1. This adjusted normalization technique ensures that differences between solutions are less drastic, particularly for extreme values, and reflects the variations in each solution's performance more equitably.

In the resulting radar plots, each axis represents one of the objectives, and each solution is depicted as a polygon whose vertices extend towards these axes. It is crucial to note that the most effective solutions in this minimization context are those with a smaller polygon area. This is because a smaller area on the plot indicates lower values in the objectives, which is desirable in our minimization problem.

In Figure 7.5, the results of the MOO, are presented through normalized radar plots. Given that the problem at hand is one of minimization, it can be observed that solutions with a smaller area indicate better performance than those with larger areas. From this perspective, the statistical-based repair operator generally yields superior outcomes compared to the other two operators. Notably, the proximity-based repair operator appears to be the least effective, exhibiting the largest area in the radar plot, which signifies suboptimal results across the evaluated objectives.

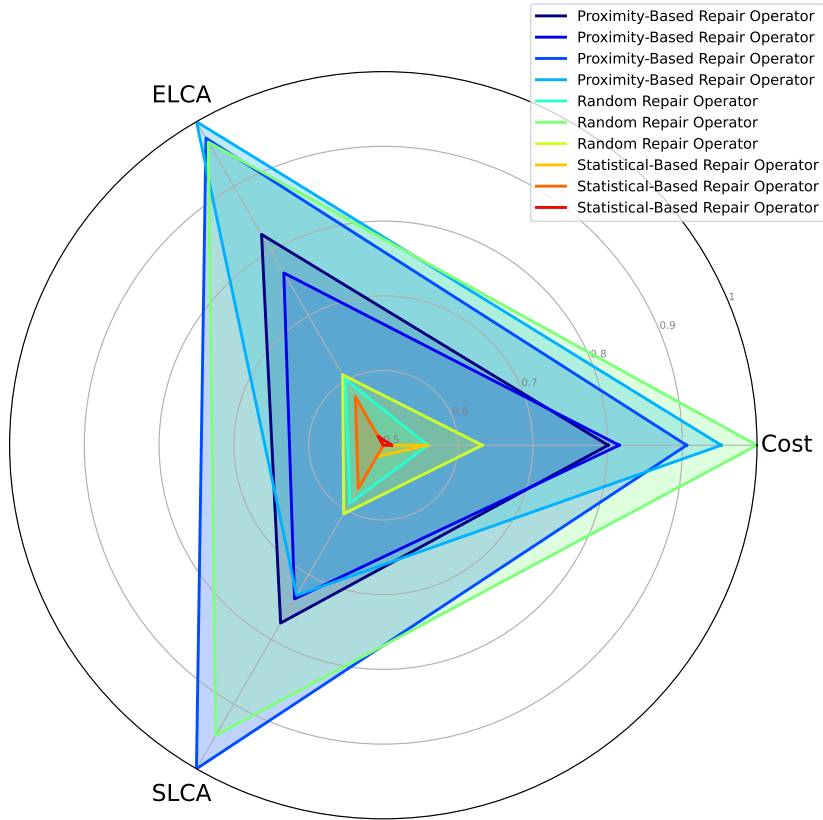


Figure 7.5: Normalized Radar Plot Comparison of Repair Operators. Smaller areas indicate superior performance in this minimization problem.

7.3.2 Multi-Criteria Decision Analysis for Structural Design Optimization

Table 7.6 displays the non-dominated optimal solutions derived from the MOO for each of the different repair operators used. It includes the actual area, A_{re} , for each longitudinal reinforcement and the area per linear meter for shear reinforcement. The areas are determined by factoring in the rebar area, the number of bars, and the branch separation for each result.

Figure 7.6 illustrates the results for the geometry variables associated with each repair operator. A notable advantage of applying MOO techniques to the structural design problem is avoiding preconditioning. In this sense, the designs produced by the proximity-based and random repair operators exhibit sections with variable

depths. The lateral walls and upper slab depths are consistently larger than those found in designs generated by the statistical-based repair operator.

Table 7.6: Non-dominated solutions optimization variables for each repair operator.

	Proximity-Based				Random			Statistical-Based		
	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
w_d	0.757	0.480	0.507	1.096	0.329	0.647	0.695	0.389	0.389	0.428
us_d	1.189	0.857	1.089	1.544	1.143	0.916	0.889	0.831	0.831	1.020
ls_d	1.031	0.749	0.800	0.783	0.667	0.955	0.808	0.925	0.925	0.651
A_{wli}	5.03E-03	9.82E-03	6.91E-03	6.28E-03	2.41E-03	1.13E-02	6.43E-03	4.40E-03	4.40E-03	3.22E-03
A_{wle}	9.05E-04	5.89E-03	9.42E-04	5.89E-03	7.85E-04	7.54E-03	3.93E-03	2.01E-03	2.01E-03	6.28E-03
A_{wui}	3.77E-03	1.58E-03	8.04E-03	4.02E-03	3.22E-03	9.82E-03	3.14E-03	2.26E-03	2.26E-03	2.81E-03
A_{wue}	5.89E-03	7.54E-03	5.89E-03	1.73E-03	4.91E-03	4.02E-03	9.42E-04	5.65E-03	5.65E-03	4.40E-03
A_{ub}	6.91E-03	1.37E-02	8.17E-03	1.08E-02	7.85E-03	8.80E-03	8.80E-03	1.28E-02	1.28E-02	8.84E-03
A_{ur}	1.26E-02	1.37E-02	1.26E-02	6.84E-03	5.23E-03	8.84E-03	1.28E-02	4.83E-03	4.83E-03	8.80E-03
A_{ut}	3.14E-03	2.04E-03	1.61E-02	1.58E-03	1.81E-03	1.57E-03	5.89E-03	2.49E-03	2.49E-03	1.10E-03
A_{tb}	2.71E-03	6.87E-03	2.41E-03	2.26E-03	5.89E-03	4.91E-03	2.41E-03	3.93E-03	3.93E-03	2.81E-03
A_{tr}	1.93E-02	7.64E-03	5.03E-03	5.03E-03	6.84E-03	5.03E-03	9.42E-03	1.77E-02	1.77E-02	6.03E-03
A_{tt}	6.28E-03	4.83E-03	2.51E-03	3.14E-03	1.01E-02	4.02E-03	2.36E-03	2.94E-03	2.94E-03	5.23E-03
A_{tc}	2.71E-03	2.26E-03	3.14E-03	9.42E-04	1.58E-03	5.89E-03	2.41E-03	1.13E-03	1.13E-03	3.22E-03
A_{uc}	2.81E-03	1.13E-03	1.10E-03	1.81E-03	6.91E-03	3.14E-03	9.42E-04	2.71E-03	2.71E-03	1.61E-03
A_{uv}	6.55E-03	1.78E-03	3.28E-03	2.97E-03	1.68E-03	4.53E-03	3.99E-03	2.14E-03	2.14E-03	1.38E-03
A_{lv}	1.95E-03	3.60E-03	2.15E-03	2.94E-03	5.66E-04	7.82E-04	9.16E-04	6.37E-04	6.37E-04	4.32E-03
lc_v	1.459	2.089	1.212	2.930	2.062	2.408	1.319	2.726	2.726	1.291
lc_h	3.982	3.510	4.877	3.384	4.587	4.081	4.371	4.712	4.712	4.073
uc_v	1.594	1.499	1.237	1.170	1.988	1.503	1.040	1.000	1.000	1.236
uc_h	3.350	3.181	2.595	4.985	4.334	2.791	1.629	1.516	1.518	2.007
wv_l	3.084	3.841	3.146	4.975	3.194	3.061	2.149	3.192	3.192	3.629
lv_l	2.324	2.259	1.170	4.497	1.700	2.286	1.282	3.140	2.813	2.423
wr_l	6.276	7.225	7.050	7.686	6.209	5.968	7.436	9.551	9.551	5.290
lr_l	7.303	5.233	5.204	5.045	5.658	7.680	5.533	9.061	9.110	5.201
c_g	25.00	25.00	30.00	25.00	30.00	25.00	35.00	35.00	30.00	35.00
s_g	500.00	500.00	500.00	500.00	400.00	500.00	400.00	400.00	400.00	500.00

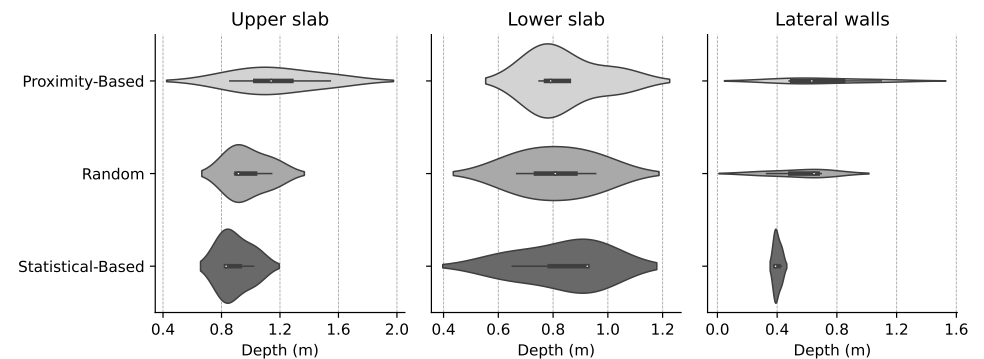


Figure 7.6: Multi-objective optimization results main geometry characteristics for each repair operator.

Figure 7.7 displays the outcomes for the reinforcement design variables, specifically concentrating on the middle-span area of the upper and lower slabs and the overall reinforcement density RCPMF. Notably, the statistical-based algorithm identified two distinct solutions exhibiting very similar characteristics, which differ in their selection of concrete grades. Regarding the grades of structural materials, the analysis reveals a varied distribution: four solutions employ concrete with a strength of 25 MPa, three utilize 30 MPa concrete, and the remaining three opt for 35 MPa. In terms of steel reinforcement, the majority of the designs favor the higher grade steel, with approximately 40% of them choosing 400 MPa steel.

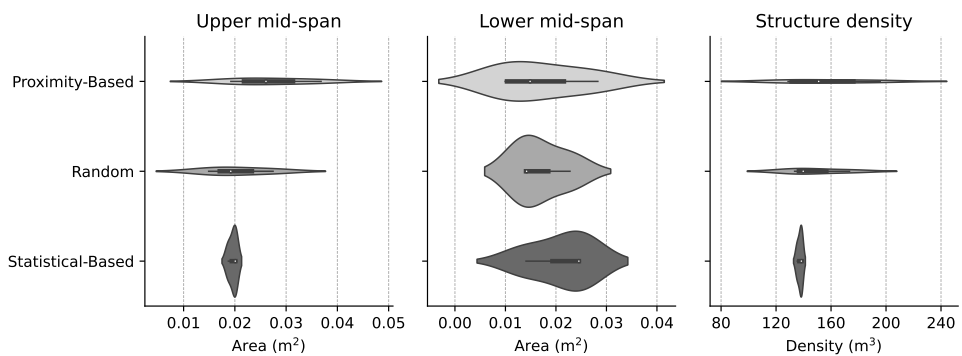


Figure 7.7: Multi-objective optimization results main reinforcement characteristics for each repair operator.

Selecting the most suitable option in structural design scenarios is inherently complex. Table 7.7 displays the decision matrix for the MCDM problem formulated in this research within this framework. Additionally, it presents the entropy weight assigned to each criterion, along with the scores and rankings derived from addressing the MCDM problem through the SAW and FUCA techniques.

The SAW and FUCA methodologies yield the same ranking order for the alternatives, yet they assign different scores to each. Figure 7.8 compares the set of scores from each method and illustrates the correlation between them, which is notably high at 0.9816. The normalization of scores from both methods is achieved using the modified Min-Max technique detailed in Section 7.3.1. This technique scales the values for each objective so that the minimum value is set to a predefined threshold higher than zero (e.g., 0.5). In contrast, the maximum value is adjusted to 1.

Table 7.7: Multi-criteria decision-making results.

W_j	Cost	ELCA	SLCA	Scores		Ranks	
	0.33540	0.33243	0.33216	S_i^{SAW}	S_i^{FUCA}	R_i^{SAW}	R_i^{FUCA}
A_1	6859.12	1888.47	1.021E07	0.91433	6.99676	7	7
A_2	6916.66	1843.53	1.004E07	0.90446	6.66756	6	6
A_3	7265.14	2000.79	1.003E07	0.98085	8.99676	9	9
A_4	7444.46	2019.94	1.001E07	0.95596	8.33595	8	8
A_5	5928.4	1719.59	0.937E07	0.82081	4.00305	4	4
A_6	7628.83	1995.95	1.000E07	0.98915	9.00296	10	10
A_7	6209.17	1724.68	0.904E07	0.83616	5.00143	5	5
A_8	5926.73	1642.59	0.904E07	0.79841	2.00296	2	2
A_9	5697.68	1699.12	0.927E07	0.80425	2.32919	3	3
A_{10}	5740.80	1653.04	0.896E07	0.78957	1.66783	1	1

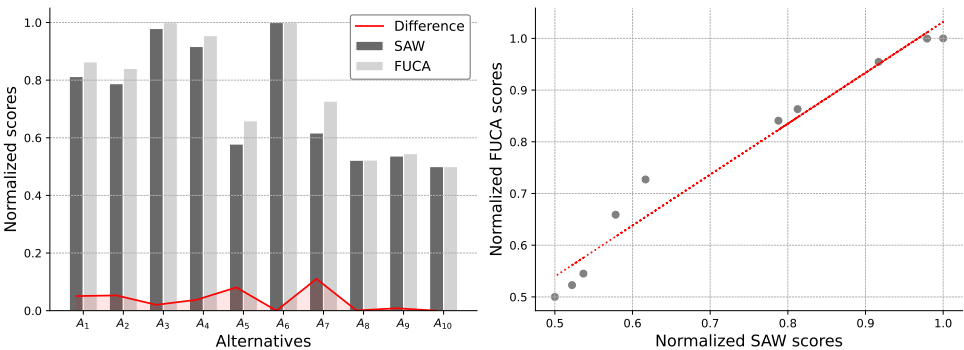


Figure 7.8: Multi-criteria decision-making results obtained through SAW and FUCA where: a) Sets of normalized scores comparison; and b) Correlation between the two sets of scores.

Alternative A_{10} , when evaluated using the SAW and FUCA methodologies, consistently achieved the highest scores. This consistency leads to the conclusion that, according to the MOO criteria defined in this study, the most efficient alternative is the last solution produced by NSGA-II in conjunction with the statistical-based repair operator. Moreover, the statistical-based repair operator demonstrates superior performance compared to the proximity-based and random repair operators. All solutions generated by the statistical-based repair operator are among the top-ranked alternatives in the MCDM problem as solved by both methods. The random repair operator, on the other hand, presents a wide range of outcomes, securing both the

fourth highest and the lowest scores, which reflects the inherent variability of this algorithm.

7.4 Conclusions

This paper introduces a novel method to enhance decision-making in transportation infrastructure. The research integrates MOO techniques with MCDM methodologies for designing and selecting modular structures, aiming for high economic, social, and environmental efficiency. Specifically, it addresses the design problem of a RCPMF, encompassing three objective functions that represent the pillars of structural life cycle sustainability: economic cost, ELCA, and SLCA.

The MOO problem in this research is formulated through a Python-developed mathematical model and resolved using a tailored NSGA-II algorithm. This customized version of the algorithm is designed to manage the different nature of the variables in the MOO problem: choice (discrete), integer, and real (continuous). Additional configurations are introduced for the crossover and mutation operations, along with three distinct repair operators. Subsequently, the MCDM problem, which comprises the non-dominated solutions derived from the MOO, is addressed using the SAW and FUCA methodologies. The criteria weights in the MCDM problem are calculated based on entropy theory.

The primary geometric and reinforcement design characteristics of the MOO results are addressed, revealing designs featuring variable thicknesses and significantly dense reinforcement. The proximity-based and random repair operators yield varied results in terms of geometry, assembly layout, and the employment of structural materials. Conversely, the statistical-based repair operator discerns two closely related solutions, primarily differentiated using 30 MPa and 35 MPa concrete. The optimal solution is identified using 35 MPa concrete, characterized by slender sections complemented by a densely reinforced design utilizing B500S steel.

The solution to the MCDM problem employing the SAW and FUCA techniques reveals that both methodologies rank the alternatives similarly. However, a detailed examination of the scores for each methodology, normalized using the modified Min-Max technique, uncovers minor differences along with a notable correlation of 0.9816. The findings suggest that, despite the operational differences between the two algorithms, they converge on very similar outcomes. This convergence highlights the solution generated by the statistical-based repair operator as the most efficient in the case study.

The outcomes of this study hold significant implications for the field of structural engineering in transportation infrastructure. The case study exemplifies the development, implementation, and evaluation of innovative methodologies that incorporate full life cycle sustainability into the design and selection of RCPMF. The customization of the NSGA-II algorithm, coupled with the subsequent assessment of the developed repair operators, provides a clear picture of how the statistical-based repair operator algorithm is optimally suited for the MOO problem. Moreover, applying the SAW and FUCA techniques facilitates the identification of designs attained through said repair operator that exhibit superior efficiency under the predefined criteria.

While this study presents a detailed framework for enhancing sustainable transportation infrastructure, it operates within certain constraints, including limitations to specific geographical areas, climatic conditions, and project sizes. Recognizing these limitations provides valuable directions for future research. Future work could broaden the scope of our methodology to encompass a wider range of geographical environments, climate issues, and project dimensions. Such expansion aims to test our optimization and decision-making framework's resilience and flexibility and increase its applicability across a wider range of structural engineering challenges. By incorporating designs that represent diverse real-world situations, future research could make our findings more universally applicable. This strategy aims to significantly improve the practicality and impact of our contributions to sustainable development in transportation infrastructure, ensuring our work continues to address the complex issues in this essential sector effectively.

Chapter 8

Enhancing Robustness in Precast Modular Frame Optimization: Integrating NSGA-II, NSGA-III, and RVEA for Sustainable Infrastructure

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Abstract

The advancement toward sustainable infrastructure presents complex multi-objective optimization (MOO) challenges. This paper expands the current understanding of design frameworks that balance cost, environmental impacts, social factors, and structural integrity. Integrating MOO with multi-criteria decision-making (MCDM), the study targets enhancements in life cycle sustainability for complex engineering projects using precast modular road frames. Three advanced evolutionary algorithms NSGA-II, NSGA-III, and RVEA are optimized and deployed to address sustainability objectives under performance constraints. The efficacy of these algorithms is gauged through a comparative analysis, and a robust MCDM approach is applied to nine non-dominated solutions, employing SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR decision-making techniques. An entropy theory-based method ensures systematic, unbiased criteria weighting, augmenting the framework's capacity to pinpoint designs balancing life cycle sustainability. The results reveal that NSGA-III is the algorithm converging towards the most cost-effective solutions, surpassing NSGA-II and RVEA by 21.11% and 10.07%, respectively, while maintaining balanced environmental and social impacts. The RVEA achieves up to 15.94% greater environmental efficiency than its counterparts. The analysis of non-dominated solutions identifies the A_4 design, utilizing 35 MPa concrete and B500S steel, as the most sustainable alternative across 80% of decision-making algorithms. The ranking correlation coefficients above 0.94 demonstrate consistency among decision-making techniques, underscoring the robustness of the integrated MOO and MCDM framework. The results in this paper expand the understanding of the applicability of novel techniques for enhancing engineering practices and advocate for a comprehensive strategy that employs advanced MOO algorithms and MCDM to enhance sustainable infrastructure development.

Keywords: multi-objective optimization; multi-criteria decision-making; NSGA-II; NSGA-III; RVEA; SAW; FUCA; TOPSIS; PROMETHEE; VIKOR

8.1 Introduction

Transportation infrastructure stands as the most pivotal component of a nation's core infrastructure, often representing its largest subcomponent and serving as a critical foundation for economic prosperity and societal welfare. The allocation of resources towards this sector is perceived as a direct contribution to a nation's economic and social growth, evidenced by leading institutions such as the World Bank allocating substantial financial support to transportation infrastructure, surpassing contributions

towards health or education [152]. This strategic emphasis highlights transportation infrastructure's crucial role in catalyzing societal progression. Amidst an increasingly marked transition towards sustainable development, the investment strategy in transportation infrastructure now necessitates a holistic life cycle evaluation [1]. This approach ensures that fiscal commitments address immediate needs and champion enduring, sustainable solutions that protect future generations' interests. It integrates environmental sustainability and global interconnectivity into the essence of infrastructure development, fostering a paradigm that balances immediate benefits with long-term viability.

Within the crucial role of transportation infrastructure, the construction sector stands as a dynamic catalyst, essential for the fruition of these projects. The construction industry is poised for substantial growth, with forecasts indicating a surge beyond 14 trillion dollars globally in the ensuing year, significantly influencing the global economic landscape [153]. This expansion illustrates the industry's immense scale and its vital role in propelling economic advancement through the generation of employment opportunities, both during the design and construction phases and in the ongoing maintenance of infrastructure. Its operation strengthens job prospects within the sector and related fields, underscoring the construction industry's contribution to broad-based economic development.

However, positioned as one of the most resource-intensive and environmentally impacting sectors, the construction industry is under increasing scrutiny to reform antiquated practices in favor of more sustainable approaches [155]. This juxtaposition of the industry's considerable economic contributions against its environmental and social implications has sparked a critical examination. Acknowledging this challenge has prompted a realignment of capital investment strategies, prioritizing incorporating life cycle sustainability encompassing economic, environmental, and social considerations right from the conceptual stages of transportation infrastructure projects [12]. This shift is not merely a nod to ethical standards but emerges as a strategic necessity to secure investment and champion the cause of sustainable development. The construction sector is compelled to embrace a comprehensive strategy that transcends traditional methodologies. Adopting an integrated approach in designing highly efficient infrastructure is instrumental in realizing economically sound, environmentally sustainable, and socially equitable projects, marking a significant stride towards a balanced development paradigm.

Adopting an integrated framework incorporating sustainable design strategies from the outset is essential for aligning transportation infrastructure construction with overarching sustainable development objectives [154]. This strategy ensures that efforts in construction engineering are developed with a comprehensive outlook, evaluating aspects such as economic viability, environmental preservation, and social respon-

sibility. Embracing this broader framework, which considers the project's entire life cycle, can stimulate innovation and foster more profound collaboration among all stakeholders. Moreover, it sets a foundational standard for integrating life cycle sustainability considerations, facilitating more enlightened decision-making throughout the critical phases of conception, design, and funding acquisition of transportation infrastructure projects. This refined approach ensures the immediate project needs are met while incorporating a shift towards more responsible and forward-thinking infrastructure development practices.

Embracing a life cycle standpoint necessitates the evaluation and objective quantification of environmental, social, and economic impacts spanning from a project's inception to its decommissioning. This perspective fosters sensitive material and energy use, emphasizing long-term benefits for communities and the environment. Applying advanced life cycle and structural mathematical modeling signifies a pivotal transition from traditional to innovative design strategies. This shift promotes the early integration of optimization and decision-making techniques, significantly enhancing the alignment of infrastructure projects with sustainable development goals. Such an approach underlines the importance of a holistic view in infrastructure development, ensuring that projects are not only designed for immediate functionality under economic viability constraints but also for their long-term sustainability, operational efficiency, and positive societal impact throughout their entire life cycle.

The transition from single-objective optimization (SOO) to MOO in the context of structural design optimization signifies a substantial advancement [158], [160], [161]. MOO enables the simultaneous evaluation of multiple critical factors, including economic efficiency, environmental sustainability, and social impact. This holistic approach broadens the scope of design considerations and ensures a deeper congruence between infrastructure design and overarching sustainable development purposes. The advancement of MOO strategies represents a paradigmatic evolution, enriching the design process with a multifaceted perspective that better captures the complexity of real-world engineering challenges.

In Ruiz-Velez et al. [173], a novel design strategy is presented and applied to a real-world challenge in construction engineering. The study specifically focuses on the life cycle design optimization of reinforced concrete precast modular frames (RCPMF). Building on previous SOO results for the precast and cast-in-place typologies [128], [130], the study introduces a customized non-dominated sorting genetic algorithm II (NSGA-II), enhanced with three novel repair operators, to navigate the complex handling of the mixed integer programming (MIP) during the optimization process [169]. Furthermore, the framework proposed in the study is particularly relevant for its integration with MCDM techniques, computing the criteria weights via an entropy-

based approach and applying the simple additive weighting (SAW) and faire un choix adéquat (FUCA) methods for assessing the optimization results [164].

The statistical-based repair operator was identified as the preeminent algorithm for navigating the hurdles intrinsic to the MIP nature of the RCPMF optimization problem. Despite the inherent differences in the strategies for scoring and evaluating decision-making alternatives, the SAW and FUCA techniques ranked the optimal solutions similarly. This consistency attests to the capabilities of the proposed structural design framework and the potential of integrating MOO and MCDM. As a result, the study introduced and demonstrated a pioneering framework that leverages the strengths of MOO and MCDM to elevate the sustainability and efficacy of structural engineering projects. The research strongly supports deploying this integrative strategy in practical structural engineering scenarios, particularly those aimed at enhancing the sustainability of transportation infrastructure projects.

Integrating MOO with MCDM techniques presents a forward-looking strategy for refining structural design frameworks considering the life cycle implications of construction projects. The case study on optimizing the structural design of RCPMF sets a reliable standard for assessing the effectiveness of sophisticated design strategies in transportation infrastructure development. The results of exploring the NSGA-II algorithm alongside SAW and FUCA techniques underscored the potential benefits of integrating MOO and MCDM for addressing the complex task of embedding sustainability into structural design engineering, representing an important stride towards further analytical advancements. Consequently, this initiates a pivotal conversation about exploring and evaluating the performance of additional MOO algorithms and MCDM approaches. This scrutiny seeks to assess the framework's efficacy and broaden its relevance throughout the structural design domain.

This paper focuses on the development stage of precast modular frames, adopting a comprehensive perspective on life cycle sustainability. By integrating optimization processes early in the foundational phase, the framework is conceived to significantly influence the entire life cycle from inception to decommissioning ensuring that every design decision upholds long-term sustainability objectives [174]. The research builds substantially upon previous efforts by incorporating a broad spectrum of MOO algorithms and MCDM techniques, enhancing the framework's ability to navigate the complex and multifaceted challenges common to diverse modern engineering projects and boosting its applicability and robustness.

Furthermore, by embedding life cycle sustainability objectives directly into the optimization process, aligning these objectives with decision-making criteria, and utilizing an entropy theory-based weighting method, the framework ensures robustness and impartiality. This holistic approach deepens the understanding of life cycle sus-

tainability and improves the replicability and reliability of outcomes across various engineering domains, fostering real-world scalability for these advanced practices. The research showcases the practical implementation of the MOO and MCDM integrated framework, closely aligning with established best practices for sustainable infrastructure development.

Within this context, the present research implements and critically evaluates the performance of novel MOO algorithms and MCDM techniques for enhancing structural design efforts. Three optimization algorithms and five decision-making techniques are implemented within the integrated design framework and then employed to solve the RCPMF problem. This paper aims to comprehensively characterize and enhance the integrated design strategy's capabilities for solving practical engineering challenges. This paper introduces and evaluates the performance of three novel MOO algorithms, NSGA-II, non-dominated sorting genetic algorithm III (NSGA-III), and reference vector guided evolutionary algorithm (RVEA), for solving the MOO RCPMF problem [159], [163], [175], [176]. The statistical-based repair operator, previously identified as the best-performing repair algorithm, is implemented in all of them. This paper further innovates by substantially extending the scope of the MCDM problem by comparing five different decision-making techniques: SAW, FUCA, technique for order of preference by similarity to ideal solution (TOPSIS), preference ranking organization method for enrichment evaluation (PROMETHEE), and "visekriterijumska optimizacija i kompromisno resenje" (VIKOR), Serbian for multi-criteria optimization and compromise solution [31], [177]. This exhaustive examination improves the understanding of the MOO and MCDM integrated life cycle design strategy's suitability and efficiency in promoting sustainable development within transportation infrastructure.

The NSGA-III algorithm is identified as the best-performing MOO strategy across all objective functions. While differing in scoring and evaluation procedures, the decision-making strategies continue to rank the MCDM problem alternatives similarly. These findings are congruent with what was described in previous research, displaying a robust array of decision-making techniques to be considered when assessing transportation infrastructure development. The results of this study further validate the design framework combining advanced MOO algorithms with MCDM techniques and provide new insights into its application and performance.

The subsequent sections detail and thoroughly explain the methodologies utilized in this study. Section 8.2.1 provides an overview of the RCPMF problem which serves as a standard for evaluating the effectiveness of the optimization algorithms. Section 8.2.2 elaborates on the operation and tailored adjustments of the optimization algorithms, while Section 8.2.3 offers similar clarification for the decision-making tech-

niques. The analysis and interpretation of the results are presented in Section 8.3, enabling the formulation of relevant conclusions highlighted in Section 8.4.

8.2 Methods

This section provides a straightforward overview of the RCPMF problem used to assess the performance of optimization algorithms within the integrated MOO and MCDM life cycle design framework. Furthermore, it thoroughly delineates the optimization algorithms and defines the criteria weighting procedure and the decision-making techniques implemented in this research.

8.2.1 Optimization Problem Overview

This study builds upon the MOO problem in Ruiz-Vélez et al. [173], focusing on the structural design of a 10-meter-span and 5-meter-height RCPMF constructed 5 m deep into a roadway embankment. The MOO process involves determining a set of values for n variables constituting a solution vector $\vec{X}$ efficient per its corresponding values for predefined objective functions. These functions strive to achieve life cycle sustainability while adhering to constraints that prioritize structural integrity and performance. The ultimate aim is to navigate the solution space effectively, uncovering non-dominated solutions that simultaneously minimize k objective functions and meet m constraints. This approach follows the standard framework for MOO problems, as detailed by Equations (8.1)–(8.3).

$$\vec{X} = x_1, x_2, \dots, x_n \quad (8.1)$$

$$\min(f_i(\vec{X})) = \min(f_1(\vec{X}), f_2(\vec{X}), \dots, f_k(\vec{X})) \quad (8.2)$$

$$g_m(\vec{X}) \leq 0 \quad (8.3)$$

Section 8.2.1 outlines the variables and parameters relevant to the RCPMF problem, detailing the specific values and ranges utilized in the MOO process. Section 8.2.1 elaborates on the constraints that categorize a given variable vector as feasible or infeasible, integrating a concise overview of the constraint-verification process. This process encompasses checks for ultimate and serviceability limit states (ULS and SLS), which are crucial for assuring structural integrity and performance. Finally,

Section 8.2.1 provides an exhaustive description of the three objective functions devised to assess economic viability along with environmental and social impacts at the life cycle endpoint.

Variables and Parameters

A set of 41 design variables defines the RCPMF design in the MOO problem in this study. These variables, represented in Figure 8.1, determine the structural geometry, the configuration of passive reinforcement, and the selection of material grades. In addition, a series of predetermined values are set as optimization parameters that reflect on the mechanical properties of materials, account for environmental conditions, adhere to legislative standards, or address specific design requirements related to the project's location.

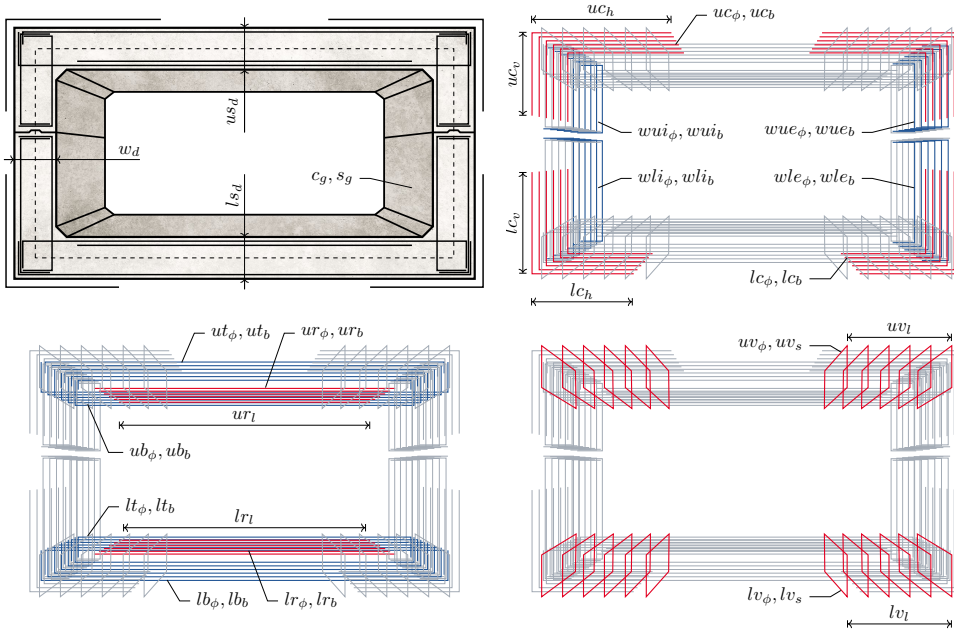


Figure 8.1: Optimization variables for the RCPMF design problem.

In exploring the MOO problem's solution landscape, the optimization algorithms systematically assign values within defined limits to the variables comprising the solution vector. This step is followed by assessing the objective functions for each solution set and a verification process to determine the solution's feasibility based on its ad-

herence to the constraints. While variables are altered to explore potential designs during optimization, parameters essential for fully delineating the design, objective function evaluation, and constraint verification remain unchanged. Comprehensive modeling and testing of the optimization process ensures a thorough exploration of viable solutions within the predetermined bounds of the optimization variables.

The RCPMF comprises three distinct types of optimization variables: real (continuous), choice (discrete), and integer. The MIP nature of the problem requires different handling for each during mutation, crossover, and repair operations throughout the optimization process. Given its notable efficacy when integrated with the NSGA-II algorithm, this study employs a statistical-based repair operator.

The RCPMF structural design is characterized by three continuous variables related to the depths of the upper and lower slabs and the lateral walls. Additionally, six continuous variables specify the effective lengths of passive reinforcement bars at the corners and within the central sections of both slabs. Four more continuous variables are allocated to determining the placement lengths of shear reinforcement in the slabs and their branch separation, summing up to thirteen continuous variables. Specific upper and lower bounds are defined for each continuous variable, allowing the optimization algorithm to select any value within this range throughout the optimization process.

Fourteen discrete variables are designated to specify the rebar diameters at all positions within the passive reinforcement layout. This approach is designed to be open-ended, permitting the optimization algorithm to consider unconventional designs by allowing rebar variables to adopt any standard diameter from 8, 10, 12, 14, 16, 20, 25, to 32 mm. Therefore, the discrete variables for rebar diameters are confined between 8 and 32 mm as their lower and upper bounds, respectively. Moreover, two discrete variables are introduced to select the grades for structural concrete and reinforcement steel, constrained to standard options of 25, 30, 35, and 40 MPa for concrete and 400 and 500 MPa for steel, offering a structured yet flexible framework for material selection.

Finally, a set of 12 integer variables contains the remaining data regarding the number of bars, which is necessary for fully defining the passive reinforcement design of the RCPMF. Handling the integer variables is relatively straightforward, requiring the establishment of specific lower and upper bounds. Following the above-mentioned non-restricting efforts, all integer variables are bounded within 4 to 20, corresponding to the minimum and maximum number of bars. The algorithm can then allocate any integer within said bounds for each variable. Table 8.1 compiles the full array of optimization variables, indicating their units, specific upper and lower bounds, and variable type.

Table 8.1: Optimization problem variable units, bounds, and classification.

Variable	Unit	Lower limit	Upper limit	Type
us_d	m	0.60	1.60	continuous
ls_d	m	0.40	1.40	continuous
w_d	m	0.30	1.20	continuous
ut_ϕ	mm	8	32	discrete
ut_b	bars	4	20	integer
ub_ϕ	mm	8	32	discrete
ub_b	bars	4	20	integer
lt_ϕ	mm	8	32	discrete
lt_b	bars	4	20	integer
lb_ϕ	mm	8	32	discrete
lb_b	bars	4	20	integer
wui_ϕ	mm	8	32	discrete
wui_b	bars	4	20	integer
wue_ϕ	mm	8	32	discrete
wue_b	bars	4	20	integer
wli_ϕ	mm	8	32	discrete
wli_b	bars	4	20	integer
wle_ϕ	mm	8	32	discrete
wle_b	bars	4	20	integer
uc_ϕ	mm	8	32	discrete
uc_b	bars	4	20	integer
uc_h	m	1	5	continuous
uc_v	m	0.70	1.80	continuous
lc_ϕ	mm	8	32	discrete
lc_b	bars	4	20	integer
lc_h	m	1	5	continuous
lc_v	m	0.70	2.80	continuous
ur_ϕ	mm	8	32	discrete
ur_b	bars	4	20	integer
ur_l	m	5	9.50	continuous
lr_ϕ	mm	8	32	discrete
lr_b	bars	4	20	integer
lr_l	m	3	8	continuous
uv_ϕ	mm	8	32	discrete
uv_s	m	0.1	0.4	continuous
uv_l	m	1.50	4.80	continuous

Continued on next page

Table 8.1 – continued from previous page

Variable	Unit	Lower limit	Upper limit	Type
lv_ϕ	mm	8	32	discrete
lv_s	m	0.1	0.4	continuous
lv_l	m	1.50	4.80	continuous
c_g	MPa	25	40	discrete
s_g	MPa	400	500	discrete

Table 8.2: Optimization problem parameters and specific values.

Parameter	Unit	Value
Vertical height	m	5
Horizontal span	m	10
Hinge height	m	3
Embankment depth	m	5
Section depth	m	1
Terrain density	kN/m ³	20
Concrete density	kN/m ³	24
Steel density	kN/m ³	78.5
Terrain internal friction angle	°	30
Active earth pressure	–	0.33
Resting earth pressure	–	0.50
Heavy vehicle load	kN	150
Heavy vehicle length	m	1.20
Uniform overload	kN/m ²	10
Ballast coefficient	MN/m ³	10
Economic costs	EUR	Table 8.3
Environmental impact	point	Table 8.3
Social impact	mrh	Table 8.3
Standard regulations	CEN [93], [94]/MFOM [95]	
Applicable codes	MFOM [90]	

When determining the structural integrity of an RCPMF, several critical aspects need consideration. These include the structure's geometric parameters, the properties of materials, and numerous indications per relevant standards, all essential for defining and modeling structural loads. Moreover, specific data are required to calculate objective function values for each feasible solution accurately. Table 8.2 summarizes these principal parameters, which equip the mathematical model with the necessary

representativeness and precision for this analysis in combination with the optimization variables.

Constraints

As with any structural design, the RCPMF solutions are deemed feasible based on compliance with standard regulations concerning ULS, SLS, and further considerations. The verification of these constraints was modeled and integrated within the Python 3-based model utilized for the optimization [167]. The mathematical model incorporates global Finite element method (FEM) models for stress analysis alongside several local models for sectional verification, ensuring a thorough examination of structural integrity and performance.

Algorithm 4 Constraint verification for ULS.

```

1: Function ULS_Verification(model)
2: Input: model – RCPMF Python model
3: Output: ULS_compliance_vector
4: ULS_compliance_vector  $\leftarrow$  Array of size len(model.sections)
5: Fill ULS_compliance_vector with “non-compliant”
6: Conduct Global FEM Analysis on model.global
7: Initiate ULS Local Analysis on model.sections
8: for each load_case in model.ULS_load_cases do
9:   for section_id, section in enumerate(model.sections) do
10:     shear  $\leftarrow$  section.shear_stress  $\leq$  section.compute_shear_resistance()
11:     bending  $\leftarrow$  section.bending_stress is within section.compute_N_M_interaction()
12:     fatigue  $\leftarrow$  section.fatigue_stress  $\leq$  section.compute_fatigue_resistance()
13:     geometry  $\leftarrow$  section meets model.regulation for geometry
14:     reinforcement  $\leftarrow$  section meets model.regulation for reinforcement layout
15:     if shear AND bending AND fatigue AND geometry AND reinforcement then
16:       ULS_compliance_vector[section_id]  $\leftarrow$  “compliant”
17:     end if
18:   end for
19: end for
20: return ULS_compliance_vector

```

Achieving compliance with ULS is critical to ensuring the structural integrity of the RCPMF under various load cases as dictated by standard regulations. The ULS

compliance check encompasses a multi-step process outlined in Algorithm 4. It begins with evaluating the shear stress resistance across the entire structure. Subsequently, it involves calculating the increase in bending moment stress due to shear interaction, which is then integrated into the overall stress analysis. Following this, the model computes the N-M interaction diagrams for each section, gaining detailed insight into the structural capacity at all sections of the RCPMF. This comprehensive analysis culminates in verifying normal stresses, explicitly checking if the combined axial-bending stress pair for each section falls within its N-M interaction diagram's safe region. A favorable evaluation across all sections indicates the RCPMF's capacity to withstand shear and normal stresses. The verification process also includes fatigue assessment and checks on geometrical configurations and reinforcement layouts. A design meeting all ULS requirements will be reflected in the optimization process as a constraint vector devoid of non-null values, signifying full compliance.

Algorithm 5 Constraint verification for SLS.

```

1: Function SLS_Verification(model)
2: Input: model – RCPMF Python model
3: Output: SLS_compliance_vector
4: SLS_compliance_vector  $\leftarrow$  Array of size  $\text{len}(\text{model.sections})$ 
5: Fill SLS_compliance_vector with “non-compliant”
6: Conduct Global FEM Analysis on model.global
7: Initiate SLS Local Analysis on model.sections
8: for each load_case in model.SLS_load_cases do
9:   displacement  $\leftarrow$  model.max_displacement meets model.regulations for displacements

10:  for section_id, section in  $\text{enumerate}(\text{model.sections})$  do
11:    crack  $\leftarrow$  section.crack  $\leq$  section.allowed_crack
12:    if crack AND displacement then
13:      SLS_compliance_vector[section_id]  $\leftarrow$  “compliant”
14:    end if
15:  end for
16: end for
17: return SLS_compliance_vector

```

After verifying compliance with ULS, the assessment proceeds to SLS to ensure the structure not only remains safe under all relevant load cases but also retains its aesthetic and functional integrity. The SLS verification, outlined in Algorithm 5, is a multi-step process aimed at preventing crack formation and spread throughout the struc-

ture. Additionally, it limits displacements to prevent significant global deformations that might induce non-structural damage to the RCPMF's auxiliary systems. Analogous to the ULS procedure, a design that satisfies all SLS criteria is represented by a constraint vector entirely free of non-zero values, indicating full adherence to serviceability requirements.

Objective Functions

As delineated in the introductory paragraph of the section, the MOO process aims to identify a set of values for the n variables that compose $\vec{X}$. This set must comply with the constraints outlined in Section 8.2.1 while simultaneously minimizing the values of specific objective functions. The MOO problem focuses on achieving highly efficient RCPMF designs from a life cycle endpoint perspective. A comprehensive evaluation of RCPMF sustainability necessitates a clear definition and meticulous analysis of objective functions that reflect the complex dimensions of sustainability. Accordingly, the RCPMF MOO problem addressed in this study introduces three objective functions to assess the economic viability and the environmental and social ramifications throughout the RCPMF's life cycle, each contributing to a holistic sustainability evaluation.

During the optimization, all three objective functions are calculated through the Python mathematical model, taking into account the complete life cycle of the RCPMF. This approach entails defining parameters that encapsulate economic, environmental, and social data relevant to the materials and processes employed in the production, construction, upkeep, and eventual decommissioning of the RCPMF. In line with previous research, the economic analysis primarily evaluates the direct costs associated with concrete and steel, referencing prices from the BEDEC database [92]. For environmental and social impacts, the environmental life cycle assessment (ELCA) and social life cycle assessment (SLCA) endpoint results are determined by aggregating impacts across the RCPMF's four life cycle stages. This process is informed by unit impact values previously computed using OpenLCA 2.1, incorporating data from the Ecoinvent 3.7.1 and soca v2 databases, and analyzed through the ReCiPe 2008 and SWIM Life cycle impact assessment (LCIA) methodologies [145]. Table 8.3 specifies the specific values employed in the evaluation of objective functions [133], [147], [149], [171].

The first of the three objective functions is dedicated to assessing the economic cost of structural materials. The product of the unitary cost, c_i , and quantity used, m_i , for concrete and steel is added as per Equation (8.4).

Table 8.3: LCA processes and environmental and social unit impact values [133], [149], [171].

Material	Unit	Cost (EUR)	$elca_i$ (Point)	$slca_i$ (mrh)
concrete 25 MPa	m ³	1.129×10^2	2.037×10^1	1.254×10^5
concrete 30 MPa	m ³	1.262×10^2	2.631×10^1	1.668×10^5
concrete 35 MPa	m ³	1.293×10^2	2.478×10^1	1.554×10^5
concrete 40 MPa	m ³	1.331×10^2	2.585×10^1	1.623×10^5
steel B400S	kg	1.790×10^0	2.417×10^{-1}	1.941×10^3
steel B500S	kg	1.840×10^0	2.538×10^{-1}	2.067×10^3
clay	kg	0.000×10^0	1.062×10^{-3}	8.475×10^0
gravel	kg	0.000×10^0	1.196×10^{-3}	2.617×10^0
sand	kg	0.000×10^0	1.718×10^{-3}	3.543×10^0
transport, lorry 16–32 ton	t·km	0.000×10^0	2.502×10^{-2}	4.116×10^1
transport, lorry 3.5–7.5 ton	t·km	0.000×10^0	7.755×10^{-2}	1.655×10^2
transport, car	km	0.000×10^0	2.760×10^{-4}	1.417×10^{-1}
digger, operation	min	0.000×10^0	7.876×10^{-2}	8.825×10^2
skid plate, operation	min	0.000×10^0	7.651×10^{-2}	8.657×10^2
diesel, building machine	MJ	0.000×10^0	1.361×10^{-2}	8.764×10^0
carbon dioxide	kg	0.000×10^0	4.369×10^{-2}	0.000×10^0
mortar	kg	0.000×10^0	3.084×10^{-2}	1.415×10^2
epoxy	kg	0.000×10^0	8.399×10^{-1}	4.107×10^3
rock crushing	kg	0.000×10^0	7.223×10^{-5}	8.304×10^{-1}

$$C(\vec{X}) = \sum_{i=1}^n c_i \cdot m_i(\vec{X}) \quad (8.4)$$

The remaining two objective functions focus on the environmental and social ramifications of the RCPMF life cycle, analyzing the impacts from an endpoint perspective. A detailed analysis of every process throughout the RCPMF life cycle's four stages is conducted to calculate endpoint results, aligning with ISO 14040:2006 [134]. These stages are the manufacturing, construction, use and maintenance, and end-of-life. Additional insights into the life cycle model of the RCPMF, including discussions on the carbon capture capabilities of structural concrete, are elaborated in prior research [173].

The calculation for the ELCA endpoint results utilizes Equation (8.5). This formula aggregates the environmental impacts of materials and processes by multiplying each unit impact $elca_i$ by its corresponding quantity m_i , summing these across j life cycle stages. A parallel method, outlined in Equation (8.6), applies for calculating the

SLCA endpoint results, ensuring both environmental and social impacts are comprehensively assessed.

$$ELCA(\vec{X}) = \sum_{i=1}^n \sum_{j=1}^4 elca_{i,j} \cdot m_{i,j}(\vec{X}) \quad (8.5)$$

$$SLCA(\vec{X}) = \sum_{i=1}^n \sum_{j=1}^4 slca_{i,j} \cdot m_{i,j}(\vec{X}) \quad (8.6)$$

8.2.2 Optimization Algorithms

This section introduces a framework for multi-objective optimization that includes the NSGA-II, NSGA-III, and RVEA algorithms. Section 8.2.2 is an initial setup involving a repair operator shared by all three methods, illustrating a consistent method for managing solutions. Detailed in Section 8.2.2 is the 'Algorithmic Enhancement Module' phase, in which the NSGA-II, NSGA-III, and RVEA algorithms are run. This approach allows for the algorithms' performance to be directly compared, as discussed in Section 8.3.2, using measures such as generational distance and inverted generational distance. During this phase, unique operators tailored to each algorithm are employed, indicating the different strategies used for optimization. Figure 8.2 shows the standardized process and methods applied across these algorithms within the framework.

The enhancements detailed in our study include the application of a custom repair operator and specific tuning of the crossover and mutation operators, initially developed for NSGA-II and now extended to NSGA-III and RVEA. These adaptations enable a consistent application across different algorithms, enhancing their capability to address diverse optimization challenges. By integrating these tailored modifications into each algorithm, the framework facilitates a nuanced evaluation of their effectiveness in complex multi-objective environments.

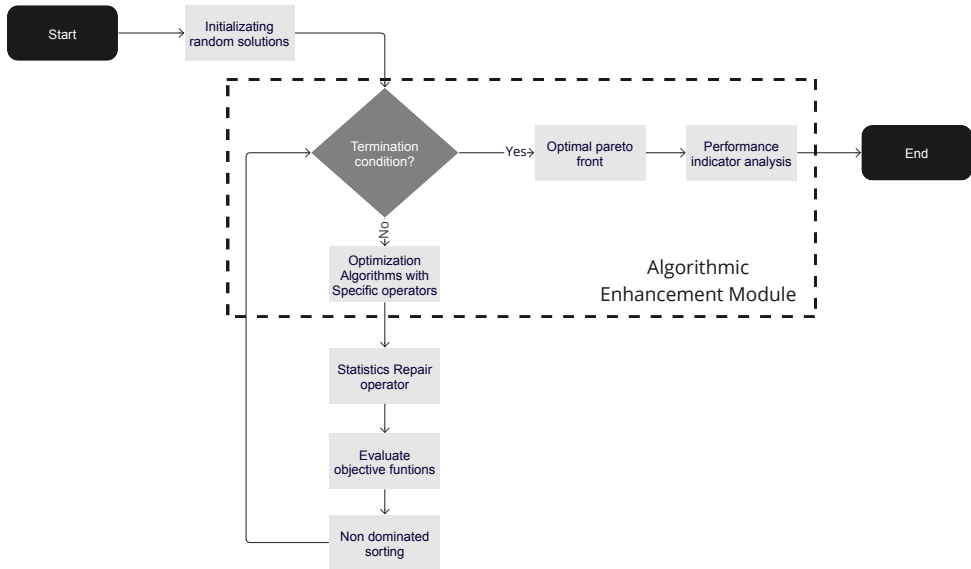


Figure 8.2: Flowchart depicting the framework with algorithmic enhancement module for NSGA-II, NSGA-III, and RVEA.

Statistical Repair Operator

A statistical-based repair operator, as outlined in Algorithm 6, is characterized by the integration of statistical measures—mean and median—with a probabilistic approach to enhance solutions in an optimization algorithm. In every iteration, solutions are processed using a probability parameter β to determine the chosen repair strategy. When a generated random number falls below β , the median is applied to discrete variables (choice and integer) and the mean to continuous (real) variables. The median is advantageous for discrete variables, providing resilience against outliers and representing the population's most common values. In contrast, the mean calculates an average value for continuous variables, capturing the population's central tendency.

Algorithm 6 Statistical repair operator.

```
1: Function ProbabilisticRepair( $Y, \beta$ )
2: Input:  $Y, \beta$ 
3: Output:  $repaired\_Y$ 
4:  $repaired\_Y \leftarrow$  copy of  $Y$ 
5:  $average \leftarrow$  mean of  $Y$  along axis 0
6:  $midpoints \leftarrow$  median of  $Y$  along axis 0
7: for each solution  $y$  in  $repaired\_Y$  do
8:   for each variable index  $i$  in  $y$  do
9:      $varType \leftarrow$  variable type at index  $i$ 
10:    if random number  $< \beta$  then
11:      if  $varType$  is Choice or Integer then
12:         $medianValue \leftarrow$   $midpoints[i]$ 
13:        if  $varType$  is Choice then
14:           $y[i] \leftarrow$  closest value to  $medianValue$  in  $varType.choice$ 
15:        else
16:           $y[i] \leftarrow$  round  $choice$  to nearest integer within  $var.bounds$ 
17:        end if
18:      else if  $varType$  is Real then
19:         $y[i] \leftarrow$  clip  $average[i]$  within  $varType.bounds$ 
20:      end if
21:    else
22:      Standard repair is applied based on variable type and bounds
23:    end if
24:  end for
25: end for
26: return  $repaired\_Y$ 
```

Multi-Objective Optimization Algorithms

Custom NSGA-II: In the custom NSGA-II algorithm outlined in Algorithm 7, two pivotal operators are utilized: simulated binary crossover (SBX) and polynomial mutation (PM), each instrumental for strategic navigation within the search space. The SBX operator is finely tuned to generate offspring in close proximity to their parent solutions, fostering a concentrated exploration within the immediate vicinity of the solution space. Governed by a distribution index, it calibrates the closeness of the offspring

to the parent solutions, striking a delicate balance between exploration and exploitation. Conversely, the PM operator introduces a subtle variation in the population by minutely altering the real-valued attributes of solutions. Similarly influenced by a distribution index, PM is essential for maintaining genetic diversity in the population and avoiding early convergence to suboptimal solutions. In concert, these operators propel the bespoke NSGA-II algorithm, ensuring a harmonious equilibrium between convergence to optimal solutions and diversity preservation, which is fundamental for the efficacy of multi-objective optimization.

Algorithm 7 Custom NSGA-II.

```

1: Input: Population size pop_size, crossover probability crossover_prob, mutation probability mutation_prob, crossover distribution index crossover_index, mutation distribution index mutation_index
2: A set of non-dominated solutions
3: Initialize population P with pop_size individuals
4: Evaluate the initial population P
5: Set generation count gen = 0
6: while termination condition not met do
7:   Select parents from P using binary tournament selection
8:   Apply SBX crossover with probability crossover_prob and distribution index crossover_index
9:   Apply PM mutation with probability mutation_prob and distribution index mutation_index

10:  Evaluate the offspring population Q
11:  Combine populations:  $R = P \cup Q$ 
12:  Perform non-dominated sorting on R
13:  Perform crowding distance assignment on each front
14:  Select the next generation population P from R
15:  gen = gen + 1
16: end while
17: return Population P containing non-dominated solutions

```

Custom NSGA-III: In the elaboration of Custom NSGA-III, depicted in Algorithm 8, a strategic integration of selection, crossover, and mutation processes is employed to address complex many-objective optimization tasks. The algorithm adopts simulated binary crossover (SBX) and polynomial mutation (PM) to generate a diverse offspring pool, while a set of predefined reference directions aids in maintaining a well-distributed set of solutions across many objectives. This synergy of mechanisms distinguishes Custom NSGA-III from its predecessor, NSGA-II, by enhancing its capability to explore and exploit the multi-dimensional objective space. The reference-point-based selection strategy is particularly pivotal, effectively guiding the population towards a Pareto front that is representative of the entire objective space, a critical

aspect for many-objective optimization. The detailed procedure, as formalized in the provided pseudocode, encapsulates the algorithm's systematic approach towards achieving a comprehensive and diverse solution set.

Algorithm 8 Custom NSGA-III.

```
1: Input: Population size pop_size, crossover probability crossover_prob, mutation probability mutation_prob, crossover distribution index crossover_index, mutation distribution index mutation_index, reference directions ref_dirs
2: A set of non-dominated solutions distributed across the reference directions
3: Initialize population P with pop_size individuals
4: Evaluate the initial population P
5: Compute the reference points ref_dirs
6: Set generation count gen = 0
7: while termination condition not met do
8:   Select parents from P using tournament selection
9:   Apply SBX crossover with probability crossover_prob and distribution index crossover_index
10:  Apply PM mutation with probability mutation_prob and distribution index mutation_index

11:  Evaluate the offspring population Q
12:  Combine populations:  $R = P \cup Q$ 
13:  Perform non-dominated sorting on R to get fronts  $F_1, F_2, \dots$ 
14:  Select the next generation population P using reference point based selection
15:  gen = gen + 1
16: end while
17: return Population P that approximates the Pareto front
```

Custom RVEA: In the development of the Custom RVEA, as outlined in Algorithm 9, elements are incorporated to effectively navigate and exploit the multi-objective optimization landscape. The algorithm leverages a set of reference directions (*ref_dirs*), which act as guiding vectors in the objective space, facilitating the distribution of solutions along the desired Pareto front. A novel feature, *prob_neighbor_mating*, introduces a mating preference mechanism that enhances diversity and exploration by favoring mating between solutions that are neighbors, thereby ensuring a more thorough search across the entire solution space. Additionally, the adaptation parameter (*alpha*) dynamically adjusts the pressure exerted by the reference vectors, allowing for a flexible balance between convergence and diversity throughout the evolutionary process.

Algorithm 9 Custom RVEA with specific parameters.

-
- 1: **Input:** Reference directions ref_dirs , number of neighbors $n_neighbors$, probability of neighbor mating $prob_neighbor_mating$, adaptation parameter $alpha$, population size pop_size
 - 2: A set of solutions approximating the Pareto front
 - 3: Initialize population P with pop_size individuals
 - 4: Evaluate the initial population P
 - 5: Compute the reference vectors based on ref_dirs
 - 6: Set generation count $gen = 0$
 - 7: **while** termination condition not met **do**
 - 8: Assign each individual in P to a reference vector
 - 9: Calculate fitness of each individual based on angular distance to reference vectors and $alpha$
 - 10: Select parents, preferring those with closer neighbors with probability $prob_neighbor_mating$
 - 11: Generate offspring using crossover and mutation
 - 12: Evaluate the offspring
 - 13: Update the population P based on fitness and $alpha$ adaptation
 - 14: $gen = gen + 1$
 - 15: **end while**
 - 16: **return** Population P that approximates the Pareto front
-

8.2.3 Evaluation and Decision-Making Methods

The MOO introduced in Section 8.2.1 is tackled using the optimization algorithms described in Section 8.2.2. This approach yields a collection of non-dominated solutions indicative of highly efficient RCPMF designs. Embedding sustainability into the development of transportation infrastructure presents a multifaceted challenge. Therefore, this study broadens its examination beyond merely generating optimal designs that foster sustainability enhancements. It aims to assess and contrast the outcomes achieved through various decision-making strategies applied to the MCDM problem involving the highly efficient RCPMF designs result of the MOO. In this analysis, the subsequent phase of the design framework entails employing decision-making strategies to systematically and objectively rank the most effective design alternatives. Selecting a decision-making algorithm can turn into a MCDM problem itself. Within this context, the comparative analysis of the outcomes from each decision-making strategy aims to validate their use via a precise exploration of their utility in advancing sustainable development within transportation infrastructure.

Recognizing the vast considerations required for complex MCDM problems in any engineering field is crucial, especially given the sustainability-focused efforts of this research. Factors far exceeding the scope and objectives of this paper can profoundly

impact the decision-making outcomes. With various conditions, including specific stakeholder interests, logistical and supply chain challenges, or temporary resource shortages, significantly shaping sustainable infrastructure development worldwide, this study acknowledges its limitations. The focus remains on examining the effectiveness of different decision-making algorithms and identifying the variances and parallels in their results for the RCPMF problem within the specific considerations outlined throughout the document.

Addressing the MCDM problem involves constructing a decision matrix $X = r_{ij}$ encompassing m alternatives $A_i = \{A_1, A_2, \dots, A_m\}$, evaluated across n criteria. Element r_{ij} within this matrix offers insights into how well alternative i performs relative to criterion j . This study enhances previous research, applying five distinct decision-making algorithms: SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR. These algorithms necessitate initial criteria weighting as a preliminary step, providing essential information for their operation rather than being an intrinsic aspect of the algorithms.

Entropy Theory-Based Criteria Weighting

This paper utilizes entropy theory to calculate the criteria weights W_j for an objective and systematic approach to weighting [165]. This approach is crucial for maintaining the integrity of the analysis and mitigating the influence of subjective biases that could skew the results. Determining entropy weights unfolds in four stages. The initial step involves the normalization of X per Equation (8.7).

$$X' = r_{ij} \left\langle \sum_{i=1}^m r_{ij} \right\rangle^{-1} \quad (8.7)$$

The normalized matrix X' enables a direct comparison among criteria that, as seen in the MCDM problem of this study, may have different units and orders of magnitude. Entropy, indicative of a system's disorder, quantifies the requisite information to describe its state comprehensively. In this research, criteria exhibiting higher entropy are interpreted as yielding less reliable information, thereby influencing the decision-making efficiency of the algorithms. Subsequent steps in this methodology involve calculating the entropy E_j for each criterion and determining the degree of divergence D_j using Equations (8.8) and (8.9).

$$E_j = \frac{-1}{\ln \langle m \rangle} \left\langle \sum_{i=1}^m r_{ij} \cdot \ln \langle r_{ij} \rangle \right\rangle \quad (8.8)$$

$$D_j = 1 - E_j \quad (8.9)$$

The final step in the process calculates W_j by normalizing D_j across all criteria following Equation (8.10). These weights are subsequently utilized as input data for the decision-making algorithms, ensuring that each criterion's relative importance is accurately reflected in the analysis.

$$W_j = \frac{D_j}{\sum_{j=1}^n D_j} \quad (8.10)$$

Decision-Making Algorithms

The strategic selection of SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR is founded on their capability to navigate the complexities and variances of decision-making scenarios encountered in MOO within sustainable engineering. Each MCDM technique offers a unique decision-making approach, strengthening the framework by utilizing diverse aspects of decision analysis, thus increasing the framework's overall robustness. The choice of these decision-making techniques enhances the decision-making process and ensures the framework's flexibility in accommodating different levels of data quality, stakeholder preferences, and sustainability criteria. This flexibility is essential for advancing the primary research goal of enhancing the robustness within the integrated application of MOO and MCDM.

SAW: The SAW technique streamlines decision-making by directly aggregating weighted criteria. This method provides a precise, quantitative evaluation of sustainability criteria, resulting in an immediate and explicit ranking of alternatives based on their aggregated scores. This paper integrates the SAW technique as a well-established and effective method that seamlessly integrates within the design framework, enhancing its efficiency and clarity in evaluating options.

Algorithm 10 depicts the operation of the SAW technique [178]. The SAW algorithm unfolds in three steps, initially computing the normalized decision matrix X' . After normalization, the S_i score for each alternative is evaluated as the sum of the products of each element r_{ij} and the entropy weight W_j across the criteria. The final phase involves sorting them in ascending order based on the scores S , thereby identifying the most to least sustainable alternatives.

Algorithm 10 SAW algorithm implementation.

```
1: Function SAW( $X, W$ )
2: Input:  $X, W$ 
3: Output: ranking
4:  $S \leftarrow$  vector of zeros with size  $n$ 
5:  $X' \leftarrow$  normalize  $X$  along axis 0
6: for each alternative  $i$  in  $n$  do
7:    $S_i \leftarrow 0$ 
8:   for each criterion  $j$  in  $m$  do
9:      $r_{ij} \leftarrow X'_{ij}$ 
10:     $S_i \leftarrow S_i + W_j \cdot r_{ij}$ 
11:   end for
12: end for
13: ranking  $\leftarrow$  sort  $S$ 
14: return ranking
```

FUCA: The FUCA method ranks alternatives by systematically assessing them against multiple criteria. This approach considers the individual scores of each alternative and examines the distribution of these scores across various evaluations. FUCA's ability to effectively integrate and process variable data makes it a valuable tool in this study, supporting the goal of strengthening the robustness of the design framework for sustainable engineering solutions.

Algorithm 11 outlines the FUCA technique [164]. The FUCA starts by sorting alternatives in ascending order for each criterion. Following this, the score S_i results from aggregating the products of the rankings R_{ij} and the entropy weights W_j for all criteria. The concluding step involves a second sorting of the alternatives based on the ascending S scores.

Algorithm 11 FUCA algorithm implementation.

```

1: Function FUCA( $X, W$ )
2: Input:  $X, W$ 
3: Output:  $ranking$ 
4:  $S \leftarrow$  vector of zeros with size  $n$ 
5: for each alternative  $i$  in  $n$  do
6:   for each criterion  $j$  in  $m$  do
7:      $r_{ij} \leftarrow X_{ij}$ 
8:      $Q \leftarrow \text{sort } X_j$ 
9:      $R_{ij} \leftarrow \text{index of } r_{ij} \text{ within } Q$ 
10:     $S_i \leftarrow S_i + W_j \cdot R_{ij}$ 
11:   end for
12: end for
13:  $ranking \leftarrow \text{sort } S$ 
14: return  $ranking$ 

```

TOPSIS: The TOPSIS method assesses alternatives by measuring their distances to the most desirable (ideal) and least desirable (nadir) outcomes. Utilizing the Euclidean distance metric, TOPSIS ranks alternatives based on their geometric proximity to the ideal and their separation from the nadir. Focusing on optimal and suboptimal scenarios helps reduce the risk of selecting inferior solutions. Consequently, it ensures that the decision-making process upholds the overarching goal of enhancing the robustness of the integrated design framework.

Algorithm 12 corresponds to the TOPSIS decision-making technique [179]. The TOPSIS algorithm also starts by computing the normalized decision matrix X' . The following step involves evaluating the normalized weighted matrix T_{ij} . The next phase identifies the ideal and the least favorable solutions, A^+ and A^- , by pinpointing the highest and lowest values for each criterion j within T_{ij} . The essence of the TOPSIS algorithm is to measure how closely each alternative aligns with the ideal solution and how far it is from the least favorable one. This is achieved by determining the Euclidean distances D_i^+ and D_i^- of each alternative to the A^+ and A^- solutions, respectively. Following this, the algorithm evaluates the similarity index (S_i) as the ratio of the distance to the least favorable solution. In alignment with the previously described methods, the concluding step organizes the alternatives in descending order based on S .

Algorithm 12 TOPSIS algorithm implementation.

```

1: Function TOPSIS( $X, W$ )
2: Input:  $X, W$ 
3: Output: ranking
4:  $S \leftarrow$  vector of zeros with size  $n$ 
5:  $X' \leftarrow$  normalize  $X$  along axis 0
6: for each criterion  $j$  in  $m$  do
7:    $T'_j \leftarrow X'_j \cdot W_j$ 
8: end for
9:  $A^+, A^- \leftarrow \max(T'_j)$  and  $\min(T'_j)$  for each criterion  $j$  in  $m$ 
10:  $D^+, D^- \leftarrow$  vectors of zeros with size  $n$ 
11: for each alternative  $i$  in  $n$  do
12:   for each criterion  $j$  in  $m$  do
13:      $D_i^+ \leftarrow D_i^+ + (T'_{ij} - A_j^+)^2$ 
14:      $D_i^- \leftarrow D_i^- + (T'_{ij} - A_j^-)^2$ 
15:   end for
16:    $D_i^+ \leftarrow (D_i^+)^{0.5}$  distance to  $D^+$ 
17:    $D_i^- \leftarrow (D_i^-)^{0.5}$  distance to  $D^-$ 
18:    $S_i \leftarrow D_i^- / (D_i^- + D_i^+)$ 
19: end for
20: ranking  $\leftarrow$  sort  $S$ 
21: return ranking

```

PROMETHEE: The PROMETHEE method employs a pairwise comparison approach to rank alternatives, evaluating each option relative to others based on specific criteria and utilizing preference functions to ascertain the degree of preference for one alternative over another. The selection of PROMETHEE for this research is founded on its robust ability to accommodate both qualitative and quantitative criteria, promoting a thorough framework well-suited to the complexities of engineering decisions. This method facilitates nuanced decision-making, effectively capturing the subtle trade-offs and priorities essential to sustainable design and construction.

Algorithm 13 illustrates the PROMETHEE method [180]. Initially, it constructs a preference matrix by comparing each pair of alternatives. This paper applies a preference function that quantifies the extent to which one alternative is preferred over another, factoring in the criteria weights W . This matrix is crucial for determining the positive and negative flows, Φ^+ and Φ^- , representing how much an alternative is preferred and opposed across all comparisons. The core of PROMETHEE lies in

synthesizing these flows into a net flow Φ for each alternative, assessing its overall performance by offsetting its positive flow against its negative. The procedure concludes with the alternatives ranked in descending net flow order, identifying the top choices. This systematic process, marked by pairwise preference aggregation, refines the decision matrix into an explicit hierarchy.

Algorithm 13 PROMETHEE algorithm implementation.

```

1: Function: PROMETHEE( $X, W$ )
2: Input:  $X, W$ 
3: Output: ranking
4:  $F \leftarrow$  matrix of zeros with size  $n \times n$ 
5: for each alternative  $i$  in  $n$  do
6:   for each alternative  $j$  in  $n$  do
7:     if  $i \neq j$  then
8:        $P_{ij} \leftarrow \max(0, X_i - X_j) \cdot W$ 
9:        $F_{ij} \leftarrow \sum P_{ij}$ 
10:    end if
11:  end for
12: end for
13:  $\Phi^+, \Phi^- \leftarrow$  vectors of zeros with size  $n$ 
14: for each alternative  $i$  in  $n$  do
15:   for each alternative  $j$  in  $n$  do
16:      $\Phi_i^+ \leftarrow \Phi_i^+ + F_{ij} \cdot (n-1)^{-1}$  positive flow
17:      $\Phi_i^- \leftarrow \Phi_i^- + F_{ji} \cdot (n-1)^{-1}$  negative flow
18:   end for
19:    $\Phi_i \leftarrow \Phi_i^+ - \Phi_i^-$  net flow
20: end for
21: ranking  $\leftarrow$  sort  $\Phi$ 
22: return ranking

```

VIKOR: The VIKOR method ranks and selects alternatives by determining a compromise solution representing the closest agreement to the ideal. This method computes a utility measure for each alternative, reflecting the group utility, and a regret measure, indicating the individual regret of not achieving the ideal, to determine the rankings. VIKOR's methodological approach aligns well with the entropy-based weighting system used in the study, ensuring that the final decision reflects a balanced consideration of all relevant factors.

Algorithm 14 introduces the VIKOR method [181]. Initially, the VIKOR algorithm normalizes the decision matrix X to X' . It then identifies each criterion's best (f^+) and worst (f^-) performance values. For each alternative, the algorithm computes two metrics: S_i , the utility, calculated as the weighted sum of the distances from an alter-

native to the optimal solution, normalized by the total range of criterion values; and R_i , the regret, identifying the maximum of these normalized distances to indicate the furthest deviation from the optimal in the worst-case scenario. These measures are merged into a composite index Q_i using v , a balance coefficient to poise the overall group utility against individual regret. This paper considers a balance coefficient of 0.5 for this purpose. The final phase of VIKOR ranks the alternatives based on their Q values, effectively delineating the most from the least sustainable options.

Algorithm 14 VIKOR algorithm implementation.

```
1: Function VIKOR( $X, W$ )
2: Input:  $X, W$ 
3: Output: ranking
4:  $X' \leftarrow$  normalize  $X$  along axis 0
5:  $f^+, f^- \leftarrow \max(X'_j)$  and  $\min(X'_j)$  for each criterion  $j$  in  $m$ 
6:  $S, R \leftarrow$  vectors of zeros with size  $n$ 
7: for each alternative  $i$  in  $n$  do
8:   for each criterion  $j$  in  $m$  do
9:      $S_i \leftarrow S_i + W_j \cdot (f_j^+ - X'_{ij}) \cdot (f_j^+ - f_j^-)^{-1}$ 
10:     $R_i \leftarrow \max(R_i, W_j \cdot (f_j^+ - X'_{ij}) \cdot (f_j^+ - f_j^-)^{-1})$ 
11:   end for
12: end for
13:  $S^* \leftarrow \min(S), S^- \leftarrow \max(S)$ 
14:  $R^* \leftarrow \min(R), R^- \leftarrow \max(R)$ 
15:  $Q \leftarrow$  vector of zeros with size  $n$ 
16: for each alternative  $i$  in  $n$  do
17:    $Q_i \leftarrow v \cdot (S_i - S^*) / (S^- - S^*) + (1 - v) \cdot (R_i - R^*) / (R^- - R^*)$ 
18: end for
19: ranking  $\leftarrow$  sort  $Q$ 
20: return ranking
```

Evaluating the outcomes of these five decision-making techniques allows for assessing the design framework's robustness. Further, by examining the set of non-dominated solutions resulting from the MOO problem, this approach directly evaluates the efficacy of the NSGA-II, NSGA-III, and RVEA optimization algorithms in identifying high-quality optimums within the intricate solution space of the RCPMF problem. Consequently, this enhances the existing knowledge of their capabilities in promoting sustainable structural design and validates its integration with one or several decision-making algorithms.

8.3 Results

This section presents the outcomes of deploying optimization algorithms on the RCPMF problem and the subsequent decision-making approach. Sections 8.3.1 and 8.3.2 analyze each MOO algorithm's effectiveness in generating non-dominated solutions equivalent to highly efficient, sustainable designs. Subsequently, Section 8.3.3 delves into evaluating the MCDM problem concerning ranking optimal solutions derived from the MOO.

8.3.1 Algorithm Comparisons

The tuning process for the crossover and mutation operators within the NSGA-II algorithm was conducted methodically in two phases, with the hypervolume metric serving as the primary evaluation criterion. For the calculation of the hypervolume, each configuration was executed five times. In the initial exploratory phase, a range of η values—0.2, 0.5, and 0.9—were examined to assess their impact on offspring distribution relative to their parent solutions, applied to both the SBX and PM operators. Furthermore, the probabilities for these operators were tested across a range of values 0.01, 0.1, 0.2, and 0.3 to find a wide variety of potential settings aimed at improving the optimization efforts. This was followed by an exploitation phase considering values 0.1, 0.08, 0.06, 0.04, and 0.02. This stage aimed to find an initial setup that could support a balanced approach to exploration and exploitation in the multi-objective optimization environment.

Following the same structured approach, the tuning process was extended to the NSGA-III algorithm, adhering to the established η and probability values to ensure consistency in the evaluation. For NSGA-III, the final η value was settled at 0.5 after a comprehensive assessment, mirroring the decision-making process in NSGA-II. In the probability tuning phase, an expanded range of values—0.01, 0.03, 0.04, 0.05, 0.06, and 0.07—was investigated, ultimately selecting 0.05 as the optimal setting. Additionally, the partitioning count for determining reference directions was fixed at 12, aiming to capture a broad diversity of solution directions and thus enriching the algorithm's ability to uniformly cover the Pareto front.

The tuning methodology was applied to the RVEA algorithm, with an emphasis on the conceptual underpinnings of the parameters being adjusted. Initially, the process focused on the probability of mating between neighboring solutions, exploring values of 0.2, 0.5, and 0.8, before refining the search to 0.15, 0.2, 0.25, and 0.3 in a subsequent phase. The optimal value was determined to be 0.2, highlighting the algorithm's preference for exploiting local solution neighborhoods to enhance diversity and exploration. Similarly, the adaptation of the algorithm's convergence rate, guided

by the conceptually defined adaptation parameter, was explored through initial values of 1.0, 1.5, and 2.0, with further refinement to 2.1, 2.0, and 1.9. A final value of 2.0 was selected, underscoring the balance achieved between fast convergence and the maintenance of solution diversity over generations. The setting for the number of partitions used to determine the distribution of reference directions was maintained at 12, mirroring the approach in NSGA-III and ensuring a consistent framework for analysis. In the table shown in Table 8.4, the different configurations tested, along with the optimal values identified for each parameter, are presented.

Table 8.4: Tuning summary of NSGA-II, NSGA-III, and RVEA algorithms using hypervolume as a factor to identify the best outcome.

Algorithm	Parameter	Tested Values	Optimal Value
NSGA-II	η (SBX & PM)	0.2, 0.5, 0.9	0.5
	Probability	0.02, 0.04, 0.06, 0.08, 0.1, 0.2, 0.3	0.02
NSGA-III	η	0.2, 0.5, 0.9	0.5
	Probability	0.01, 0.03, 0.04, 0.05, 0.06, 0.07	0.05
	Partition count	-	12
RVEA	Probability of mating	0.2, 0.5, 0.8, 0.15, 0.2, 0.25, 0.3	0.2
	Adaptation parameter	1.0, 1.5, 2.0, 2.1, 2.0, 1.9	2.0
	Partition count	-	12

Table 8.5 showcases the quantitative analysis of the non-dominated solutions generated by the NSGA-II, NSGA-III, and RVEA optimization algorithms for the MOO problem. It includes the specific values of the objective functions for each design, facilitating an objective assessment of each algorithm's performance based on three criteria: cost, ELCA, and SLCA.

Table 8.5: Multi-objective optimization results for each algorithm.

Algorithm	Cost (EUR)	ELCA (Point)	SLCA (mrh)
NSGA-II	5.92679×10^3	1.64259×10^3	9.04790×10^6
NSGA-II	5.69768×10^3	1.69912×10^3	9.27121×10^6
NSGA-II	5.74080×10^3	1.65304×10^3	8.96734×10^6
NSGA-III	4.78051×10^3	1.44901×10^3	7.20000×10^6
NSGA-III	4.51830×10^3	1.52920×10^3	7.65131×10^6
NSGA-III	5.03727×10^3	1.50440×10^3	7.00960×10^6
RVEA	5.23727×10^3	1.51671×10^3	8.09550×10^6
RVEA	5.19441×10^3	1.41667×10^3	8.24518×10^6
RVEA	5.34868×10^3	1.54679×10^3	8.05434×10^6

This study utilizes an adapted min–max normalization technique to address the disparities in measurement units and magnitude scales across the evaluation criteria. In this framework, the radar charts depicted in Figure 8.3 illustrate the performance of each algorithm against the three evaluation metrics, applying this normalized approach. The adjusted normalization method sets a baseline of 0.5 for the lowest value and a cap of 1 for the highest value in the dataset. In this setup, radar charts with smaller areas indicate superior performance by the algorithms. This superior performance is indicative of RCPMF designs that exhibit enhanced sustainability throughout their life cycle.

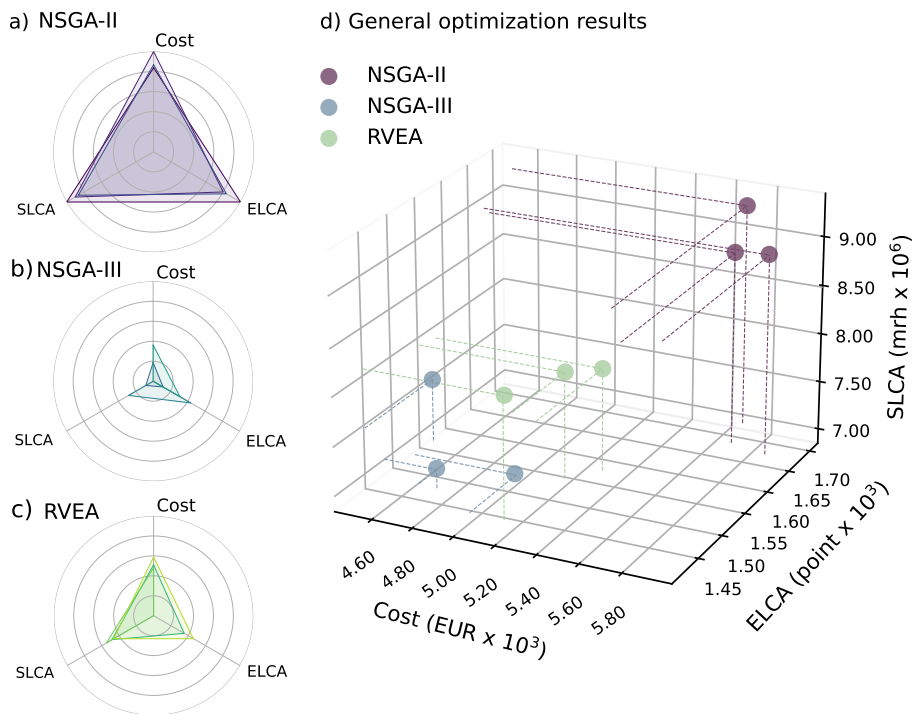


Figure 8.3: Algorithm comparison across three objective functions: a) normalized NSGA-II; b) normalized NSGA-III; c) normalized RVEA; and d) general algorithm performance in terms of cost (EUR), ELCA (point), and SLCA (mrh).

The analysis of the multi-objective optimization results, presented in Table 8.5 and Figure 8.3, underscores the performance of the NSGA-II, NSGA-III, and RVEA algorithms across three critical objectives: cost, environmental life cycle analysis (ELCA), and social life cycle analysis (SLCA). The findings are instrumental in elucidating the

algorithms' efficiencies and shortcomings in navigating the complex multi-objective landscape of sustainable infrastructure projects.

It was observed that NSGA-II consistently yielded the least favorable outcomes across all three objectives, indicating a relative underperformance in integrating cost efficiency with environmental and social sustainability metrics. In contrast, NSGA-III emerged as the most adept in minimizing costs and achieving superior SLCA outcomes compared to RVEA, suggesting a robust capability in optimizing for economic and social dimensions simultaneously. The distinction in performance between NSGA-III and RVEA became particularly pronounced when examining their ability to balance cost reduction with social sustainability, with NSGA-III demonstrating a more effective optimization pathway. Meanwhile, RVEA displayed good performance in the ELCA domain, albeit with outcomes closely rivaled by NSGA-III, highlighting its effectiveness in environmental sustainability optimization with marginally superior ELCA values. This nuanced performance profile underscores RVEA's potential in addressing environmental aspects of sustainability, albeit within a competitive margin when juxtaposed with NSGA-III.

8.3.2 Performance Indicator Analysis

This study conducted a systematic experiment to assess the performance of three multi-objective optimization algorithms: NSGA-II, NSGA-III, and RVEA. The experiment consisted of 30 separate runs, during which five points were generated for each algorithm using the same predefined parameters. This methodology allowed for the direct comparison of the algorithms' performance under fixed parameter settings. A min–max normalization procedure was applied to each function separately to ensure comparability among the results from different objective functions. This method involved standardizing the units of the variables for all data points, including those on the Pareto frontier. For each experiment, points from each algorithm were normalized by adjusting their values from the minimum to the maximum observed across the dataset. This process facilitated a consistent comparison across different optimization landscapes by transforming the varied scales into a uniform metric.

Two performance metrics were introduced to evaluate further the effectiveness of the optimization algorithms: generational distance (GD) and inverted generational distance (IGD). Both metrics quantify the quality of the solutions generated by the algorithms in terms of their convergence and diversity concerning a known Pareto frontier.

Generational distance (GD) quantifies the average Euclidean distance from each solution in a set to the nearest point in the Pareto front, reflecting the convergence of the algorithm-generated solutions. For this paper's experiment, the size of set A

was 5, representing the five points obtained in each run. The GD is calculated using Equation (8.11).

$$GD(A) = \left(\frac{1}{5} \sum_{i=1}^5 (d_i^2) \right)^{\frac{1}{2}} \quad (8.11)$$

where d_i is the Euclidean distance from the i -th solution a_i in set A to its nearest point in the Pareto front Z . Here, A and Z are defined as $A = \{a_1, a_2, \dots, a_5\}$ and $Z = \{z_1, z_2, \dots, z_{|Z|}\}$. This measure is pivotal for assessing the proximity of the obtained solutions to the ideal solutions on the Pareto front.

Inverted generational distance (IGD) inverts the generational distance and measures the distance from any point in Z , the Pareto front, to the closest point in A . For this paper's experiment, set A contained five points generated in each run. The IGD is calculated using Equation (8.12).

$$IGD(Z) = \left(\frac{1}{|Z|} \sum_{i=1}^{|Z|} (\hat{d}_i^2) \right)^{\frac{1}{2}} \quad (8.12)$$

In which $\hat{d}_i$ is the Euclidean distance (with $p = 2$) from a point z_i in the Pareto front to its nearest reference point in set A . The set A is defined as $A = \{a_1, a_2, \dots, a_5\}$, representing the solutions obtained from each run. This metric is crucial for evaluating how well the generated set of solutions covers the Pareto front.

Advantages of each metric: By incorporating both GD and IGD, this study evaluates the algorithms' ability to generate solutions that are close to and well-distributed across the ideal solution set, capturing the nuanced performance differences between the algorithms in multi-objective optimization tasks.

- **GD** is particularly useful for assessing the convergence of the generated solutions to the Pareto front. A lower GD value indicates that the algorithm-generated solutions are closer to the optimal set of solutions, suggesting better performance in terms of convergence.
- **IGD** offers insight into the convergence and diversity of the generated solutions. It shows how close the solutions are to the Pareto front and how well the solutions are distributed across the entire front. A lower IGD value signifies that the generated solutions uniformly cover the Pareto front, indicating a good spread in addition to proximity.

Table 8.6: Results of GD and IGD for various algorithms across experiments.

Experiment	GD			IGD		
	NSGA-II	NSGA-III	RVEA	NSGA-II	NSGA-III	RVEA
1	0.9664	0.1292	0.0803	0.9904	0.2348	0.3808
2	1.1340	0.1481	0.1411	1.1619	0.2332	0.3784
3	1.0045	0.1446	0.1585	1.0451	0.2529	0.4040
4	0.9965	0.1473	0.1649	1.0108	0.2353	0.3645
5	0.9698	0.1307	0.1207	1.0364	0.2456	0.3426
6	0.9280	0.1646	0.1637	1.0216	0.2630	0.3281
7	1.0534	0.1377	0.1285	1.0095	0.2308	0.3363
8	0.9312	0.1602	0.1236	0.9675	0.2456	0.3999
9	1.0279	0.1439	0.1100	1.0708	0.2088	0.3326
10	1.0039	0.0922	0.1418	1.0574	0.2283	0.3736
11	0.9841	0.1511	0.1540	0.9471	0.2505	0.3859
12	1.0160	0.1127	0.1062	1.0275	0.2276	0.4011
13	0.9124	0.1421	0.1101	0.9132	0.2248	0.3524
14	1.0595	0.1332	0.1593	1.0609	0.2242	0.3418
15	1.0723	0.1619	0.1378	1.0425	0.2533	0.3504
16	1.0322	0.1222	0.1239	1.0990	0.2283	0.3710
17	0.9758	0.1384	0.1359	0.9857	0.2270	0.3422
18	1.0865	0.1748	0.1186	1.0432	0.2433	0.3254
19	1.0100	0.1614	0.1290	0.9320	0.2634	0.3570
20	1.0245	0.1132	0.1392	1.0530	0.2236	0.3336
21	1.0509	0.0986	0.1460	1.1170	0.2397	0.3483
22	1.0935	0.1298	0.1329	1.1163	0.2362	0.3871
23	1.0668	0.1190	0.1615	1.0783	0.2398	0.4041
24	0.9923	0.1247	0.1603	1.0493	0.2368	0.3667
25	1.0751	0.1264	0.1212	1.0994	0.2288	0.3500
26	0.9908	0.0817	0.1362	1.0070	0.2435	0.3412
27	0.9587	0.1581	0.1603	0.9125	0.2582	0.4232
28	1.0647	0.1084	0.1573	1.0251	0.2343	0.3747
29	1.0590	0.1223	0.1274	1.0541	0.2556	0.3851
30	0.9676	0.1280	0.1158	0.9620	0.2351	0.3446
Mean	1.0169	0.1336	0.1355	1.0299	0.2384	0.3642
Std Dev	0.0528	0.0219	0.0203	0.0598	0.0127	0.0259
Max	1.1340	0.1748	0.1649	1.1619	0.2634	0.4232
Min	0.9124	0.0817	0.0803	0.9125	0.2088	0.3254
Median	1.0130	0.1320	0.1361	1.0395	0.2358	0.3608
Kruskal–Wallis p-value	1.29×10^{-13}			6.59×10^{-18}		

Descriptive statistics were computed, providing basic insights into the distribution of results for each algorithm to evaluate the performance of the optimization algorithms. These included the mean, standard deviation, maximum, minimum, and median values, essential for summarizing the central tendency and dispersion of the data. Furthermore, the non-parametric Kruskal–Wallis test was employed to ascertain statistically significant differences between the algorithms. This test was chosen due to its robustness in handling non-normally distributed data and its ability to compare more than two groups without assuming equal variances, making it well-suited for the ordinal data generated in this experiment.

In Table 8.6, the descriptive statistics reveal patterns in the performance of the MOO algorithms NSGA-II, NSGA-III, and RVEA. Regarding generational distance (GD), NSGA-III and RVEA display similar mean values, indicating comparable proficiency in converging to the Pareto front. This similarity is also reflected in the median and standard deviation values, suggesting consistent performance across the 30 experiments. On the other hand, a pronounced difference is observed for inverted generational distance (IGD). NSGA-III presents a substantially lower mean and median compared to RVEA, highlighting its enhanced capability to generate a diverse set of solutions that effectively span the entire Pareto front.

The non-parametric Kruskal–Wallis test was conducted to statistically affirm the differences in performance observed between the algorithms, as detailed in Table 8.6. This test is ideal for data that do not follow a normal distribution, which often happens in the case of multi-objective optimization because it compares the median values across groups without assuming data normality. The resulting p-values for both average generational distance (Avg GD) (1.29×10^{-13}) and inverted generational distance (IGD) (6.59×10^{-18}) were significantly low, leading to the rejection of the null hypothesis and confirming differences in algorithm performance. The results indicate that NSGA-III may be more effective in generating a diverse set of solutions, as demonstrated by its IGD results.

8.3.3 Multi-Criteria Decision Analysis for Structural Design Optimization

This paper comprehensively evaluates the efficacy of the NSGA-II, NSGA-III, and RVEA optimization algorithms within a structural design context. This section presents the analysis of the non-dominated solutions produced by each optimization algorithm in addressing the RCPMF challenge. Additionally, the results of deploying a comprehensive range of decision-making methods are examined to gauge the applicability of these techniques within the structural design framework and the robustness and replicability of its results, considering both optimization and MCDM perspectives.

Within this context, Table 8.7 presents the collection of optimization variables that delineate the non-dominated solutions. The configuration of passive reinforcement, encompassing aspects like diameter, the amount of bars, and separation of shear branches, is combined into an effective area A_{re} parameter. This method facilitates its interpretation, offering direct insight into the sectional properties and streamlining the comprehension of these elements.

Table 8.7: Non-dominated solution optimization variables for each optimization algorithm.

	NSGA-II			NSGA-III			RVEA		
	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9
w_d	3.89E-01	3.89E-01	4.28E-01	3.08E-01	3.01E-01	3.00E-01	3.80E-01	3.58E-01	3.54E-01
us_d	8.31E-01	8.31E-01	1.02E+00	7.84E-01	1.06E+00	8.29E-01	7.86E-01	7.53E-01	1.07E+00
ls_d	9.25E-01	9.25E-01	6.51E-01	6.01E-01	6.58E-01	7.05E-01	6.43E-01	8.29E-01	6.60E-01
A_{wli}	2.20E-03	2.20E-03	1.61E-03	2.95E-03	4.02E-03	1.21E-03	3.93E-03	3.93E-03	2.51E-03
A_{wle}	1.01E-03	1.01E-03	3.14E-03	1.21E-03	5.50E-04	1.24E-03	5.65E-04	7.07E-04	1.01E-03
A_{wui}	1.13E-03	1.13E-03	1.41E-03	2.95E-03	7.85E-04	1.41E-03	2.41E-03	2.45E-03	1.26E-03
A_{wue}	2.83E-03	2.83E-03	2.20E-03	7.07E-04	8.04E-04	1.96E-03	1.02E-03	1.88E-03	4.71E-04
A_{ub}	6.38E-03	6.38E-03	4.42E-03	4.71E-03	4.08E-03	4.42E-03	4.91E-03	3.93E-03	4.42E-03
A_{ur}	2.41E-03	2.41E-03	4.40E-03	2.41E-03	3.02E-03	4.40E-03	3.77E-03	2.81E-03	4.42E-03
A_{ut}	1.24E-03	1.24E-03	5.50E-04	8.64E-04	3.93E-04	2.01E-03	1.01E-03	6.28E-04	8.04E-04
A_{lb}	1.96E-03	1.96E-03	1.41E-03	2.45E-03	7.92E-04	1.13E-03	1.26E-03	1.88E-03	8.04E-04
A_{lr}	8.84E-03	8.84E-03	3.02E-03	7.36E-03	1.81E-03	3.42E-03	3.42E-03	1.92E-03	2.04E-03
A_{lt}	1.47E-03	1.47E-03	2.61E-03	2.01E-03	1.36E-03	8.64E-04	2.61E-03	7.85E-04	5.40E-03
A_{lc}	5.65E-04	5.65E-04	1.61E-03	3.14E-04	3.14E-04	1.88E-03	1.01E-03	7.92E-04	7.92E-04
A_{uc}	1.36E-03	1.36E-03	8.04E-04	1.61E-03	5.65E-04	9.42E-04	1.26E-03	4.52E-04	1.96E-03
A_{uv}	3.42E-03	3.42E-03	2.50E-03	1.81E-03	1.44E-03	4.68E-03	3.27E-03	5.16E-03	3.36E-03
A_{lv}	1.00E-03	8.97E-04	5.24E-03	1.08E-03	5.84E-03	8.60E-04	2.84E-03	7.67E-04	8.48E-04
lc_v	2.73E+00	2.73E+00	1.29E+00	1.08E+00	2.18E+00	1.50E+00	1.24E+00	2.02E+00	1.20E+00
lc_h	4.71E+00	4.71E+00	4.07E+00	3.57E+00	3.20E+00	3.92E+00	3.07E+00	4.43E+00	4.69E+00
uc_v	1.00E+00	1.00E+00	1.24E+00	1.27E+00	1.51E+00	1.62E+00	1.51E+00	1.15E+00	1.14E+00
uc_h	1.52E+00	1.52E+00	2.01E+00	1.51E+00	4.59E+00	4.06E+00	2.46E+00	3.53E+00	2.04E+00
wv_l	3.19E+00	3.19E+00	3.63E+00	3.03E+00	3.22E+00	3.70E+00	3.03E+00	3.06E+00	4.24E+00
lv_l	3.14E+00	2.81E+00	2.42E+00	3.67E+00	1.22E+00	2.94E+00	3.42E+00	1.07E+00	2.52E+00
ur_l	9.55E+00	9.55E+00	5.29E+00	7.95E+00	7.96E+00	7.64E+00	7.26E+00	8.58E+00	7.04E+00
lr_l	9.06E+00	9.11E+00	5.20E+00	6.69E+00	9.01E+00	5.19E+00	5.88E+00	6.15E+00	5.13E+00
c_g	3.50E+01	3.00E+01	3.50E+01	3.50E+01	2.50E+01	3.50E+01	3.50E+01	3.50E+01	2.50E+01
s_g	4.00E+02	4.00E+02	5.00E+02	5.00E+02	5.00E+02	5.00E+02	4.00E+02	5.00E+02	4.00E+02

Figure 8.4 showcases the primary geometric features of the upper and bottom slabs and the lateral walls for the structures yielded by each optimization algorithm. Across all the alternatives, optimal designs feature upper slab depths ranging between 0.75 and 1.07 m, with the RVEA algorithm exhibiting the most significant variability in its results. The NSGA-II algorithm, in particular, favors designs that incorporate wider lower slabs, reaching up to 0.93 m. This tendency towards increased lower slab depths is not as pronounced in the non-dominated solutions produced by NSGA-III and RVEA, which tend towards more moderate section depths, averaging 0.65 and 0.71 m, respectively. Despite the distinct variability observed in the designs of the

upper and lower slabs, a consistent pattern emerges among all three optimization algorithms, converging on solutions with specified lateral wall depths, thereby narrowing the variability across these sections of the RCPMF.

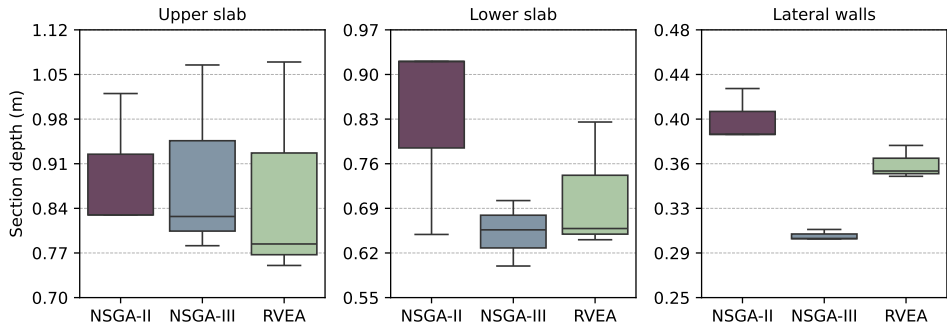


Figure 8.4: Sectional geometry comparison of the non-dominated solutions for each algorithm.

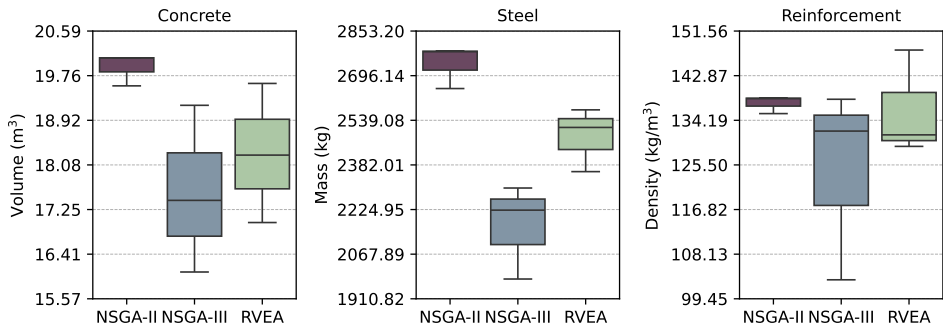


Figure 8.5: Structural material comparison of the non-dominated solutions for each algorithm.

Figure 8.5 portrays the analysis of the use of material resources for each non-dominated solution derived from the NSGA-II, NSGA-III, and RVEA optimization algorithms. Notably, the NSGA-III and RVEA algorithms lead to designs that consume less concrete. This trend correlates with the more pronounced sectional depths in solutions from NSGA-III for the RCPMF. Moreover, NSGA-III tends to converge towards designs that make more efficient use of passive reinforcement, thereby reducing the required mass of steel. In contrast, the NSGA-II algorithm exhibits less favorable outcomes in this regard, with its solutions generally demanding higher quantities of

concrete and steel resources. Despite these differences, all solutions maintain passive reinforcement densities exceeding 100 kg/m^3 . Within this spectrum, the NSGA-III algorithm trends towards solutions with somewhat lower reinforcement densities, whereas NSGA-II and RVEA display closely aligned results in terms of structural material usage.

This manuscript comprehensively evaluates the NSGA-II, NSGA-III, and RVEA algorithms, focusing on their proficiency in generating non-dominated optimal solutions within a MOO for the RCPMF design challenge. Sections 8.3.1 and 8.3.2 meticulously explored how these optimization algorithms perform against three sustainability metrics pertinent to the life cycle of the RCPMF. Previous paragraphs detailed the primary attributes of the RCPMF designs. This paper now critically assesses the design framework integrating MOO algorithms with MCDM approaches. Table 8.8 analyzes the results of deploying the SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR decision-making algorithms on the MCDM problem, explicitly focusing on ranking the non-dominated solutions generated from the MOO process.

Table 8.8: Multi-criteria decision-making for structural optimization results.

	Cost	ELCA	SLCA	Scores						Ranks			
W_j	0.33368	0.33165	0.33467	S_t^S	S_t^F	S_t^T	S_t^P	S_t^V	R_t^S	R_t^F	R_t^T	R_t^P	R_t^V
A_1	5.92E+03	1.64E+03	9.04E+06	0.9809	8.0020	0.8964	0.9014	0.9728	8	8	8	8	8
A_2	5.69E+03	1.69E+03	9.27E+06	0.9871	8.3326	0.9019	1.0000	1.0000	9	9	9	9	9
A_3	5.74E+03	1.65E+03	8.96E+06	0.9657	7.6653	0.8609	0.8657	0.8441	7	7	7	7	7
A_4	4.78E+03	1.44E+03	7.20E+06	0.8118	2.0000	0.1366	0.0840	0.0000	1	1	1	2	1
A_5	4.51E+03	1.52E+03	7.65E+06	0.8310	2.9959	0.2420	0.2834	0.2244	3	3	2	3	3
A_6	5.03E+03	1.50E+03	7.00E+06	0.8296	2.3306	0.2424	0.0000	0.1550	2	2	3	1	2
A_7	5.23E+03	1.51E+03	8.09E+06	0.8831	4.6683	0.4696	0.4801	0.3307	5	5	5	5	5
A_8	5.19E+03	1.41E+03	8.24E+06	0.8666	3.6743	0.4322	0.5462	0.2988	4	4	4	6	4
A_9	5.34E+03	1.54E+03	8.05E+06	0.8937	5.3306	0.5117	0.4619	0.4178	6	6	6	4	6

The radar plot featured in Figure 8.6 employs the modified min–max normalization technique to represent the scoring outcomes of the nine alternatives utilizing the five distinct decision-making techniques. This methodology bypasses the scoring disparities inherent to the varied algorithmic structures of these techniques. Despite their operational discrepancies, the scoring outcomes from the five decision-making approaches exhibit remarkable uniformity across all alternatives. This consistency is further observed in the correlation heatmap, which effectively highlights the strong correlation among the five decision-making techniques.

The entropy-based weighting showcases a commendable equilibrium among the three life cycle assessment metrics, underscoring the importance of cost, ELCA, and SLCA in informing the decision-making process. The scoring outcomes reveal significant similarity in how the five decision-making techniques score and rank the

alternatives, with correlation coefficients exceeding 0.94. This high correlation denotes a substantial uniformity in evaluation outcomes despite the inherent differences in each algorithm's methodology. Interestingly, this consensus is particularly pronounced among the highest and lowest-ranked alternatives, whereas the most noticeable discrepancies in ranking occur among those in the middle. This pattern suggests a decision-making framework that effectively differentiates between the most and least sustainable options, with slight variations observed among the moderately performing alternatives.

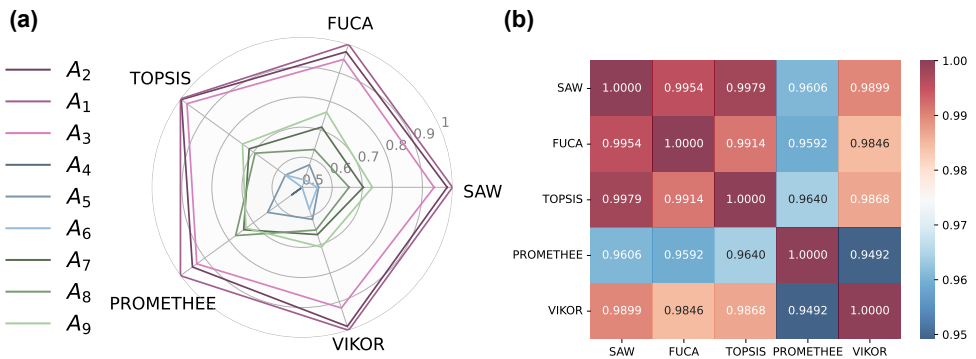


Figure 8.6: Decision-making algorithm result comparison: a) radar plot with normalized alternative scores; and b) scoring correlation across all decision-making algorithms (SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR).

Alternatives A_4 to A_6 , representing the non-dominated solutions produced by the NSGA-III algorithm, consistently emerge as the top three selections for the MCDM problem. Notably, alternative A_4 is deemed the highest-ranked RCPMF design by four decision-making techniques, with only PROMETHEE favoring A_6 as the leading option. On the other end of the spectrum, alternatives A_1 to A_3 , derived from the NSGA-II algorithm, are identified as the least favorable options. Each technique unambiguously categorizes these RCPMF designs as offering minimal life cycle sustainability benefits within highly efficient structures. This observation does not detract from their efficiency but underscores the NSGA-III's superior compatibility with the RCPMF within the outlined MOO framework. Meanwhile, the alternatives A_7 to A_9 , generated by the RVEA algorithm, occupy the intermediate positions in the ranking.

The high correlation among the outcomes derived from the five decision-making algorithms highlights the replicability and reliability of the methodology that combines MOO and MCDM within the design framework for the RCPMF challenge. This section provided an in-depth assessment of the performance of various MOO algorithms

in developing RCPMF designs that prioritize life cycle sustainability. Further, by applying a range of decision-making techniques, this analysis scrutinized the efficacy of the NSGA-II, NSGA-III, and RVEA algorithms, endorsing their incorporation into a cohesive structural design framework combining MOO and MCDM. This holistic strategy demonstrates the decision-making process's integrity, validates the integrated design framework capabilities, and extends the range of techniques available to advance sustainable structural design methodologies.

8.4 Conclusions

This paper critically evaluates the life cycle optimization performance of three optimization algorithms within a cohesive design framework that integrates for advancing sustainable transportation infrastructure. Combining MOO techniques with MCDM methodologies, this work expands upon and substantiates a systematic approach to addressing the intricate challenges in efficient structural engineering design. The investigation employs the RCPMF design problem, leveraging an array of MOO algorithms: NSGA-II, NSGA-III, and RVEA. These algorithms are enhanced with specialized crossover, mutation, and statistical-based repair operators to address the MIP nature of the MOO problem. The algorithms' performance is evaluated against life cycle sustainability metricseconomic cost, ELCA, and SLCA across every non-dominated solution. The analysis highlights the NSGA-III as the best-performing algorithm, offering a nuanced understanding of its potential to facilitate sustainable design approaches.

Following the optimization phase, the MCDM problem is rigorously evaluated, addressing nine non-dominated solutions generated by the optimization algorithms. This study utilizes a comprehensive set of decision-making techniques, including SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR, coupled with an entropy theory-based methodology for unbiased criteria weighting. This combination further enhances the framework's capabilities in identifying efficient designs. The results corroborate and expand the methods available for a cohesive MOO and MCDM design framework, demonstrating the strategy's efficiency and reliability. Such findings advocate for a transformative approach to infrastructure development, steering towards more advanced and sustainable engineering solutions.

- NSGA-III is highlighted as the most effective algorithm, with its non-dominated solutions for the RCPMF designs consistently ranked as the top three choices by all applied decision-making techniques. RVEA positions next, with its solutions ranked in the mid-range, yet exhibiting some of the best scores for life cycle sustainability metrics.

- On the other end, NSGA-II shows less favorable outcomes for RCPMF optimization within the defined framework of this study, pointing towards its limited applicability under the examined conditions. This evaluation outlines the relative performance of each algorithm, contributing valuable insights into their suitability for addressing the specific characteristics of the RCPMF problem within sustainable transportation infrastructure design.
- The analysis of performance indicators has offered insights into the potential efficacy of the NSGA-II, NSGA-III, and RVEA algorithms. Descriptive statistics, based on 30 experimental runs, suggest that NSGA-III is relatively consistent in its approach towards the Pareto front, as reflected by its similar mean and GD values when compared to RVEA. In the case of IGD, NSGA-III appears to have an edge, hinting at its capability to produce a more varied set of solutions. The Kruskal–Wallis test lends statistical support to these observations, suggesting significant differences in performance among the algorithms.
- In addressing the MCDM problem, a significant alignment is observed in the ranking of alternatives by the five decision-making algorithms despite the intrinsic differences in their algorithmic structure and scoring methodologies. This concurrence, represented by correlation coefficients from 0.94 to 0.99, underscores the robustness of the decision-making process within the integrated MOO and MCDM frameworks, demonstrating a cohesive understanding and evaluation of the alternatives' sustainability performances.
- Four out of five decision-making algorithms identified the alternative A_4 as the most sustainable design for the RCPMF over its life cycle. This design utilizes 35MPa structural concrete to construct slender lateral walls and features restrained section depths for both the upper and lower slabs. Although it does not secure the lowest values in cost, ELCA, or SLCA, the design effectively leverages B500S steel for passive reinforcement, conforming to a well-rounded design. This outcome emphasizes the necessity of an integrated approach that employs MOO to address multiple aspects of sustainability simultaneously.
- By applying and critically evaluating the design framework for the RCPMF optimization problem, this study aims to validate and expand upon a practical method for incorporating life cycle considerations right from the design phase. The findings underscore the effectiveness and reliability of combining MOO and MCDM techniques. This integrated approach aims to produce economically viable designs that excel in environmental and social sustainability across their life cycle. These solutions signify a significant stride towards embedding holistic sustainability criteria in structural design processes.

While the outcomes align with previous research and further underscore the efficacy and robustness of integrating MOO with MCDM, the authors recognize the limitations arising from the assumptions and premises articulated throughout this study. These constraints were essential to develop a comprehensive mathematical model capable of facilitating the design process, including structural calculation, constraint verification, objective function assessment, and exploration of the optimization landscape. Additionally, considering the modular nature of the structural solution, integrating factors related to supply chain and transportation challenges could lay the groundwork for further evaluating the scalability of the specific case study discussed in this paper. Given the focus on sustainable infrastructure development, the authors consider these additions a crucial direction for future research efforts. Nonetheless, these factors delineate the scope of the present investigation. Future work that delves into varied scenarios, optimization benchmarks, and data variability holds promise for refining this approach, potentially broadening its applicability and enhancing its precision in structural design optimization.

Given the observed variances in the convergence and diversity metrics among the NSGA-II, NSGA-III, and RVEA algorithms, future studies should thoroughly investigate the underlying mechanisms contributing to these differences. A detailed examination of algorithmic parameters, such as selection pressure, mutation rates, and crossover strategies, could provide insights into their impact on convergence behaviors. Additionally, exploring the interaction between these parameters and the specific problem characteristics of the RCPMF designs might reveal why certain algorithms outperform others in specific contexts. Pursuing these inquiries could lead to more tailored algorithmic adjustments that enhance performance across a broader range of optimization scenarios, optimizing the algorithms for specific types of multi-objective problems.

Chapter 9

Discussion

This PhD research investigates a novel framework for the life cycle sustainability optimization of RCPMF designs as a potential alternative to conventional cast-in-place solutions. The dissertation focuses on the application of this approach to optimize and assess precast modular solutions for transportation infrastructure. The study incorporates several single and multi-objective optimization algorithms, life cycle assessments, and decision-making strategies within the RCPMF case study.

9.1 Research Question RQ1

How effective are trajectory-based, local search and hybrid metaheuristics in generating non-traditional sustainable RCPMF designs under cost-minimization constraints?

In addressing Research Question RQ1, the research employs a mathematical model-based design approach for applying SOO algorithms targeting cost reductions for RCPMF. Chapters 2 to 4 elaborate on the application and performance evaluation of trajectory-based local search and hybrid metaheuristics for the single-objective cost-minimization of RCPMF, demonstrating the strategies' effectiveness and efficiency.

Chapter 2 elaborates on the case study of a precast modular solution for a standard road frame layout with 31 optimization variables. The SA, TA, and OBA metaheuristics are applied to the economic SOO, and the algorithm's performance is evaluated across the RCPMF final cost and post-computed CO₂ emissions. The three metaheuristics effectively converged towards non-traditional resource-efficient designs aligning economic viability with environmental sustainability. With a 1 EUR reduction in final cost preventing up to 1.96 kg of CO₂ emissions, the study identifies single-objective cost minimization as an effective avenue for optimizing resource consumption.

The SA and TA outperform the OBA, achieving cost and emissions reductions of 24.40% and 30.50% compared to a cast-in-place alternative [69]. These reductions stem from RCPMF with reduced self-weight, which lowers structural loads and enables efficient material use through slender structural designs featuring dense passive reinforcement layouts up to 91 kg/m³. Conversely, the OBA designs portrayed lower passive reinforcement density and larger section depths, leading to still significant cost and emissions reductions of 21.75% and 24.90%. The results display differences in the computational cost of generating optimal designs across the metaheuristics. SA and TA require more computational resources to achieve higher-quality solutions. In contrast, the OBA's solution quality and computational cost performance do not directly correlate, suggesting a unique operational characteristic.

In Chapter 3, the best-performing SA algorithm in Chapter 2 is hybridized with a mutation operator. The SAMO is deployed for the cost-minimization of a road frame layout with 38 optimization variables. The tuned algorithm achieves a 1% final cost reduction compared to the Pareto-optimal solution in Chapter 2 and 25% compared to the cast-in-place benchmark. The SAMO achieves these reductions within an extended mathematical model encompassing five additional design optimization variables while only incurring the 40% computational expense of the Pareto-optimal solution in Chapter 2. The results validate the hybridization as a strategy for enhancing the efficacy of the SA, achieving remarkable material efficiency.

Chapter 4 implements the mutation operator to the TA and OBA metaheuristics. The three hybrid algorithms are tuned and evaluated, and the SAMO is selected as the best-performing hybrid metaheuristic and deployed within a parametric mathematical model for the cost-minimization of 25 frame configurations with varying spans and earth cover depths. The algorithm's performance is examined through a comprehensive parametric regression analysis focusing on the final cost, CO₂ emissions and embodied energy across 225 cost-minimized solutions.

The SAMO and TAMO with higher computational expenses tend to find the solutions with minimal economic cost. However, due to the significant computational effort required, these solutions do not achieve Pareto optimality and are not deemed the most efficient alternatives in the performance evaluation of the algorithm. Nonetheless, all three hybrid metaheuristics successfully navigate the RCPMF SOO, with SAMO and TAMO outperforming OBAMO. The regression analysis on the cost-minimized designs offers relevant insights into RCPMF design, revealing that the final cost and environmental KPIs correlate strongly with the structure's horizontal span and earth cover depth, as evidenced by high R^2 values for quadratic and linear regressions.

The SA, TA and OBA metaheuristics proved effective in generating economically viable designs with enhanced environmental KPIs compared to traditional cast-in-place alternatives within a RCPMF case study encompassing 33 optimization variables. The SAMO significantly reduced computational costs when deployed to an upgraded optimization model with five additional design variables. Further testing on the SAMO, TAMO and OBAMO within a parametric optimization model encompassing 25 road frame layouts pinpointed SAMO as the most suitable hybrid algorithm, consistently yielding cost-efficient designs with reduced environmental KPIs. These outcomes comprehensively address RQ1, delineating the effectiveness and applicability of the SA, TA, OBA, SAMO, TAMO and OBAMO optimization algorithms for generating efficient RCPMF designs under single-objective cost-minimization constraints.

9.2 Research Question RQ2

Do the cost-optimized RCPMF conform to a viable alternative to cast-in-place solutions in terms of environmental and social life cycle impacts?

In investigating Research Question RQ2, the research evaluates the case study post-computed environmental KPIs in Chapter 2 for a straightforward understanding of the RCPMF environmental performance compared to a cast-in-place counterpart. The findings portray the cost-optimized RCPMF as a less polluting alternative, achieving CO₂ reductions between 24.90% and 30.76%. Recognizing the limitations of this comparison in assessing the lifecycle sustainability of cost-optimized RCPMF, the study employs ELCA and SLCA according to ISO 14040:2006 [134], [135]. This approach allows for a comprehensive comparative analysis of midpoint and endpoint sustainability impacts across several RCPMF structural layouts.

Chapter 6 elaborates on the environmental and social life cycle performance comparison of the cost-optimized RCPMF discussed in Chapter 4 and cast-in-place alternatives in Perea et al. [69]. The analysis evaluates the ELCA and SLCA midpoint and endpoint results across 25 layouts, identifying the most sustainable alternative for each configuration. ELCA midpoint results position RCPMF as the superior alternative for all layouts, with a detailed examination of GWP revealing RCPMF designs generate up to 16.98% lower CO₂ emissions than their cast-in-place counterparts. This reduction is most pronounced in layouts spanning 8 to 12 meters and buried at shallower depths. Endpoint results from ELCA further establish RCPMF as the environmentally preferable choice, indicating less impact across ecosystems, resources, and human health. The ELCA findings conclude with single-score results, affirming the precast modular solution's environmental sustainability across the 25 layouts. Notably, smaller RCPMFs buried at shallower depths achieve the most significant relative impact reductions, while modular structures over 12 meters exhibit higher absolute reductions.

The SLCA endpoint analysis presents a more complex interplay between RCPMF and RCCPF performance. Findings are congruent with Chapter 4, identifying a quadratic and linear relationship between ELCA and SLCA with the horizontal and earth cover depth, respectively. This dynamic is particularly pronounced in precast modular structures, where social life cycle impacts increase significantly for layouts extending beyond 10 meters. On average, cast-in-place alternatives exhibit lower social impact over their lifecycle than precast modular solutions. However, the data does not indicate a uniformly more socially sustainable alternative across all scenarios. Detailed examination of specific configurations shows that for spans exceeding 10 meters, cast-in-place structures are deemed more socially sustainable. In road

frames with spans within 8 to 10 meters, RCPMFs achieve reductions in social harm. Thus, cast-in-place solutions are generally highlighted as potentially more beneficial in limiting social impacts, especially for projects with larger horizontal spans.

Chapter 5 provides insight into the SLCA behaviour through the RCPMF case study optimized using the SAMO algorithm, as introduced in Chapter 3. The analysis reveals that the manufacturing phase and structural steel are responsible for most social damage throughout the RCPMF life cycle. These findings suggest that the resource-demanding manufacturing and the design choices involving high-density passive reinforcement in cost-optimized RCPMF designs concord with the SLCA findings in Chapter 6.

The post-computed environmental KPIs indicate the precast modular solution as the most sustainable alternative. The midpoint and endpoint ELCA results further emphasize the environmental benefits of RCPMF over cast-in-place counterparts across all road frame layouts. However, a complex interplay between layout-specific characteristics and SLCA endpoint results reveals no general most socially sustainable alternative. The results comprehensively address RQ2, presenting a detailed evaluation of the cost-optimized RCPMF as a viable alternative to cast-in-place solutions across environmental and social life cycle sustainability metrics for layouts spanning 8 to 10 meters. In projects requiring larger road frames spanning 12 to 16 meters, a more comprehensive and case-specific evaluation is required to ascertain whether extensive the environmental benefits achieved by the RCPMF offset the somewhat higher social ramifications.

9.3 Research Question RQ3

How does the precast modular nature of RCPMF influence the generation and distribution of environmental and social life cycle ramifications?

The research utilizes relative and absolute contribution analyses to address Research Question RQ3. The detailed examinations within Chapters 5 and 6, focusing on the ELCA and SLCA of cost-optimized RCPMFs presented in Chapters 3 and 4, characterize the structure's life cycle behaviour. The findings enable a comprehensive assessment of the influence of the precast modular nature of the RCPMF on the generation and distribution of environmental and social damage across its life cycle.

The findings underscore the manufacturing stage as the most significant contributor to the environmental and social ramifications across the RCPMF life cycle. This stage, encompassing processes from raw material extraction to delivering ready-for-assembly structural sets, stands out as a critical impact point, particularly influencing

larger precast structures with greater horizontal spans. Findings in Chapters 5 and 6 reveal that most of the total social and environmental damage throughout the life cycle is directly attributed to this stage, indicating a significant polarization towards the first phase of the structure's life cycle. The results in Chapter 6 underscore that this pattern is consistent across RCPMF and traditional cast-in-place alternatives. However, it is more accentuated in modular solutions due to the extended in-plant activities intrinsic to precast manufacturing.

The construction phase of RCPMF exhibits a marked reduction compared to traditional cast-in-place methods. This localized enhancement is attributed to the efficient assembly process of modular structural components. Despite the larger modular structures displaying higher relative contributions during manufacturing, the environmental and social impacts of the construction phase remain stable across all layouts, underscoring the efficiency of the on-site assembly process regardless of the structure's size. The analysis suggests that the primary impact of this phase is on the local community, positioning RCPMF as a preferable option in scenarios where minimizing disruption during construction is especially relevant. Furthermore, Chapters 5 and 6 elaborate on how the modular nature of RCPMF simplifies the decommissioning stage, offering easier disassembly and recycling capabilities compared to conventional demolition practices, thus enhancing the sustainability of the end-of-life stage.

In this research, modular and cast-in-place alternatives are modelled to operate similarly during the use and maintenance stage. However, the controlled RCPMF in-plant manufacturing environment enables enhanced durability of precast concrete, potentially reducing the need for surface repairs. Findings indicate that life cycle modelling could further benefit from incorporating these operational efficiencies.

The materials analysis points to structural steel as the primary material responsible for the most significant portion of social harm, notably exceeding the impact of any other material or process involved in the life cycle of the case study. The high-density passive reinforcement density of the cost-optimized RCPMF designs in Chapters 2 to 4 underscores the need for sustainable sourcing and rebar manufacturing practices.

The SLCA and ELCA analyses, encompassing midpoint and endpoint evaluations, reveal a pronounced concentration of social and environmental impacts during the RCPMF manufacturing stage. Although present in cast-in-place alternatives, this trend is more pronounced in RCPMF due to the processes intrinsic to the in-plant production of precast structural elements ready for on-site assembly. In addressing Research Question RQ3, the research thoroughly maps out the precast modular solution's unique environmental and social lifecycle attributes. The significant impact of the manufacturing stage is identified as a potential limitation, highlighting the

early stage of the RCPMF's life cycle as a critical area for implementing targeted reductions in social and environmental harm. The results reveal reduced impacts in the construction and end-of-life stages attributed to the modular system's efficient assembly and disassembly processes. Sustainable sourcing and improving steel rebar manufacturing processes are critical for mitigating the social life cycle impacts attributed to the high-density reinforcement layouts of the cost-minimized RCPMF designs.

9.4 Research Question RQ4

Can the concurrent minimization of economic, environmental, and social factors affect the RCPMF optimization outcomes?

This study addresses Research Question RQ4 by introducing a design framework incorporating multi-objective algorithms and decision-making techniques. Findings detailed in Chapters 7 and 8 facilitate a comparative analysis between optimization processes that account for life cycle sustainability and those solely focused on cost reduction, as explored in Chapters 2 to 4.

Chapters 2 to 4 analyses reveal a clear preference within single-objective optimization strategies for using 25 MPa concrete and B500S steel for passive reinforcement. This choice is uniform across designs derived from trajectory-based and hybrid algorithms targeting cost-minimization. However, a significant transition occurs in Chapters 7 and 8, where the optimization process extends to include the concurrent minimization of RCPMF cost along with ELCA and SLCA endpoint impacts. A shift towards higher-grade materials becomes apparent when employing the NSGA-II, NSGA-III, and RVEA multi-objective algorithms. The selection of 35 MPa concrete, alongside B500S and B400S steel, emerges as a preferred option for achieving a balance between cost, environmental, and social life cycle sustainability across various RCPMF designs. This evolution demonstrates the profound effect of integrating life cycle sustainability considerations into the optimization objectives, moving beyond a purely cost-driven approach towards a more holistic sustainability-oriented design philosophy. Moreover, the research indicates that although MOO-derived designs retain the slender profiles typical of SOO results, there is a noticeable increase in lower slab depths and passive reinforcement densities, particularly in those designs incorporating lower-graded steel. These observations further highlight the intricate nature of the intrinsically complex solution space of the MOO problem integrating multiple sustainability objectives.

Transitioning from SOO to MOO requires upgrading the optimization model to incorporate revised material costs and the life cycle environmental and social impacts. Factoring the unit cost differences in the optimization models into the comparison, the RCPMF designs in Chapters 7 and 8 reveal that considering all sustainability dimensions concurrently results in bearable increases in economic costs for specific modular designs, compared to the SOO outcomes discussed in Chapter 4. Furthermore, the RCPMF designs that harmonize cost with ELCA and SLCA considerations remain economically viable alternatives to conventional cast-in-place solutions.

In Chapters 7 and 8, the RCPMFs ranked as the best-performing alternatives across several decision-making approaches exhibit ELCA endpoint outcomes somewhat more severe than those of the equivalent cost-optimized structures. However, the SLCA endpoint outcomes demonstrate improved social benefits compared to the cost-optimized RCPMFs. These shifts underscore the intrinsic differences of the optimization process and potential benefits of employing MOO, which, despite leading to slightly higher environmental impacts in some cases, still result in ELCA reductions of up to 5.8% relative to conventional cast-in-place options. Crucially, MOO strategies yield lower social impacts than SOO approaches, an essential consideration for projects involving larger road frames where social impacts are a significant concern. While acknowledging economic minimization as an avenue for enhanced environmental sustainability, the findings point out the limitations of SOO in addressing social ramifications. Consequently, MOO emerges as a tool for a more inclusive optimization process, addressing a broader spectrum of sustainability issues, especially those social factors deemed pivotal for a thorough life cycle sustainability evaluation.

The research elucidates that incorporating environmental and social endpoints as optimization objectives shifts material selection away from strategies purely focused on minimizing costs. RCPMF designs that equitably consider economic, environmental, and social sustainability remain economically viable, showcasing slight increases in ELCA impacts but significant improvements in SLCA outcomes. Adopting environmental and social criteria as objective functions within the optimization process is particularly necessary for limiting social harm, an essential factor for projects involving road frames exceeding 10 meters in span. These insights pertinent to RQ4 affirm that integrating economic, environmental, and social considerations affects RCPMF optimization results, marking a shift from a cost-centric to a comprehensive sustainability-focused optimization paradigm. This broader approach maintains economic viability while optimizing material selection and structural design to balance environmental and social ramifications. Additionally, decision-making techniques emerge as crucial to objectively and systematically evaluating and ranking the op-

timal designs, further enriching the design framework approach towards achieving balanced and sustainable design solutions.

9.5 Research Question RQ5

How do evolutionary and genetic optimization algorithms perform across different decision-making strategies within a robust design framework integrating MOO and MCDM for sustainable RCPMF?

In addressing Research Question RQ5, the thesis establishes an integrated design framework that applies MOO algorithms and MCDM techniques to optimize cost, ELCA, and SLCA for RCPMF designs. Chapters 7 and 8 detail the use and performance assessment of three genetic and evolutionary algorithms for the multi-objective life cycle impact minimization applied to a RCPMF case study. The framework incorporates an entropy theory-based criteria weighting alongside five MCDM techniques to rigorously evaluate the alternatives through an objective and systematic scoring and ranking process.

Chapter 7 elaborates on the case study of a precast modular solution for a standard road frame layout with 41 optimization variables. Three NSGA-II variants are applied, each incorporating custom crossover, polynomial mutation, and distinct repair operators tailored for the MIP life cycle MOO. The study addresses the MCDM challenge by analyzing non-dominated solutions from the MOO, utilizing SAW and FUCA methodologies. Criteria weights for the MCDM are derived using entropy theory. The NSGA-II versions incorporating the random, proximity-based and statistical-based repair operators effectively converge towards non-dominated designs that balance economic viability with environmental and social sustainability. Among these, the statistical-based repair operator is highlighted as particularly effective, better aligning with the MIP characteristics of the optimization challenge.

Further analysis of the MCDM problem using SAW and FUCA techniques shows that, despite differences in scoring, both methods yield similar rankings for the alternatives. An in-depth analysis of normalized scores from each method quantifies these slight variations, indicating a high correlation coefficient of 0.9816. These findings validate the MOO optimization approach and introduce the integration of two MCDM algorithms with entropy-based weighting. This integration is crucial for objective performance evaluation and the ranking of alternatives within the comprehensive design framework.

Chapter 8 delves deeper into the efficacy of the NSGA-II algorithm, particularly when integrated with the statistical-based repair operator, and broadens the inves-

tigation by comparing its performance with that of NSGA-II and RVEA. The three multi-objective algorithms are tuned in two phases, using the hypervolume metric as the primary evaluation criterion. The non-dominated solutions resulting from MOO are further assessed using five different MCDM algorithms, all employing entropy-based criteria weighting. The decision-making results from SAW, FUCA, TOPSIS, PROMETHEE, and VIKOR decision-making algorithms underscore the NSGA-III's superior performance, followed by RVEA, with NSGA-II identified as yielding the least attractive but still sustainable solutions. When expanding the MCDM algorithms from two to five, the findings indicate that a significant alignment in ranking alternatives remains despite the differences intrinsic to the decision-making algorithms. Furthermore, the results identify correlation coefficients between 0.94 and 0.99, underscoring the reliability of the decision-making process within the integrated MOO and MCDM framework. The decision-making strategies effectively pinpoint the leading and lagging non-dominated solutions, with most ranking discrepancies observed within the intermediate performance range.

The study delineates performance variances among the NSGA-II, NSGA-III, and RVEA algorithms within a unified design framework that merges MOO and MCDM techniques. Additionally, it spotlights the differential performance of the NSGA-II algorithm when paired with various repair operators, with the statistical-based repair operator and the NSGA-III algorithm demonstrating superior efficacy across all evaluated decision-making approaches. Pertinent to RQ5, these findings underscore performance differences among optimization algorithms when applied alongside different decision-making strategies. The research confirms the robustness of these evolutionary and genetic algorithms for generating non-dominated balanced solutions within the MOO and MCDM integrated design framework. The findings underscore that different decision-making algorithms consistently yield similar rankings despite scoring and algorithmic approach variations, indicating a robust alternative evaluation process. By scrutinizing the set of non-dominated solutions from the MOO challenge, this method directly assesses the NSGA-II, NSGA-III, and RVEA algorithms' ability to pinpoint high-quality solutions within the complex RCPMF solution landscape. The findings expand the understanding of their potential to generate sustainable structural designs and highlight the significance of their integration with decision-making algorithms, enhancing the strategic depth of sustainable design optimization.

Chapter 10

Conclusions

This chapter concludes the dissertation with a structured three-step approach to encapsulate the research findings and implications. First, it offers a coherent summary of the general conclusions from the PhD research. This overview is followed by specific conclusions from the detailed analyses in research journal papers covered in Chapters 2 to 8, highlighting specific insights. The dissertation concludes with potential avenues for future research stemming from this thesis.

10.1 General Conclusions

This thesis, aimed at advancing sustainable transportation infrastructure construction, is structured into three main areas. The first section focuses on minimizing economic costs for specific RCPMF case studies and broader parametric designs using primarily SOO. Chapter 2 deploys the SA, TA and OBA metaheuristics on a RCPMF optimization problem encompassing 31 design variables. These trajectory-based local search metaheuristics successfully identify cost-efficient designs within the framework of single-objective cost minimization. Notably, the SA and TA algorithms, employing extended chain lengths, converge towards optimal solutions that markedly surpass those achieved by the OBA algorithm. Evaluating Pareto-optimality and considering case-specific application contexts of these metaheuristics is critical. This assessment must determine if the enhancements from longer chain lengths justify the significant rise in computational demands.

Chapter 3 introduces the SAMO hybrid metaheuristic applied to an extended optimization model with seven additional design variables. Integrating a population-based mutation operator into the SA algorithm significantly improves the metaheuristic's exploratory capabilities. Inducing higher variability through random mutations equips the hybrid metaheuristic with refined navigation abilities within a complex solution space. Consequently, SAMO manages to identify economically viable designs with limited computational costs, a point further underlined in Chapter 4. Proper tuning of the optimization parameters for both the SAMO and TAMO algorithms is crucial, as it substantially influences their performance potential.

Targeting cost efficiency in RCPMF design through SOO is suitable for improving environmental outcomes. Specifically, optimizing designs for cost-effectiveness leads to more efficient use of materials, where a reduction of 1 EUR correlates with decreases in CO₂ emissions by up to 1.96 kg. The geometrical parameters that define road frames significantly affect both their cost and environmental KPIs. A quadratic relationship exists between the final cost, CO₂ emissions, embodied energy, the structural horizontal span, and a linear relationship with the depth of the earth cover within the embankment. These patterns are linked to the quadratic and linear increases in

structural loads and internal stress resulting from extending the horizontal span or increasing the burial depth. The cost-minimized designs share material selection and sectional geometry characteristics, with a combination of lower-grade concrete and higher-grade steel emerging as the cost-effective choice for slender structures featuring dense passive reinforcement layouts.

The second core of the thesis, detailed in Chapters 5 and 6, expands the discussion to include environmental and social sustainability. This comprehensive analysis covers the entire life cycle, employing SLCA and ELCA for extensive parametric evaluations. The comparison between the life cycle impacts of cost-optimized RCPMF and traditional cast-in-place solutions proves effective for identifying sustainable alternatives among various road frame configurations. Within the 25 structural layouts examined in Chapter 4, RCPMFs are identified as more environmentally sustainable alternatives. While the environmental advantages of choosing modular solutions over cast-in-place options are more pronounced in smaller structures, the absolute differences become significant in larger layouts. In every environmental endpoint category assessed, the precast modular solution outperforms the cast-in-place alternative, underscoring that cost-optimization benefits economic performance and enhances environmental outcomes, as evidenced through post-computed KPIs and substantiated across the life cycle via ELCA.

The assessment of social impacts presents a more nuanced scenario, not distinctly identifying an overall more sustainable alternative. For smaller structures, particularly those spanning 8 to 10 meters, RCPMFs demonstrate slightly reduced social ramifications, suggesting an advantage in these scenarios. However, for spans exceeding 12 meters, the cast-in-place method emerges as the superior option in terms of social performance. These findings highlight the importance of adopting a comprehensive approach to RCPMF design optimization. While SOO targeting cost minimization leads to environmentally beneficial designs, it falls short in addressing social sustainability throughout the lifecycle of road frames. Additionally, the parametric analysis emphasizes the need for an objective and systematic decision-making process for sustainable transportation infrastructure. Within this context, evaluating whether the economic and environmental gains sufficiently counterbalance the social impacts is crucial for informed decision-making in specific project contexts, locations, or temporal circumstances.

The analysis of life cycle stage contributions reveals a significant emphasis on the initial phases of the RCPMF life cycle, a trend evident in both environmental and social impact assessments across all LCA endpoint categories. The ELCA, in particular, demonstrates that the impact's focus on the manufacturing stage becomes increasingly pronounced as the structure sizes grow. This heightened impact is primarily due to the extended processes required to produce ready-for-assembly structural compo-

nents, which necessitate in-plant precasting activities. Thus, targeting enhancements in precast manufacturing processes is a crucial area for potential improvement. In contrast, the construction and end-of-life phases for RCPMF are markedly facilitated by the modular structure's ease of assembly and disassembly. Unlike cast-in-place alternatives, where construction impact escalates with structure size, the impact for modular solutions remains consistently low across various layouts, a pattern that extends to the decommissioning phase. This process stability positions RCPMF as a compelling choice for projects where minimizing disruption during construction and decommissioning is critical. Consequently, the in-plant precasting's controlled environment emerges as ripe for strategies to boost operational efficiency or reduce energy consumption, further enhancing the life cycle sustainability profile of RCPMF designs.

Chapter 5 underlines that steel, especially in dense passive reinforcement layouts standard to cost-optimized structures, is the primary contributor to life cycle social damage. This finding, coupled with the intricate insights from the cost-optimized parametric SLCA, underscores the critical need for a multi-objective approach encompassing economic, environmental, and social factors in the optimization process. Moreover, the comprehensive evaluation of specific alternatives underscores the importance of combining MOO with decision-making techniques. These techniques are essential for an objective and systematic assessment of the MCDM problem, facilitating a balanced consideration of all sustainability aspects in the decision-making process.

The final portion of the thesis significantly extends the research scope by focusing on reducing life cycle impacts and improving the ranking of sustainable alternatives. The research introduces a design framework that combines MOO with MCDM, rigorously tested through a case study on a standard road frame layout, as explored in Chapters 7 and 8. Within this framework, genetic and evolutionary multi-objective algorithms are adept at finding optimal designs that comply with minimizing life cycle ramifications. Notably, the statistical-based repair operator is highlighted as particularly effective in adapting to the MIP nature of the RCPMF life cycle optimization problem. The NSGA-III is the most proficient algorithm for this MOO case study across all decision-making techniques. RVEA is recognized for producing well-balanced results, while NSGA-II, though offering slightly less compelling outcomes, still contributes valuable solutions.

The entropy theory-based strategy demonstrates its applicability to objective and systematic criteria weighting. Despite the scoring differences arising from the unique characteristics of each MCDM algorithm, the decision-making techniques consistently produce similar rankings. The FUCA technique and the established SAW approach are suitable for individual and combined applications. Furthermore, in-

corporating TOPSIS, PROMETHEE, and VIKOR methods within the integrated design framework proves effective, providing a robust platform for their application and underscoring their applicability and effectiveness in enhancing the decision-making process.

MOO-generated designs share similarities with SOO outcomes regarding section geometry, exhibiting slender profiles with marginally increased lower slab depths and dense passive reinforcement. However, incorporating environmental and social considerations into the life cycle introduces a notable diversity in material selection. Unlike the uniform preference for lower-grade concrete seen in SOO results, MOO strategies frequently adopt 35 MPa concrete, balancing performance, cost, and life cycle impacts. These MOO-driven RCPMF designs retain economic competitiveness and outperform cast-in-place alternatives in environmental metrics. Integrating social factors into the optimization equation is crucial, as designs optimized for cost and environmental impact also yield social advantages. These considerations underscore the importance of embedding life cycle sustainability into the optimization framework, highlighting the comprehensive benefits of such an approach in sustainable infrastructure development.

10.2 Specific Conclusions

- For spans up to 10 meters, RCPMFs are the most sustainable solution. For greater spans, a detailed assessment of specific project contexts is essential to evaluate if the broad environmental advantages balance the somewhat increased social impacts.
- In optimal RCPMF design, single-objective cost minimization directly correlates with reductions in environmental impact. However, relying solely on post-computed environmental KPIs offers a partial view of life cycle sustainability. Therefore, integrating more complex sustainability assessments is necessary for a complete and detailed evaluation.
- In the context of single-objective RCPMF optimization, trajectory-based local search and hybrid metaheuristics are practical approaches. However, hybrid metaheuristics show superior ability to navigate the solution space. These metaheuristics, particularly those incorporating population-based mutation operators, quickly identify and converge towards cost-effective solutions.
- Most RCPMF designs originate from single-objective cost minimization, utilizing the minimally graded 25 MPa concrete in slender designs. However, when optimization algorithms simultaneously consider costs, ELCA and SLCA, a shift

occurs towards selecting higher-grade concrete. Although more costly, this selection offers environmental or social life cycle improvements.

- Within the solution space of the RCPMF optimization problem, trajectory-based local search and hybrid algorithms excel initially by swiftly identifying viable solutions and methodically progressing towards optimal designs. In contrast, population-based algorithms initially demand more computational resources to locate multiple solutions but ultimately offer superior performance in life cycle sustainability, achieving this within comparable total computational expenses.
- The design framework presented, which merges multi-objective optimization algorithms and multi-criteria decision-making techniques within a mathematical model for life cycle design, effectively identifies and ranks RCPMF compromise solutions balancing life cycle sustainability.
- Custom crossover, polynomial mutation and solution vector repair operators proficiently discretize the MIP problem. Employing a statistical method to address the mixed integer characteristics of the RCPMF yields the most effective results when integrated with evolutionary and genetic optimization algorithms.
- Although variations in algorithmic structure and operational approach result in differences in scoring, all decision-making strategies consistently rank the non-dominated RCPMF balancing life cycle sustainability. Notably, these techniques uniformly identify the leading and lagging optimum solutions, particularly when paired with an objective criteria weighting method like the entropy-based strategy.
- The manufacturing phase is critical to the life cycle sustainability of the RCPMF. Strategies aimed at enhancing controlled in-plant operations, along with material sourcing and processing, have a significant potential to positively impact the sustainability outcomes of the RCPMF.
- The construction and end-of-life stages of the RCPMF, owing to its modular design, offer environmental and social benefits that are notably significant within life cycle categories related to the construction site's location. The RCPMF is a practical choice for projects where localized disruptions during these phases could result in substantial life cycle ramifications.

10.3 Future Lines of Research

This dissertation successfully demonstrates the development and validation of an integrated design framework that merges multi-objective optimization algorithms with multi-criteria decision-making techniques. While it specifically addresses the optimization of life cycle sustainability for precast modular solutions in transportation infrastructure, the unified methodology is versatile enough to substantially improve a variety of design challenges encountered in construction and structural engineering. Moreover, with appropriate mathematical modelling and a profound technical understanding, this strategic approach holds potential for broad application across diverse engineering domains, including mechanical design, management, supply chain optimization, and process engineering.

Within this context, several potential lines of research stem from this doctoral research. A primary direction for subsequent investigations entails tackling the limitations identified throughout this dissertation. This approach includes refining the life cycle mathematical model to encompass a broader range of locations, materials, and process alternatives. Enhancing the model in this manner would broaden the applicability of the findings, enabling a focus on projects in diverse locations that operate under a variety of conditions and requirements.

The second path for future research involves broadening the spectrum of optimization algorithms applied to the mathematical model. Emerging algorithms could offer enhanced performance for mixed integer programming combinatorial optimization problems. Adapting and integrating these novel algorithms represents a valuable opportunity to advance the field of structural design optimization. Such initiatives aim to deepen our understanding of these algorithms' functionalities and operational nuances. Additionally, enriching the model with new or expanded objective functions presents a promising direction for further refining the life cycle performance of precast modular solutions, potentially leading to more sustainable and efficient design outcomes.

The third avenue extends to decision-making algorithms, considering the inclusion of Bayesian techniques and alternative criteria weighting methods. Pursuing this direction would build on the existing findings and enrich the understanding of various techniques to facilitate improved decision-making in complex engineering challenges. This research could significantly advance how engineering decisions are approached and optimized, offering a more nuanced and practical toolkit for addressing multifaceted issues.

As a final remark, this dissertation provides a comprehensive view of the logical steps taken towards designing a systematic approach for enhancing engineering practices.

As engineering professionals, we are responsible for directing our efforts toward efficient problem-solving. This responsibility involves continuous learning, adapting and integrating novel techniques to automate the simple and be able to focus on the complex. Mathematical modelling, statistical techniques, optimization and decision-making algorithms, machine learning or deep learning are some essential aptitudes we must endorse. This PhD research displays the author's efforts towards advancing the use and current understanding of how these techniques can help us improve our practices and align our efforts towards more sustainable engineering.

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