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Multi-criteria optimization for sustainability-based design of reinforced concrete frame buildings

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ABSTRACT

This paper implements the multi-criteria design optimization of three-dimensional reinforced concrete frame building structures, considering aspects such as the realistic design of the elements, including foundations within the structural assembly, or considering the soil-structure interaction. The criteria for a more comprehensive sustainable approach are related to environmental, constructive, and durability aspects. The environmental factor is measured through CO_2 emissions, considering its capture due to concrete carbonation. The use of multi-objective strategies is evident in solving the multi-criteria problem. Still, it is also proposed to formulate this problem with a single function containing all the criteria to solve it as a single-objective optimization problem. Strategies are also offered to perform multi-objective optimization based on Kriging metamodels. Several alternatives for multi-criteria decision-making are explored. The results show that multi-objective metamodel-based optimization is a good strategy for solving this problem. Alternatively, the results of the single-objective optimization of the multi-criteria problem are very satisfactory. The solutions obtained are analyzed according to the type of optimization and the decision-making criteria. Optimized solutions significantly improve the sustainability indexes compared to traditional design. Multi-criteria optimization contributes significantly to achieving these indexes. Therefore, the proposed methodology allows for the sustainable design of any reinforced concrete frame structure. It highlights the importance of integrating more encompassing formulations and advanced optimization techniques into traditional design procedures to adopt cleaner production practices in the construction sector. Finally, several promising lines of research are presented.

1. Introduction

While traditional design methods rely heavily on the designer's experience, optimization procedures can efficiently handle the immense number of solutions that can be given to a design problem. Consequently, the design optimization of structures is a field that has been gaining importance in recent years due to the need to improve the sustainability indexes of the construction sector (Pons et al., 2018). Both recycling and the use of novel building materials directly influence the improvement of these indexes (Gartner, 2004). It can also be achieved through the more rational use of these materials due to design optimization.

Measuring the sustainability of structures has been evolving, starting from essential criteria such as the economic (Carbonell et al., 2011) and incorporating others, such as environmental, to complete a series of results that give us a complete idea of how sustainable a given construction is. In addition to the two criteria above, social (Navarro et al., 2018), constructive, and durability aspects should be considered (Penadés-Plà et al., 2020). Using these five criteria makes it possible to formulate optimization problems that result in designing structures increasingly in line with today's requirements.

Reinforced concrete (RC) frame building structures represent a significant construction sector group and are associated with high economic costs and environmental impacts (Olivier et al.,). Thus, it is necessary to obtain designs that reduce the adverse effects and increase the benefits of this type of construction. The complexity of the case studies has limited previous research. Many of these focus on simple elements such as RC bridge piers (Martínez et al., 2010), columns (Medeiros and Kripka, 2014, 2016) or beams (Yepes et al., 2015). Plane RC frames are another type of structures that have been widely studied, including cases as simple as a simple frame with one bay and one level (Yeo and Potra, 2015), two bays and four levels (Paya et al., 2008) or

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two bays and six levels (Camp and Huq, 2013). However, optimization of three-dimensional structures has been limited (Mergos, 2021). Some studies have included frame buildings with several bays in both directions distributed asymmetrically (Esfandiari et al., 2018) or symmetrically reaching five (Martins et al., 2019) and six levels (Salimi et al., 2022). Another limitation of research in this field lies in supports. Many of these studies do not consider the foundations as part of the structural assembly, which is very significant in the structure's design (Negrin et al., 2023a). On the one hand, not only the consumption of materials for its construction is influential in the total impact of the structure, but also associated activities such as earthworks. On the other hand, the optimization of their design (and shape) directly influences the design of the superstructure. It is another major problem in optimizing the design of frame structures. These structures are usually modeled with rigid supports, even though, in reality, the structure's base displaces due to settlement. Therefore, the consideration of soil-structure interaction (SSI) is another limitation of the investigations developed so far, even though it has been demonstrated that its influence is highly significant in the stress redistribution of the superstructure and, therefore, of its design (Negrin et al., 2023a).

In addition to the simplicity of the analyzed structures, there are also certain limitations related to the optimization objectives. Prior studies on RC structures often focused on primary objectives, such as economic optimization (Kim and Kwak, 2022) or CO_2 emissions (Yeo and Potra, 2015). Some studies combined objectives in single objective optimization (SOO), such as economic cost with CO_2 emissions (Sahebi and Dehestani, 2023) or even with embodied energy (Negrin and Chagoyén, 2022). Others utilized multi-objective optimization (MOO) to incorporate multiple criteria, such as economic, environmental, constructive, and safety factors (Paya et al., 2008). In their study, (Tanhadoust et al., 2023) incorporate the water footprint to the economic cost as an objective measuring environmental impact. However, only some studies have fully integrated durability aspects. For instance, (Yepes et al., 2015) used MOO to consider economic, environmental, and durability criteria for an RC I-beam's service life, including CO_2 emissions and concrete carbonation phenomenon. Therefore, it can be established that combining complex actual structures with their design optimization with a global approach is not a subject that has been dealt with in depth. That is, if the case study is complex, the formulation of the optimization problem is limited. On the contrary, if the formulation is comprehensive by including several criteria that define a more sustainable approach, the problem is applied to the design of a simple case study, far from actual structures.

One of the reasons for the simplicity of the structures analyzed is that design optimization of realistic 3D RC frame structures is computationally complex and time-consuming. Professional software can be used as a structural calculation engine, but its high-fidelity simulations (HFS) are costly for the iterative optimization process. As an alternative, metamodel-assisted structural design optimization (MASDO) decreases computation time, allowing investigations of the system under analysis and making heuristic optimization procedures more accessible. Although MASDO has been applied to concrete structures such as beams (Martí-Vargas et al., 2013), wind turbine foundations (Mathern et al., 2022), and bridges (Yepes-Bellver et al., 2022), its application to 3D RC frame buildings remains limited. Common MASDO strategies for structure optimization are based on Kriging, neural networks, and polynomial regression (Penadés-Plà et al., 2019). The literature review on MASDO applied to structural engineering by (Negrin et al., 2023b) concluded that metamodels are a very efficient strategy for addressing complex optimization procedures. This study demonstrates that Kriging-type metamodels combined with the Latin Hypercube Sampling (LHS) technique to perform the design of experiments is the most used strategy in this field.

Therefore, three fundamental gaps can be discerned in the development of RC frame building design optimization. The first is the limited complexity of the case studies. The second is the formulation of the optimization problem, where most studies focus on primary objectives. Moreover, they do not go as far as implementing several objectives in a single optimization process to ensure an overall sustainable design. How these problems are solved begins to play an important role here. The third aspect is closely related to the previous one and is the difficulty of solving an exceptionally computationally expensive problem. It is also directly influenced by the first one since the complexity of the structure is crucial for the computational consumption of its model. Consequently, this paper aims to overcome these limitations by implementing a multi-criteria design optimization problem of a three-dimensional RC frame structure. As an additional novelty, it is highlighted the consideration of the foundations within the structural assembly and their corresponding interaction with the soil. The optimization problem is formulated considering environmental, constructive, and durability criteria. The environmental criterion is measured through CO_2 emissions, allowing for the concrete carbonation phenomenon. The constructive criterion is measured regarding the number of longitudinal reinforcement bars, while the durability criterion is measured by calculating the structure's service life. To "facilitate" the resolution of the problem, it is proposed to convert the MOO into a single-objective formulation to simplify the solution using an SOO algorithm. In MOO, several strategies for using Kriging-based optimization are presented. Thus, alternatives for multi-criteria decision-making (DM) in multi and SOO are explored. A parameter tuning process in MOO is performed to select the best strategy. The application of the proposed methods offers several solutions, which allow to analysis and compare different points of view related to the sustainable design of the structure.

Consequently, the organization of the paper is as follows. Section 2 explains the methodology, including the case study description, the approaches adopted to formulate the optimization problem, and the strategies to solve it. Section 3 is devoted to presenting and discussing the results. In addition, an analysis of the shortcomings of the proposed methodology, and future lines of research to overcome them, is developed. Finally, section 4 provides the conclusions.

2. Methodology

This research is based on the one carried out by Negrin et al. (2023a). Here, the design of several structures was optimized, including the case study of this work. Alternatives were explored to optimize the environmental criterion, proposing Kriging-based metamodeling strategies to accelerate the convergence of the processes with very satisfactory results. However, more than the environmental criteria up to the design stage may be required since structures impact the environment throughout their life cycle. In this research, objectives measuring performance during the structure's lifetime, such as buildability and service life (SL), are considered alongside CO_2 emissions to achieve more encompassing sustainable results. Structures that are difficult to build are more prone to construction errors, leading to premature deterioration and additional maintenance. Thus, buildability impacts long-term performance. Similarly, structures with longer SL will require less maintenance.

When dealing with multiple objectives, MOO is the typical approach, using multi-criteria DM strategies. However, since MOO is more challenging to implement, strategies are explored to convert it into a SOO problem by combining objectives into a single function. It must efficiently reflect ("a priori") the decision maker's priorities since it will only provide a single solution. Applying these new objectives introduces additional variables, such as reinforcing steel covering or configuration, which makes it necessary to explore new solutions to the problem addressed.

2.1. Problem description and special considerations

The case study is the same as the one used in (Negrin and Chagoyén, 2022; Negrin et al., 2023a), although the first did not consider the foundations and their interaction with the soil. For the modeling, analysis, and design of the structure, certain factors usually ignored by researchers are taken into account. For example, the consideration of the foundations and SSI, or the bar cutoff and detailing of longitudinal reinforcing steel (see Fig. 1). All this, even though it complicates the problem to be solved, improves alignment with reality. The use of professional software as a calculation engine (SAP2000) and its interaction with a programming language (MATLAB) through API functions allows all these factors to be considered. It also enables the automation of the process and the implementation of optimization strategies.

One of the most important aspects to highlight is the inclusion of SSI during modeling. It directly influences the design of the superstructure (Negrin et al., 2021). The structures modeled with classic supports are designed at specific points with less longitudinal reinforcement than they need. It happens due to not considering the differential settlements that exist in reality. These differential settlements, even in admissible intervals, cause the appearance of additional stresses resulting from the vertical displacement of specific points of the superstructure induced by the foundations settlements. This phenomenon is not reflected in a structure with idealized supports. Therefore, if this research considers improving the durability of RC structures, it is essential to introduce this aspect usually ignored by researchers. Designing a structure without considering these additional stresses will cause a gradual and accelerated deterioration of the structure. All this decreases the structure's durability and increase the need for extra maintenance during its life cycle, making the design optimization procedure futile (Negrin et al., 2023a).

A Winkler-type model (Klepikov, 1969; Klepikov et al., 1987) is used to consider the SSI. The soil is modeled as a linearly elastic half-space, considering the compressible thickness depth constraint, while the foundation is considered a shallow slab footing. The stiffness coefficient is calculated according to Klepikov et al. (1987). For more detailed information, see (Negrin et al., 2021, 2023a). The soil considered is a predominantly cohesive one, with a soil friction angle (FI) of 8°, cohesion (C) of 60 kPa, modulus of elasticity (E) of 12 000 kPa, and a density (γ) of 19 kN/m^3.

2.2. Formulation of the optimization problem

The problem in question is based on the single-objective formulation performed by (Negrin et al., 2023a), with the addition of new objectives and variables. The formulation is based on three objective functions: CO_2 emissions (E, see Eq. (1)), service life (SL, see Eq. (3)), and buildability, measured through the amount of longitudinal reinforcing bars (B, see Eq. (4)).

$$E = \sum_{i=1,n} e_i \times m_i(x) - C_{CO2}(x) \tag{1}$$

Here, e_i represents the unit CO_2 emissions (see Table 1), and m_i is the measures relative to the construction units as a function of the design variables (x). In this study, the CO_2 captured by the concrete surfaces during the structure's lifetime (C_{CO2}) is incorporated to the emissions calculation. It is calculated using Eq. (2), as is done in (Yepes et al., 2015) based on the predictive models of Fick's First Law of Diffusion and the Lagerblad study (Lagerblad, 2005) and Collins (2010).

$$C_{CO2} = k(x)\sqrt{SL(x)}\cdot c(x)\cdot CaO\cdot pc\cdot A(x)\cdot M \tag{2}$$

This value depends on the carbonation rate coefficient ($k(x)$), which depends on the concrete strength (see Table 2); the years of the structure's service life ($SL(x)$); the quantity of Portland cement per cubic meter of concrete ($c(x)$) (see Table 2); the CaO content in Portland cement (0.65); the proportion of calcium oxide that can be carbonated ($pc = 0.75$); the exposed surface area of concrete, which depends on the geometric variables; and the chemical molar fraction CO_2/CaO ($M = 0.79$). The SL can be measured as in Eq. (3). It is characterized by the number of years that the RC structure can last, depending on its exposure to the environment's different physical and chemical conditions. The Spanish Concrete Code (Fomento, 2008) considers that service life is the sum of corrosion initiation and its propagation (Tuutti, 1982).

Table 1
Unit CO_2 emissions for materials and activities.

Material		Units	CO_2 em (kg)
Formwork		m^2	2.53
Steel (G-60)[a]		kg	3.01
Concrete 30 MPa		m^3	279.21
Concrete 35 MPa		m^3	305.96
Concrete 40 MPa		m^3	307.06
Concrete 45 MPa		m^3	307.06
Activities			
Concrete placement	Beams	m^3	34.72
	Columns	m^3	37.20
	Found	m^3	19.84
Earthwork	Excavation	m^3	3.99
	Refill	m^3	12.80

[a] fy = 420 MPa, E = 220 GPa.

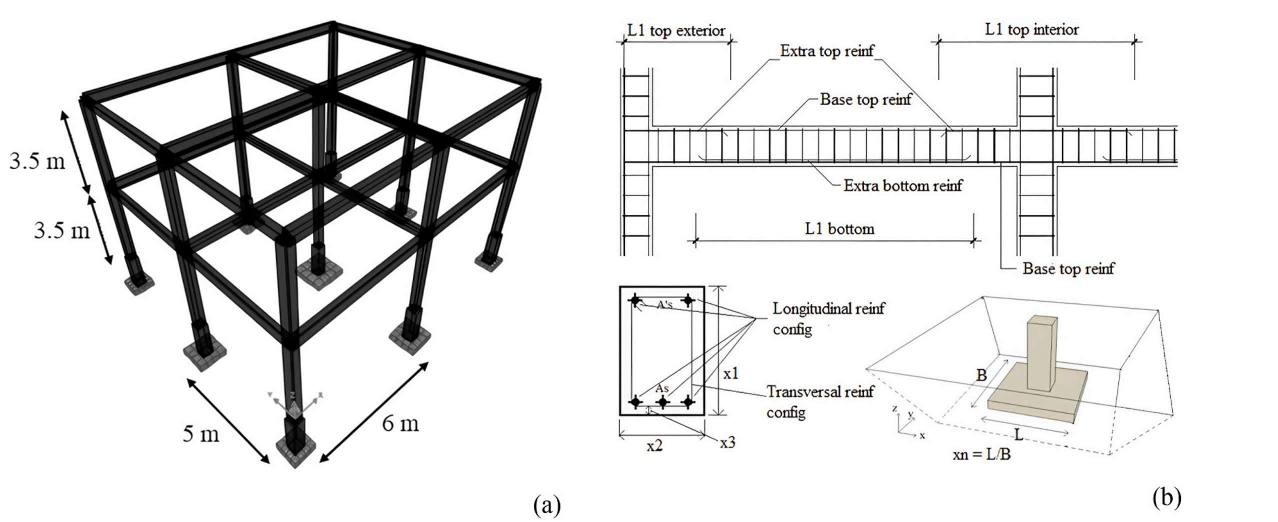

Fig. 1. (a) Case study, (b) special considerations (bars cutoff and detailing), an example of design variables ($x1$ and $x2$ are cross-sectional dimensions, $x3$ is the covering and xn is the foundation rectangularity) and a shallow foundation with an excavation scheme.

Table 2
Mix design properties and cement content.

Unit	k (mm/year$^{0.5}$)	c (kg/m^3)
Concrete 30 MPa	3.71	280
Concrete 35 MPa	3.01	300
Concrete 40 MPa	2.50	320
Concrete 45 MPa	2.11	350

$$SL(x) = \left(\frac{r(x)}{k(x)}\right)^2 + \frac{80 \cdot r(x)}{\varphi_r \cdot v_c} \tag{3}$$

Here, r is the variable reinforcing steel cover, k is the carbonation rate coefficient (mm/year$^{0.5}$) (see Table 2), $\O_r$ is the most restrictive variable for the bar diameter (mm), and v_c is the corrosion speed (2 mm/year for this case). The SL value taken is the most critical among all the elements.

It should be noted that the values represented in Table 1 are those used in previous work obtained from the 2016 database of the Institute of Construction Technology of Catalonia (ITEC BEDEC, 2016). These represent emissions produced by materials and construction activities. Fig. 2 shows a diagram representing the considerations assumed for calculating these indicators. Note how the starting point is the acquisition of raw materials, transportation to the factory, manufacturing of building materials, construction activities on site, and finally, the carbonation process of the concrete during the service life of the building. The first four elements release CO_2 into the atmosphere, while the fifth absorbs it, as calculated with Eq. (2). It is important to note that certain aspects are not included in this calculation, such as the transportation of materials/elements to the construction site, the materials and activities involved in the maintenance stages during the structure's service life, and the demolition phase of the building. In the section on future lines of research, an analysis is made on considering a more encompassing approach for future works. For more information on these considerations, refer to the related references.

Buildability is measured as the number of longitudinal reinforcing bars in the structure, as shown in Eq. (4). It is considered that the fewer bars that need to be assembled, the "easier" the structure will be to construct, and the possibility of construction errors will be reduced. The reduction of these errors ensures greater durability of the structure.

$$B(x) = Nb_{BEAMS}(x) + Nb_{COL}(x) + Nb_{FOUND}(x) \tag{4}$$

Here, Nb_{BEAMS}, Nb_{COL} and Nb_{FOUND} are the number of longitudinal reinforcing bars for beams, columns and foundations, respectively.

In addition to the 12 "basic" variables implemented by Negrin and Chagoyén (2022) (dimensions of the elements cross-sections and type of concrete), other variables related to the rectangularity of the foundations (as in Negrin et al. (2023a)), the reinforcing steel cover and its configuration are added. Variables related to foundations rectangularity (L/B, see Fig. 1) can take nine possible values representing four possibilities for each direction plus the square configuration, e.g., [0.50, 0.68, 0.75, 0.88, 1.00, 1.25, 1.50, 1.75, 2.00]. There are three variables related to this issue, one to regulate the rectangularity of each group of foundations (interior, exterior and corner). Two new variables are defined for the reinforcing covering in beams and columns. The minimum cover is 4 cm for a very aggressive environment and can increase up to 8 cm at a rate of 0.5 cm. Thus, these two variables can take nine values. The other group of variables is related to the distribution of longitudinal reinforcing steel. In previous work, the reinforcement was a dependent variable (of the cross-section dimensions), and the configuration immediately above the steel area required by design was selected. Now, to include other combinations, what is implemented is the selection of one of the five possible immediate superior solutions. For example, once the variables related to cross-sections take specific values, the required reinforcement area is calculated (e.g., 13.00 cm^2). Then, a five-element solution vector is created, containing the five immediately higher configurations that provide an area greater than the calculation one, e.g., 7ø16 representing 13.93 cm^2, 5ø19 representing 14.20 cm^2, and so on. The optimization algorithm selects one of these five solutions, and the reinforced section is then configured. In general, eight variables are implemented to regulate the reinforcement configuration in beams (one for the upper reinforcement and one for the lower for all four design groups). These groups are: (1) interior and (2) exterior beams in the x-axis direction, and (3) interior and (4) exterior ones in the y-axis direction. Additionally, three more variables are formulated for each column design group (interior, exterior, and corner). The problem is formulated with 29 design variables. The formulation of the variables can be found in more detail in (Negrin et al., 2021).

This new formulation conditions the fulfillment of some constraints that were rarely violated in previous problems, such as the ductility of beams. Increasing the covering in a cross-section reduces the mechanical arm of the reinforcing steel in tension, which will be less stressed. It may be the case that, at the failure stage, the steel in tension is not yielding. The possibility of implementing reinforcement solutions with an area of steel well above that required by design also influences this phenomenon. It makes it necessary to be particularly careful with this constraint. This type of problem holds two fundamental kinds of constraints: design (or explicit) constraints and behavioral (or implicit) ones. The first are imposed directly on the design variables and function as limits on the movement of them. The second are sometimes referred to as state equations. These constraints deal with the fulfillment of the design limit states, i.e., they define the values the variable parameters must meet to satisfy behavioral requirements. In structural optimization, the behavioral constraints are usually set by design standards. The frame structure is designed according the ACI 318–14 code. The constraints related to the strength (ultimate) limit state for RC frame elements are automatically satisfied through the API SAP2000-MATLAB platform (reinforcing steel area calculation). Constraints related to serviceability limit state accomplishment are deflections in beams, limit displacement at the top of the building, or cracking of concrete members. The way to verify these behavioral constraints is that when any of them is not fulfilled, the value of the objective function for the solution is penalized. The previously cited papers offer more information on working with constraints.

2.3. Solution of the optimization problem

Several alternatives are proposed to solve the problem. It is intended

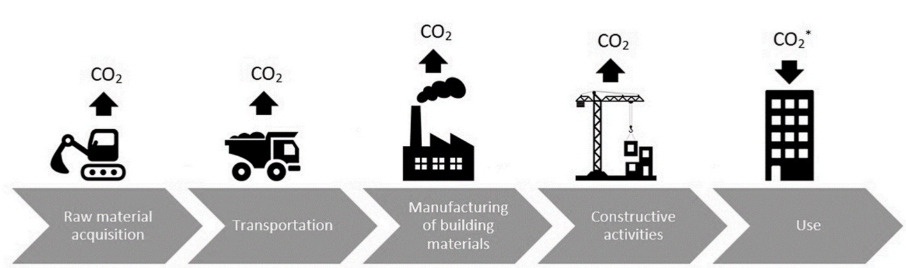

Fig. 2. Stages considered in the emissions calculation. *As the concrete is exposed to air, it absorbs CO_2 according to Eq. (2).

to combine the objectives set out in the MOO in the SOO. It is suggested since, in previous work (Negrin et al., 2023a), excellent results were obtained by applying metamodeling techniques to the SOO of this structure. Therefore, if formulating the multi-criteria problem as a single objective provides promising results, it is possible to use the previous work methodology to improve the optimization convergence. However, when several objectives are included in a single function, several aspects, such as their normalization or "a priori" DM procedures, must be considered.

On the other hand, heuristic methods, especially evolutionary strategies, are selected to solve the proposed optimization problems. It is due to their excellent adaptation to the solution of the problems where the objective function evaluations are computationally costly, as in this case. There are other more accurate methodologies, such as global solvers. However, they require many evaluations to arrive at the final solution. Alternatively, evolutionary strategies offer very competent solutions relatively quickly, which is desired in these computationally costly optimization processes. Furthermore, if, as in this study, a parameter tuning process is performed, the results are even more efficient.

2.3.1. Single, multi-objective optimization, and decision making

Implementing SOO processes with multiple criteria in a single function can be less complex and costly than MOO. To construct a function with multiple objectives, it is essential to normalize them so that each objective carries equal weight on the result. Since, in this case, the procedure is to be done in a dynamic process (optimization), normalization should be done with variable data. That is why it is suggested to normalize using the arithmetic mean of a previously defined population large enough to have a normal distribution. The normalized value is calculated by dividing the value being analyzed by the arithmetic mean of the population. The quotient is returned as a normalized value as a function of 1. The normalized values are then affected according to the implemented weight distribution assigned to each objective. If the objective is to minimize (cost), the value of the quotient is used. However, if the objective is to maximize (benefit), the opposite effect is obtained by subtracting two (2) from the quotient. Then, the normalized value decreases as the value of the objective increases. It is done with the SL (see Eq. (7)). Therefore, the function is minimized as the sum of the three normalized values of each objective decreases.

In the case of MOO, four evolutionary strategies will be used in principle: the Non-dominated Sorting Genetic Algorithm II (Deb et al., 2002) and III (Deb and Jain, 2014) (NSGA-II and III), the Pareto Envelope-based Selection Algorithm II (PESA-II) (Corne et al., 2000) and the Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler et al., 2001). These strategies are subjected to a parameter-tuning process, and the best-performing one is selected. The metric used to measure the performance of MOO algorithms is the hypervolume. In this case, the common hypervolume indicator (Zitzler and Thiele, 1999) is used, which measures the volume of the space delimited by the Pareto front and a reference point. A reference point consisting of values higher than those obtained in the case analyzed was taken. It ensures that the calculation of this indicator is correct.

2.3.1.1. Decision-making process.

To address the evaluation of the competing dimensions of sustainability in a context such as structural design, using multi-criteria decision-making (MCDM) techniques has proven to be the most appropriate approach. MCDM techniques allow the DM to evaluate complex problems involving multiple and divergent criteria (Navarro et al., 2019). It can be done based on the subjective judgments of a group of experts or stakeholders affected by the decision or simply by assigning weights based on statistical analysis. Revise the reference above for more information on applying these techniques to sustainable design.

In this work, these techniques are vital as they allow the selection of the best designs within a range of solutions that vary according to each criterion. This DM process is generally used to select one of the solutions offered by the MOO algorithm. However, converting the various objectives into a single quantifiable indicator is also a MCDM problem. For this study, several alternatives are explored. The strategies to be tested are: (1) using the same weight for each objective, (2) a 50-25-25 distribution with more weight for the environmental criterion, and (3) a distribution derived from the CRITIC method (Diakoulaki et al., 1995).

As this is the first step in the multi-criteria optimization of this type of structure, the assignment of weights is done in a reasonably simple way to understand their influence on the final result. The first two options are fundamental, which allows a better interpretation of the results. On the other hand, the CRITIC method belongs to the branch of criteria weighting methods. It was chosen because of the possibility of assigning weights without needing expert assessment to give objective importance to each criterion. In addition, this method provides some information on the behavior of the criteria and the correlation between them. It weights the criteria so that the greater the variance (higher standard deviation) and the more information different from the other criteria (lower correlation coefficient between criteria), the greater the weight. Other methods that consider a more objective criteria analysis could be more beneficial in this area. However, it should be remembered that the intention is to have a primary approach to the performance of the design results in terms of the importance given to each criterion. Future work will consider other methodologies such as Analytic Hierarchy Process (AHP) or the RANking COMparison (RANCOM) method (Więckowski et al., 2023), which additionally includes the management of expert hesitation in decision-making.

Therefore, the objective functions for the single-objective optimization are shown in Eqs. (5)–(7).

$$F_1(x) = \frac{E(x)}{Em} + \frac{B(x)}{Bm} + \left(2 - \frac{SL(x)}{SLm}\right) \tag{5}$$

$$F_2(x) = 2 * \left(\frac{E(x)}{Em}\right) + \frac{B(x)}{Bm} + \left(2 - \frac{SL(x)}{SLm}\right) \tag{6}$$

$$F_3(x) = E_{CRITIC}\left(\frac{E(x)}{Em}\right) + B_{CRITIC}\left(\frac{B(x)}{Bm}\right) + SL_{CRITIC}\left(2 - \frac{SL(x)}{SLm}\right) \tag{7}$$

Here *F1(x)*, *F2(x)*, and *F3(x)* are the functions to minimize and are formed by the terms of the three objectives *E(x)*, *B(x)*, and *SL(x)*. *Em*, *Bm* and *SLm* are the arithmetic mean of the values of emissions, buildability, and service life, respectively. In the second function, a weight distribution is being made as a function of four (2-1-1). The same is done for the third function. It is obtained by applying the CRITIC method to the population mentioned above. The normalized weights for each objective remain at 0.31–0.26-0.43, which assigns more weight to the SL. Distributing these values as a function of four, the E_{CRITIC}, B_{CRITIC}, and SL_{CRITIC} coefficients are 1.24, 1.04, and 1.72, respectively.

2.3.2. Metamodel-assisted multi-objective optimization

Conventional heuristic optimization is usually expensive, especially MOO processes. There is also the difficulty of using professional software as a calculation engine. Solving these problems is quite a time-consuming task. Therefore, an alternative strategy based on metamodels is applied to reduce the computation time significantly. In general, optimization supported by metamodels consists of constructing a surrogate model from a sample of points whose actual value is known. This surrogate model can predict the output data (objective response) from any input data (design variables) in the design space.

To select the initial sample of points to construct the metamodel (DoE), the sample size and the position of these points must be considered. On the one hand, the sample size (N) is directly related to the number of variables. Once the number of points has been selected, they must be positioned to collect as much information as possible. In this work, the *DoE* is performed through LHS, which was first proposed by McKay et al. (1979). After selecting an appropriate set of points and performing the correspondent HFS, the next step is to select a metamodel and a fitting strategy. In this study, considering that Kriging-based models are flexible and time-efficient strategies, the metamodel construction is based on the Kriging formulation and the DACE Kriging Toolbox V 2.0 (Lophaven et al., 2002a). This combination of LHS and Kriging is widely used in MASDO (Negrin et al., 2023b). A more detailed explanation of the LHS technique and Kriging formulation can be found in Penadés-Plà et al. (2019), Lophaven et al. (2002a) and Lophaven et al. (2002b).

As stated, the effectiveness of the metamodel is a function of the number of points N used to create it. It is measured in two ways. The first is through the maximum absolute percentage error (MAPE), calculated as shown in Eq. (8). It is obtained from ten n points generated using LHS. The primary objective (CO_2 emissions) is used to measure the metamodels' efficiency. A coefficient of penalization of 1.05 is used to penalize unfeasible solutions, as recommended by Negrin et al. (2023a).

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i}}{n} \times 100\% \tag{8}$$

Here, n is the number of points used for the measurement, while y_i and $\hat{y}_i$ are the actual and predicted values. Fig. 3 shows the experiment's results to test the accuracy of the metamodels created using four different values of N. Three metamodels are constructed for each value, and the MAPE is calculated as explained above. The figure shows the MAPE averages of each of the three metamodels created for each value of N. In addition, the box plots represent the distribution of the 30 errors of the 30 points generated (10 for each model). As can be seen, for N = 50, the results are unstable, although, from N = 100 onwards, they begin to be stable. Therefore, from this experiment, it can be deduced that using 100 points distributed by LHS, metamodels with reasonable accuracy are obtained.

The second way to study the N's influence depends on optimization and is measured using the hypervolume mentioned previously. For this, three strategies are designed (see Fig. 4). The first two are based on creating an appropriate metamodel to optimize it using the MOO strategy. This cloud of low-fidelity solutions obtained (Pareto front) is sorted according to the DM strategy, and some of the supposed best solutions are selected. These solutions are updated with their real value through HFS (FE analysis) to finally obtain the best solution using the DM process. As defined in the diagram, in strategy 1.1, the ten best points are selected, while in strategy 1.2, fifty are chosen.

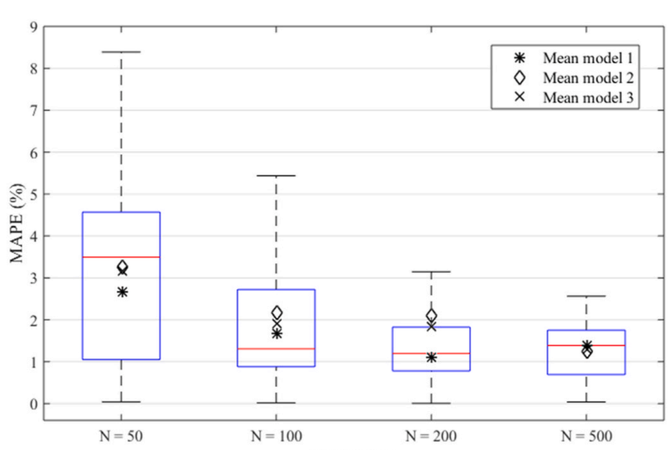

Fig. 3. Statistical analysis of the experiment to study the influence of the N value. In the box plots, bottom whisker, box bottom, middle, top and top whisker denote the minimum, 25th percentile, median, 75th percentile and maximum MAPE of each process, respectively.

On the other hand, strategy two uses both types of simulations (high and low-fidelity) in the same optimization process. Assuming that the solutions found when optimizing the metamodel (low-fidelity values) are good, the process is started in this way. After a specific number of iterations, the optimization is finished using HFS. In other words, the process is "updated" using the real model.

These strategies are compared with classical MOO regarding solution quality and computational consumption. For this, the hypervolume of the ten best points found by each is used. The quality of the best solution is also compared, as shown in the results section.

2.3.3. Parameter tuning

The first step to approaching a heuristic optimization process is to tune the parameters of the method(s) used. The strategy implemented for SOO is Biogeography-based Optimization (BBO) (Simon, 2008). It is an excellent strategy for dealing with this discrete structural optimization problem. For this case, it is not necessary to tune the BBO parameters due to the results of previous studies in which the method has been deeply studied in similar problems (Negrin et al., 2021).

However, for MOO, it is necessary to tune the four methods to make the comparison fair and to solve each optimization problem in the most efficient way possible. A full-factorial design of experiments with each method's four most important parameters is implemented. Four levels are studied for each parameter, and ten simulations are performed for each combination, making 2560 optimization processes for each of the four methods. The processes using HFS are incredibly costly, so a surrogate model is built based on the results obtained in the previous section. This model is used to replace the real one in parameter tuning processes. These low-fidelity models are less accurate but much less expensive to simulate. Moreover, they replicate in a precise way the fundamental characteristics of the high-fidelity models, as can be seen in Fig. 5, i.e., they are an excellent alternative to tuning the parameters of the optimization methods with a considerable decrease in the computational cost.

3. Results and discussion

The results and discussion section is divided into several parts. First, the parameter tuning results of the MOO methods are analyzed, and the method to be used and its configuration are selected. The second part is devoted to analyzing and discussing the optimization results, starting with studying the different metamodeling strategies in the MOO. Subsequently, the main differences between the proposed optimization strategies compared to the traditional design method and the single-criteria optimization (emissions) are presented. Also, the different results of both strategies (SOO and MOO) are compared regarding DM. Finally, the sustainable design of the structure is analyzed according to the different solutions obtained.

3.1. Parameter tuning results

Fig. 6 shows the statistical results for the five best configurations of each MOO method. The PESA-II and SPEA2 methods are the best options. However, PESA-II using its best configuration is the best option. Thus, it is selected with the following configuration: population size of 200 individuals, a crossover probability of 50% (which guarantees a mutation probability of the other 50%), the *gamma* parameter (which regulates the crossover process) with a value of 0.20 and the h parameter (in charge of regulating the mutation process) with a value of 0.40. For more information on how this strategy works, refer to the corresponding reference.

3.2. Optimization results

With the optimization strategies defined, it is proceeded to carry out the processes. The first point to be studied is using metamodels to assist

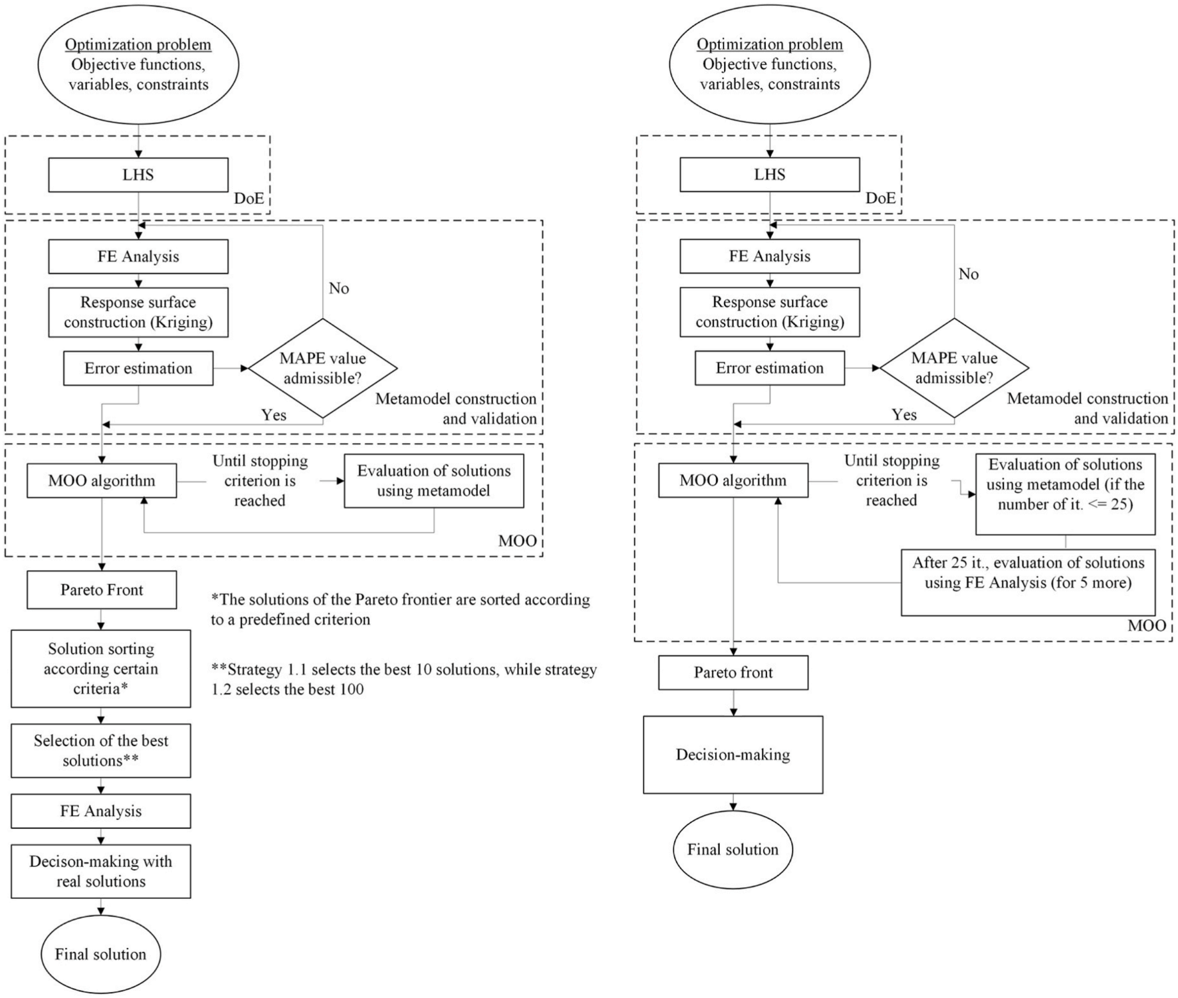

Fig. 4. Flow chart for the three proposed strategies for the use of metamodels in the MOO. Left: strategies 1.1 and 1.2. Right: strategy 2.

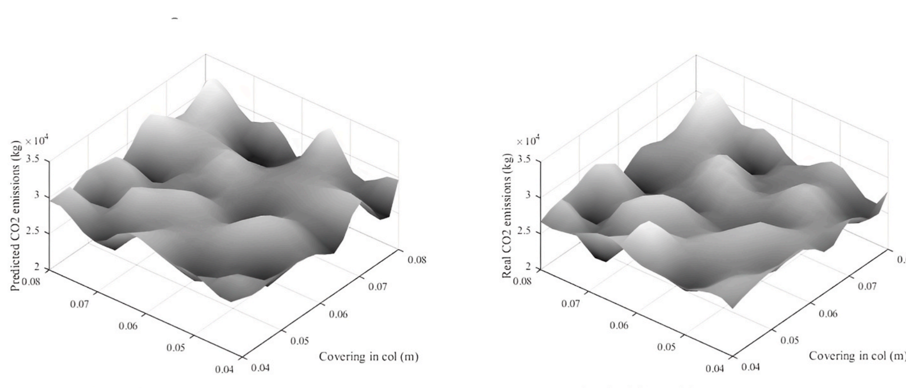

Fig. 5. Similarities of the response surfaces of metamodels (left) and real models (right).

the MOO procedures. The other results are focused on the various ways of approaching the inclusion of several criteria in the optimization problem. With the implementation of the proposed multi-criteria optimization strategies, it is possible to observe considerable improvement in the sustainability of the design of this type of structure.

3.2.1. *Implementation of metamodel-assisted optimization*

In this case, three metamodeling strategies have been proposed to assist the MOO processes. The implementation results are shown in Fig. 7 and Table 3. This figure represents an experiment to determine the influence of the N value on the quality of the metamodels. In this case, the quality is measured directly by optimizing them. The results at the top correspond to the average (of three processes) of the hypervolume calculated for the ten best solutions obtained in each strategy. Here it cannot be checked a sure consistency in terms of N values, although it can be stated that strategy 2 is the most efficient in terms of solution quality. This figure also shows each strategy's average computational consumption (of the same three processes) for each value of N. The

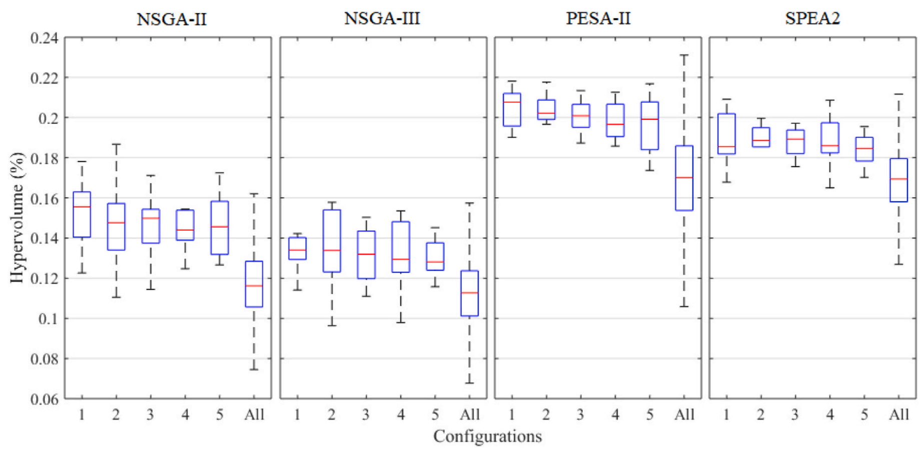

Fig. 6. Statistical results of the parameter tuning process. Box plots represent the same statistical analysis as in Fig. 3.

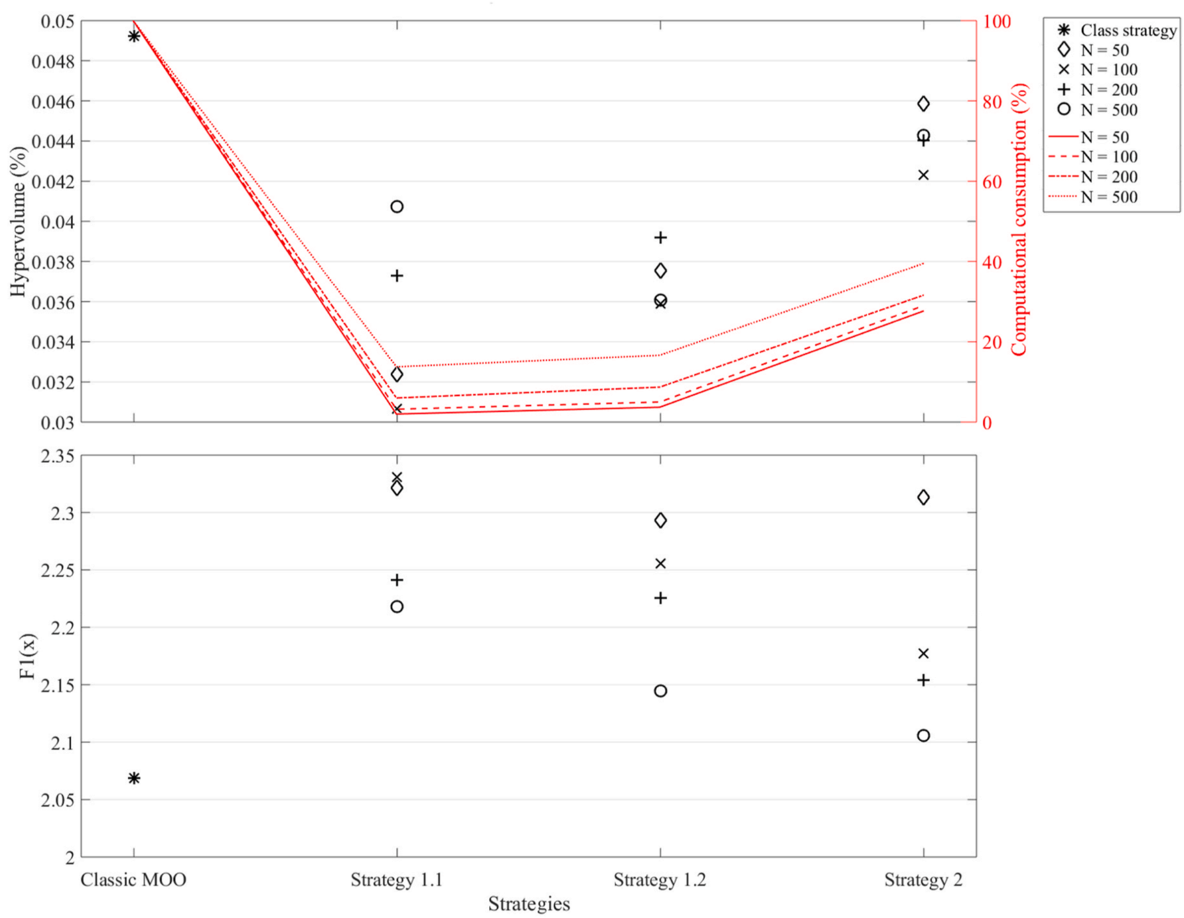

Fig. 7. Comparison of the results provided by the proposed metamodeling strategies with the classical MOO using DM 1. Top: average hypervolume value of three tests for each strategy as a function of N, and average computational consumption. Bottom: the value of the best solution obtained in the three simulations for each strategy as a function of N.

graph at the bottom goes a little further. It shows the best solution obtained (out of the three processes) using the first DM strategy (same weight for all criteria), evaluating the solutions with Eq. (5). Here, we can observe a trend in terms of N since the best solutions are obtained for 200 and 500. Considering these and the results of Fig. 3, it can be said that N = 200 would be the best alternative to build metamodels to support the optimization processes.

Table 3 shows the best solution obtained by performing the three optimization processes for each MOO type and DM strategy. In general, it can be said that the proposed metamodeling strategies are efficient, considering the computational savings involved. Strategy 1.1 seems to be inappropriate. However, strategy 1.2 yields result with an accuracy of 96.62% for DM 1, 92.93% for DM 2, and 97.42% for DM 3. These results are achieved with an average computational saving of about 90%. On the other hand, strategy 2 achieves accuracies of 98.07, 95.41, and 100% for DM 1, 2, and 3, respectively, with an average computational saving of about 70%. It is important to note that this precision is calculated from the value that measures the quality of the solution

Table 3
Results of the application of the proposed metamodeling strategies and their comparison with classical multi-objective optimization for each DM strategy.

	Strategy 1 for DM (DM 1)				Strategy 2 for DM (DM 2)				Strategy 3 for DM (DM 3)			
	CO_2 em (kg)	Build (N°B)	SL (years)	Value	CO_2 em (kg)	Build (N°B)	SL (years)	Value	CO_2 em (kg)	Build (N°B)	SL (years)	Value
Class MOO	22 666	358	1600	2.07	21 499	378	1600	2.83	21 499	378	1600	2.71
Strat 1.1	22 680	402	1560	2.22	22 705	448	1580	3.08	23 480	436	1600	2.91
Strat 1.2	22 470	391	1600	2.14	22 285	421	1560	3.03	23 317	425	1640	2.78
Strat 2	22 845	365	1580	2.11	22 645	390	1580	2.96	23 098	396	1640	2.71

according to each weighted criterion so that different solutions can have the same final value. It is the case with strategy 2 in DM 3, where the emission and buildability values are evidently of worse quality than those obtained in the classical optimization. However, this strategy gives more weight to the third criterion (SL), so the final indicator is equal.

3.2.2. Influence of optimization and decision-making

The first aspect to highlight, and the main contribution of the research, is the notable improvement in the sustainability indexes of the structure designed with an optimization process. The traditional design process was carried out using criteria usually employed by designers: beams with sections of 0.50 × 0.30 m, the column sections and the foundation footings with square configurations, the minimum allowable steel covering (4 cm), and the reinforcement configuration that provides the smallest steel area. Concrete of 30 MPa is established for the entire structure.

The optimized results tend to obtain beams of 0.55 × 0.25 m section. This beam configuration is more slender, with greater stiffness as the height increases. It means the columns receive less bending, making their design more rational. The columns tend to have mainly rectangular cross-sections. The interiors remain with their largest dimension in the direction of the smallest spans (5 m) to strengthen the horizontal stiffness in the critical direction of the wind load. The interior columns are not subjected to bending due to gravity loads since the structure is symmetrical. Therefore, its configuration is conditioned by the wind load. Exterior columns are optimally designed with sections of the largest dimension in the direction that receives the most significant deflections due to gravity loads (see Fig. 8). Corner columns are generally conformed by square cross-sections. The foundations are designed with the base of the foundation following the same criteria as the columns. As for the concrete, foundations tend to be designed with the lowest quality concrete. It is logical since they are basically bending elements, and the quality of the concrete is not very influential in their design. On the other hand, the beams also work mainly in bending. In previous works, the results were the same as for foundations: use of low-quality concrete. However, with the current approach, the opposite is obtained. It increases the element's durability since higher quality concretes offer more durable solutions. In addition, due to the large steel coverings obtained in the solutions, a higher quality concrete means a stronger compressive block, increasing the strength of the section. Columns are also generally designed with high-strength concrete. It is expected in elements that fundamentally work under axial force since, here, the quality of the concrete is a determining factor in the section's resistance. As mentioned, the solutions tend to establish reinforcement configurations with large covering to guarantee more durability. In addition, the steel solutions are only sometimes immediately superior to those required by design (as in previous studies). Now that the aim is also to reduce the number of bars, the longitudinal reinforcement is usually increased to obtain a more straightforward structure to build. All these differences are shown in Fig. 8.

All these differences between the traditional solutions and those obtained by the optimization algorithms can be seen in the values of the three criteria formulated. Table 4 and the lower graph in Fig. 9 show how all the solutions provided by the optimization (including the single-objective optimization of the emissions) significantly improve the results of the traditional design (see also Fig. 9). Compared to the single-criteria optimization solution, the environmental criterion is enhanced by 15% and the durability criterion by more than 600%. The constructive criterion is worse when only emissions are optimized. It is important to note that the constructive and durability criteria can be very arbitrary, i.e., they depend on factors that are difficult to identify by the human eye since they will not show appreciable trends. That is why their analysis by an optimization algorithm is much more efficient. Compared to the SOO solution for DM2, for example, the solution is 8% better in environmental terms, 21% better in terms of buildability, and more than 750% better in terms of durability. It is, therefore, very accurate to say

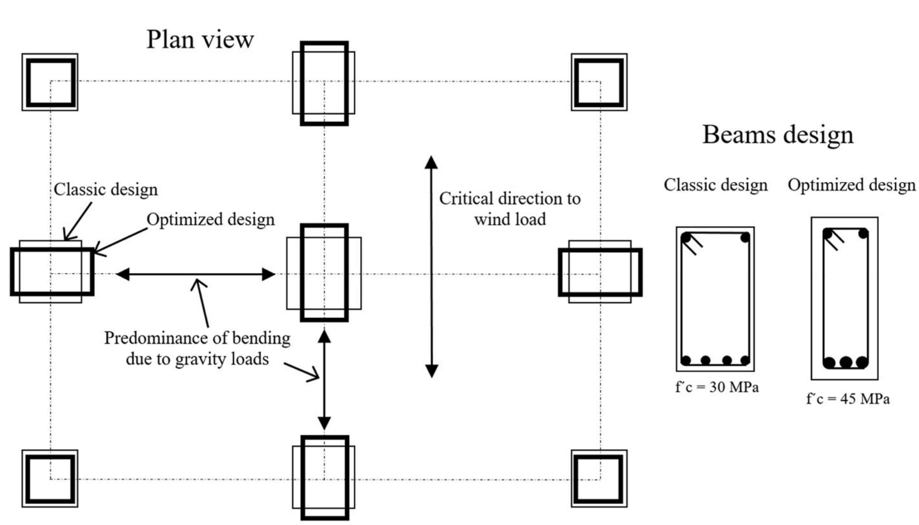

Fig. 8. Some differences between classic and optimized designs. Left: plan view (not to scale) to schematize the differences of the cross sections of the columns with a traditional (thin line) and optimized design (thick line). The base of the foundations follows the same criteria. Right: schematic (not to scale) of the classic and optimized beam designs. The cross-section shown would correspond to one in the center of the element.

Table 4
Summary of the best solutions obtained in single and multi-objective optimization for the different DM strategies. Results of the traditional design are also shown.

	Single-objective optimization			Multi-objective optimization		
	CO_2 em (kg)	Build (N°B)	SL (years)	CO_2 em (kg)	Build (N°B)	SL (years)
Trad. Design	24 145	422	215	–	–	–
CO_2 optim.	20 525	462	1420	–	–	–
DM 1	22 493	329	1560	22 666	358	1600
DM 2	22 214	335	1640	21 499	378	1600
DM 3	23 239	344	1640	21 499	378	1600

that design optimization, in the first place, is a far superior design method to traditional ones.

On the other hand, the superiority of multi-criteria optimization over emissions optimization can be appreciated. However, for this particular case, the results of the single-criteria optimization are acceptable. New variables have been incorporated compared to previous research formulations, opening a broader spectrum of possible solutions. Table 4 and Fig. 9 show how CO_2 optimization gives good SL results since the increase of the steel covering generally produces a decrease in emissions. It is due to the decrease of the shear reinforcing steel (reduction of the length of the stirrups, see Fig. 8), even when the amount of longitudinal reinforcement increases. The consideration of realistic aspects such as obtaining real reinforcement (discrete) solutions means that often the increase of the reinforcement cover (decrease of the mechanical arm of the longitudinal reinforcing steel, which causes a change in the required design area) does not cause changes in the real solution. In contrast, the shear reinforcement is always affected due to the continuous decrease of the stirrup length. Another aspect such as the cutoff of longitudinal reinforcing bars, which reduces the total volume of this type of steel, causes it to lose prominence to the shear reinforcement. The buildability results could be better compared to those obtained in the multi-criteria optimization, although, in general, the solution seems efficient.

Other aspects of relevance dealt with in the paper are related to the influence of DM strategies in multi-criteria optimization and the possibility of converting a MOO problem into a SOO one. Table 4 summarizes the best solutions for each type of formulation according to the criteria for DM. When comparing the multi-criteria optimization using the single and multi-objective formulation, the former offers solutions with a tendency to improve the constructive aspects and, to a lesser extent, the SL. The SOO results of the multi-criteria problem are quite efficient.

The other comparison is based on using different DM criteria in both types of optimization. In Fig. 9, it is introduced, in addition to the values in Table 4, a series of Pareto fronts of five solutions obtained by performing MOO processes and selecting the five best solutions using the three proposed DM strategies. Here it can be seen how each strategy has a clear trend. Strategy 1 (asterisks) tends to offer intermediate solutions, with worse results than strategy 2 (crosses) for criteria 1 and 2, but better for criterion 3. Strategy 2 offers better solutions regarding emissions (as its weight distribution seeks), but also of buildability, although decreasing the quality of the third criterion, which is improved by the third strategy (circles). Overall, obtaining the lowest emissions increases the construction difficulty by 40% and decreases the SL by 13%. Getting the most straightforward structure to build is equivalent to increasing emissions by 10% and decreasing SL by 5%. The most durable structure can be achieved by combining several solutions since it does not depend on many factors. In the best case, this structure would increase emissions by 8% and make the structure 2% more difficult to build. Apparently, the solution in the SOO using DM 2 seems to be the most complete (see Fig. 9). However, selecting the best solution lies in the importance given to each criterion. Future work intends to incorporate DM methodologies that consider the weight assigned to each criterion more objectively, such as AHP or RANCOM.

It is essential to highlight the high values obtained for the SL

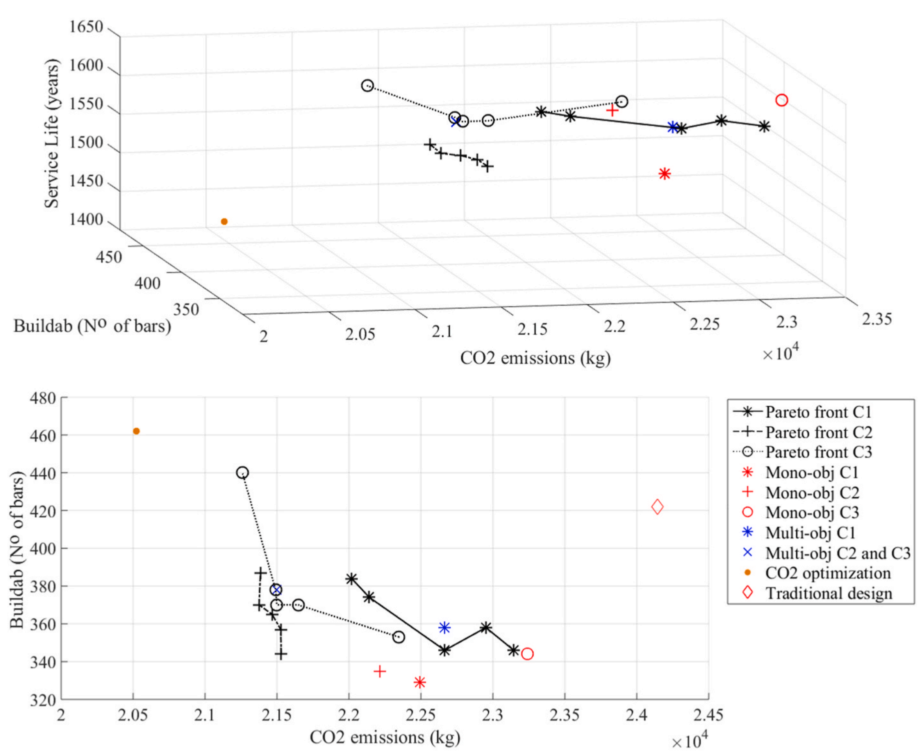

Fig. 9. Representation of significant points in the solution space. Above: three-dimensional representation. Below: representation in the XY plane (emissions and buildability). It can be seen how the representation of these points itself looks like a Pareto frontier. The outputs of the traditional design are shown only in the plane representation.

criterion. First, it must be said that these high values result from design optimization. Additionally, it is due to the formulation of the variables associated with the covering of the reinforcement bars, which start from a very high value due to the structure's location in a very aggressive environment. If it is also accounted that increasing these covering values (as far as the *ductility* constraint allows) is favorable for reducing emissions, the high SL values can be explained. It could be argued that obtaining such high values for this indicator is unnecessary. However, even though the structure is not designed for that period, the SL value is beneficial since the structure's deterioration will be very slow, even in a highly aggressive environment. The problem in obtaining these low-emission, easy-to-build, and exceptionally durable structures lies in their *ductility*. Even in the acceptable range, these sustainable structures present a low ductility, which is dangerous to deal with, for example, natural phenomena. Future work will include ductility as another criterion in optimizing RC frame structures.

Fig. 10 is a graphical representation of the solutions as a function of the elements. Note that the inverse of the SL is plotted to make the intention to minimize the three values uniform. It gives us a better overall visualization of the quality of each solution. This representation confirms that the solution provided by the SOO using DM 2 seems to be the most complete. However, this depends on the importance assigned to each criterion. The figure also shows the distribution of emissions and the number of reinforcing bars per element (beams, columns, and foundations). It allows deducing specific patterns of structure behavior according to the design obtained. One of these patterns is the importance of the beams as bending regulators in the structure. It can be seen how the increase of emissions in these elements leads to a decrease in the columns. This increase is generally associated with higher beam heights, increasing the axial load distributed to columns and foundations but decreasing bending. Columns do not "suffer" too much from this increase in axial load, but they do "appreciate" the bending decrease, meaning less reinforcement is required. In addition, regarding emissions, the foundations are the elements with the most significant values, unlike previous investigations. It is due to the inclusion of CO_2 capture in calculating total emissions, where beams and columns contribute to this phenomenon, while foundations do not. It is remarkable since these elements are usually ignored in these studies.

3.3. Research limitations and future directions

Although the proposed methodology presents several novel aspects concerning previous studies, some limitations exist. First, the formulation of this problem has a deterministic approach. Other methods consider uncertainty in a better way, which could be implemented. The optimization problem should consider additional criteria, such as the social one. Moreover, these criteria should be measured more than up to the construction stage. Although this methodology considers aspects that regulate the long-term behavior of the structure (constructive criteria, service life, concrete carbonation process), specific measurements do not consider other fundamental stages in the impact of the building. One aspect that stands out in the study is the improvement of the three criteria formulated at the expense of worsening others, such as the structure's ductility. This criterion is of particular importance for other aspects, such as seismic-resistant design, for example. Another area for improvement is the way the problem is solved. Multi-criteria decision-making methods have a basic approach, as do multi-objective optimization methods. Although promising results are obtained in multi-objective optimization assisted by Kriging metamodeling, other alternatives exist to improve the results. In addition, single-objective optimization of the multi-criteria problem proved to be a promising strategy, but using metamodels to enhance its convergence still needed to be tested. In other words, the optimization problem remains exceptionally computationally expensive, and the proposed methods can be improved. Another weakness of the study is the implementation of the proposed strategies in a single case study.

Consequently, several lines of research are proposed that added to the approach and results of this work, can provide significant contributions to the sustainable design of structures not only in concrete but in general.

- Formulate the problem with approaches beyond the deterministic one. Reliability-based or Robust Optimization concepts have been gaining importance and could provide more competent designs by incorporating uncertainty into their methodologies. In addition to the formulated criteria, others will provide a more globally sustainable approach. The issue of ductility should be incorporated into future works. It can be incorporated into a criterion that is gaining importance in structural engineering as the "Resilience" or "Robustness" of the constructions. Another criterion being incorporated more frequently is the social criterion, which should also be considered in the future. Finally, the criteria must be evaluated over the entire lifetime of the structure. For this Life-Cycle Analysis is a tool to be exploited. Issues such as maintenance or the end-of-life phase must be considered in the design optimization, as these also significantly influence the overall impact of the structure.
- The incorporation of new criteria requires a more efficient multi-criteria decision-making process. Methods such as AHP would be a

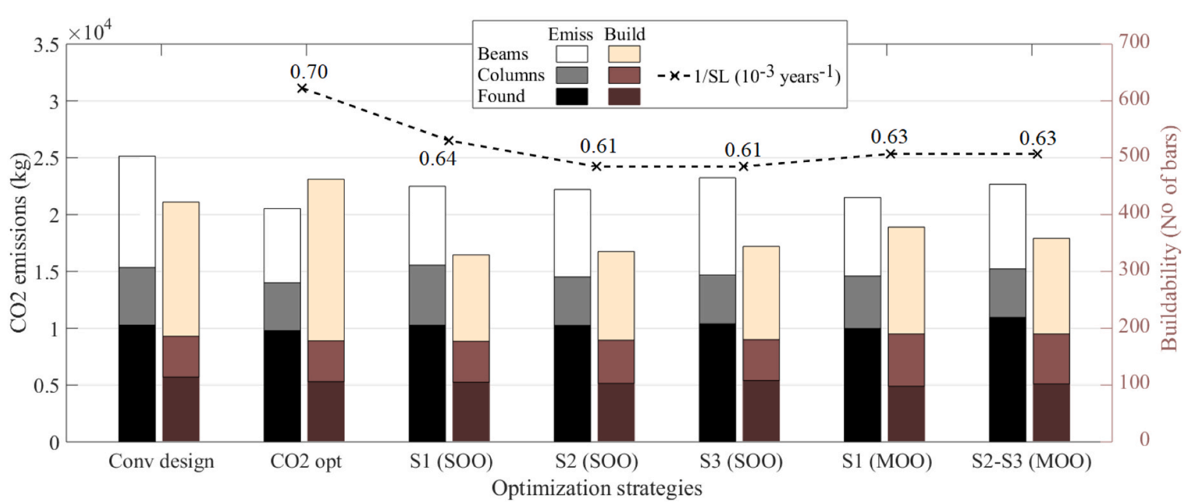

Fig. 10. Graphical representation of each solution obtained by each method. Note how the value of SL is inverted to homogenize the visual effect, i.e., low is better, and high is worse. The SL value of the conventional design is not shown for reasons of perspective.

step forward in selecting the most sustainable designs. Another method, such as RANCOM, may even be more suitable for this type of problem, as it considers experts' hesitation in decision-making. This more comprehensive approach will also require more competent optimization methods. Although classical MOO strategies offer acceptable solutions, other methods, such as those based on the Game Theory, may be more effective. Combining these with decision making-methods such as RANCOM could be a fascinating subject to develop. On the other hand, there is the possibility of combining several criteria into a single objective, as has been successfully developed in this study. It could be beneficial to reduce the number of objectives to be considered, even to the point of formulating a single-objective optimization problem. Previous work has achieved excellent results in metamodel-based optimization of similar structures, so incorporating these methodologies into this problem could be very interesting. Other metamodeling alternatives for both single and MOO should be explored.

- Another promising research line would be the application of these strategies to other case studies. Different typologies could be investigated (e.g., type "I" or "T" beams) and compared with other alternatives. Substituting beams and obtaining a slab-column typology could be a variant to explore. The comparison with typologies of other materials, such as structural steel, could be another alternative. If the case study becomes more complex, the foundation typology implemented in this study will become ineffective. Others could be suitable, such as combined footings, mat foundations, or mat-pile combinations. The comparison between the sustainability of each of these could be another exciting problem to solve.

4. Concluding remarks

This paper optimizes the design of RC frame structures, considering environmental, constructive, and durability criteria in search of a more comprehensive sustainable design approach. CO_2 emissions are considered for the environmental criterion, including the phenomenon of its capture due to concrete carbonation. Buildability is measured by the total number of longitudinal reinforcement bars, while durability is considered through the structure's service life. Implementing multi-objective optimization strategies is necessary, and Kriging-based metamodels are proposed to assist them. The objectives are converted into a single function encompassing all the criteria to give a solution using a single-objective optimization algorithm to simplify the multi-criteria formulation.

The results show that multi-objective optimization based on Kriging metamodels is a good alternative for dealing with these problems. The single-objective optimization of the functions composed of the three implemented criteria also offers excellent results, demonstrating that it is a viable alternative considering the simplicity of these processes compared to the multi-objective ones. Obtaining various solutions depending on the type of optimization and DM strategies allows us to investigate various aspects related to the sustainable design of this type of structure. In general terms, optimized designs offer much more efficient sustainability indexes compared to the traditional design method. Implementing multi-criteria optimization also offers more sustainable results than single environmental optimization. Thus, the proposed methodology not only aims the design of structures with a lower carbon footprint up to the design stage. Increasing buildability means less probability of construction errors and more outstanding durability. This last aspect is also significantly improved by directly increasing the structure's service life. Therefore, more sustainable buildings are obtained, with less negative impacts throughout their life cycle. It shows that to adopt cleaner production technologies, several criteria must be considered that define a broader concept of sustainability. On the other hand, more complex formulations mean more difficult problems to solve. Therefore, integrating advanced optimization strategies and artificial intelligence into traditional design processes is becoming increasingly necessary.

However, this research can still be improved. Promising lines of research in this field should focus on reliability-based or robust formulations. Other criteria, such as social ones, should be included. They should be measured beyond the design phase, considering the LCA. In addition, it should be considered that the solutions obtained in this research achieve excellent indexes in the criteria addressed at the expense of worsening others, such as ductility, which is very important for designing earthquake-resistant structures, for example. Therefore, ductility could be considered a constructive criterion within the multi-criteria optimization process. On the other hand, other more objective multi-criteria DM strategies can be explored, such as the AHP or the RANCOM methods. Finally, considering the high computational consumption of these processes, additional forms of metamodel-assisted optimization can be implemented.

CRediT authorship contribution statement

Iván Negrin: Conceptualization, Methodology, Software, Investigation, Formal analysis, Visualization, Writing – original draft. **Moacir Kripka:** Conceptualization, Writing – review & editing, Supervision, Project administration. **Víctor Yepes:** Conceptualization, Resources, Supervision, Project administration, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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