UNIVERSITAT POLITÈCNICA DE VALÈNCIA

HYDRAULIC AND ENVIRONMENTAL ENGINEERING DEPARTMENT

Ph.D. Programme in Water and Environmental Engineering

Ph.D. Thesis

METHODOLOGICAL DEVELOPMENT BASED ON THE ANALYSIS OF FLOW DISTRIBUTIONS TO IMPROVE THE DESIGN AND MANAGEMENT OF PRESSURIZED IRRIGATION NETWORKS FOCUSED ON IMPROVING SUSTAINABILITY.

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Abstract

Irrigation plays a vital role in productive and sustainable agriculture. In the current context, it is determined not only by water availability but also by the efficient management of resources. Several authors have attempted to measure the performance of irrigation networks through various approaches in terms of technical indicators. To promote sustainable development in the sizing of pressurized irrigation networks, models from different authors were evaluated to discuss the advantages and disadvantages to be considered in future methodologies, ensuring optimal operation of the network and improving sustainability.

To develop this methodology, the initial step will be to review the state of the art of network design methods. Once the methodology is established, the design audit will be developed by assigning indicators for design and management, quantifying their impact in terms of energy and sustainability. Finally, it will be applied to real cases and integrated as part of a tool for energy improvement in distribution systems.

This thesis presents the development of a comprehensive methodology for designing and analyzing pressurized irrigation networks, focused on optimizing flow distribution and improving technical, economic, and environmental sustainability indicators. The research is divided into several key stages, from reviewing the state of the art to applying the developed methodology.

(i) Contextualization: First, a comprehensive review of the state of the art of existing methods of irrigation network design and analysis was carried out. This analysis allowed identifying the limitations and areas for improvement in current methodologies, laying the foundations for developing an advanced analytical model.

(ii) Methodology development: In the second stage, a methodology was established to develop an analytical model capable of evaluating and optimizing flow distribution in irrigation networks. In parallel, a design audit was developed using specific design and management indicators to assess the impact of energy efficiency and sustainability. This methodology was validated through initial tests that demonstrated its robustness and adaptability.

(iii) Application to case studies: In the final stage, the developed methodology was applied to real cases using experimental data, which allowed its effectiveness to be verified in practical situations. In addition, a practical tool based on this methodology was developed and designed to facilitate the energy improvement of irrigation distribution systems.

The results obtained throughout this research were published in 3 publications in JCR-indexed journals.

The contextualization corresponds to results presented in *Publication I*, setting the foundation for the following steps and the research process. This publication highlights the importance of agronomic variables, crop patterns, weather conditions, and user interactions in accurately forecasting irrigation. It also emphasizes the need for robust sustainability indicators in irrigation practices.

The methodology development corresponded to *Publication II* and consisted of two parallel steps. The first step was establishing an analytical model development methodology for evaluating flow distributions. A multi-criteria approach was employed, incorporating various technical and environmental factors to ensure a sustainable design. The second step consisted of a design audit implementation, assigning energy and sustainability indicators to measure the impact of design decisions. Identifying areas for improvement and measuring the effects of design decisions, ultimately leading to significant material savings and CO_2 emissions reduction.

Publication II and *Publication III* contained the results for the practical applications. The methodological development was applied to the case study, and its results were contained in *Publication II*. Then, in *Publication III*, a tool for energy improvement in distribution systems was developed and applied to the case studies, thus increasing efficiency and sustainability in the case study.

The results confirm that the proposed methodology is viable and effective and significantly improves sustainability and energy efficiency in pressurized irrigation networks. This research contributes significantly to the advancement of the efficient management of water resources in agriculture, promoting more sustainable and responsible practices.

Resumen

El riego desempeña un papel vital en la agricultura productiva y sostenible. En el contexto actual, está determinado no solo por la disponibilidad de agua, sino también por la gestión eficiente de los recursos. Varios autores han intentado medir el desempeño de las redes de riego a través de diversos enfoques en términos de indicadores técnicos. En aras de impulsar el desarrollo sostenible en el dimensionamiento en redes de riego presurizadas, se evaluaron modelos de diferentes autores para discutir las ventajas y desventajas a considerar en futuras metodologías, garantizando la operación óptima de la red y mejorando la sostenibilidad.

Para el desarrollo de dicha metodología, el paso inicial será la realización de una revisión del estado del arte de los métodos de diseño de redes. Una vez establecida la metodología se desarrollará la auditoría de diseño a través de la asignación de indicadores para diseño y gestión cuantificando su impacto en términos energéticos y de sostenibilidad. Por último, se aplicará a casos reales y ser integrará como parte de una herramienta para la mejora energética en sistemas de distribución.

En esta tesis se presenta el desarrollo de una metodología integral para el diseño y análisis de redes de riego presurizadas, centrada en la optimización de la distribución de caudales y en la mejora de los indicadores de sostenibilidad técnica, económica y ambiental. La investigación se divide en varias etapas clave que abarcan desde la revisión del estado del arte hasta la aplicación práctica de la metodología desarrollada.

(i) Contextualización: Primero, se realizó una revisión exhaustiva del estado del arte de los métodos existentes de diseño y análisis de redes de riego.

Este análisis permitió identificar las limitaciones y áreas de mejora en las metodologías actuales, sentando las bases para el desarrollo de un modelo analítico avanzado.

(ii) Desarrollo metodológico: En la segunda etapa, se estableció una metodología para desarrollar un modelo analítico capaz de evaluar y optimizar la distribución de caudales en las redes de riego. Paralelamente, se desarrolló una auditoría de diseño que utiliza indicadores específicos de diseño y gestión para evaluar el impacto en términos de eficiencia energética y sostenibilidad. Esta metodología fue validada mediante pruebas iniciales que demostraron su robustez y adaptabilidad.

(iii) Aplicación a casos de estudio: En la etapa final, la metodología desarrollada fue aplicada a casos reales utilizando datos experimentales, lo que permitió comprobar su efectividad en situaciones prácticas. Además, se desarrolló una herramienta práctica basada en esta metodología, diseñada para facilitar la mejora energética de los sistemas de distribución de riego.

Los resultados obtenidos a lo largo de esta investigación fueron publicados en 3 publicaciones en revistas indexadas en JCR.

Los resultados de la contextualización se presentan en la *Publicación I*, sentando las bases para los siguientes pasos y el proceso de investigación. Esta publicación destaca la importancia de las variables agronómicas, los patrones de cultivo, las condiciones climáticas y las interacciones de los usuarios para pronosticar con precisión el riego. También enfatiza la necesidad de indicadores de sostenibilidad robustos en las prácticas de riego.

El desarrollo de la metodología correspondió a la *Publicación II* y estuvo compuesta de dos pasos paralelos. El primer paso fue establecer una metodología de desarrollo de modelos analíticos para evaluar las distribuciones de caudal. Se empleó un enfoque multicriterio, incorporando varios factores técnicos y ambientales para asegurar un diseño sostenible. El segundo paso consistió en la implementación de una auditoría de diseño, asignando indicadores de energía y sostenibilidad para medir el impacto de las decisiones de diseño. Identificando áreas de mejora y midiendo el impacto de las decisiones de diseño, lo que en última instancia condujo a un ahorro significativo de material y una reducción de emisiones de CO_2.

La *Publicación II* y la *Publicación III* contenían los resultados para las aplicaciones prácticas. El desarrollo metodológico se aplicó al estudio de caso y sus resultados se incluyeron en la *Publicación II*. Luego, en la *Publicación III*, se desarrolló una herramienta para la mejora energética en los sistemas de distribución y se aplicó a los estudios de caso, aumentando así la eficiencia y la sostenibilidad en el caso de estudio.

Los resultados obtenidos confirman que la metodología propuesta no sólo es viable y eficaz, sino que además ofrece una mejora significativa en términos

de sostenibilidad y eficiencia energética en redes de riego a presión. Esta investigación contribuye significativamente al avance de la gestión eficiente de los recursos hídricos en la agricultura, promoviendo prácticas más sostenibles y responsables.

Resum

El reg exercix un paper vital en l'agricultura productiva i sostenible. En el context actual, està determinat no sols per la disponibilitat d'aigua, sinó també per la gestió eficient dels recursos. Diversos autors han intentat mesurar l'acompliment de les xarxes de reg a través de diversos enfocaments en termes d'indicadors tècnics. A fi d'impulsar el desenrotllament sostenible en el dimensionament en xarxes de reg pressuritzades, es van avaluar models de diferents autors per a discutir els avantatges i desavantatges a considerar en futures metodologies, garantint l'operació òptima de la xarxa i millorant la sostenibilitat.

Per al desenrotllament d'esta metodologia, el pas inicial serà la realització d'una revisió de l'estat de l'art dels mètodes de disseny de xarxes. Una vegada establida la metodologia es desenrotllarà l'auditoria de disseny a través de l'assignació d'indicadors per a disseny i gestió quantificant el seu impacte en termes energètics i de sostenibilitat. Finalment, s'aplicarà a casos reals i ser integrarà com a part d'una ferramenta per a la millora energètica en sistemes de distribució.

En esta tesi es presenta el desenrotllament d'una metodologia integral per al disseny i anàlisi de xarxes de reg pressuritzades, centrada en l'optimització de la distribució de cabals i en la millora dels indicadors de sostenibilitat tècnica, econòmica i ambiental. La investigació es dividix en diverses etapes clau que abasten des de la revisió de l'estat de l'art fins a l'aplicació pràctica de la metodologia desenrotllada.

(i) Contextualització: Primer, es va realitzar una revisió exhaustiva de l'estat de l'art dels mètodes existents de disseny i anàlisi de xarxes de reg. Esta anàlisi

va permetre identificar les limitacions i àrees de millora en les metodologies actuals, establint les bases per al desenrotllament d'un model analític avançat.

(ii) Desenrotllament metodològic: En la segona etapa, es va establir una metodologia per a desenrotllar un model analític capaç d'avaluar i optimitzar la distribució de cabals en les xarxes de reg. Paral·lelament, es va desenrotllar una auditoria de disseny que utilitza indicadors específics de disseny i gestió per a avaluar l'impacte en termes d'eficiència energètica i sostenibilitat. Esta metodologia va ser validada mitjançant proves inicials que van demostrar la seua robustesa i adaptabilitat.

(iii) Aplicació a casos d'estudi: En l'etapa final, la metodologia desenrotllada va ser aplicada a casos reals utilitzant dades experimentals, la qual cosa va permetre comprovar la seua efectivitat en situacions pràctiques. A més, es va desenrotllar una ferramenta pràctica basada en esta metodologia, dissenyada per a facilitar la millora energètica dels sistemes de distribució de reg.

Els resultats obtinguts al llarg d'esta investigació van ser publicats en 3 publicacions en revistes indexades en JCR.

Els resultats de la contextualització es presenten en la *Publicació I*, establint les bases per als següents passos i el procés d'investigació. Esta publicació destaca la importància de les variables agronòmiques, els patrons de cultiu, les condicions climàtiques i les interaccions dels usuaris per a pronosticar amb precisió el reg. També emfatitza la necessitat d'indicadors de sostenibilitat robustos en les pràctiques de reg.

El desenrotllament de la metodologia va correspondre a la *Publicació II* i va estar composta de dos passos paral·lels. El primer pas va ser establir una metodologia de desenrotllament de models analítics per a avaluar les distribucions de cabal. Es va emprar un enfocament multicriteri, incorporant diversos factors tècnics i ambientals per a assegurar un disseny sostenible. El segon pas va consistir en la implementació d'una auditoria de disseny, assignant indicadors d'energia i sostenibilitat per a mesurar l'impacte de les decisions de disseny. Identificant àrees de millora i mesurant l'impacte de les decisions de disseny, la qual cosa en última instància va conduir a un estalvi significatiu de material i una reducció d'emissions de CO_2.

La *Publicació II* i la *Publicació III* contenien els resultats per a les aplicacions pràctiques. El desenrotllament metodològic es va aplicar a l'estudi de cas i els seus resultats es van incloure en la *Publicació II*. Després, en la *Publicació III*, es va desenrotllar una ferramenta per a la millora energètica en els sistemes de distribució i es va aplicar als estudis de cas, augmentant així l'eficiència i la sostenibilitat en el cas d'estudi.

Els resultats obtinguts confirmen que la metodologia proposada no sols és viable i eficaç, sinó que a més oferix una millora significativa en termes de sostenibilitat i eficiència energètica en xarxes de reg a pressió. Esta investigació contribuïx significativament a l'avanç de la gestió eficient dels recursos hídrics en l'agricultura, promovent pràctiques més sostenibles i responsables.

Contents

Chapter 1
Introduction

1.1. Motivation

More than 800 million inhabitants will be added to the current number in less than ten years, with the world's population exceeding 8.5 billion by 2030 (United Nations, 2019). These substantial increases present several challenges in meeting essential food, housing, water, and energy demands. To meet them, the United Nations (UN) estimated the need for increases of 35% in food supply, 40% in water resources, and 50% in energy to prevent the consequences of several human crises (World Economic Forum, 2013; WWDR & UN, 2014). Access to available resources is crucial in a growing demand to perform the required tasks.

Water and energy are closely linked; for example, the water sector is a significant energy consumer in all phases: extraction, purification, storage, distribution, and treatment. At the same time, the power generation sector uses large amounts of water for all its stages and processes (Bauer et al., 2014; Flammini et al., 2014).

The Paris Agreement and the 2030 Agenda recognize that the long-term development of humanity depends on the sustainable management of resources (Olabi et al., 2022; United Nations, 2015a). For productive and sustainable agriculture, irrigation plays a vital role. In the current context, it is determined not only by the availability of water but also by optimal management from the project's conception to its launch and the system's entire life cycle.

Irrigation is a crucial component of rural economies, especially in areas that maintain sustainable small-scale local production and the Mediterranean region (Moragues-Faus, 2014; Rodríguez Díaz et al., 2007) As an undeniable reality, climate change has accelerated due to the current development model based on fossil energy consumption. High climatic variability (temperatures and precipitation), prolonged episodes of drought, and extreme events are recurrent. These scenarios increase insecurity in the future management of crop areas, so it is necessary to develop models and tools that allow agricultural viability within the sustainable use of resources (IPCC, 2019).

Considering the great stress on non-renewable resources, the classic economic and crop criteria should not be the only parameters for evaluating their performance. Measuring productivity only as a ratio between the benefits and the money invested in a food production process maintains the misunderstanding of an integral process where multiple costs and benefits, economic, environmental, social, and cultural variables, interact in the short, medium, and long term (O'Donnell, 2010).

Given the impossible dissociation between humans and their environment, stakeholders should introduce performance-tracking tools to manage complexity in our new paradigm (Arduini et al., 2023). Identifying the components of food supply challenges within agricultural ecosystems, their relationships and boundaries, and the socioeconomic, environmental, and cultural context allow us to understand the production process due to multiple interconnected factors (Sharma et al., 2020).

As a tool to reduce a complex evaluation of a system's performance, focused on better resource management, sustainability indicators for agricultural ecosystems are a clear and objective value (Olabi et al., 2022). In addition, they also include the correlation between water-energy factors, environment (climatic factors, soil factors), sociocultural factors, commercial factors, and gender factors, among others (Alvarez Morales, 2015; FAO, 2014; Seager, 2015).

An accurate diagnosis of indicators can effectively align demands and vulnerabilities, identifying patterns, trends, and cause-effect relationships in irrigation activities. Benchmarks improve the efficient use of resources, the effectiveness of activities and decisions, equity and environmental improvement, and the reduction of social impacts. The objective is to guarantee long-term resilience systems and the sustainable well-being of users (Delang & Yu, 2019; Nogueira Vilanova et al., 2015; Schepelmann et al., 2009; UNDP, 2022).

Several authors have tried to measure the performance of irrigation networks using various approaches in terms of design flow, such as comparative analysis (Rodríguez-Díaz et al., 2008), flow distribution and pressure studies (Pereira et al., 2003), conventional energy and cost reduction (Carrillo-Cobo et al., 2014), correlations between water and energy (Rodríguez Díaz et al., 2011), quantification of losses (Lorenzini & De Wrachien, 2005) and finally, water footprint, performance in water use, water savings in environmental and economic viability criteria using effective irrigation sustainability indicators (Darouich et al., 2012; Pereira et al., 2012; Pérez-Sánchez, Carrero, et al., 2018; Raes et al., 2018; Zoidou et al., 2017).

The improvement of efficiency in terms of energy recovery through micro-hydrogeneration systems has been discussed by different authors (Adhau et al., 2012; Crespo Chacón et al., 2020; Garcia-Espinal et al., 2022; García Morillo et al., 2018; Rossi et al., 2021; Sitzenfrei & Von Leon, 2014), proposing different methodologies for its application in both irrigation and supply systems. The development of tools that allow the analysis and design of these systems is crucial for their implementation in any distribution system, allowing network managers to manage these systems in terms of circulating flows, optimal operation, and established electrical regulation.

This research evaluates the different existing methods to estimate the maximum flows to address the design of facilities. This stage is crucial in infrastructure investment and impacts the estimation and evaluation of the different targets of the Sustainable Development Goals (SDGs).

In addition, approaching the estimation of flows with different methodologies can lead to differences in evaluating sustainability indicators and energy audits that address the installation of micro-hydrogeneration equipment.

The thesis proposes the development of a methodology that, based on experimental data, can consider the distribution of flows as the optimization of technical, economic, and environmental sustainability indicators in the design of pressurized irrigation networks, as well as the development of tools that allow network managers to analyze and design systems for the improvement of these indicators.

1.2. Aim and Objectives

The main objective of this thesis is to develop a methodology that considers the distribution of flows, as well as the optimization of technical, economic, and environmental sustainability indicators in the design of pressurized irrigation networks.

To achieve the main objective, the following specific objectives have been set:

1. To review the state of the art of irrigation network design and analysis methods. This review will identify the strengths and weaknesses of current approaches and establish a solid theoretical basis for developing the new analytical model.

2. To establish an analytical model development methodology that allows the evaluation of flow distributions. This model will be able to evaluate and optimize flow distributions in irrigation networks, considering various technical

and environmental factors. The proposed methodology must be robust and adaptable to different scenarios and operating conditions.

3. To develop a design audit by assigning design and management indicators and establishing their impact on energy and sustainability. This audit will identify areas for improvement and measure the impact of design decisions regarding energy efficiency and environmental sustainability. Implementing these indicators will be crucial to ensure an optimal and sustainable design.

4. To apply the methodological development to real cases with experimental data. To validate the developed methodology, this stage is essential to verify the viability and effectiveness of the model in practical situations. Tests will be carried out on various existing irrigation networks to ensure that the results obtained are representative and applicable in a real context.

5. To develop a tool for use in energy improvement in distribution systems. This tool will be designed to facilitate the energy improvement of irrigation distribution systems, providing engineers and managers with an efficient and sustainable solution for optimizing their networks. The tool must be capable of being integrated into daily irrigation network management operations.

Considering the three stages of this research, objective 1 is related to the contextualization stage, whereas objectives 2 and 3 correspond to the methodology development stage, and objectives 4 and 5 to its case study application.

1.3. Thesis Organization

This thesis document consists of 7 chapters, following the structure required by the Universitat Politècnica de València for a thesis by publication.

Chapter 1 presents the overall introduction of this research, providing the context and describing the motivation, the main aim and objectives, and the structure of the document.

The following three chapters correspond to the three papers published in JCR-indexed journals during this thesis, according also to the specific requirements of the Ph.D. Programme in Water and Environmental Engineering.

Chapter 2 corresponds to Publication I, "*Irrigation Distribution Network Design Parameters and Their Influence on Sustainability Management*," where the challenge of meeting basic needs for an anticipated world population of over 8.5 billion by 2030 is addressed, emphasizing the critical role of irrigation in sustainable agriculture. The article evaluates 25 different models for pipe sizing in pressurized irrigation networks, examining their advantages and disadvantages to inform future methodologies. These models aim to ensure network operation while enhancing sustainability. These tools help water managers improve resource management and sustainability indicators in agricultural ecosystems by simplifying the evaluation of irrigation system performance.

Chapter 3 corresponds to Publication II, "*Enhancing Sustainability in the sizing of irrigation Networks: A Multicriteria Method for Optimizing Flow Distribution and Reducing Environmental Impact*", where the article highlights the dual role of irrigation systems in boosting agricultural productivity and consuming significant water, energy, and resources. To address this, agronomic engineering has developed methods for optimizing irrigation network design and management. The focus is creating a tool to determine optimal flow distribution based on irrigation needs, aiming to enhance sustainability by optimizing pipe diameters. This includes reducing CO_2 emissions, minimizing service pressure, and maximizing energy recovery. The research introduces a novel tool applying a multicriteria approach to define the best flow distribution.

Chapter 4 corresponds to Publication III, "*Improvement of the Electrical Regulation of a Microhydropower System using a Water Management Tool*", which focuses on the use of renewable energy systems in water distribution networks (WDNs), specifically pumps operating as turbines (PATs) to recover energy. The research introduces an optimized regulation tool developed in Simulink MATLAB to maximize energy recovery in WDNs. This tool uses empirical methods to estimate characteristic curves and applies optimization and iterative steps. Tested in a real case study, the tool defines hydraulic-electrical regulation strategies, including machine operation, frequency inverter settings, and pressure-reducing valve adjustments.

Chapter 5 presents a general discussion of the results obtained throughout this research, simultaneously evaluating the fulfillment of the established objectives.

Chapter 6 summarizes the main conclusions of this thesis and provides some recommendations for further research.

Chapter 7 includes the list of references.

The publication data of the three articles are included as chapters 2, 3, and 4 are the following:

Publication I: "*Irrigation Distribution Network Design Parameters and Their Influence on Sustainability Management*"

Authors: Melvin Alfonso Garcia-Espinal, Modesto Pérez-Sánchez, Francisco-Javier Sánchez-Romero and P. Amparo López-Jiménez

Journal: Water. ISSN: 2073-4441. JCR IF: 3.0 (2023); Q2 (Water Resources; Environmental Sciences); Position 40/127

Status: Published in April 2024. Water 2024, 16(8), 1131
https://doi.org/10.3390/w16081131

Publication II: *"Enhancing Sustainability in the sizing of irrigation Networks: A Multicriteria Method for Optimizing Flow Distribution and Reducing Environmental Impact"*

Authors: Melvin Alfonso Garcia-Espinal, Modesto Pérez-Sánchez, Francisco-Javier Sánchez-Romero and P. Amparo López-Jiménez

Journal: Results in Engineering. Online ISSN: 2590-1230. JCR IF: 5.0 (2023); Q1 (Engineering, Multidisciplinary); Position 10/174

Status: Published in July 2024. Results in Engineering, Volume 23, September 2024, 102609
https://doi.org/10.1016/j.rineng.2024.102609

Publication III: *"Improvement of the Electrical Regulation of a Microhydropower System using a Water Management Tool"*

Authors: Melvin Alfonso Garcia-Espinal, Pilar Conejos, P. Amparo López-Jiménez and Modesto Pérez-Sánchez

Journal: Water. ISSN: 2073-4441. JCR IF: 3.4 (2022); Q2 (Water Resources; Environmental Sciences); Position 38/103

Status: Published in May 2022. Water 2022, 14(10), 1535
https://doi.org/10.3390/w14101535

Chapter 2
Publication I

"Irrigation Distribution Network Design Parameters and Their Influence on Sustainability Management"

Authors: Melvin Alfonso Garcia-Espinal, Modesto Pérez-Sánchez, Francisco-Javier Sánchez-Romero and P. Amparo López-Jiménez

Journal: Water (ISSN: 2073-4441)

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The Editor version can be found in PDF format at the following link:

https://www.mdpi.com/2073-4441/16/8/1131

Abstract

In 2030, the world population will exceed 8.5 billion, increasing the challenges to satisfy basic needs for food, shelter, water, and/or energy. Irrigation plays a vital role in productive and sustainable agriculture. In the current context, it is determined not only by water availability but also by optimal management. Several authors have attempted to measure the performance of irrigation networks through various approaches in terms of technical indicators. To improve the sustainability in the pipe sizing of the pressurised irrigation networks, 25 different models were evaluated to discuss the advantages and disadvantages to consider in future methodologies to size water systems, which guarantee the network operation but contribute to improving the sustainability. They enable water managers to use them as tools to reduce a complex evaluation of the performance of a system, and focusing on better management of resources and sustainability indicators for agricultural ecosystems are clear and objective values.

Keywords

hydraulic networks; water distribution systems; irrigation; forecasting; water demand.

2.1. Introduction

By 2030, the world's population will be above 8500 million. Over 800 million inhabitants will add to the current quantity in less than ten years (United Nations, 2019). These substantial increases present several challenges for cover inputs, such as food, shelter, water, and energy. To satisfy them, the United Nations Organisation (UN) estimated necessary increases of 35% in the food supply, 40% in water resources, and 50% in energy to prevent the consequences of several human crises (World Economic Forum, 2013; WWDR & UN, 2014). Undeniably, access to available resources is crucial in a rising demand scenario to accomplish the required tasks.

According to experts, in terms of quantity, roughly 3% of the total water on the planet is available for human activities (FAO, 2017). Among these, the agricultural sector remains the largest consumer of freshwater (Figure 2.1). Its consumption is around 70% of withdrawals and 90% of consumptive usages, compared to 10% required for municipal purposes or 20% for industrial processes (UNESCO WWAP, 2019; WWDR & UN, 2014; D. D. Zhang et al., 2011). For example, rice produced requires around 3400 L of water per kilo. Considering daily water requirements per person are about 100 L, this consumption is equivalent to the domestic needs of 34 people (Chapagain & Hoekstra, 2011; Harper & Snowden, 2017).

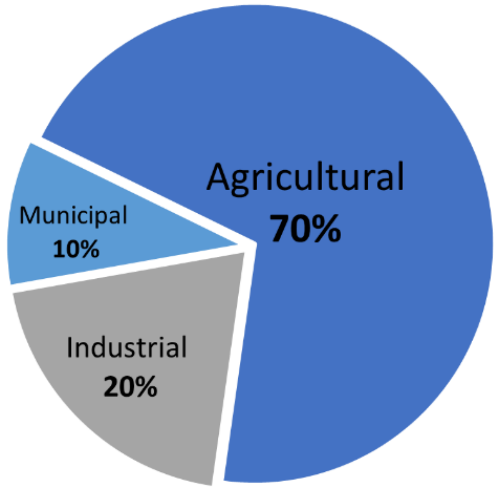

Figure 2.1. *World freshwater allocation sectors.*

Water and energy are inextricably linked; for instance, the water sector is a heavy energy consumer in all life cycle phases: withdrawal, purification, storage, distribution, and treatment. At the same time, the energy generation sector uses extensive amounts of water for all its stages and processes (Bauer et al., 2014; Flammini et al., 2014). In Europe, an estimated 18% of the total water consumed in energy production is used for cooling (Del Borghi et al., 2020; EEA, 2019, 2022). With a growing population, urbanisation, and rising living standards in many countries, the future picture implicates increased energy use and water consumption (Del Borghi et al., 2020). However, several factors can affect the predictions, including efficient and renewable technologies and water-smart energy choices, to achieve a more sustainable integrated water cycle (Averyt et al., 2011; Kanakoudis et al., 2015; Kohli & Frenken, 2011).

Direct and indirect energy inputs are also crucial for the whole chain in agriculture. Supply agri-food production accounts for 30% of the world's total energy consumption. Irrigated pumping has revolutionised food production, providing 40% of worldwide cereal demand (FAO, 2011a). Nevertheless, despite intensification providing higher efficiency rates, it is directly connected with more energy demands and elevated GHG emissions, putting human mitigation and adaptation aspiration at risk (FAO, 2014; Joseph et al., 2014). Improving a "climate-smart agriculture" behind and beyond the "farm gate" can achieve substantial savings in water–energy areas, reducing the impact of the food supply system on the environment (FAO, 2014; Godfray et al., 2010; Tilman & Clark, 2015).

As the environment establishes the initial conditions, societies expand and climate changes; therefore, the vision on energy and water concerns must shift, too. The Paris Agreement and the 2030 Agenda recognise that humanity's long-term development depends on the sustainable management of resources (United Nations, 2015b, 2015a). According to the data, considering a 75% population benefit, the irrigation sector is critical in a sustainable goal contributing to the world's GDP and global food security (Rai et al., 2017).

Irrigation plays a vital role in productive and sustainable agriculture (Y. Wang et al., 2022). Currently, it is determined not only by water availability since optimal management from project idea to building is necessary for the entire system life cycle (Ben-Alon et al., 2021). Increasing knowledge about irrigation systems and underlying internal processes improved our understanding of how new conditions affect the systems and how the systems affect the environment. It can provide detailed information and a solid base for a decision maker to develop smart strategies towards a goal.

2.1.1. Irrigation Water Use

Agriculture is the way to provide the additional billion tons of food needed for consumption shortly. Irrigation is vital for food security in most crops globally, especially in arid and semiarid areas. Furthermore, artificial rainfall makes it possible to provide the required water, nutrition, and pest control with crop growth (Chartzoulakis & Bertaki, 2015; De Vrese et al., 2016; FAO, 2011b), as well as diminish drought losses, frost hazards, and climate variability (Olayide et al., 2016).

Moreover, irrigation is a crucial component of rural economies, especially in areas that maintain sustainable local small-scale production and the Mediterranean region (Moragues-Faus, 2014; Rodríguez Díaz et al., 2007). Figure 2.2 shows the world's irrigated area divided into three groups: developed, developing, and least developing countries, in which the developing countries have a significant role in food production (ICID, 2021). Nevertheless, poor management represents a high extraction of freshwater resources and energy investment. Likewise, it carries a process of progressive deterioration of the environment. Pollution of wastewater, groundwater table reduction, eutrophication, soil salinisation, displacement of native diversity, significant greenhouse gas emissions (GHGs), and micro-residual pollutants, among other consequences, can lead to unsustainability (Fernández-Cirelli et al., 2009; García-Tejero et al., 2011).

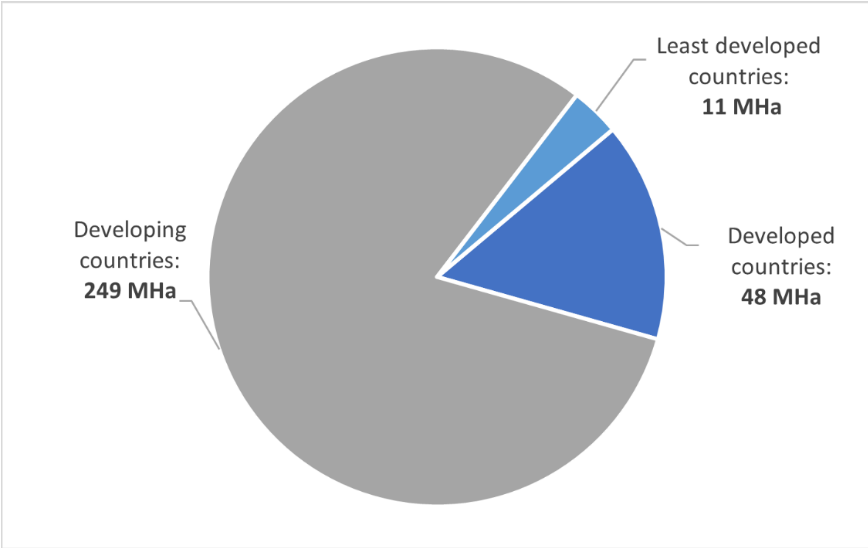

Figure 2.2. *World irrigated area data from 2021 using data from* (ICID, 2021).

Figure 2.3 shows the different uses (i.e., agricultural, industrial, and urban) in the different continents. It shows that agricultural use represents between 20 and 70% of the consumption. Water use and pollution of resources for growing agriculture will reinforce global water competition for municipal and industrial sectors.

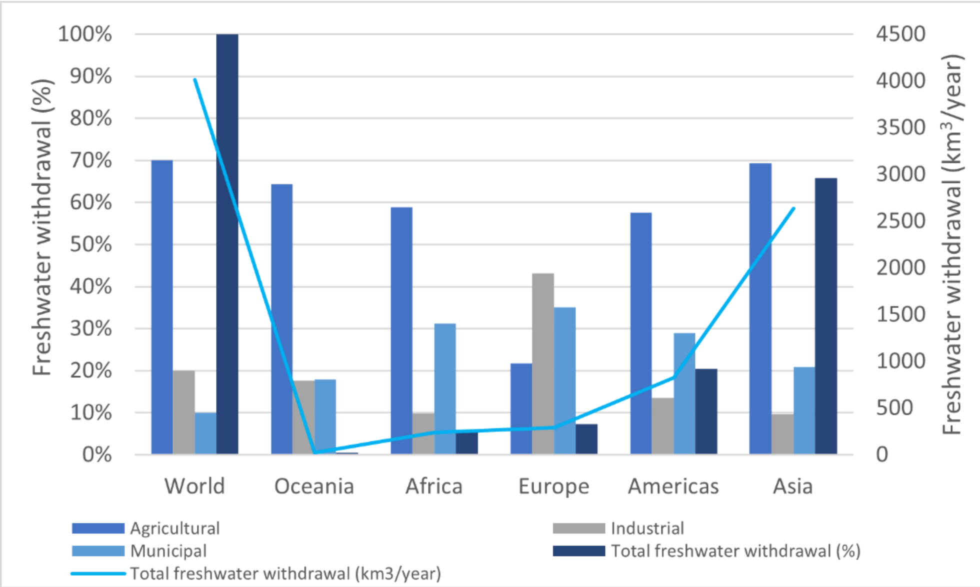

Figure 2.3. *World water withdrawal. Data obtained from* (Frenken & Gillet, 2012).

It is essential to pay attention to discrepancies between low rainfall regions where the water resources are already in sustainable borders, such as Spain's Mediterranean regions and emerging or developing countries with significant water potential (Eliasson et al., 2003; Frenken & Gillet, 2012; IPCC, 2019).

Figure 2.4 shows the high pressure in Mediterranean Europe in the freshwater, especially in Spain.

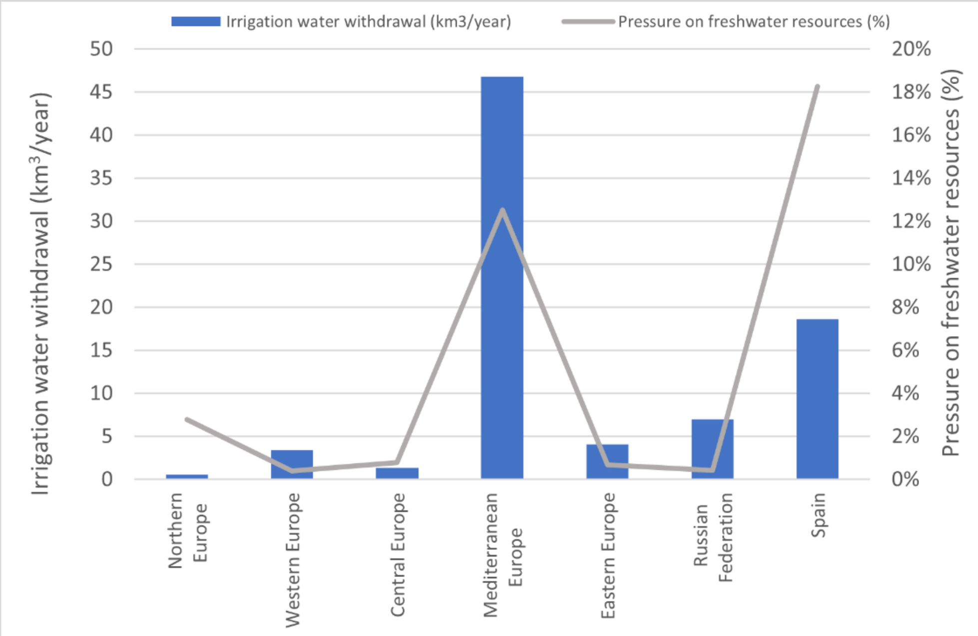

Figure 2.4. *Water withdrawal. Data obtained from Europe* (Eliasson et al., 2003) *and the world* (FAO, 2022; Frenken & Gillet, 2012).

In the unclear future, the key to success relies on the availability of the resources to satisfy user's needs—enough demand, disposable energy, and acceptable cost for pumping water—without neglecting the environmental premise, which currently must be at the forefront of all the actors involved, especially water decision makers (Kehrein et al., 2020).

2.1.2. Environmental Implications

As an undeniable reality, climate change accelerated due to the current development model built upon fossil energy consumption (Corwin, 2021). High climate variability (temperatures and precipitation patterns), prolonged episodes of drought, and extreme events are recurrent. Those scenarios increase the insecurity in the future management of crop areas, making it necessary to develop models and tools that allow farm viability within a sustainable use of resources (IPCC, 2019).

Considering the high stress on non-renewable resources and crop, classical economic criteria must not be the only performance evaluation parameters (Roga et al., 2022). Measuring productivity only as a rate between income benefits and inverted monetary inputs in a food production process keeps the misunderstanding of an integral process where multiple costs and benefits interact with economic, environmental, social, and cultural variables in the short, medium, and long term (O'Donnell, 2010).

Given the impossible dissociation between human beings and their surroundings, the stakeholders should introduce performance monitoring instruments to manage complexity in our new paradigm (Arduini et al., 2023). Identifying components of food supply challenges within agriculture ecosystems, their relationships and boundaries, and the socioeconomic, environmental, and cultural context lets water managers understand the production process because of multiple interconnected factors (Sharma et al., 2020).

As a tool for reducing a complex assessment of a system's performance, focused on better management of resources, sustainability indicators for agricultural ecosystems are a clear and objective value (Olabi et al., 2022). Moreover, they also include the correlation between water–energy factors (WF-EFs), the environment (climatic factors (CFs), soil factors (SFs)), socio-cultural factors (SCFs), trade factors (TFs), and gender factors (GFs), among others (Alvarez Morales, 2015; FAO, 2014; Seager, 2015).

An accurate indicator diagnosis can effectively align exigencies and vulnerabilities, identifying patterns, tendencies, and cause–effect relations in irrigation activities (Islam et al., 2024). Indicator benchmarks improve the efficient use of resources, the effectiveness of activities and decisions, equity and the environmental, and the reduction in social impacts. The goal is to ensure long-term resilience systems and sustainable user welfare (Delang, 2019; Nogueira Vilanova et al., 2015; Schepelmann et al., 2009; UNDP, 2022).

The global dimension of water–energy management leads to evaluating the environmental footprint in food production and the entire set of negative and positive responses that agriculture systems impose (Wang et al., 2021). Special attention to irrigation systems is justified because these are required in more places. However, its non-negligent critical water needs, inherent pollution, and our uncertain context impose clear boundaries (Tucker et al., 2022).

Considering limitations in environmental and sustainable terms, holistic knowledge of irrigation systems brings a framework to reflect the wide margins of water and energy savings in irrigated agriculture. For instance, in Spain, savings have increased by more than 70% in 15 years (Carrillo-Cobo et al., 2014; Tarjuelo et al., 2015). Quantifying the performance and constraints of irrigation systems provides a global view of a present system condition and the possible further achievements according to the targets and criteria for appraising the improvements within the water–energy–human nexus. It implies the evaluation of the different sustainability indicators based on different targets of the Sustainable Development Goals (Garcia et al., 2023).

Several authors attempted to measure the performance of irrigation networks by several approaches, such as benchmarking analysis (Rodríguez-Díaz et al., 2008), flow-driven deliveries and pressure studies (Calejo et al., 2008; Fouial et al., 2017; Pereira et al., 2003), conventional energy and cost reduction (Carrillo-Cobo et al., 2014), water and energy correlations (Rodríguez Díaz et al., 2011), loss quantification (Lorenzini & De Wrachien, 2005), and, finally, water footprint, water use performance, and water savings in environmental and economic viability criteria utilising the effective sustainability irrigation indicators (Darouich et al., 2012; Manoliadis, 2001; Pereira et al., 2012; Raes et al., 2018; Romero et al., 2017; Van Halsema & Vincent, 2012; Zoidou et al., 2017).

The present investigation is an evaluation of the different existing methods for estimating peak flow rates to address the design of installations. This stage is crucial not only in the investment of infrastructures but it also impacts the estimation of the evaluation of the different targets of the Sustainable Development Goals (SDGs). Also, approaching the estimation of flow rates with different methodologies can lead to differences in the assessment of sustainability indicators and energy audits that address the installation of micro-hydro generation.

2.2. Evaluation Methodology and Materials

The research methodology is established in different steps, according to Figure 2.5.

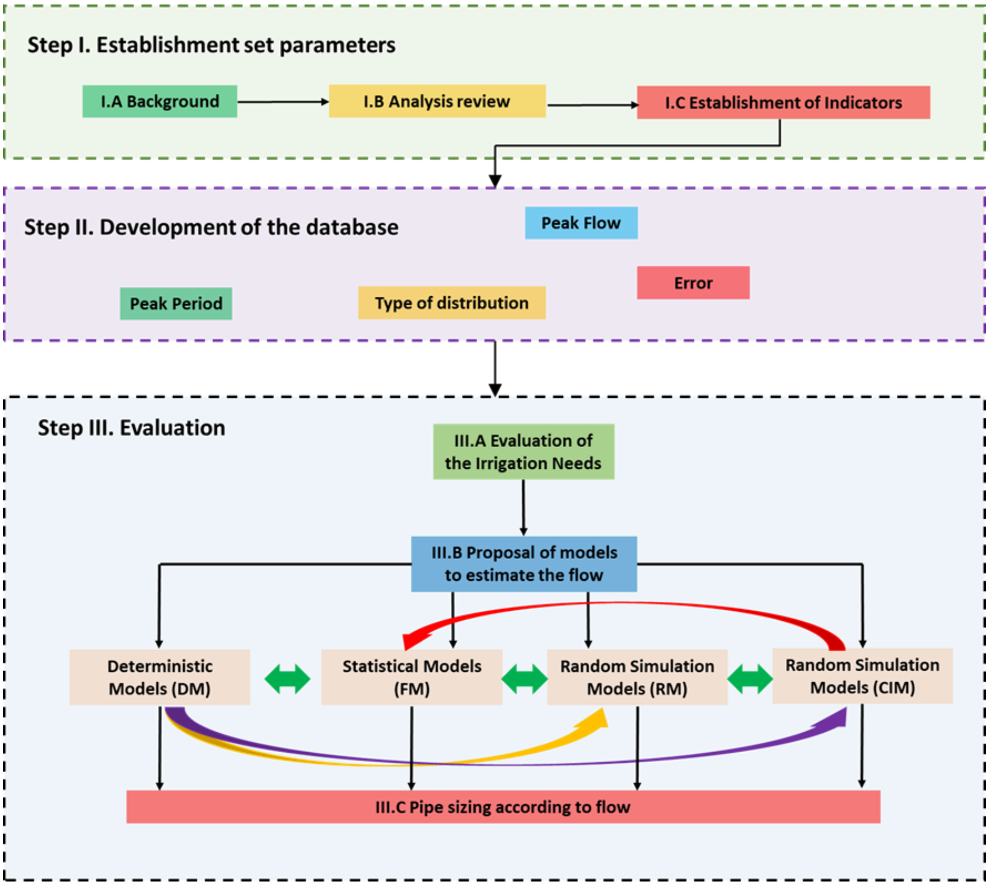

Figure 2.5. *Evaluation methodology of the models to estimate the circulate flow.*

Step I.—Establishment of the parameters. This set is divided into three parts, and a background review is developed to search for the maximum number of proposal models, enabling peak flow estimation. The second step of this block, called I.B analysis review, elaborates a parameter list in which the main variables and characteristics are discretised in the database by indicators or variables (Step I.C).

Step II.—Database development. A database was established using information and data gathered from the consulted bibliographic sources. The indicators utilised in the other examined case studies were chosen to populate the database, encompassing not only measurements and variables but also reference values. It is noteworthy that certain indicators were employed across multiple case studies discussed in the published research. The main variables were peak flow, error between estimation and experimental data, peak period, and type of distribution, among others.

Step III.—This third block constitutes the main block of the research. In the first part (Step III.A), an estimation of the evapotranspiration and possible inputs allowing the development of the different models to determine the peak flow, addressed in Step III.B, was carried out. In this block, a detailed analysis of four different typologies was carried out. A discussion was established evaluating different deterministic, statistical, random, and artificial intelligence models.

According to the review of the background, 45 references were analysed, obtaining 25 different models distributed in Europe, according to Figure 2.6.

Figure 2.6. *Distribution of the different analysed models.*

2.3. Determination of Flows to Design Irrigation Water Networks

Whereas measuring water consumed in the municipal sector is usual in most countries and almost essential in the industrial sector, water control in agriculture is not a strict requirement (Molden, 2013). Nevertheless, assessing water needs is a fundamental part of sustainable water resource use to avoid losses and obtain “more crop per drop” (Giordano et al., 2015; Kang et al., 2017). In addition, operating losses throughout the life cycle of the network are difficult to identify and quantify (Lorenzini & De Wrachien, 2005).

The lack of control, absence, or inaccuracy causes inefficient use of irrigation, affects expected crops, and generates unnecessary environmental expenses. Boosting food production in uncertain conditions calls for effective and sustainable irrigation management and flexible supplies, which means full appraisal of water–energy deliveries. Qualifying the systems and approaching the knowledge about demands initially imposed on the design process can allow for implementation strategies and plans to improve the profit margin of water–energy inversion (Bigas et al., 2012; Green et al., 2006).

Flow and pressure in the network are highly variable throughout the day and the operation cycle. Said variations are closely connected to established area limitations of irrigation systems and decision management in the phenological cycle determined by agroclimatic variables and farmers’ perceptions. The real flows may differ from prior requirements assumed at the design stage, causing operation problems impacting network capacity, demand forecast, and environmental resilience (Pérez Urrestarazu et al., 2009).

2.3.1. Parameters of Study

A realistic approach to the dynamic interactions between water irrigation and sustainability requires modelling the conditions and relations in a farm (Cao et al., 2022). These are relative to the cropping patterns demands over the growing process, hydrant discharges, established network design, environmental conditions and reactions, irrigation technology available, and crop responses, as well as user habits along different temporary and spatial scales (Foster et al., 2020).

To understand these complex interactions in agricultural, biological, and environmental systems and enhance our ability to make predictions, decision makers should study the interconnected components rather than isolating them (Uralovich et al., 2023). A machine learning approach was developed to represent diverse Earth systems models through mathematical relations and schematic concepts nourished with extracted interpretable information from uncountable data sources (Reichstein et al., 2019).

Systems models play a primary role in the development of sustainable agroecosystems. Several crop models with different scales of complexity and limitations are available to understand the interaction between soil–water–plant–atmosphere (Gavasso-Rita et al., 2024). Different tools have been developed to estimate yield production and the effects of crops that interact with weather resources and management practices (Schauberger et al., 2020). Scientific and decision/policy makers have underpinned the different approaches for increasing the understanding of growing crop processes and the interaction of soil–water–nitrogen along the life cycle, as well as the impacts of cropping patterns and irrigation distribution under climate variability (Di Paola et al., 2016; Jones et al., 2017; Pérez Urrestarazu et al., 2010; Siad et al., 2019).

Different issues emerged in agricultural model sciences developed for researchers and decision maker stakeholders, reinforced by the available data, technology and supporting tools, cost–benefit relation, expected results, and specific targets. Purposeful development of the model, increasing scientific tools, and decision/policy support lead to understanding the agroecological systems improve under research questions about processes control and agroclimatic interactions (Jones et al., 2017). Description process, understanding relations, and forecast tools motivate the development of models, which target simplifying complex processes where more of the hypothesis and assumptions are not linked with real cases but decrease uncertainty for reasonable results compared with data from the field.

There are models, which consider the soil–water process, reflected in crop water space–time requirements and water balance (Lopez-Jimenez et al., 2022). They include calculating the inputs and outputs of the system, effective rainfall, evapotranspiration, and crop requirements using soil, climate, and crop data (Narmilan & Sugirtharan, 2020). Soil moisture varies dynamically and at any time in a crop cycle. Therefore, it is crucial to never drop below the wilting point without exceeding the field capacity (Saleem et al., 2013).

The Penman–Monteith and Priestley–Taylor equations for soil–water relation modelling are highly simplified but widely applicable. According to FAO's functional model, the physically based approach, FAO-56, allows for the soil–water balance to be obtained following Equation (2.1) (Allen et al., 1998).

$$r + I + D_d \pm \Delta SM \pm R + W_g - ET_c = 0 \tag{2.1}$$

where rainfall (r), irrigation (I), and capillary rise (W_g) are the inputs of the system. Surface runoff (R), water loss out of the root due to deep percolation (D_d), and crop evapotranspiration (ET_c) are the outputs that compute the soil moisture change (ΔSM).

Evapotranspiration (ET) is the most important variable in the balance (Gong et al., 2006). These phenomenological processes correlate soil evaporation and plant transpiration, which depend on the climate factors, crop characteristics, and water availability in the soil.

In 1998, the FAO-56 ET model was launched. Several definitions and simulation procedures are broadly used following the advances in computing calculation, modern techniques, and tools (Kisekka et al., 2017; Pereira et al., 2015).

Climate factors are introduced in this methodology by estimating the daily potential evapotranspiration of a hypothetical parameterised surface—reference evapotranspiration ($ET0$)ET0—using Penman–Monteith, described in Equation (2.2) (Allen et al., 1998, 2005).

$$ET_0 = \frac{0{,}408\, \Delta\, (R_n - G) + \gamma\, \frac{900}{T + 273} u_2\, (e_s - e_a)}{\Delta + \gamma\, (1 + 0{,}34\, u_2)} \qquad (2.2)$$

where detailed energy and aerodynamic data are required, and shortwave radiation at crop surface (R_n), soil heat flux (G), air temperature (T), wind speed (u_2), psychrometric constant (γ), relative humidity by saturation vapour pressure deficit ($e_s - e_a$), the slope vapour pressure curve ($\varDelta$) are found in the equation. Although it is currently used and widely implemented for decades, the accuracy of this method depends on the available data.

Other approaches imply evaluating the reference evapotranspiration when lacking in measures required. The Hargreaves method is proposed as an alternative for assessing ET_0 with fewer data, only air temperature, as shown in Equation (2.3) (Berti et al., 2014; Hargreaves & Samani, 1985).

$$ET_0 = 9{,}388\ 10^{-4} R_a \left(T_{avg} + 17{,}8\right)\ TD^{0{,}5} \qquad (2.3)$$

The advantage of this method is that the average daily temperature (T_{avg}) and temperature range (TD) are the only values that require a dataset of measures (maximum and minimum daily temperatures). Extraterrestrial radiation (R_a) is a tabulated value. This method is recommended for use, especially in the absence of existing data or dubious quality (Hargreaves et al., 2003).

Secondly, for assessing crop evapotranspiration, the FAO-56 method integrates the crop characteristics (crop type and growth phases) via K_c. This is the dual coefficient that combines soil transpiration and crop evaporation along the development stages (Allen et al., 1998). This coefficient is mainly connected to the canopy dynamics, leaf area, and ground cover (Farg et al., 2012). Although K_c can be evaluated, crop coefficient tables and curves reported in the literature adjusted to local conditions and midseason periods are widely used (Allen & Pereira, 2009; Martínez-Cob, 2004; Mateos et al., 2013).

Thus, it is possible to calculate potential evapotranspiration for a given crop at any moment of its growth following Equation (2.4).

$$ET_c = ET_0 K_c \tag{2.4}$$

Another parameter in irrigation that needs quantification is effective rainfall (Pe), a fraction of total valuable rainfall for meeting the water needs to be used by crops, excluding surface runoff, deep percolation, and soil surface evaporation from Equation (2.1) (Brower & Heibloem, 1986). FAO-25 describes several approaches for calculating it by the fixed percentage method, the potential evapotranspiration/precipitation ratio method, Renfro equation, empirical relationships, the US Bureau of Reclamation method, and the USDA SCS method (Dastane, 1978).

The simplest methodology generally applies a percentage between 70 and 90% of the monthly rainfall. The FAO manual proposes maximum slops in the 4–5% range for Equation (2.5).

$$\begin{gathered} Pe = 0{,}8\,P - 25 \text{ if P>75 mm/month} \\ Pe = 0{,}6\,P - 10 \text{ if P>75 mm/month} \end{gathered} \tag{2.5}$$

where rainfall or precipitation, in mm, is represented as (P), and effective rainfall, mm/month, is (Pe).

Equation (2.6) is used to determine the irrigation net water needs. It shows how these descriptive, empirical, and functional models allow researchers to better understand the relationships between agro-environmental pieces combining physical and biological components and mechanisms, permitting an approach to the possible system's responses due to certain strategies and decisions adopted within simplified scenarios.

$$IN = ET_c - Pe \tag{2.6}$$

In another approach, dynamic systems can integrate conceptual physical models and mathematical equations with the data collected and provide outputs related to time changes and responses to different externalities, such as climate change or users' practices (DeJonge & Thorp, 2017; Wallach et al., 2014). Sometimes highly complex, although robust, these models need experts to achieve interpretable results and adapt them to specific issues. However, it is not always a straightforward task due to knowledge gaps, and unavailable data add uncertainty to the outputs (Dzotsi et al., 2013; Zoidou et al., 2017). Examples of such crop models related to irrigation crop water supply, among others, are FAO agronomic models CROPWAT (FAO, n.d.), AquaCrop (Raes et al., 2018), DSSAT (Jones et al., 2003), CropSyst (Stöckle et al., 2014), and software tools (Kisekka et al., 2017).

There is extensive experience developing agroecosystem models, science, and analytics tools (Prost et al., 2023). The gaps are primarily related to accurately integrating analytical knowledge into the user's decision tools (Ara et al., 2021). Moreover, various factors are needed to build an integrative agricultural approach, such as the interactions between crops, farms, socioeconomic, cultural, and landscape context, climatic, environmental, and ecological variables, trades, and agro-economic business on different scales (Mouratiadou et al., 2024).

Food security crises, sustainability concerns, technology and computer advances, open information and data accessibility, interdisciplinary and transboundary science, and user-adapted models summarise a new context that must lead to a new generation model focused on management for sustainability and productivity (Antle et al., 2017).

Agro-crop modelling under an irrigation environment forecasts the amount of water needed, which determines irrigation scheduling, such as when and how much water quantity is necessary to irrigate (Hussain et al., 2023). Therefore, it is necessary to have integral knowledge of the internal crop process and system input/output estimable responses to decrease uncertainties. Achieving an accurate system's behaviour characterisation allows the implementation of measures to reduce the water–energy quota invested without the possible detriment of production results expected by farmers.

However, despite the substantial advances in system modelling, the disparity between calculated and real flow demanded is frequently observed. This discrepancy is most often attributable to unpredictable weather conditions, users' practices, and local management in the present new context of uncertainties (Dehghan et al., 2019; Pérez Urrestarazu et al., 2010).

2.3.2. Proposed Methods: Forecasting Irrigation Demand Flow

To determine the flow rate in a distribution system, the complexity of the agricultural ecosystems mentioned must be taken into account (Zhai et al., 2020). Additionally, particular consideration of the relationships between crop pattern, crop growth stage, water and energy requirements, weather conditions, and users' interactions must be given. They are several approaches considered for studying the distribution of water discharges and irrigation scheduling for on-demand irrigation networks (Akbari Variani et al., 2022).

Space–time analysis of the randomness process in irrigation was introduced for the flexibility of use and very low probability for a simultaneous operation of all hydrants in a network, which allowed a mathematical approach for calculating the flow distribution. Of all the methods developed, Clément's first formula (CFF) has had great acceptance since its publication (Clément, 1966).

This formula introduces a statistical analysis for the calculation, implementing a distribution law of probabilities for hydrants' operation in the network. Given the simple application of the algorithm, this methodology has transcended until today. Despite several errors in simulated flow distribution (since the assumed simplifications are not entirely assured), it is the most widely used method (Calejo et al., 2008; Monserrat et al., 2004; Pulido-Calvo et al., 2003b; Rodríguez Díaz, Camacho Poyato, et al., 2007). Nevertheless, the accuracy of these calculations has significant implications for the overall sustainability of the system assessment, such as economic, energetic, hydric budget, flexibility, and safety parameters in all stages, from construction to operation management.

Different approaches have been implemented recently due to technological and computational developments that improve forecasting results. Generally called black box methods, these computational methodologies allow correlating physical parameters with advanced statistical routines to integrate existing uncertainties when correlating inputs and outputs.

Tables 2.1 — 2.4 summarise some of the most significant research work. According to the methodological approach to influence data and involved variables in the circulating flows forecast, with predictive and management purposes, the methods are differentiated into four groups: deterministic models (D), statistical models (F), random simulation models (R) and computational intelligence models (CI).

1. *Deterministic Models (D)*

The deterministic conceptual models—empirical, functional, or mechanistic—assume that uncertainties are external to the process (Srikrishnan et al., 2022). These models aim to establish a relationship between variables and constants that are well known or measurable and aim to produce "accurate" results under specific facts and considerations. Their theoretical approach does not include random methods (Tangirala, 2018). This model entirely determines flow rates by inputs and initial and boundary conditions, and since the model does not contain any haphazard approach to the phenomena, it is necessary to understand and define the problem through a vast set of existing information. Moreover, the methodologies described must gather as much information as possible and use complex models to determine those that cannot be measured directly or introduce any uncertainty.

D'Urso (2001) simulated the flow distribution in the network using the SIMODIS methodology, where remote sensing satellite data worked under techniques of temporal space evaluation of soil–water balance by the numerical soil–water flow model (SWARP). The studied network was in Gromola (southern Italy) using a daily forecast horizon, a one-year temporal dataset and a 33-day peak period. The model assumes that the network's hydrograph is a product of implicit needs and boundaries related to biophysical parameters concerning crop water requirements—vegetation status, crop pattern and stage, potential evapotranspiration rates, surface reflectance, soil properties, groundwater interactions, and hydraulic capacity of the network, among others. Comparing the total irrigation daily values from the irrigation season to the simulated data, the method underestimated the volumes by 9%.

Minacapilli et al. (2006, 2008) conducted two studies, in 2006 and 2008, in a network in Sicily (Italy) with different goals. In the first, the main goal was to create geohydrological models for improving water management in irrigation. Instead, the latter tried to create a distributed model for the assessment of water in irrigation networks. The irrigation phase is scheduled based on two parameters: soil–water pressure head threshold and soil–water deficit to be refilled. Several exposed case studies were conducted, and the outcomes for a simulated Sicilian district were compiled, resulting in overestimating the modelled flows.

Rodríguez Díaz et al. (2007) developed a model centred on water balance, simulating the whole irrigation season by calculating the circulating flows through the network at any time based on the soil moisture deficit. This network was in Santaella, Córdoba (southern Spain), with a daily forecast horizon and two years' worth of data accompanied by a 2-week peak period. Using several climatic and study area characteristics (crop, network, system type, farmer practices) as inputs, the model performs a complete simulation of the irrigation season and provides an hourly consumption on each farm and the operation probability for each event. After evaluating the simulated data and the seasonal volume by year, this method overestimated the demand by 11.6%. The evaluation for each study is summarised in Table 2.1.

Table 2.1. *Summarised deterministic models articles reviewed.*

ID	Reference	Main Results
D.1	(D'Urso, 2001)	• The temporal variation of water demand at the district level was satisfactorily reproduced. • Irrigation efficiency was evaluated using indicators calculated from the real transpiration rate and irrigation values computed by SIMODIS. • The results of SIMODIS are exceptionally reliable at the primary unit scale while obtaining reliable results at the secondary unit level.
D.2	(Minacapilli et al., 2006)	• Agrohydrological simulation models and remote sensing can be effectively combined to improve irrigation water management in semiarid regions. • The SIMODIS procedure predicted the water demand satisfactorily at district and secondary levels. • The distributed approach performed better than the lumped one at a large scale to define the upper boundary conditions.
D.3	(Rodríguez Díaz et al., 2007)	• Real demand tends to be concentrated at certain times of the day. • During peak demand periods, water requirements can exceed the design flow. • Demand is not uniform throughout the day; it increases in the morning until peaking, remains constant for several hours, and then decreases at midday. This process is repeated in the afternoon. • To be used in other districts, the gamma model should be applied considering local farmers' practices and network constraints. • Human behaviour affects uniform probability prediction.
D.4	(Minacapilli et al., 2008)	• Differences between simulated and measured irrigation volumes were attributed to different management behaviours. • The threshold value of the soil water pressure head in the root zone (h_m) and the fraction of soil water deficit to be refilled (Δ) can be tuned adequately to reproduce the spatial and temporal evolution of crop water use. • Depends on water availability and farmers' subjectivity to recognise the crop water requirement. • This approach can be effectively used to support the decision-making process in managing irrigation water resources and improving the efficiency of irrigation systems.

2. *Statistical Models (F)*

More extended statistical models aim to find a relative frequency associated with different flows during the irrigation season (Cui et al., 2023). Through the assumption of certain hypotheses and, despite the random behaviours of some variables, it is possible to arrive at a particular degree of accuracy by utilising an adequate problem definition (Valizadeh et al., 2020).

These models focus on finding hydrants' operation probability at a given period, often during peak periods, in the function of maximum crop requirements and own parameters of the probability distribution that describe the system's behaviour to meet a determined water demand for a given supply (Naderi et al., 2021).

Granados García (2013) made a detailed description of principal statistical methodologies: Clément, (Clément, 1955, 1966), de Boissezon and Haït, (de Boissezon & Haït, 1965), and Mavropoulos, (Mavropoulos, 1997). Also, he summarised various research works where authors contrast mathematical flows and calibrate parameter implications with real or simulated flows in real irrigation networks.

Clément proposed that flows circulating into the network follow the normal distribution when the number of outlets is significant enough by associating farmers' activities with hydrant usage as a binomial variable in a Bernoulli experiment, assuming uniform open probability and uniform nominal flow rate downstream of a line section (Clément, 1955, 1966).

According to Clément's first formula (CFF), it is possible to determine the downstream flow for a study section using a standardised outlet flow under a service guarantee, as shown in Equation (2.7).

$$\mathrm{Q}_{Clem} = \sum p_i d_i + U\sqrt{\sum p_i d_i^2 (1 - p_i)} \tag{2.7}$$

where the variables are flow to forecast (Q_{Clem}), fixed flow assignment of an outlet (d), probability operation hydrant (p), and guaranteed service level (U). The subscript i indicates the group of outlets with the same flow assignment and probability.

Mavropoulos (1997) changed the perspective and described the system's performance by defining the oversaturation of the network based on the rate of recurrence of demands in the network, for instance, how unusual or recurrent demand requests are.

The time between two successive irrigation calls, defined as a random variable (r.v.), follows an exponential distribution and is associated with the flow discharged at any time during a peak period using a Weibull distribution. This distribution was selected due to its high flexibility, making it possible to adapt in several flow distribution cases. Equation (2.8) shows the generalised formula proposed by Mavropoulos and Lotidi (Mavropoulos & Lotidi, 2016).

$$\mathrm{Q} = \sum_{i} Q_i = \sum_{i} n_i p_i c_i + 0.5284 \sum_{i} n_i p_i q_i c_i \sqrt[\alpha_W]{t_i} \qquad (2.8)$$

The equation considers variables such as the number of outlets with the same assigned flow (n), open hydrant probability (p), shape parameter of the Weibull distribution related to available time use of the network (α_W), outlet flow assignment (c), the time between two demands (t), and i = index that groups uniform population outlets.

Between the articles that pursue the analysis, validation, and contrast of these equations, the results that evaluate the theoretical hypothesis assumed for the models are crucial for future developments.

An entirely random variable is not a precise definition for an open hydrant demand because external factors can influence it. (Pulido-Calvo et al., 2003b) analysed energy tariff constraints that affect farmers' decisions in the township of Cordoba located in Southwest Spain, using data from 8 years. Their work shows that the probability of outlet operation cannot be the same over the day and defines different probabilities according to different energy cost rates.

Monserrat et al. (2004) analysed the CFF model's hypothesis in networks located in the Ebro River basin (northeast Spain), concluding that only the independent operation of the outlets is satisfied. Setting the daytime irrigation as a preference rejects the random probability. As a result, the calculated flow was underestimated compared to the observed data; a higher standard deviation than calculated in real data, especially connected with human irrigation preferences, is observed.

Rodríguez Díaz et al. (2007) also concluded that human behaviour affects predicted probability and shows a more significant deviation in distribution flows due to a greater probability of higher flows. The normal distribution is only shown in a peak period, not according to CFF. Furthermore, after simulating a complete irrigation season in a case study, the gamma distribution was proposed as a better fit with elevated suppleness.

The same appreciation was established by Moreno et al. (2007) in the network and peak period analysed, where a larger hydrant group operated during weekends in contrast with low cumulative operation on weekdays. This behaviour is justified due to a higher time availability for the farmers and lower energy costs; also, a variable hourly probability operation avoided costly and high evaporation periods.

For Mavropoulos' method validation, the author published the verification through a real network with registered data for monthly peak irrigation. Despite the good fit found with Weibull's asymmetric distribution, the uniform probability assumed in the model could not be corroborated. Therefore, introducing $\lambda 3$, a correction factor, is necessary, representing the non-random farmer's behaviour and other uncertainties (Mavropoulos & Lotidi, 2016).

Unsuccessful demand forecasting and the assumed hypothesis for CFF are also disclosed in the work of Soler et al. (2016). The authors also mention that the flow rate cannot be assumed as a random variable if the number of outlets is not large enough or the operating conditions are not homogeneous.

Pérez-Sánchez et al. (2018) conducted various tests to compare CFF's calculated distribution with observed flow data compiled from a real system. The results showed that the expected normal distribution did not match the observed data in any month of the analysis period. The records had a strong right skew, showing that other distribution functions, such as GEV, could be a better fit. Farmers' behaviour and preferences like duration, quantity, and hourly and weekly trends can explain the gap between data. As exposed by Pérez-Sánchez et al., (2016b), human influence determines irrigation patterns, and it is unreasonable to consider uniform probability as a valid hypothesis for forecasting irrigation flows.

Table 2.2. *Summarised statistical models articles reviewed.*

ID	Reference	Type	Main Results
S.1	(Pulido-Calvo et al., 2003b)	Statistical	• Probability operation is not a constant due to cost energy discrimination. Farmers prefer low- and medium-cost hours and avoid high-price hours. • Human behaviour is influenced by time discrimination rate costs. • The recommendations of optimum pump combination produced significant reductions in energy costs.
S.2	(Monserrat et al., 2004)	Frequentist	• Hypothesis 1: only two possible states of the hydrants (open/closed). Not fulfilled. CV = 25%. • Hypothesis 2: Uniform hydrant opening throughout the day. • Not fulfilled. CV = 5.7% daily and CV = 13% hourly. • Hypothesis 3: The hydrants function randomly and independently. - Random functioning is rejected since the Kolmogorov–Smirnov p-value = 0. - Independent operation is fulfilled. • The normal distribution hypothesis is not fulfilled. • Moreover, the model with Clément's first formula seems robust enough in the conditions studied, so using more complicated models is unnecessary.

Table 5.2. (Continuation)

ID	Reference	Type	Main Results
S.3	(Rodríguez Díaz, Camacho Poyato, et al., 2007)	Deterministic	• The generated distribution tends towards a normal distribution only in the peak demand month (July) and will not coincide with Clément's distribution. • Because the standard deviation is higher, a greater probability of higher flows exists. • Although most of Clément's hypotheses were not fulfilled, his formula is a valid design criterion. • The formula used to determine Clément's design flow adjusts better to demand behaviour than Mavropoulo's does, particularly for a small number of outlets.
S.4	(Mavropoulos & Lotidi, 2016)	Statistical	• The validity of the probability theory in on-demand irrigation networks was largely verified on the study network. • The goodness of fit test results shows that the same crop in a plain area with the same climate, and general slope and high territorial homogeneity can significantly alter the irrigation water demand, favouring the randomisation of demand over time.
S.5	(Moreno, Planells, et al., 2007)	Random Simulation	• Normal distribution fit hypothesis: the Kolmogorov–Smirnov test with a p-value lower than 0.05. Therefore, it cannot be assumed to be a better approximation to a gamma distribution for 2003 and a Weibull for 2004. • Daily and hourly opening hydrant probability hypothesis: The analysis of a variance p-value was lower than 0.05. Thus, it is concluded that there are significant differences between the peak period days for each season. • In the peak period week of the first season, farmers used weekends to irrigate because they had more time and lower costs. In the following one, the behaviour of the network was not the same, which may be due to some breakdown in the network or weather conditions. The underestimation caused by the Clément methodology is due to using the average opening hydrant probability concept.
S.6	(Pérez-Sánchez, Carrero, et al., 2018)	Statistical	• Data were not distributed in the network under CTD (in which the mean and standard deviation were calculated under Clément's parameters) in any of the months of the year. • Normal distribution does not satisfactorily explain the behaviour of the random variables. • Other distributions were proposed, obtaining a better fit for distributions of the observed flows in each month.

3. Random Simulation Models (R)

Random simulation models focus on system behaviour analysis through a random approach. The target is a model configuring the relations between variables associated with the portion of the irrigation problem that cannot be known accurately, thus introducing uncertainty to the results.

Some parameters influenced by uncertainties are defined randomly within established assumptions and scopes. Often used for performance analyses of existing networks, these models propose considering stochastic flow variability due to farmers' management strategies. Defined by the users' decisions related to the perception of crop stage, the number and location of open hydrants define the complete system performance (Khadra et al., 2013). Also, the flow rate is a product of a random computer simulation, a random variable within a sample space of possible events, which can include potential combinations satisfying the corresponding constraints and integral network spatial–time variability.

After considering the CFF model, Soler et al. (2016) proposed calculating the flow rate distribution as a non-normalised random variable; they implemented two random methods based on the number of downstream outlets of the section analysed. Thus, the first step was to create a complete sample space of irrigation events. Associates knew the constant operation probability for each hydrant, the corresponding nominative discharge with a randomly generated vector, and the operational state of the hydrant (on/off) configured by 1 or 0, respectively.

When the number of hydrants is sufficient, the authors used the Monte Carlo approach to build an incomplete sample space according to known probability and discharge rates.

$$k^j = \left(k_1^j, k_2^j, \dots, k_{n_1}^j\right) \to Q_I^j = \sum_{i=1}^{n_1} k_i^j \cdot q_i \to P\left[Q = Q_1^j\right] = \prod_{i=1}^{n_1} f\left(k_i^j\right)\ \forall\, j = 1, \dots, m_I$$

where the jth-event on/off vector is (k^j), the total number of event vectors is (m_I), the probability for the event is ($P[Q = Q_i]$), the nominal flow rate is (q_i), and the index for each hydrant is (i).

$$Q = \begin{cases} Q_I^1 \\ \cdot \\ \cdot \\ Q_I^j \\ \cdot \\ \cdot \\ Q_I^{m_1} \end{cases};\quad f(Q) = \begin{cases} P[Q = Q_I^1] \\ \cdot \\ \cdot \\ P[Q = Q_I^j] \\ \cdot \\ \cdot \\ P\left[Q = Q_I^{m_1}\right] \end{cases};\quad F(Q) = \begin{cases} P[Q = Q_I^1] \\ \cdot \\ \cdot \\ \sum_{i=1}^{j} P[Q = Q_I^j] \\ \cdot \\ \cdot \\ \sum_{i=1}^{m_1} P[Q = Q_I^{m_1}] \end{cases}$$

where Q is the discrete random variable flow vector, $f(Q)$ is the probability density function, and $F(Q)$ is the cumulative distribution function.

On the other hand, Labye (1988) introduced it as part of the design process considering the temporal variability of flows circulating through the network and the importance of Several Flow Regimes (SFR approach). Likewise, as opposed to the "only a single flow", Lamaddalena et al. (2000) provide a Random Generated Model (RGM) for obtaining different combinations of hydrants simultaneously open among the total of hydrants in the network, satisfying a given discharge and considering an upstream demand hydrograph at the end of the network as an input.

The flow circulating in a specific section is calculated by adding the discharges withdrawn from the downstream open hydrants. This tool serves different purposes, such as analysing an existing network or designing a new one while computing the upstream end demand input by a CFF-based model.

In a different approach, without considering an average operation probability, Moreno et al. (2007) assumed a random starting opening time for the hydrants and the irrigation set time for each one according to the cropping requirements and the crop yield characteristics. The method builds vast Random Daily Demand Curves through a dataset of open hydrants and the operation time of the network.

Adding these open hydrants makes it possible to calculate the total demand upstream of the study section in a determined time. Obtaining the main line flow associated with an operational quality service is possible. The case study provides a good fit between measured and calculated data.

Table 2.3. *Summarised random models articles reviewed.*

ID	Reference	Conclusions
R.1	(Lamaddalena et al., 2000)	• A good fit exists between the theoretical Gaussian curve and the histogram of frequencies obtained using field data. This means the population of the discharges during this period is well represented by CFF. • The r coefficient should be intended only as a calibration coefficient aiming to understand the farmer's behaviour. • Using field calculations, the Clément operation quality corresponded to 97.6% (exceeding the designed value of 95%). This implies a lower probability of exceeding the maximum discharge.
R.2	(Calejo et al., 2005)	• The IRDEMAND model was able to generate hourly discharge hydrographs of pressurised irrigation systems operating on demand. • This methodology considers the deterministic component (crop irrigation requirements) and the uncertainty associated with farmers' decisions on crops, farm irrigation systems, seeding dates, irrigation performances, and scheduling.

Table 2.3. (Continuation)

ID	Reference	Conclusions
R.3	(Khadra & Lamaddalena, 2006)	• The comparison has shown good correspondence, particularly for daily withdrawn volumes. • A stochastic approach simulated the farmers' management strategy. • The simulated hourly discharges showed, sometimes, hourly peaks higher than the measured ones. • Model results show good agreements between the registered and simulated values for both the daily and hourly irrigation volumes.
R.4	(Moreno et al., 2007)	• RDDC has a better fit with the measured data compared to the Clément methodology. • Considering a normal flow distribution in each line, Clément's underestimation is due to the use of opening hydrant probability. • The proposed methodology avoids the problem of using average opening hydrant probability.
R.5	(Zaccaria et al., 2013)	• The HydroGEN model was conceived based on a methodology consisting of deterministic and stochastic components. • The model's short approach cannot simulate the hourly configurations of hydrants in simultaneous operations. • The model applicability varies from system design and redesign to the analysis of operation and evaluation of the performance of on-demand irrigation networks.
R.6	(Soler et al., 2016)	• The alternative methods proposed work well in the analysed scenarios, mainly because the normality hypothesis is not required. • The programs allow the applicability of Clément's method to be checked and provide two alternative solutions when the CFF fails.
R.7	(Fouial et al., 2020)	• DESIDS module (Decision Support for Irrigation Distribution Systems) • The model proved to be a crucial tool for decision making, providing information, flexibility, and the ability to predict PID operation.

Hybrid models exposed by Khadra et al. (2013), Calejo et al. (2005), Zaccaria et al. (2013), and Fouial et al. (2020) are a combination of deterministic and random stochastic models. They assume the presence of variables within the model requiring random treatment due to wider spatial–temporary variability, higher uncertainty contribution in the process, and low viability to assess an accurate soil–water balance.

Deterministic components, water budget, and crop requirements are estimated utilising the soil–water balance at the plot irrigated level. Uncertainties and variability of some parameters, such as those introduced by the farmers' management decisions—seed day, irrigation depths, irrigation efficiencies, and starting irrigation time—are modelled by a stochastic approach.

Similarly, Pérez-Sánchez et al., 2016b proposed a new methodology for determining flow allocations, crop water demand, and consumption patterns, which are considered by a deterministic approach. Assuming indeterminate irrigation farmers' habits are the stochastic part, and the model included weekly and hourly trends and the irrigation duration using information about users' behaviour obtained from farm interviews.

4. Computational Intelligence Models (CI)

Fourthly, some proposals face the complex problem of flow distribution in the networks in a varying and uncertain environment under the influence of knowing computational intelligence models. Focused on understanding systems' behaviour through the design of "intelligent agents" that represent real problems, these models propose applications that exhibit an ability to learn from historical data and adapt it to predict new data, inspired by the biological and organisational models (Engelbrecht, 2007; Poole et al., 1998).

The branches composing the computational intelligence that promotes efficient forecasting solutions include fuzzy logic, decision trees, neural networks, and evolutionary algorithm models (Palit & Popović, 2005).

Krupakar et al. (2016) performed a comparative analyses of a broad spectrum of methods regarding the performance and accuracy of predictions. Some of the analysed methods are summarised below.

A Computational Neural Network, CNN, is a non-linear mathematical structure that tries to reproduce the human brain's performance to solve problems and its ability to replicate complex non-linear problems, finding patterns and correlations. Learning from the relations between inputs and outputs allows it to apply the knowledge acquired to solve different situations in a new context (Ponce Cruz, 2011; Pulido-Calvo & Gutiérrez-Estrada, 2009).

The performance of CNN models in predicting water irrigation demands was presented by Pulido-Calvo et al. (2003a), taking past and present data on water demands and climatic and crop parameters as inputs.

In a four-layer feed-forward CNN structure (i.e., in a model where the previous information travels only in one way from the input to output layers and with hidden layers), a learning–training algorithm to determine the interconnecting weights between the nodes and neurons of each layer is implemented.

Activation functions were linear, and sigmoidal non-linear functions were used for the output layer and hidden layers, respectively. The controlled index chosen for the model was the determination coefficient ($R_t{}^2$).

Fuzzy logic rules (FL) introduce the mathematics of fuzzy theory (Yadav, 2023), which allows one to study and describe the systems within a scale that includes partial values, such as the Boolean logic of zeros (0) and ones (1), gaining knowledge of the information that involves a certain degree of uncertainty.

This alternative to the binary systems resembles the human decision procedure that can make a choice based on the information with much imprecision, such as “it is warm” or “it is wet”, traducing it in clear values through the assigned relation functions (Zhang et al., 1996). Genetic algorithms (GAs) are used to find the optimum solution to complex problems. This approach is inspired by natural selection and heritage principles, where through crossovers, selection, and mutation rules, the initial populations defined “evolve” to better individuals as a better solution, improving their characteristics generation after generation.

A defined objective function evaluates the fitness of each new individual generated, and a constraint set penalises those who violate them (Michalewicz, 1996).

Multiple regression models are used to obtain a linear equation that explains the phenomena targeted to predict dependent variables by knowing independent variables and the assigned contributions of each one to these estimations (Michalewicz, 1996).

Pulido-Calvo et al. (2007) implemented multiple regression for predicting daily water consumed as a dependent variable in irrigation models. In a best-proposed model, the water demand of the previous two days was recorded on a farm by a telemetry system installed as input knowing variables. Equation (2.9) shows the linear equation obtained for a calibrated analysis period for olive crop farms.

$$\hat{Q}_{\mathrm{t}} = 4.01 + 0.91Q_{t-1} - 0.18Q_{t-2} \tag{2.9}$$

where $\hat{Q}_t$ is the estimated consumption on day t and Q_{t-1} and Q_{t-2} are the observed demands at one and two days before t, respectively.

Large amounts of information and variables can complicate any model and reduce the precision due to high correlations between its components. Wang et al. (2015) implemented a regression analysis method to face this problem using Principal Component Analysis (PCA) methods to identify the main factors influencing water demand, keeping as much information as possible while reducing the large amounts of inputs in a multiple-factor irrigation space.

Results show that the contribution of precipitation and irrigated areas have the strongest influence among the analysed factors. Both are used in a linear regression method in addition to a water-saving coefficient (α) representing the human influence on irrigation demand.

This coefficient includes planting structure adjustment and water-saving technologies, which can change the water demand required year by year. Equation (2.10) represents the function of the water demand for irrigation.

$$\mathrm{W} = \frac{a + b * P + c * F}{\alpha^{(t-t_0)}} \tag{2.9}$$

where W is the predicted amount of water, P is the precipitation, F is the irrigation area, α is the annual average water saving coefficient, t is the forecasting year, and t_0 is the data series corresponding to the first year.

To capitalise on the strength of several models and enhance their entire performance, combining them to create hybrid models is possible. Pulido-Calvo & Gutiérrez-Estrada (2009) developed a model combining different paradigms from CI, such as a feed-forward CNN, fuzzy logic, and genetic algorithms, to forecast daily irrigation district demands, taking only the historical data series as the input. According to the authors, the predictive capacity of this model is explained by its remarkable ability to extract the highly variable and unstable underlying patterns of the time series data.

In further work, González Perea et al. (2015) opted for the Evolutionary Robotic method (ER), which obtains the best CNN and integrates the capacity of the GA to improve precision. This method created an optimal ANGN (Artificial Neuro-Genetic Network) for a short-term (daily) forecast of irrigation demands at the district level. A GA was used to achieve the optimal parameters that structure the CNN to forecast with maximal accuracy and minimal error estimation.

After correlation analysis, the model reduced the data to twenty-seven possible weather inputs and daily historical water register data and selected seven of the best inputs to achieve the singular water demand output.

Although the model has excellent performance, matching observed and simulated data with small datasets and simulation time shows that for the peak demands, the lack of accuracy is present for the three best CNNs. The article refers to various reasons, such as a lack of adequately trained patterns with extreme values.

In another hybrid method, González Perea et al. (2018) predicted the amount of water applied on a farm. Likewise, this work combines the three methodologies (CNN, FL, and GA). Fuzzy logic was used to select relevant inputs from the vast irrigation space information and to model farmers' behaviour related to local practices, empirical thermal sensation, or holiday appreciation. Genetic algorithms were implemented to optimally split the linguistic universe for each variable (e.g., "it is warm") to be transformed in a range of mathematical inference sets.

Input variables that directly correlate with applied water forecast were, for this work, irrigation depth water from the previous and two previous days; the thermal sensation can also condition farmers' irrigation decisions. Trained with three different crops in an irrigation district, the analysis model shows that cultural and local practices defined for users' demands can differ for each crop, even when the irrigation system stays the same.

Accenting the relations between dataset attributes inputs and expected forecast outputs, decision tree models (DT) are structures with internal and external nodes, decision functions, and terminal data results, connected by branches that search for understanding logic rules between them.

González Perea et al. (2019) used the DT model to focus attention on when the irrigation event occurs at the farm level. As a binary occurrence problem capable of better-replicating farmers' behaviour, a DT was built starting with an irrigation process input vector, which included weather, phenological plant state, local practices, and daily hydrant operation, and was explicitly selected for a case study and split into two main classes.

A multi-objective GA selected the optimal tree structure. The accuracy of predicted event occurrences for the best DT designed was very high, between 90 and 100% of irrigation events in a real network.

Table 2.4. *Summarised computer intelligence models articles reviewed.*

ID	Reference	Model Type	Conclusions
CI.1	(Pulido-Calvo et al., 2003a)	Computational Neural Networks (CNNs)	• The CNN model predicted daily water demand better than multiple regression and univariate time series analysis. • The best results were obtained when inputting the water demands and maximum temperatures from the two previous days. • The model is well suited for real-time operations when the system's state is continuously monitored.
CI.2	(Pulido-Calvo et al., 2007)	Linear Regressions and Computational Neural Networks (CNNs)	• The best demand predictions were obtained when using the water demands from the two previous days as inputs. • Results could indicate that rainfall factors and other climatic variables are implicitly considered in water demand observations. • The CNN performed better than the regressions when water demand and climatic variables were considered as input data. • Short-term demand modelling can be used as input in real-time methods and/or programs for managing water delivery systems.

Table 2.4. (Continuation)

ID	Reference	Model Type	Conclusions
CI.3	(Pulido-Calvo & Gutiérrez-Estrada, 2009)	Hybrid Computational Neural Networks + Fuzzy Logic + Genetic Algorithm (CNNs + FL + GA)	• The hybrid methodology was designed to forecast one day ahead of daily water demands at irrigation districts. • Fuzzy inference was used to estimate the correction of forecasts obtained from an autoregressive neural network to find the optimal values of the parameters of the fuzzy system. • This model, with not very large data requirements, can be very suitable for decision-making strategies in networks.
CI.4	(González Perea et al., 2015)	Artificial Neuro-Genetic Networks (ANGNs)	• The model was applied to predict water demand one day ahead in the network. • The genetic algorithm was used to find the optimal neural network settings to explain the maximum water demand variance with minimal error estimation. • Without an extended dataset and time requirements, the model can be a powerful tool for developing management strategies.
CI.5	(Wang et al., 2015)	Principal Component Analysis (PCA) + Regression Analysis Methods	• The irrigation water demand forecasting method, considering multiple factors, can achieve higher modelling accuracy. • The PCA method was used to identify the main influencing factors (precipitation, irrigation area, water-saving technology) • The water-saving improvement coefficient (α) concept is introduced into the water demand forecasting model based on the dual characteristic of “artificial-natural”. • The predicted irrigation water requirements of the Haihe River basin are lower than the present situation at the moment of the study.
CI.6	(González Perea et al., 2018)	Hybrid Computational Neural Networks + Fuzzy Logic + Genetic Algorithm (CNNs + FL + GA)	• Farmers’ behaviour and cultural practices differ depending on the crop, even when the irrigation system is the same for different crops. • When several crops were trained together, the model’s representativeness and accuracy were worse than those trained independently. • Irrigation district managers can determine the amount of water to apply at each hydrant beforehand, thus making it possible to manage the pumping station in advance and maximise its efficiency. • In the event of a pumping station failure, these models allow scheduling repairs and managing the time required to fix pumps, repair equipment, and purchase materials.

Table 2.4. (Continuation)

ID	Reference	Model Type	Conclusions
CI.7	(González Perea et al., 2019)	Decision Trees + Genetic Algorithm (DTs + GA)	• DTs were successfully used as classification models to forecast when farmers irrigate. • The model focuses on the prediction of when irrigation events occur. • The optimal classification model predicted between 99.16% and 100% for the given dataset. • The model also allows the user to know each operational zone of the irrigation network one day ahead.

2.3.3. Flow Pipe Sizing: Indicators

The use of the different methodologies, as well as the study of opening probabilities as a function of the flow assessment and the estimation model, allows water managers to obtain different flow distributions over time. These distributions, which are different according to the chosen method (different colours), are represented schematically in Figure 2.7. Defining the design value and the best estimate is crucial in the design and subsequent management of water infrastructure.

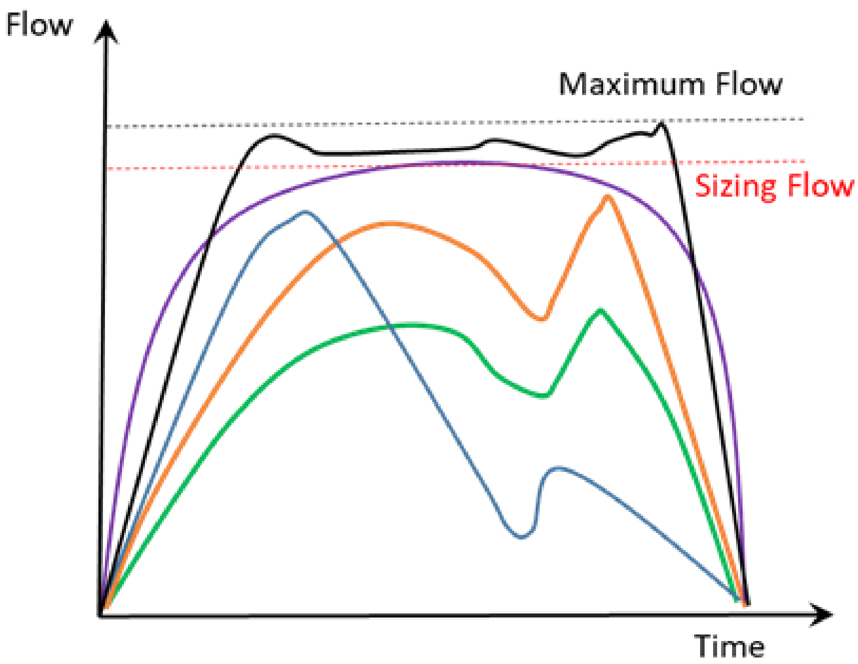

Figure 2.7. *Distribution of flow over time.*

As shown in Table 2.5, which includes 20 different distribution networks, the uniqueness of the network and its topology implies that the values of flow, leakage, and energy consumed (and thus CO_2 emitted) are different. Therefore, the analysis of flow distributions is crucial to address the design and subsequent management of distribution systems.

Table 2.5. *Variation of the flow, leakage, and annual consumed energy in irrigation networks.*

No.	Reference	Country	Average Flow (L/s)	Average Leakage (L/s)	Annual Energy Consumed (MWh)	Annual Carbon Emission ($TnCO_2$)
1	(Ramos & Ramos, 2009)	Portugal	17.36	3.47	139.09	257
2	(Perez-Sanchez et al., 2019)	Spain	31.17	6.23	2949.01	2.98
3	(Pérez-Sánchez et al., 2016b)	Spain	29.34	5.87	2776.28	2.81
4	(Pérez Urrestarazu et al., 2009)	Spain	4012	802.40	379,567.30	383.97
5	(Daccache et al., 2009)	Italy	1200	240.00	113,529.60	114.85
6	(Pardo et al., 2020)	Spain	17.81	3.56	1685.21	13
7	(Pérez-Sánchez et al., 2018)	Spain	10	2.00	946.08	0.96
8	(Rodríguez Díaz et al., 2009)	Spain	479.8	95.96	45,392.92	1140.2
9	(Rodríguez Díaz et al., 2009)	Spain	1428	285.60	135,100.22	136.67
10	(Cabrera et al., 2019)	Spain	221.80	6.76	20,984.58	21.23
11	(Cabrera et al., 2019)	Spain	0.036	0.01	1245.95	1.26

Table 2.5. (Continuation)

No.	Reference	Country	Average Flow (L/s)	Average Leakage (L/s)	Annual Energy Consumed (MWh)	Annual Carbon Emission ($TnCO_2$)
12	(Cabrera et al., 2019)	Peru	250	50.00	23,652.00	23.93
13	(Cabrera et al., 2014)	Spain	76.27	2.32	7215.78	7.3
14	(Stamouli et al., 2017)	Greece	774	154.80	73,226.59	74.08
15	(Karimov et al., 2012)	Uzbekistan	619.61	123.92	58,620.00	59.29
16	(García Morillo et al., 2018)	Spain	4800	960.00	454,118.40	459.39
17	(Adhau et al., 2012)	India	6.3	1.26	596.03	0.6
18	(Moreno et al., 2007)	Spain	120	24.00	11,352.96	11.48
19	(Al-Smairan, 2012)	Jordan	520.8	104.16	49,271.85	49.84
20	(Cabrera et al., 2015)	Italy	215.04	43.01	20,345.10	20.58

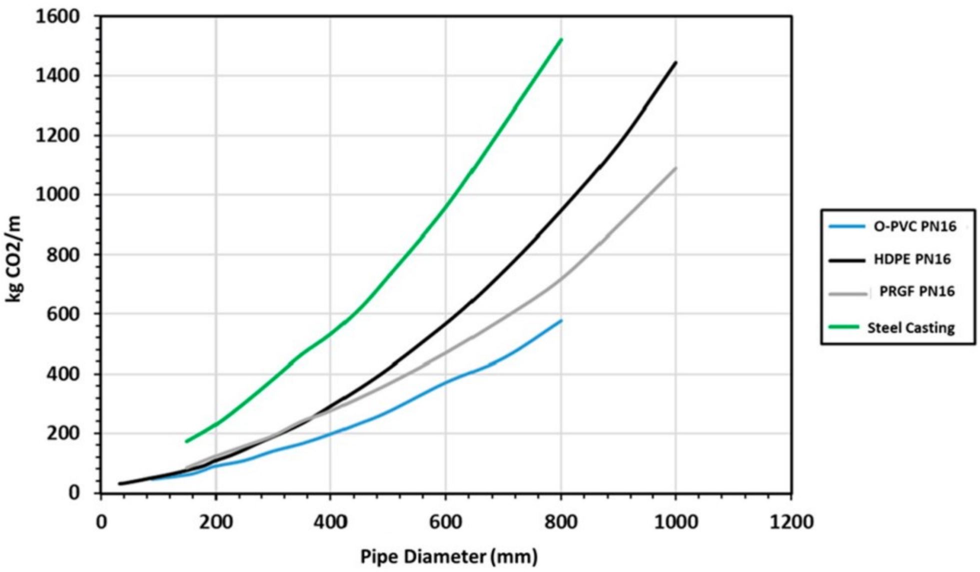

Figure 2.8. *Distribution of the different analysed models.*

Flow distributions not only involve energy consumption and CO_2 water footprint, but the construction of the network itself involves CO_2 emissions for each metre of pipeline installed when taking into account the creation, excavation, transport, and execution of the irrigation system works, as shown in Figure 2.8, which shows that the variation of CO_2 emitted varies between 50 and 150% as a function of the diameter and the material.

2.4. Conclusions

To accurately forecast irrigation demands, agronomic variables have a key role. Moreover, relationships between crop patterns, crop group stage, water and energy requirements, weather conditions, and user interactions should be considered. Various approaches have been developed, resulting in different methodologies showing the different methods to estimate the maximum flow to size the different pipes of water irritation networks.

This paper shows some of the most important articles supporting different methods for forecasting irrigation demand. Based on the variables involved, the methods are classified into four groups: (i) deterministic models (D), in which it is assumed that uncertainties are external to the process, and they need to gather as much information as possible, and (ii) statistical models (F), which aim to determine the relative frequency corresponding to different flows during the irrigation season. The main goal is obtaining the operation probability of the hydrants at a given period. (iii) Random simulation models (R) consider a random approach of variables by creating and assuming relationships with the components associated with the portion of the irrigation that cannot be known accurately. They be influenced by uncertainties or within established assumptions and scopes. (iv) Computational intelligence models (CI) can learn from historical data and use them to predict new values based on patterns and series inspired by the biological and organisational models. The comparison of the different methods was focused on the adjustment of the function and a better definition of the maximum flow rate that allows the design flow rate to be established. Addressing and/or knowing the best flow frequency distribution function according to statistical function settings can lead to improved irrigation network design and management methods in terms of sustainability and investment.

Computer intelligence science is implemented in many fields and transforming water management concepts. Progress in this area and data collection technology allow modelling variables, such as human behaviour, thus finding relationships between expected water demands and weather conditions, water applied in previous days, and even the users' thermal sensations.

It is powerful to learn from experience and quickly adapt to new information. Moreover, it is used to create robust models for getting into advanced irrigation management, saving considerable water volumes and energy and leading to better planning for each irrigation season and day-to-day operation time.

A study of the influence of flow distribution in distribution networks, considering its influence on energy consumption, the possible installation of micro-hydraulic generation systems, and its sustainability in terms of infrastructure implementation and operation, is necessary to address sustainable management of irrigated agriculture.

Chapter 3
Publication II

"Enhancing Sustainability in the sizing of irrigation Networks: A Multicriteria Method for Optimizing Flow Distribution and Reducing Environmental Impact"

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Abstract

Irrigation systems significantly enhance agricultural productivity but are also substantial consumers of water, energy, and natural resources. The need to optimize their design encouraged agronomic engineering to develop various methods for improving the design and management of these irrigation networks. This development focuses on creating a tool to define the optimal flow distribution according to the system's irrigation or consumption needs, thereby determining the design flows. The aim is to optimize the design of pipe diameters to improve sustainability (i.e., reducing CO_2 emissions, minimizing service pressure, and maximizing recoverable energy within the system). These principles ensure a better evaluation of sustainable development goals within agricultural production. The proposed procedure develops a strategy to define the best-fitting distribution using a multicriteria solution. As novel, the research develops a tool, which characterizes flow distributions deviating from the classic Clement's formulation used in irrigation systems. The proposed method was applied in a Mediterranean irrigation system in Spain, achieving a correlation coefficient above 0.9 in the model. This methodology addresses design criteria in terms of sustainability and reduces energy consumption in networks. It achieved material savings of 6.01% compared to the observed network, reducing CO_2 emissions between 5.61 and 5.72 $TnCO_2$/ha over its lifecycle.

Keywords

Irrigation networks; Water management; Sustainability; Optimal pipe sizing; Theoretical distribution curve.

3.1. Introduction

Irrigation systems are crucial in developing new agricultural practices to guarantee feasibility (Ferreira et al., 2023). The correct operation of these water systems is mandatory to guarantee the pressure and flow at each irrigation point (Gao et al., 2023). Both terms (i.e., feasibility and pressure guarantee) imply the need to consider climate change (Mohammed et al., 2022) since water management is key to optimising the available water resources, which is very important in deficit areas (Scanlon et al., 2023). Improving the management of irrigation systems starts with the correct design of irrigation systems (Et-taibi et al., 2024). For this reason, the study of flow frequency distributions is more significant than ever (Khudayorov et al., 2023), due to the need to improve flow distribution estimates to improve the assumptions in the design of pipelines, once the digitalisation of distribution systems has made it possible to better understand the evolution of flows and pressures in the systems (Rabak et al., 2023).

Water scarcity is present strongly in Mediterranean areas (Tocados-Franco et al., 2023), which should be considered when managing irrigation communities. These structures should satisfy the water demand (Ferreira et al., 2023), guarantee the water resources (Pérez-Sánchez et al., 2024) and improve the evaluation of the different targets of the sustainable development goals (SDGs) (Obaideen et al., 2022). Water demand depends on factors intrinsic to the plantation and external factors due mainly to climatic conditions, mainly temperature and rainfall, which determine the crop's evapotranspiration (Li et al., 2020). Its water requirements depend partly on the quality of the water (Ungureanu et al., 2020).

The water demand of the different crops in irrigation systems depends on the irrigation requirements by soil water balance (Jovanovic et al., 2020), which are new trends to get new volume resources (Pérez-Sánchez et al., 2024), soil type and climatic factors involved in the system (Nikolaou et al., 2020). These different approaches were reviewed by (Pereira et al., 2020), in which the use of new technologies have an enormous potential for irrigation scheduling. It includes the assessment of alternative crop management practices, as well as biophysical and economic indicators of crop water productivity. These irrigation needs and the mode of operation (e.g. scheduled or on-demand) of the network establish the different sizing systems, taking into account not only the topology but also the distribution (i.e. gravity or pumped) (Pang et al., 2023). Several times this decision support is solved by Clément's formula, which enables the establishment of the opening or closure probability of the taps. Its application allows engineers to estimate the design flow (Monserrat et al., 2021). Currently, using decision support systems and artificial intelligence supported with digital twins helped improve the networks' management once they are designed (García et al., 2020). However, management comes at a later stage than design and implementation (Gimpel et al., 2021). Therefore, the design phase is crucial to address a balanced design in terms of ensuring consumption under conditions of quality, feasibility, and sustainability. This implies approaching the sizing by estimating the circulating flow, although it is important to be able to know the distribution of flows to be able to establish criteria that do not oversize the installations (Pérez-Sánchez et al., 2018).

Water scarcity has led system managers to develop better water management within the framework of intensive agriculture in recent decades (Tilman et al., 2002). Intensive agriculture implied the irrigation transformation from gravity to pressurised irrigation systems to increase the water efficiency (Renault et al., 2007). For example, in Spanish Mediterranean irrigation, the intense modernization supported by public subsidies from European policy plans improved the efficiency from 0.49 to 0.61 of the water systems (Espinosa-Tasón et al., 2020).The improvement of water efficiency solved the water scarcity problems (Lamaddalena et al., 2000). However, the increase in profitability led and the food needs of the population to cover its needs caused an increase in the volumes demanded (Poppe Terán et al., 2023). The rise in water consumption, coupled with the reduction of water resources during drought periods due to climate change (Palagiri & Pal, 2024), necessitates that water managers establish new strategies to introduce additional water sources to balance irrigation demands with available water (Pérez-Sánchez et al., 2024). This volume increment could get from water reuse volume from wastewater treatment plants, which is currently discharged to sea (Mora et al., 2022). The irrigation modernization did not only bring advantages but also increased the energy consumption of the systems due to the pressurization of the systems. The unit energy use is around 4.5% (Espinosa-Tasón et al., 2020). This increase in energy was offset by the use of renewable systems (mainly photovoltaic and micro hydropower systems) in past years (Hassan et al., 2023). It contributed to reducing the carbon footprint of the irrigation systems (Kodirov et al., 2020), considering a potential of 2.8 Wh/m3 for each meter of difference in elevation (Belaud et al., 2020) and LCOE between 4 and 20 c€/kWh when photovoltaic systems are analysed, saving the electricity costs until 80% when it is compared to non-renewable resources (Carrêlo et al., 2020). These measures contributed to improving the evaluation of the different targets involved in the SDGs, not only in SDG6 (Clean water and sanitation), since water is involved in many targets of the 17 SDGs (Garcia et al., 2023).

Garcia-Espinal et al. (2024) established a deep review of the different methods used to estimate flow rates in irrigation networks in which 25 different models were evaluated to discuss the advantages and disadvantages to consider in future methodologies to size water systems. Based on the variables involved, the methods are classified into four groups: (i) Deterministic Models (D), these models assume that uncertainties are external to the process and aim to gather as much information as possible (Pulido-Calvo et al., 2003c); (ii) Statistical Models (F), these models seek to determine the relative frequency of different flows during the irrigation season, with the main goal of obtaining the operation probability of the hydrants at a given period (Minacapilli et al., 2008); (iii) Random Simulation Models (R), these models take a random approach to variables by creating and assuming relationships with components associated with the portion of irrigation that cannot be accurately known. They account for uncertainties or operate within established assumptions and scopes (Zaccaria et al., 2013); and (iv) Computational Intelligence Models (CI), these models can learn from historical data and use it to predict new values based on patterns and series inspired by biological and organizational models (González Perea et al., 2019). The development an analysis, which establishes the influence of the flow distribution in the sizing of irrigation systems, considering irrigation demands, agronomic variables and sustainable parameters is necessary to improve the water management systems (Garcia-Espinal et al., 2024).

The design was approached from a conceptual point of view of using probability distributions assuming a degree of confidence. It is a major challenge in designing irrigation networks, which operate on-demand to know beforehand the flows into the networks' pipes (Fouial et al., 2017). The novelty of the study is focused on developing a tool that allows to characterise the distribution of flows that deviate from Clement's formulation, which is classic in the use of irrigation systems. The fact of improving the knowledge of the distribution of flows makes it possible to address within the research a methodology of network design where not only technical aspects are taken into account but also parameters focused on sustainability, to reduce the carbon footprint as much as possible in the operating balances of the irrigation communities. The present research attempts to consider the three factors outlined above by proposing a novel methodology (objective 1) that allows the development of a tool that, considering the consumption patterns according to the crop, can estimate the best distribution (objective 2), establishing the sustainable design of the network (objective 3).

3.2. Materials and Methods

The proposed procedure is divided into five different phases, each containing different steps (Figure 3.1). The model needs different inputs and iterative procedures, which establish the energy requirements and the infrastructure sizing to supply the water irrigation demand according to available volume.

3.2.1. Optimization stages

Figure 3.1 shows the proposed methodology, which is divided into five different stages: Analysis of Observed Flow Distribution (I), Network model Calibration (II), Pipe Diameter Sizing-CO2 emission criteria (III), Energy audits (IV) and Definition of technical and sustainability criteria (V).

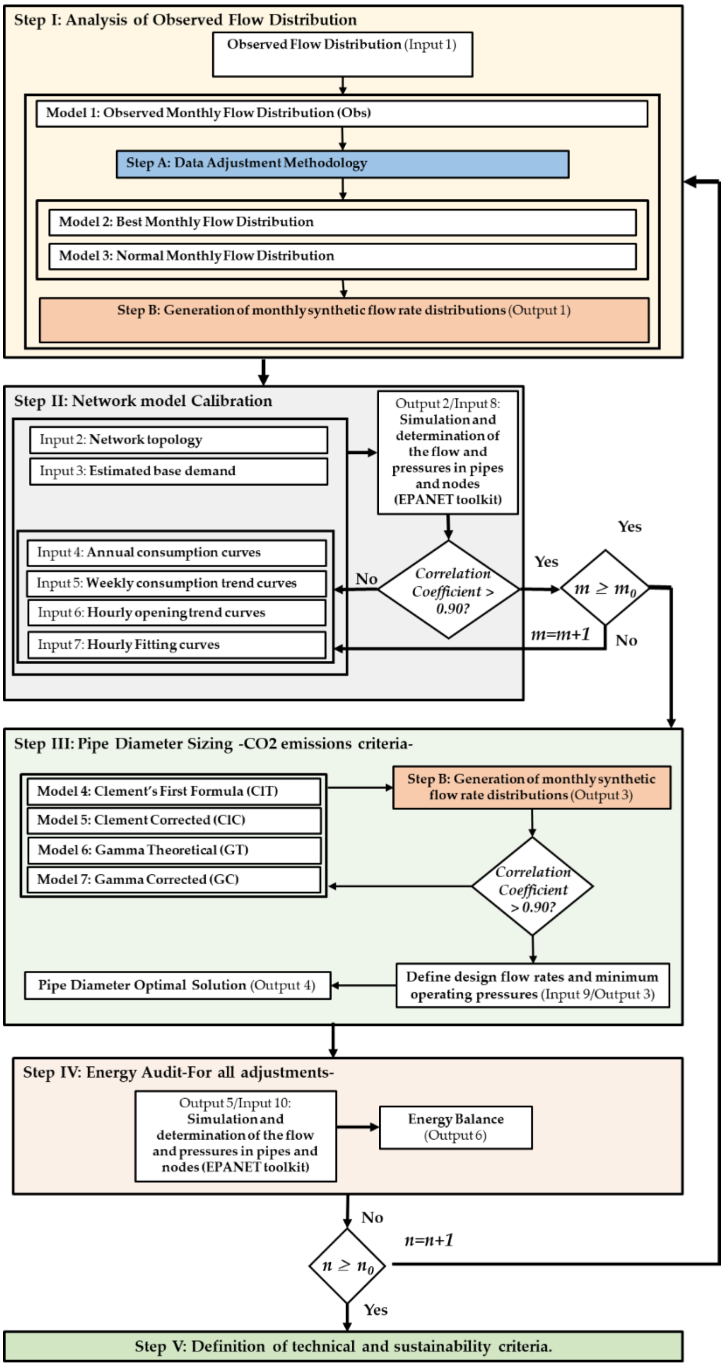

Figure 3.1. *Optimization procedure*

Step I. Analysis of Observed Flow Distribution

With the monthly flow records for the studied period, the first adjustment consisted of determining the distribution function that better fit the data for each month. The case study is based on an irrigation network in Callosa d'en Sarrià, Alicante (Spain), and it is described completely after the methodology section. However, the established methodology allows for replication in any case study as well as irrigation typology, only the data inputs described above in the methodological process are necessary.

Following the characterization of the observed data, a structured methodology for data adjustment was developed and executed in MATLAB using the Statistics and Machine Learning Toolbox (MathWorks, n.d.-d) in step A. MATLAB is a desktop software and a programming language that directly expresses mathematic expressions as matrices and arrays (vectors or arrays) (Garcia-Espinal et al., 2022). The developed tool is divided into five main steps, as shown in Figure 3.2a. A general outline of the process is described below. It receives the monthly flow data as input and fits it with all the available distributions supported by MATLAB. Subsequently, the results are sorted following defined criteria, selecting the best 10 for each month evaluated with their corresponding parameters. Lastly, goodness of fit tests are applied, and the multicriteria process is executed to select the optimal distribution for the data.

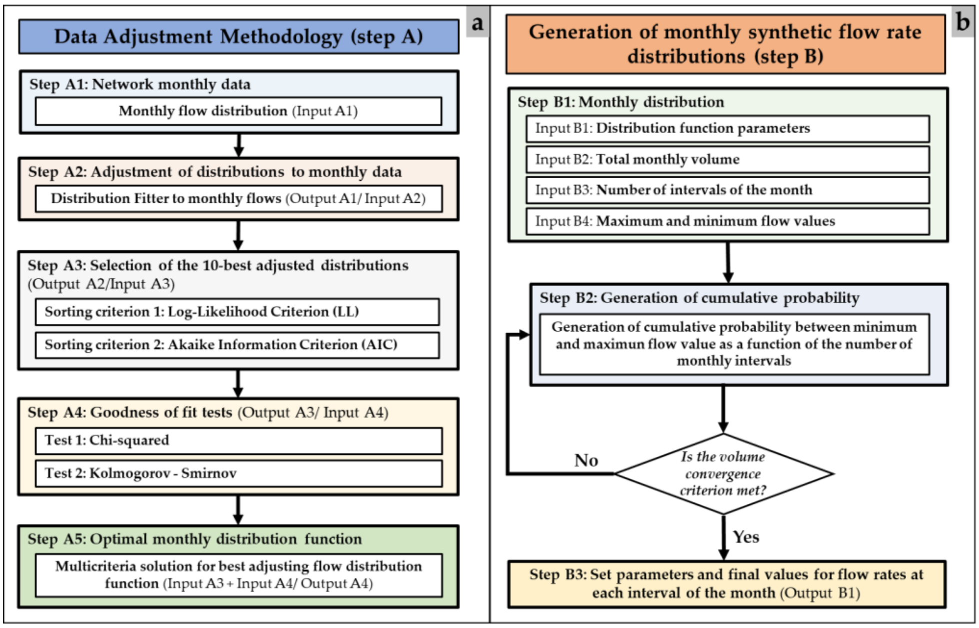

Figure 3.2. *Proposed methodology for the data adjustment. (a) Step A. (b) Step B*

Step A1, called network monthly data, consists of the data preparation process, containing the twelve months for each evaluated year. For this case, the function works with hourly readings, ranging from 672 to 744 monthly intervals.

Step A2, called Adjustment of distribution to monthly data, is focused on the fitting process. The function evaluates through a list of all the supported distribution functions, i.e. ‘Normal Distribution’, ‘Gamma Distribution’, or ‘Lognormal Distribution’, using MATLAB’s Distribution Fitter and MLE framework to fit the data to each distribution (Evans et al., 2015; MathWorks, n.d.-b, n.d.-e).

Step A3, called selection of the 10 best-adjusted distributions, selects each month's top ten adjusted distributions. The research considered 10 different functions, which appeared in all months when different iterations were developed in the iterative procedure of the methodology. This step is divided into two phases: denominated Evaluation and Sorting. In the evaluation, the tool first calculates the log-likelihood (LL) criterion after obtaining the parameters for each fitted distribution. This criterion assesses how well the distribution fits the data (Burnham & Anderson, 2002; Hastie et al., 2009). Then, after calculating the log-likelihoods, the Akaike Information Criterion (AIC) is computed for each distribution function. This criterion penalises the distributions on the number of parameters and is based on Equation (3.1) (Burnham & Anderson, 2002; Hastie et al., 2009):

$$AIC = 2 \cdot LL + 2 \cdot n_{param} \tag{3.1}$$

Where AIC is the Akaike Information Criterion value for the evaluated distribution fit; LL is the log-likelihood value for the evaluated distribution; n_{param} is the number of parameters of the distribution function. In the Sorting stage, the function returns the sorted list of distributions based on their log-likelihood and AIC values in ascending order, with the distributions yielding the top ten positions being considered the 10 best-adjusted distributions.

Step A4 is focused on performing the goodness of fit tests. Chi-squared and the Kolmogorov-Smirnov goodness of fit tests are evaluated for each best-adjusted distribution (Agresti, 2018; Everitt & Skrondal, 2010). The Chi-squared test is commonly employed to evaluate the adequacy of fitting a categorical distribution or to contrast observed frequencies with their expected counterparts. Here, the test statistic, represented as χ^2, measures the served and anticipated frequencies, operating under the null hypothesis of no difference between the observed and expected distributions (Agresti, 2018; Everitt & Skrondal, 2010).

The Kolmogorov-Smirnov (KS) test assesses the goodness-of-fit of a continuous distribution or compares the empirical distribution function of the observed data to a theoretical distribution function. The test statistic, denoted as D, measures the maximum discrepancy between the empirical and theoretical distribution function (Berger & Zhou, 2014; Rice, 2007). MATLAB's Statistics and Machine Learning Toolbox provide the ‘chi2gof’ and the ‘kstest’ functions for calculating the goodness of fit tests (MathWorks, n.d.-a, n.d.-c).

Step A5, which is called the optimal monthly distribution function, selects the optimal monthly distribution for each year following a multicriteria function (FP), using the log-likelihood (LL), the AIC, the Chi-squared test statistic, and the Kolmogorov-Smirnov statistic as inputs (Berger & Zhou, 2014; Rice, 2007). FP is a proposed criterion of the methodology as a novelty, where by mathematical definition, the value closest to one establishes that the type of distribution is repeated more times throughout the year and therefore, its behaviour can be attributed to it. Equation (3.2) is developed and evaluated for the four criteria for each year according to the research proposal:

$$FP_{criterion} = \sum_{i=0;j=1}^{i=12;j=10} \frac{n_{repi}}{12}\frac{(11-p_j)}{10} \tag{3.2}$$

Where $FP_{criterion}$ is the FP value for the evaluated criterion; i is the number of the month; j is the index of the position the distribution occupies in that month; n_{rep_i} is the number of months the distribution repeats in that position in a year, and p_j is the position of the distribution in that month. FP values closer to 1 represent the best-fitted function for that year.

This function handles additional considerations, such as benefiting the distributions that repeat more in higher positions, dealing with log-likelihood ties and providing more detailed output for selecting the optimal distribution. After calculating the FP values for each distribution and criterion in a year, Equation (3.3) determines the total FP value of every distribution and selects the distribution with the highest value as the best-adjusting distribution function for the flow data in that year.

$$FP_{distribution} = FP_{LL} + FP_{AIC} + FP_{Chi2} + FP_{KS} \tag{3.3}$$

where $FP_{distribution}$ is the total FP value for the distribution function in that year; FP_{LL} is FP value for the log-likelihood criterion; FP_{AIC} is the FP value for the Akaike Information Criterion; FP_{Chi2} is the FP value for the Chi-squared test statistic; FP_{KS} is the FP value for the Kolmogorov-Smirnov statistic. The output of this function is an array containing the best distribution for each year and the parameters for each month for that distribution. After the data adjustment process results, creating a synthetic year generator that follows the selected optimal monthly distribution was necessary.

The resultant methodology and function continued from step B. Figure 3.2b shows the process for generating synthetic monthly data and is described below. The function created uses as inputs the distribution function parameters for each month, and the number of intervals for each month and generates a vector with a set of values that follows the distribution function, ensuring the total volume is the same as the input of that original month.

Step B1: Monthly distribution. The data and parameters, such as the distribution function parameters, target monthly volume, number of monthly intervals, and maximum/minimum values allowed for the generated numbers, are imported into the tool.

Step B2: Generation of cumulative probability. The first phase of this step is to set the convergence criteria, such as the maximum number of iterations and the tolerance for the difference between the target and generated total volume and distribution parameters. The cumulative probability is generated quadratically, with the fixed points being the first interval (minimum flow) and final interval (maximum flow), and the third point (intermediate point) is recalculated to minimize the error in volumes (Larsen & Marx, 2018; Ott et al., 2019). In the iterations, the aim is to ensure that the calculated curve is close to the linear one (otherwise, the shape of the distribution can be lost), so it starts by iterating at the midpoint of the linear one.

If the convergence criteria are met, the function ends the loop and advances to the next step. If the contrary, it goes back to another iteration until reaching the target convergence.

Step B3: Set final parameters and values; the function returns the synthetic flow rate data for each month interval and the errors obtained in monthly volume, monthly mean flow rate and standard deviation concerning those calculated based on the parameter values of the defined distribution function.

Step II. Network model calibration

In this second stage, it was necessary to calibrate the network model for the three data adjustments executed in the Analysis of the observed flow distribution step. These datasets will be described as follows: (i) Observed data: The original monthly flow readings from the case study during the analysed period; (ii) Best monthly flow distribution synthetic data: A generated dataset of monthly flows that follows the optimal monthly distribution function —i.e. a Gamma distribution— and (iii) Normal monthly flow distribution synthetic data: A generated dataset of monthly flows that follows the normal distribution function.

Considering the network topology and estimated base demand inputs, the hydraulic model was developed using the EPANET Toolkit (Kyriakou et al., 2023; Rossman, 2000). This network will be calibrated with the available datasets following different scenarios, generating three main calibrated models (Pérez-Sánchez et al., 2017). Knowing the topology makes it possible to list an inventory of the number of pipes and nodes in the network. The irrigated area and crop characteristics per supply point are also known, so following (Pérez-Sánchez et al., 2018) methodology, it is possible to estimate the base demand for the network.

Once the monthly demands were determined, the WaterPAT software was used to calculate the consumption trend curves in the network for the different datasets defined by (Mercedes-Garcia et al., 2022). Water distribution systems rely on consumption trend curves to efficiently manage and optimise water usage across various temporal scales, including annually, weekly, and hourly (Sanz & Pérez, 2015; Sanz & Péreza, 2014). *Annually aggregated consumption trend curves* reveal broader trends and seasonal variations in water usage. For example, water demand typically increases during warmer months due to increased crop needs (Jiang et al., 2014; Pulido-Calvo et al., 2003b). *Weekly consumption trend curves* offer a more granular view of water usage patterns, highlighting variations in demand throughout the week. *Hourly curves* provide the most detailed insights into water usage dynamics, revealing peak demand hours and low consumption periods. These curves provide insights into water consumption patterns over time, allowing us to calibrate the model while also aiming to enhance the efficiency and sustainability of water management practices. After calculating the curves for each dataset and simulation, the opening probability for each irrigation point was calculated (Carrero Carrero, 2016).

The previous step enables the simulation and determines the flow and pressures in pipes and nodes by EPANET (Rossman, 2000). Once the model is simulated, the determination of error and flow distribution must be minimised, and flow distribution achieved to advance to the next step. The calibration process of the network model is based on the volume balance; it should meet the monthly volume per irrigation point; these are compared to the observed values. Additionally, the Correlation Coefficient is determined following Equation (3.4) (Kyriakou et al., 2023). Also, Q-Q plots are generated for each model and then compared with the observed data.

$$CC(Q_s, Q_c) = \frac{\sum(Q_s - \overline{Q_s})\,(Q_c - \overline{Q_c})}{\sqrt{\sum(Q_s - \overline{Q_s})^2 \sum(Q_c - \overline{Q_c})^2}} \tag{3.4}$$

where Q_s are the sample flows, $\overline{Q_s}$ the mean value of sample flows, Q_c are the calculated flows and $\overline{Q_c}$ the mean value of calculated flows.

According to (Schober et al., 2018), the correlation coefficient can be classified in five different approach: 1) Negligible, when it is lower than 0.09; 2) Weak, when it is between 0.1 and 0.39; 3) Moderate, when the correlation coefficient is between 0.4 and 0.69; 4) Strong, if it is between 0.7 and 0.89; and 5) Very strong when the correlation coefficient is above 0.9

Lastly, the model is calibrated if the volumes have minimal error and a solid correlation (CC > 0.90). Otherwise, the model is not considered valid and must go into the loop, calculate new trend curves, and execute all the processes until a satisfactory solution is found.

Before moving on to the next step, there is a second condition that should be met, $m \geq m_0$, where m represents the number of simulations for that model and, m_0 represents the number of simulations needed for establishing the design parameters.

Step III: Pipe Diameter Sizing -CO_2 emission criteria.

Once the different models are calibrated, the next stage is determining the pipe diameter sizing following the CO2 emissions criteria. A comparison of design flows is defined according to the following assumptions:

The following design criteria are used for the pipe sizing (Clément, 1966; Soler et al., 2016): The 100% flow rate is considered when the number of irrigation points oscillates between 1 and 10. If the number oscillates between 11 and 50, the design flow rate is the value of the 99% percentile, considering the 95% percentile when the number is above 50 (Monserrat et al., 2004). These criteria are used in each simulation to estimate the flow rates for each line.

Based on the agronomic data of the supply points (probability of operation), the design flow rates are determined, and the following models are added:

a) Clement_Theoretical (CT): All flows are calculated using Clément's First Formula in the proposed strategy from the consumption data and base demand of irrigation point, as described in Equation (3.5)(García Morillo et al., 2018; Monserrat et al., 2004; Pérez-Sánchez et al., 2018):

$$Q_d = \mu_{clement} + U \cdot \sigma_{clement} \tag{3.5}$$

Where Q_d is the design flow rate; $\mu_{clement}$ is the mean of the flow distribution; $\sigma_{clement}$ is the standard deviation of the flow distribution; U is the operating quality (OQ) of the network, for $U = 1.65$ (95%) and $U = 2.32$ (99%).

The mean and the standard deviation are determined by Equation (3.6) (Pérez-Sánchez et al., 2018) and Equation (3.7) (Pérez-Sánchez et al., 2018) respectively:

$$\mu_{Clement} = \sum_{i=1}^{i=n} p_i \cdot q_i \tag{3.6}$$

$$\sigma_{Clement} = \sqrt{\sum\nolimits_{i=1}^{i=n} p_i(1-p_i)q_i^2} \tag{3.7}$$

Where p_i is the opening probability of the irrigation point; q_i is the base demand of the irrigation point.

b) Clement_Corrected (ClC)*:* Since the standard deviation results through the Clement_Theoretical model came out smaller than the standard deviations from the Normal_Calibrated model, the flow rates provided were lower in comparison. It enables the definition of the Clement corrected distribution, which is get from Clement Theoretical compared with the experimental values. A R_σ coefficient was calculated to adjust standard deviations using Equation (3.8). This new expression was determined using the data from the Normal_Calibrated and Gamma_Calibrated, which presented very similar regression equations, opting in the end for a single expression for the two models with a $\mathrm{R}^2 = 0.9568$. The corrected standard deviation was obtained with Equation (3.9):

$$R_\sigma = 0.87818 \cdot \mu_{Clement}{}^{0.25} \tag{3.8}$$

$$\sigma_{Corrected} = R_\sigma \cdot \sigma_{Clement} \tag{3.9}$$

Where R_σ adjustment coefficient for the standard deviation; $\sigma_{Corrected}$ is the corrected standard deviation.

The corrected design flow can be calculated using Equation (3.10):

$$Q_{Corrected} = \mu_{clement} + U \cdot \sigma_{Corrected} \tag{3.10}$$

c) Gamma_Theoretical (GT): Given the relationship between the parameters of the Normal and Gamma distributions, the parameters of a Normal distribution (mean and standard deviation) can be used to estimate the shape and scale parameters using Equation (3.11) (Berger & Zhou, 2014) and Equation (3.12) (Everitt & Skrondal, 2010; Ross, 2019). After determining the parameters, the design flows can be calculated.

$$\alpha_{Theoretical} = \frac{\mu_{Clement}^2}{\sigma_{Clement}^2} \tag{3.11}$$

$$\lambda_{Theoretical} = \frac{\mu_{Clement}}{\sigma_{Clement}^2} \tag{3.12}$$

Where $\alpha_{Theoretical}$ is the shape parameter for the Gamma_Theoretical model; $\lambda_{Theoretical}$ is the scale parameter for the Gamma_Theoretical model.

d) Gamma_Corrected (GC): the research proposes the shape and scale parameters using the Clement_Corrected distribution to get the gamma corrected distribution, using analogues expressions to (3.11) and (3.12), proposing the Equation (3.13) and Equation (3.14).

$$\alpha_{\ Corrected} = \frac{\mu_{Clement}^2}{\sigma_{Corrected}^2} \tag{3.13}$$

$$\lambda_{Corrected} = \frac{\mu_{Clement}}{\sigma_{Corrected}^2} \tag{3.14}$$

Monthly synthetic flow rate distributions were generated for the models previously described, and then, a correlation coefficient verification is needed, following the same criteria where $CC > 0.90$ is needed for each model; otherwise, it needs to get in the loop until matching the desired criteria.

Pipe Diameter Optimal Solution:

The pipe sizing stage of the network was carried out using as a base the *"Economic pipe size selection"* method criteria minimizing the annual cost of the network (Munizaga Díaz, 1976; Pérez-García, 1993). For this method, instead of a cost per meter and material curve, the CO_2 emission per meter criteria was used (Rubio Sánchez, 2022), as shown in Figure 3.3.

This method aims to reduce the tons of CO_2 produced by meters of the installed network depending on the pipe material, being the optimal solution with the lowest emissions generated.

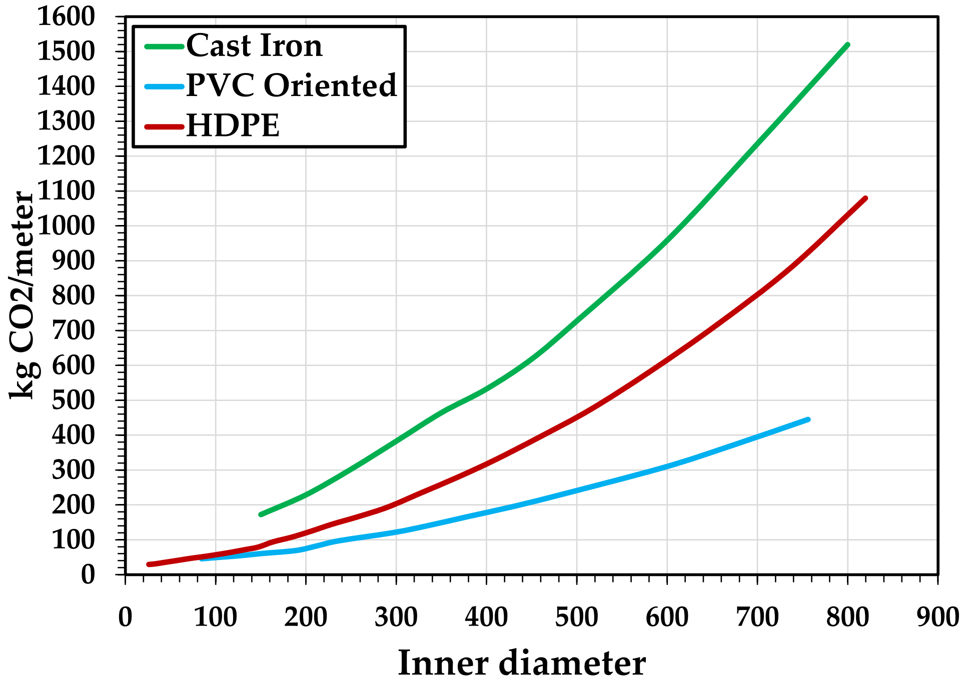

Figure 3.3. Curve inner diameter and kg of CO_2/meter for evaluated materials.

Then, the design flow rates were calculated for all the available models for the month of maximum demand, May, while considering the constraints of minimum pressure of 30 m w.c. and velocity values between 0.5 and 2.5 m/s.

Step IV. Energy evaluation

For this step, an energy audit was executed for each studied model using the optimal material solution from the previous step. First, each model simulated and determined the flow and pressures in pipes and nodes.

In the works of (Pérez-Sánchez et al., 2016a), the energy balance equations relative to different types of energy within the network were described and summarized in Equations (3.15) to (3.20), as shown in Table 3.1.

Table 1. Expressions to develop the energy balance defined by (Pérez-Sánchez et al., 2016a).

Annual Energy (kWh)	Equation	Id
Total Energy ($\mathbf{E_{T_j}}$)	$\gamma Q_j (z_o - z_j) \Delta t/3600$	(3.15)
Friction Energy ($\mathbf{E_{FR_j}}$)	$\gamma Q_j \left(z_o - (z_j + P_j)\right) \Delta t/3600$	(3.16)
Theoretical Necessary Energy ($\mathbf{E_{TN_j}}$)	$\gamma Q_j P_{min_j} \Delta t/3600$	(3.17)
Required Energy ($\mathbf{E_{RS_j}}$)	$\gamma Q_j P_{minS_j} \Delta t/3600$	(3.18)
Theoretical Available Energy (E_{TAj})	$\gamma Q_i (P_j - P_{\min j}) \Delta t/3600$	(3.19)
Theoretical Recoverable Energy (E_{TRj})	$\gamma Q_i \left(P_j - \max\left(P_{min_j}; P_{minS_j}\right)\right) \Delta t/3600$	(3.20)

Where γ is the specific weight of the water; Q_j is the demanded flow in the irrigation point or line *j*; z_o is the elevation concerning the reference plane of the water level at the supply point or line; z_j is the elevation of the irrigation point or line *j*; Δt is the timestep; P_j is the pressure at the irrigation point or line *j*; P_{min_j} is the minimum pressure at the irrigation point or line *j*; P_{minS_j} is the minimum service pressure in the irrigation point or line *j* to guarantee the demanded flow.

An additional condition is verified to determine which is the next step, $n \geq n_0$, where n represents the number of loops of the main methodology (Figure 3.1), n_0 represents the number of years of the evaluated period, this means that steps I to IV should be run three times for each model.

Step V. Definition of technical and sustainability criteria

The evaluation of the previous steps set out in the methodology (Steps III and IV) allows decisions to be made based on the most favourable results in terms of design and sustainability. The standardised assessment of energy consumption and CO_2 emissions allows the best solution to be addressed.

Sustainability indicators

Once the optimal material is determined, the sustainability indicators are obtained. Following the works of (Rubio Sánchez, 2022), sustainability indicators related to CO_2 emissions in water networks are described next.

1. *Total network environmental cost:* Indicates the total environmental cost, in tons of CO_2 emissions, for the proposed network model.

2. *CO2 emissions per linear meter of pipe*: Indicates the environmental cost, in tons of CO_2 /meter, of the network for each meter of pipe installed.
3. *CO2 emissions per hectare:* Indicates the environmental cost, in tons of CO_2 /ha, of using irrigation systems for each hectare of crop.
4. *CO2 emissions per cubic meter of supplied water ($kgCO_2/m^3$):* Indicates the environmental cost, in kg CO_2 /ha of using irrigation systems for each cubic meter of water supplied.

3.2.2. Materials and Case Study

The proposed procedure was applied in a real irrigation network. It is located on Callosa d'en Sarrià (Alicante, Spain). The irrigation network supplies a surface equal to 120 hectares. Irrigation uses water resources from wells. The water volume is regulated using a reservoir with enough elevation to supply all networks by gravity. The main crop is loquat (Eriobotrya japonica), although there are avocados and citrus fruits that combine with the main crop. The network's pipelines are over 10.6 km and constructed using asbestos cement pipes, ranging in diameter from 250 to 200 mm. Within the network, there are 34 multiuser hydrants which connect to irrigation points via pipes made of either high-density polyethene (HDPE) or steel, depending on the service pressure requirements. These hydrants supply water to 143 irrigation points. Additionally, a consumption volume meter is installed at each irrigation point to accurately record water usage from any hydrant. Concerning the experimental data, water manager have the flow meter reading for three consecutive years and the monthly reading of the meters for each of the 143 intakes. The annual volume oscillated between 512369 and 552699 m^3, while the maximum flow varied between 72.63 and 94.26 l/s. Figure 3.4 shows the case study network topology.

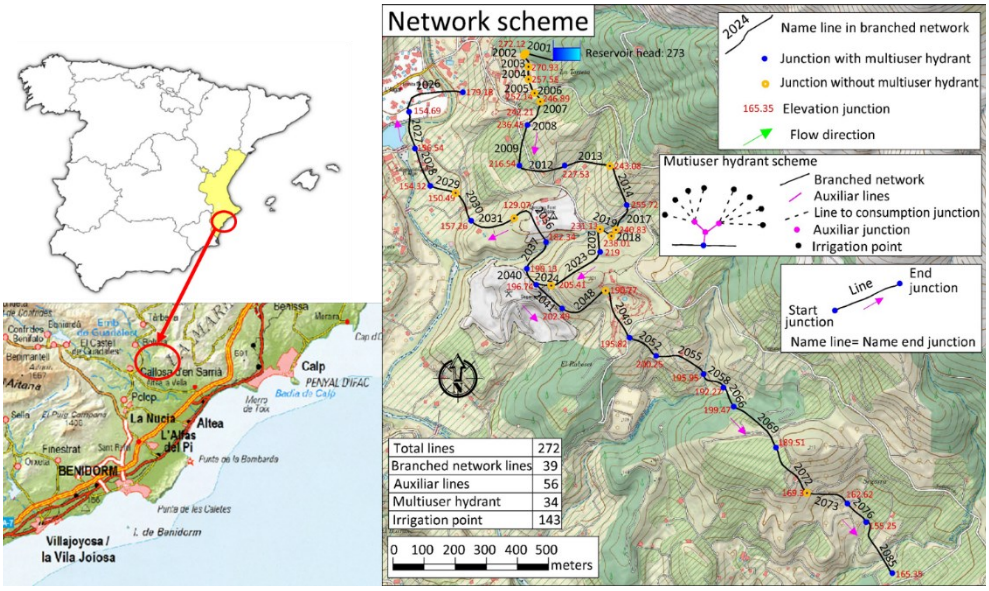

Figure 3.4. Case study scheme

3.3. Results

This section shows the different results and discussion of the applied methodology in the proposed case study. The different results are shown according to the executed steps.

Step I: Analysis of observed flow distribution:

Step I analysed the observed flows for each month during the studied period. For the three-year dataset, it was determined that the month of maximum needs was May, represented between the days 122 thru 155 in Figure 3.5a.

This result is due to the uptake in water demand caused by the increasing temperatures and the farming season, registering annual consumed volumes between 62339 and 66718 m^3. Figure 3.5b shows the flow records for May between 2015 and 2017, in which it can be observed that the consumption trend follows a similar pattern and keeps increasing from year to year.

The first adjustment (Model 1), in which every month was adjusted to a distribution function using the methodology created in MATLAB *(Step A)*, as shown in Figure 3.2a, executed Steps A1 through A3. The most common first-place distributions during this analysis were the Gamma, Weibull, GEV, and Lognormal. In the second adjustment (Model 2), the main goal was to determine the optimal monthly distribution function. The resultant function must be the best fitting for the observed dataset. After completing step A4 (Goodness of fit tests), the multicriteria solution for selecting the distribution function was carried out following Equation (3.2) in step A5. Table 3.2 shows the results of the FP value of the top distributions during the studied period, in which the Gamma distribution was selected for the three years with a wide margin over the other available options. This table shows the highest values were for Gamma and Lognormal distribution, therefore the best fit of distribution; while the lowest (poor distribution) were in the Normal and Uniform distributions.

Table 3.2. *FP value for different Distribution functions during the studied period.*

Order	Distribution	2015	2016	2017
1	Gamma	3.1167	3.1583	3.0917
2	Lognormal	3.0083	3.0083	3.0917
3	Loglogistic	2.6000	2.9167	2.9833
4	Generalized Extreme Value	2.7167	2.6750	2.8667
5	Birnbaum-Saunders	2.6333	2.4583	2.4083
6	Weibull	2.4750	2.5667	2.3750
7	Inverse Gaussian	2.1333	2.0250	2.0167
8	Exponential	1.4833	1.6000	1.6500
9	Normal	1.2167	1.1417	1.0500
10	Uniform	0.6167	0.4500	0.4667

In the last adjustment from this block (Model 3), the observed data was adjusted to a Normal monthly flow distribution. After completing the adjustments, the methodology for generating a synthetic dataset following a distribution (Step B), described in Figure 3.2b, was also executed to prepare a Gamma model and a Normal model. After completing the previous step, there will be three datasets to work on: Observed, Gamma and Normal. The first step was to create three calibrated models, one for each dataset. For this process, the main inputs were divided into two sections: on one side, the characterization of the network topology and the estimation of the base demand.

The second section is composed of the determination of the consumption curves, thus calculating the opening probability for each irrigation point. The calibration is carried out by obtaining the operating probability curves (monthly, weekly, and daily) and obtaining models that simulate the annual flow distributions of the observed ones and Normal and Gamma distribution functions. The results for each calibration are shown below.

1 - Observed data calibration: Q-Q plots were generated for each year and month of maximum needs, comparing the observations with the calibrated model. Figure 3.5a shows the results for the year 2015 and the month of May of that year for one of the simulations performed. The adjustments are greater when using a longer temporal scale. This figure shows the alignment between the values of both axes, being more deviated for the behaviour in May, but with high linearity for flows above 12 l/s (Figure 3.5b).

Table 3.1.A contains in Appendix I shows a Box and Whisker plot for each year of the studied period for the Observed_Calibrated model. In general, the correlation coefficient goes from 0.995 to 0.905, which, according to (Schober et al., 2018), sets the model with a “Very strong correlation” and, therefore, validates the calibration of the model where all the lines behave as the observed data in the network model. Also, there is a pattern where the correlation coefficient values decrease in the months from May through August, being most noticeable in the Observed_Calibrated 2017 (Table 3.1.A).

2 – Gamma distribution calibration: For the Gamma distribution model calibration, and then the results were averaged for the Q-Q plots and for determining the correlation coefficients. Figure 3.5c shows the Q-Q plots for the entire 2015 year and the month of May for one of the simulations performed, in which it can be observed that there is a substantial correlation between the generated and the simulated dataset (Figure 3.5d). Table 3.2.A in Appendix I shows the correlation coefficients for the Gamma_Calibrated model for the whole study period; the minimum value recorded was 0.95 in August 2015 and a maximum of 0.995 in November 2017. The interpretation of these values is a model with a very strong correlation following (Schober et al., 2018).

3 – Normal flow distribution calibration: Lastly, the Normal flow distribution is a process comparable to the one with the Gamma, where the Q-Q plots for the Normal_Calibrated 2015 (Figure 3.5e) and May 2015 were compared to the observed data in Figure 3.5f. For this particular year, the annual comparison and the month of maximum needs were closely related to the desired values. This model established the best correlation coefficients compared to the two previous ones. Table 3.3.A (Appendix I) shows the values, which were 0.975 for August 2016 and 0.995 for 2015. These values get for the Normal Calibrated established a very strong correlation according to (Schober et al., 2018).

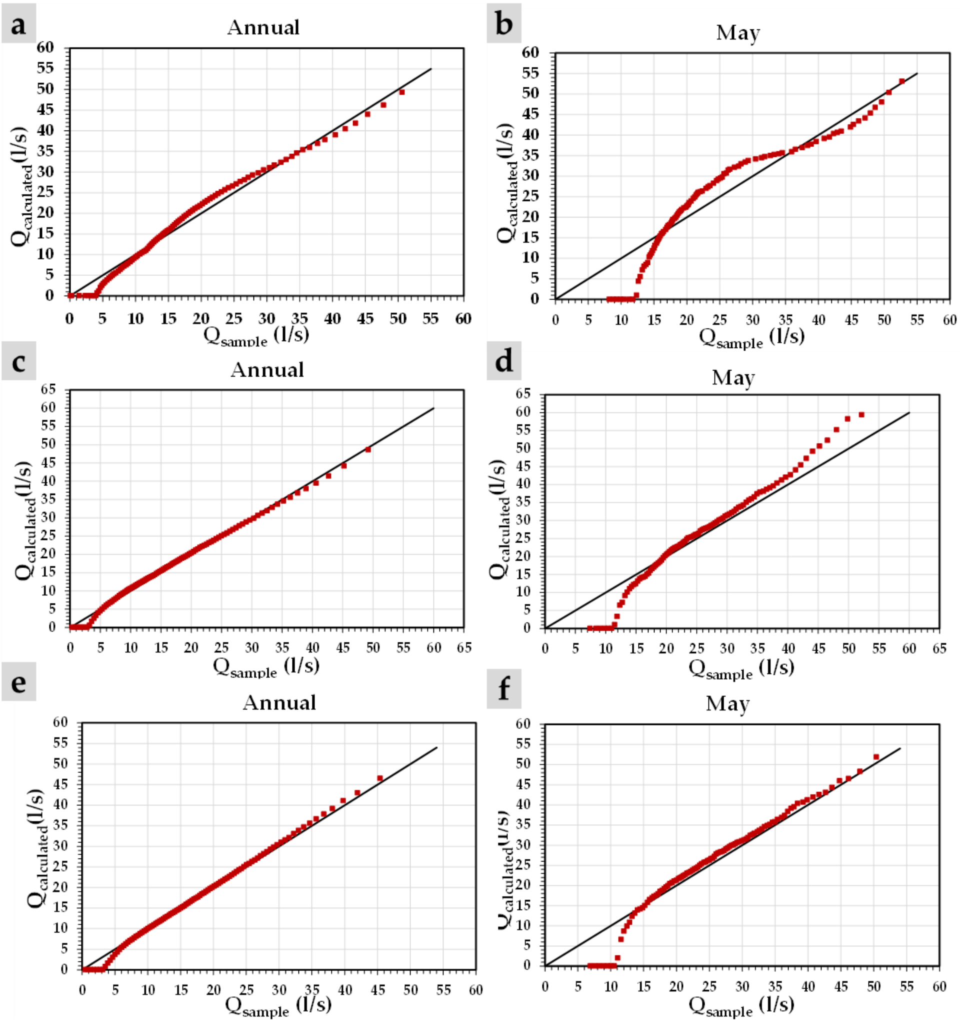

Figure 3.5. *(a) Q-Q plots for Annual Observed_Calibrated in 2015; (b) Q-Q plots for Observed_Calibrated in May 2015; Q-Q plots for Annual Gamma_Calibrated in 2015 (c); (d) Q-Q plots for Gamma_Calibrated in May 2015; (e) Q-Q plots for Annual Normal_Calibrated in 2015; (f) Q-Q plots for Normal_Calibrated in May 2015.*

The calibration for simulation of Observed_Data, Normal_Calibrated and Gamma_Calibrated models from observed data and synthetic years generated for Normal and Gamma was completed. After the analysis of the different functions as well as their graphical representation in Figure 3.5, the results obtained show a better fit for the gamma distribution in the case study. The development of the methodology allows this characterisation to be addressed for any case study, making it possible to define the best distribution to continue with the design of the network or partial renovation of the same in the interests of sustainability, showing a novelty within the adequacy to the design of networks. Table 3.4.A (Appendix I) shows the characteristic values of May, which were get in the proposed model. Figure 3.2.A (Appendix I) shows the different flow distribution for observed (Figure 3.2.Aa), Gamma distribution function (Figure 3.2.Ab) and Normal distribution function (Figure 3.2Ac).

For the theoretical and corrected models of Clement and Gamma *(Clement_Theoretical; Clement_Corrected; Gamma_Theoretical; Gamma_Corrected)*, synthetic years were also generated with the same previous methodology from Figure 3.2b. These years are compared only with the observed data from the main line. Figure 3.6 shows the maximum and minimum values for the Correlation Coefficient as well as the average values for each month and annually.

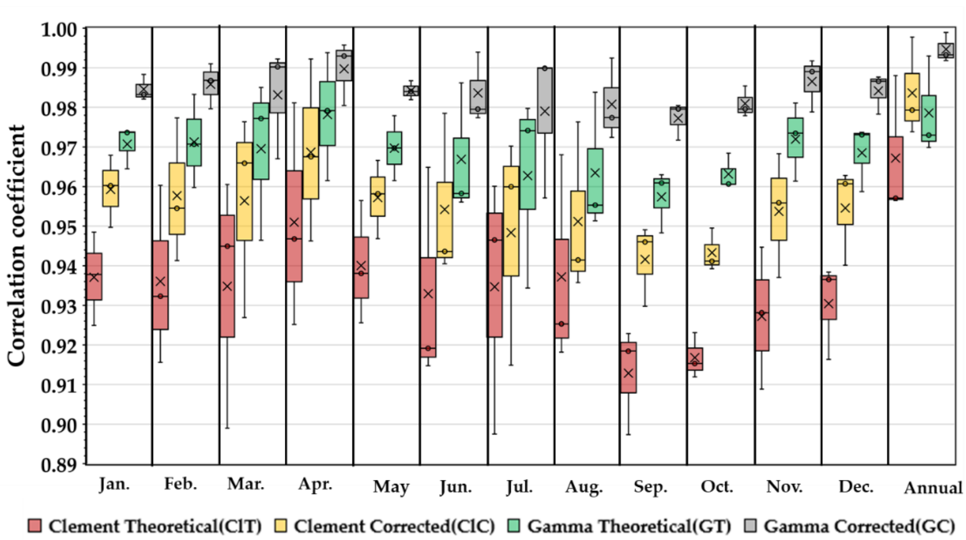

Figure 3.6. *Correlation Coefficients for the theoretical and corrected Clement and Gamma models.*

The Clement_Theoretical model (ClT) had the lowest correlation coefficients on average out of the compared models, with maximum and minimum values between 0.95 and 0.92 for May and 0.97 for the annual average. The Clement_Corrected model (ClC) followed a trend like the Clement_Theoretical, being the second to last option in terms of correlation coefficient value, with maximum and minimum values between 0.97 and 0.95 for May and averaging 0.98 for the annual series. The Gamma_Theoretical model (GT) is the second-best option, with maximum and minimum values between 0.96 and 0.98 for the month of maximum needs and averaging 0.98 for the annual. Lastly, the Gamma_Corrected model (GC) obtained the best results in the correlation coefficient with values between 0.98 and 0.99 for May, while having an average value of 0.995 for the annual series.

The weighted absolute error for the design flow was calculated for each model and it was compared with the Observed data. Figure 3.7 shows the results obtained for each model during the three years of study as well as an average for the period. The Clement_Theoretical (ClT) and Gamma_Theoretical (GT) models underestimate the design flows by 24.65% and 19.05% for the studied period; this can be explained due to the low standard deviations from Clément and since the Gamma is calculated from this model, is also affected. The Clement_Corrected (ClC) and Normal_Calibrated (NCal) had a lower weighted absolute error compared to the previous two but still underestimated the design flows, with 3.90% and 4.43%, respectively. The Gamma Corrected and Calibrated models have better overall results than the other models, which underestimate the design flow. The Gamma_Corrected (GC) has an 8.21% overestimation on average compared to the observed data, and the best result comes from the Gamma_Calibrated (CCal), overestimating 1.12% of the design flow on average for the month of May.

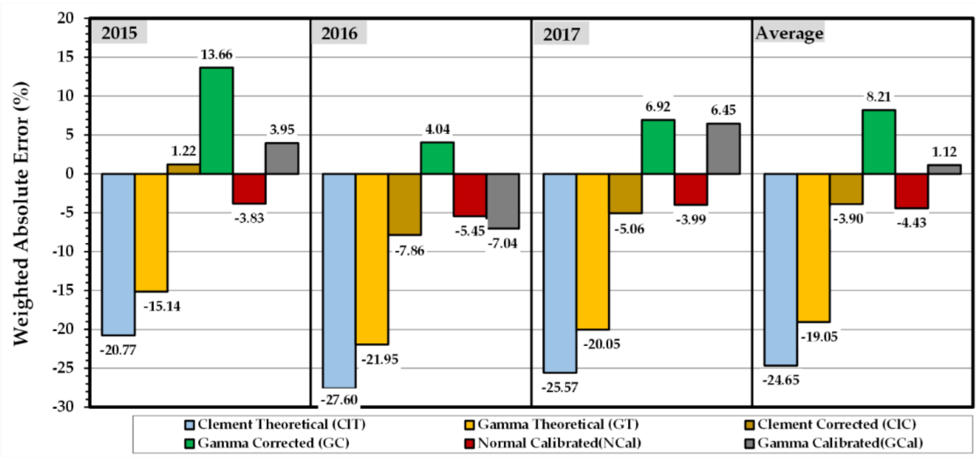

Figure 3.7. *Weighted absolute error for the design flow in May for the evaluated models.*

This figure shows how the weighted errors are greater for the Clement distribution in the case study addressed. The proposed methodological development reveals the ability to address the selection of the best distribution according to the established crop irrigation needs and/or flow records in case of irrigation network renewals or expansions thereof.

Once the design flows are calculated for each model, and the minimum pressure constraint were established. The pipe diameters were determined, using the economic method and the CO_2 emissions per meter criteria for the sizing and then for determining the total environmental cost for each model and material. Figure 3.8 shows the results for the six previous models as well as the Observed_Calibrated of the average cost for the three years, material and model used. On the vertical axis, the CO_2 tonnes are represented. The three Gamma models have the lowest general CO_2 emissions per installation while the system using cast iron showed the higher valued of carbon footprint for all flow distributions.

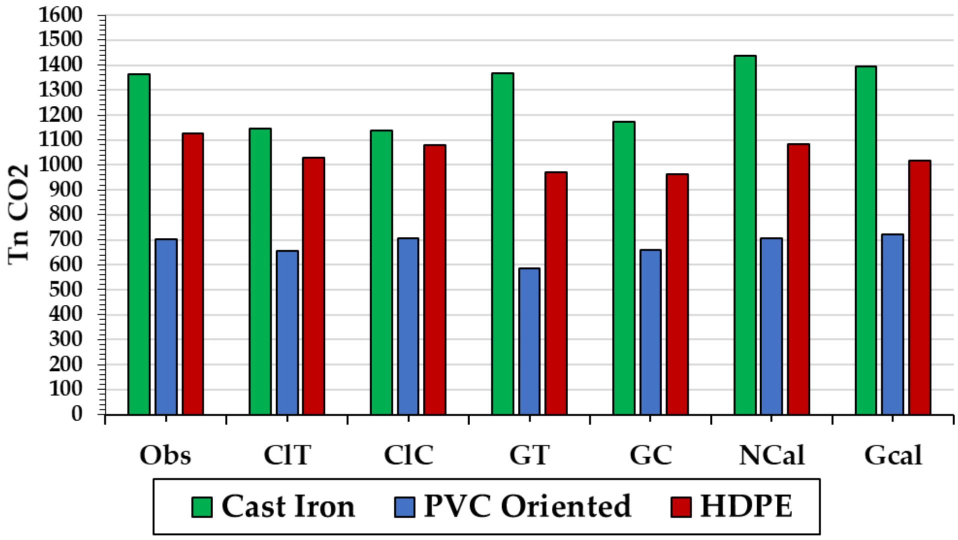

Figure 3.8. *Tons of CO_2 emissions for the different models and materials.*

Considering the same material, the distribution can contribute to variations in the carbon footprint that range between -16.45% (Clement Corrected) and 5.32% for the Normal distribution calibrated in the case of cast iron. IF the PVC-O is considered, this variation ranges between -16.91% in the case of the corrected gamma function and 2.94% if the calibrated gamma is considered. Finally, if HDPE is considered, the carbon footprint variation ranges between -14.75% of the corrected gamma and -3.86 of the calibrated normal.

The results presented by the Gamma_Corrected (GC) model represent a slight overestimation in the design flow; nonetheless, it has a decrease in costs of installation and CO_2 emissions for all the evaluated pipe materials. Therefore, the proposed methodology of flow modelization following a Gamma distribution allows the simulation of the flow not only for the design but also for monthly and yearly flows in the network, thus creating a new tool/methodology for the analysis of irrigation networks. The PVC-O was the solution with the lowest environmental cost for all the models evaluated.

The average energy balance for the studied period is calculated for the PVC Oriented and all the models in step IV. The total and required energy are the same for all the models. Table 3.3 shows the energy balance considering the different distribution hypotheses. ClC and GT shoes lower values of the friction energy, which implies these flow distributions show the higher values of the theoretical available energy. Particularly, the Clement Theoretical distribution showed a 3.9% of available recovered energy compared to the observed value in the current distribution system.

Table 3.3. *Energy balance for the different models using PVC-O material.*

Model Code	Model	Total Energy (kWh)	Friction Energy (kWh)	Required Energy (kWh)	Theoretical Available (kWh)
Obs	Observed	126424.78	21356.76 (1)	43322.78	61745.24 (1)
ClT	Clement_Theoretical	126424.78	18975.19 (0.888)	43322.78	64126.81 (1.039)
ClC	Clement_Corrected	126424.78	19476.56 (0.912)	43322.78	63625.45 (1.03)
GT	Gamma_Theoretical	126424.78	19058.65 (0.892)	43322.78	64043.35 (1.037)
GC	Gamma_Corrected	126424.78	19408.06 (0.909)	43322.78	63693.94 (1.032)
NCal	Normal_Calibrated	126424.78	20509.04 (0.96)	43322.78	62592.96 (1.014)
GCal	Gamma_Calibrated	126424.78	20856.93 (0.977)	43322.78	62245.07 (1.008)

*(XX) is the normalized value compared to the observed model.

The results for the annual total recoverable energy for each model during the studied period, expressed in kWh, for the line 2024 are shown in Table 3.5.A (Appendix I). These annual recovered values oscillated between 32838 and 34798 kWh, representing around 27.5% of the annual total energy injected in the gravity system (Table 3.3). These unit energy values, which oscillated between 0.246 and 0.279 kWh/m^3 (considering an average efficiency equal to 0.5 according to (Carravetta et al., 2013) were similar to those defined by (Garcia et al., 2021), showing ratios between 0.028 and 0.321 kWh/m^3 each year for different published case studies.

Following the results for sustainability, indicators are shown in Table 3.4 for all the used models using the PVC-O material solution for each model. This table shows the reduction of the carbon footprint equal to 16.91% when the Gamma

Theoretical distribution is considered compared to the observed value with the current size of the irrigation system.

Table 3.4. *Sustainability indicators for the evaluated models using the PVC-O material solution.*

Model Code	Model	Total network enviromental cost (Tn CO2)	CO2 emissions per network meter (Tn CO2/ m)	CO2 emissions per hectare (Tn CO2/ ha)	CO2 emissions from supplied water (kgCO2/ m3)
Obs	Observed	702.48	0.0665	5.61	1.32
ClT	Clement_Theoretical	656.22	0.0621	5.24	1.24
ClC	Clement_Corrected	706.54	0.0669	5.64	1.33
GT	Gamma_Theoretical	583.65	0.0552	4.66	1.10
GC	Gamma_Corrected	660.26	0.0625	5.27	1.25
NCal	Normal_Calibrated	705.37	0.0668	5.63	1.33
GCal	Gamma_Calibrated	723.16	0.0684	5.78	1.36

The water footprint of the system varied between 1.1 $kgCO_2/m^3$ for *GT* and 1.36 $kgCO_2/m^3$ when *GCal* is considered, being 1.32 $kgCO_2/m^3$ for observed value. These values are -16.6% and 3.03% compared to the observed value. Therefore, the selection of the flow distribution establishes the difference between the carbon footprints of the irrigation system, considering the material of the irrigation system. The carbon footprint evaluation is linked to different targets (Garcia et al., 2021): (A) SDG-6. Water and Sanitation, implement the integrated water resources management in all levels; (B) SDG-7. Clean Energy in which different targets could be considered such as (B.1) increasing substantially the share of renewable energy in the global balance energy, (B.2) doubling the global rate of improvement in energy efficiency, and (B.3) reducing the amount of greenhouse gas emissions to take action in the fight against global warming; (C) SDG-11. Sustainable Cities and Communities by Enhance inclusive and sustainable urbanization and capacity for participatory, integrated and sustainable human settlement planning and management.

This research shows the possibility of approaching the design and renovation of distribution networks taking into account sustainable aspects to improve their carbon footprint. In contrast to different methods summarized in (Garcia-Espinal et al., 2024), the research proposes a method that allows the study and definition of the best distribution to be used in the design of networks to consider the design flow. The use of the normal distribution does not always give the most optimal results. Furthermore, within the proposed methodology, the use of the correlation coefficient makes it possible to consider a global annual analysis or to be able to discretise for the different months of the year, being able to select the month of maximum needs and be able to define the distribution function for that month better. Within the proposed methodological development, the methodology includes the objective of the economic design of networks, guaranteeing the pressure and guarantee of supply. Still, as a novelty, it includes the consideration of the carbon footprint (Benalcázar-Murillo et al., 2023). It is should mandatory in new design since its consideration allows for reducing the environmental impact of the development of new distribution networks and addressing the incursion of hybrid renewable systems in them, leading to a zero-carbon balance (Chazarra-Zapata et al., 2020).

3.4. Conclusions

Irrigation systems have significantly enhanced agricultural production, and impact hydraulic system design, energy consumption, and sustainability. This research presents a comprehensive methodology to optimize flow distribution in irrigation systems, aiming to improve sustainability by employing a multicriteria solution. This proposal incorporates log-likelihood, AIC values, Chi-squared, and Kolmogorov-Smirnov goodness of fit tests. The study introduces an innovative tool to characterize flow distributions, which deviate from the traditional Clement's formulation. Six different flow distributions were analysed and the Gamma corrected function was identified as the most suitable for this case study. It demonstrated correlation coefficients above 0.9, satisfying the established criteria. The proposed methodology not only ensures pressure and service quality, it also addresses CO_2 emissions from installation and manufacturing, emphasizing a holistic approach to network design. Gamma function showed potential for energy recovery up to 3% higher than the normal distribution. This advanced approach is applicable to any supply or irrigation system, providing water managers with robust tools for enhanced digital modelling, informed network renewal planning, and sustainable material selection. Future research could explore the integration of real-time data analytics to further accurate flow distribution models, the impact of climate change on irrigation demands and system efficiency, and the development of adaptive management strategies to dynamically respond to varying water availability and usage patterns, ensuring long-term sustainability and resilience of irrigation networks.

Appendix I. Supplementary Data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rineng.2024.102609

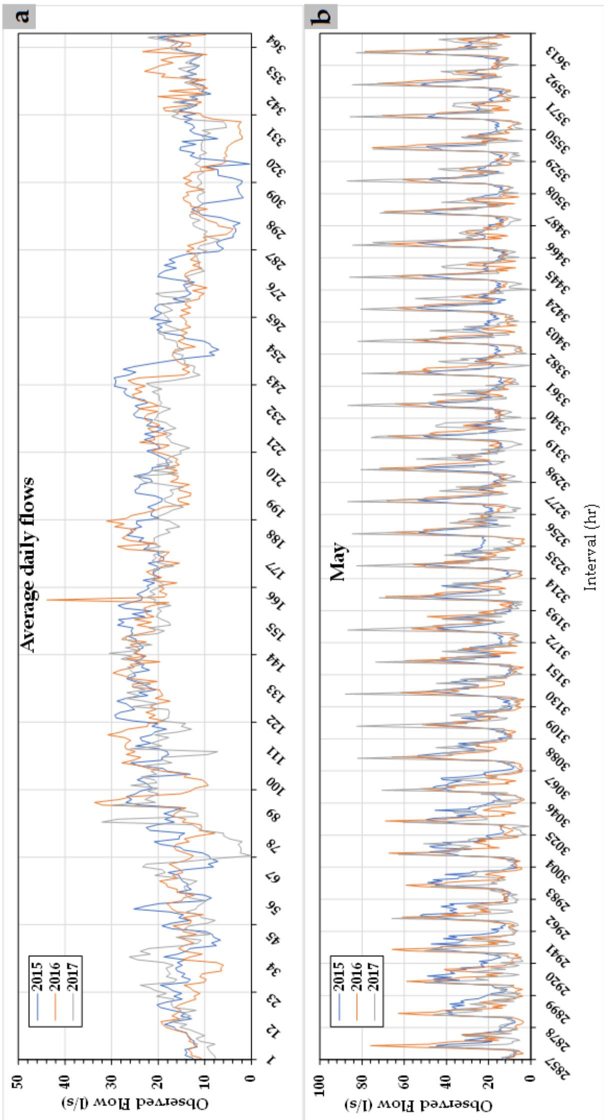

Figure 3.1A. *Observed data (a) Average daily flows for years 2015, 2016, and 2017; (b) Hourly flows for May.*

Table 3.1A. *Correlation Coefficients for (a) Observed_Calibrated 2015; (b) Observed_Calibrated 2016; (c) Observed_Calibrated 2017.*

Year		January	February	March	April	May	June	July	August	September	October	November	December	Annual
2015	Max	0.985	0.985	0.983	0.990	0.961	0.973	0.954	0.971	0.979	0.995	0.997	0.991	0.992
	Min	0.969	0.969	0.966	0.965	0.921	0.938	0.919	0.937	0.951	0.969	0.987	0.976	0.987
	Average	0.976	0.977	0.977	0.976	0.937	0.958	0.936	0.958	0.963	0.984	0.992	0.983	0.990
	Median	0.976	0.976	0.977	0.976	0.936	0.959	0.936	0.961	0.962	0.983	0.993	0.984	0.990
	Percentile 95%	0.983	0.985	0.982	0.987	0.947	0.971	0.950	0.969	0.978	0.994	0.997	0.990	0.992
	Percentile 5%	0.970	0.970	0.969	0.966	0.926	0.945	0.919	0.938	0.953	0.975	0.987	0.977	0.988
2016	Max	0.989	0.992	0.989	0.966	0.971	0.964	0.975	0.966	0.976	0.988	0.995	0.971	0.981
	Min	0.971	0.976	0.961	0.921	0.930	0.929	0.942	0.916	0.941	0.966	0.969	0.946	0.971
	Average	0.981	0.982	0.973	0.944	0.952	0.946	0.961	0.940	0.957	0.975	0.987	0.962	0.976
	Median	0.981	0.981	0.974	0.944	0.951	0.946	0.960	0.940	0.956	0.975	0.988	0.964	0.976
	Percentile 95%	0.987	0.989	0.980	0.965	0.970	0.959	0.970	0.961	0.968	0.981	0.993	0.971	0.980
	Percentile 5%	0.975	0.976	0.964	0.928	0.931	0.930	0.948	0.923	0.949	0.967	0.981	0.950	0.972
2017	Max	0.981	0.993	0.993	0.970	0.943	0.943	0.933	0.952	0.978	0.982	0.993	0.989	0.975
	Min	0.962	0.975	0.980	0.938	0.908	0.910	0.905	0.915	0.931	0.959	0.979	0.976	0.965
	Average	0.973	0.986	0.987	0.957	0.927	0.928	0.917	0.935	0.955	0.970	0.989	0.982	0.971
	Median	0.973	0.986	0.987	0.958	0.925	0.930	0.916	0.936	0.955	0.970	0.990	0.981	0.971
	Percentile 95%	0.978	0.993	0.991	0.966	0.939	0.940	0.929	0.948	0.970	0.980	0.993	0.987	0.974
	Percentile 5%	0.965	0.977	0.983	0.946	0.919	0.913	0.908	0.918	0.944	0.960	0.983	0.978	0.968

Table 3.2A. *Correlation Coefficients for (a) Gamma_Calibrated 2015; (b) Gamma_Calibrated 2016; (c) Gamma_Calibrated 2017.*

Year		January	February	March	April	May	June	July	August	September	October	November	December	Annual
2015	Max	0.990	0.989	0.992	0.982	0.992	0.989	0.978	0.969	0.976	0.982	0.987	0.986	0.998
	Min	0.985	0.984	0.984	0.974	0.986	0.976	0.951	0.950	0.961	0.968	0.974	0.970	0.997
	Average	0.987	0.986	0.989	0.978	0.989	0.983	0.967	0.962	0.967	0.974	0.980	0.980	0.997
	Median	0.988	0.986	0.989	0.977	0.989	0.983	0.967	0.965	0.966	0.976	0.981	0.980	0.998
	Percentile 95%	0.990	0.989	0.992	0.982	0.991	0.989	0.976	0.967	0.975	0.981	0.985	0.986	0.998
	Percentile 5%	0.985	0.984	0.985	0.975	0.986	0.977	0.957	0.952	0.962	0.969	0.975	0.972	0.997
2016	Max	0.992	0.992	0.992	0.988	0.982	0.990	0.980	0.975	0.980	0.989	0.991	0.987	0.992
	Min	0.982	0.983	0.984	0.979	0.966	0.979	0.963	0.963	0.965	0.980	0.985	0.976	0.988
	Average	0.989	0.988	0.989	0.985	0.972	0.985	0.970	0.968	0.975	0.985	0.988	0.983	0.990
	Median	0.991	0.988	0.989	0.985	0.971	0.984	0.969	0.969	0.977	0.985	0.989	0.982	0.991
	Percentile 95%	0.992	0.991	0.992	0.988	0.980	0.989	0.979	0.974	0.979	0.989	0.991	0.987	0.992
	Percentile 5%	0.984	0.983	0.986	0.980	0.967	0.979	0.963	0.963	0.969	0.981	0.986	0.978	0.989
2017	Max	0.987	0.990	0.992	0.981	0.993	0.987	0.984	0.990	0.988	0.992	0.997	0.988	0.989
	Min	0.973	0.980	0.986	0.964	0.986	0.980	0.965	0.976	0.972	0.988	0.989	0.975	0.986
	Average	0.981	0.985	0.989	0.976	0.990	0.982	0.970	0.982	0.982	0.990	0.993	0.982	0.988
	Median	0.982	0.985	0.988	0.977	0.991	0.982	0.968	0.983	0.983	0.990	0.994	0.982	0.988
	Percentile 95%	0.986	0.989	0.992	0.981	0.993	0.986	0.982	0.989	0.988	0.992	0.996	0.987	0.989
	Percentile 5%	0.973	0.981	0.986	0.969	0.986	0.980	0.966	0.976	0.975	0.988	0.989	0.977	0.986

Table 3.3A. *Correlation Coefficients for (a) Observed_Calibrated 2015; (b) Observed_Calibrated 2016; (c) Observed_Calibrated 2017.*

Year		January	February	March	April	May	June	July	August	September	October	November	December	Annual
2015	Max	0.996	0.998	0.994	0.996	0.989	0.997	0.993	0.993	0.995	0.998	0.999	0.999	0.999
	Min	0.992	0.994	0.988	0.990	0.979	0.990	0.985	0.985	0.984	0.992	0.995	0.995	0.999
	Average	0.994	0.997	0.992	0.992	0.983	0.994	0.990	0.990	0.990	0.996	0.997	0.997	0.999
	Median	0.994	0.997	0.992	0.991	0.982	0.994	0.990	0.990	0.991	0.996	0.997	0.998	0.999
	Percentile 95%	0.995	0.998	0.994	0.995	0.988	0.996	0.992	0.993	0.993	0.998	0.999	0.998	0.999
	Percentile 5%	0.992	0.995	0.989	0.990	0.979	0.990	0.985	0.986	0.986	0.993	0.996	0.996	0.999
2016	Max	0.995	0.997	0.996	0.998	0.993	0.998	0.998	0.987	0.993	0.998	0.995	0.995	0.998
	Min	0.988	0.993	0.990	0.995	0.984	0.995	0.996	0.975	0.985	0.994	0.992	0.991	0.997
	Average	0.992	0.995	0.993	0.997	0.989	0.996	0.997	0.982	0.989	0.997	0.993	0.993	0.997
	Median	0.993	0.995	0.993	0.997	0.990	0.996	0.997	0.982	0.989	0.996	0.993	0.993	0.997
	Percentile 95%	0.995	0.997	0.995	0.998	0.993	0.998	0.998	0.987	0.992	0.998	0.995	0.995	0.998
	Percentile 5%	0.989	0.993	0.991	0.995	0.985	0.995	0.996	0.977	0.985	0.995	0.992	0.992	0.997
2017	Max	0.994	0.989	0.995	0.995	0.989	0.990	0.989	0.988	0.995	0.997	0.997	0.997	0.994
	Min	0.989	0.981	0.989	0.991	0.981	0.982	0.981	0.980	0.988	0.994	0.993	0.989	0.993
	Average	0.992	0.986	0.992	0.994	0.985	0.986	0.985	0.983	0.991	0.995	0.996	0.994	0.993
	Median	0.992	0.986	0.991	0.994	0.985	0.985	0.986	0.983	0.990	0.995	0.996	0.994	0.994
	Percentile 95%	0.994	0.989	0.995	0.995	0.988	0.989	0.989	0.987	0.994	0.996	0.997	0.997	0.994
	Percentile 5%	0.990	0.982	0.990	0.991	0.982	0.983	0.982	0.980	0.988	0.994	0.994	0.990	0.993

Table 34A. *Characteristic values for the month of May*

Year	2015	2016	2017
Volume (m^3)	66718.24	62339.07	64353.61
Min Flow (l/s)	6.11	0.39	0.40
Max Flow (l/s)	55.35	74.28	87.95
Average Flow (l/s)	24.91	23.27	24.03
Standard Deviation (l/s)	10.19	16.21	16.40
Gamma Optimal Distribution			
Shape Parameter (α)	4.81	2.26	1.94
Scale Parameter (λ)	5.18	10.30	12.39

Table 34A. *Total Recoverable Energy (kWh) in line 2024*

Model Code	Model	2015	2016	2017	Average
Obs	Observed	34243.28	32727.49	31545.74	32838.83
ClT	Clement_Theoretical	36142.68	34509.41	33743.56	34798.55
ClC	Clement_Corrected	35719.87	34067.86	33514.41	34434.04
GT	Gamma_Theoretical	35914.49	34219.32	33911.63	34681.81
GC	Gamma_Corrected	35976.11	33918.90	33453.77	34449.59
NCal	Normal_Calibrated	34937.77	33205.80	32786.11	33643.22
GCal	Gamma_Calibrated	35242.88	32877.35	32011.49	33377.24

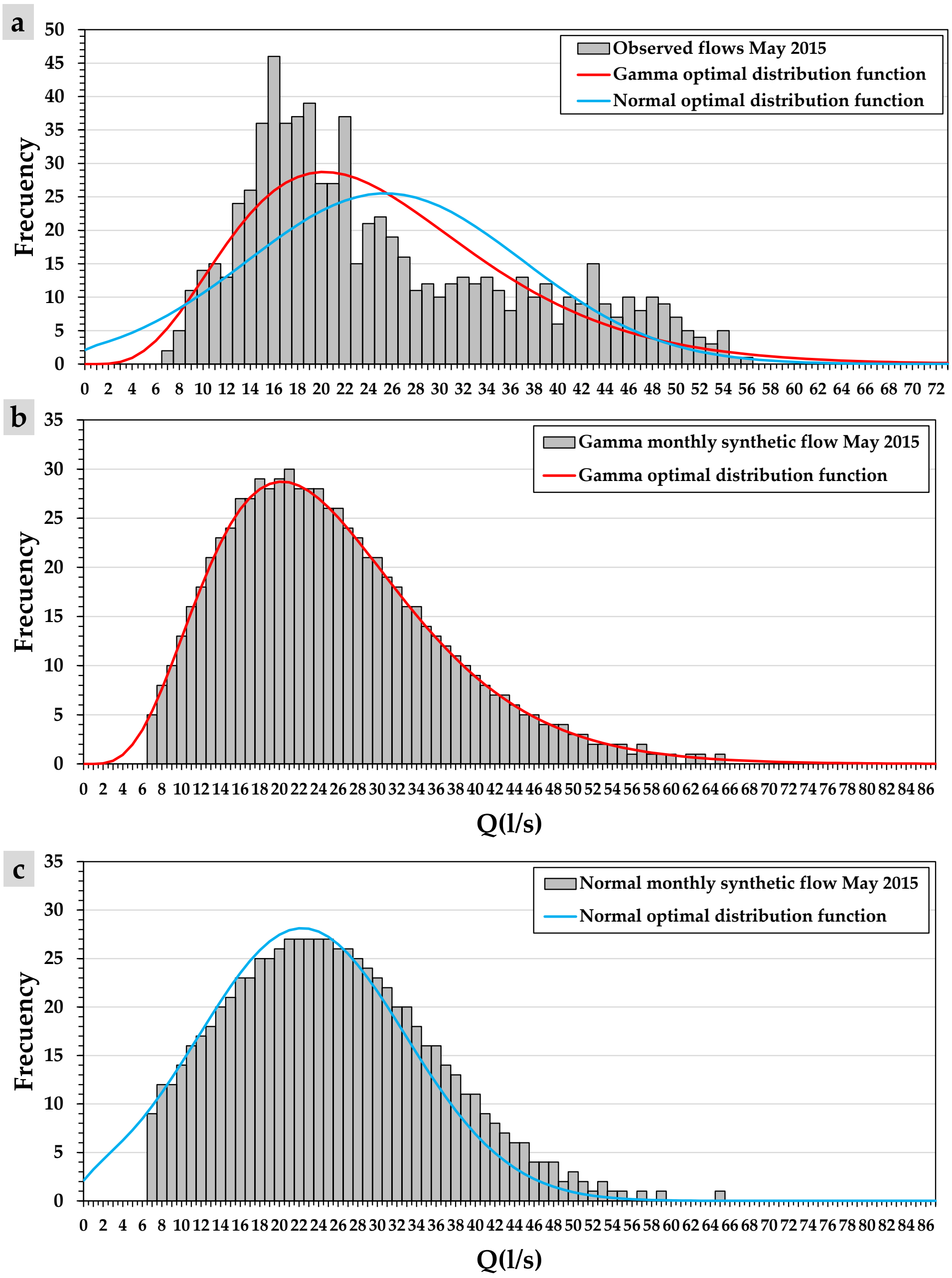

Figure 3.2A. *Flow Distributions for the month of May 2015 (a) Observed (b) Gamma monthly synthetic flow (c) Normal monthly synthetic flow.*

Chapter 4
Publication III

"Improvement of the Electrical Regulation of a Microhydropower System using a Water Management Tool"

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Abstract

The constant growth of the population and the increase in the need for resources create challenges, and it is necessary to seek more sustainable solutions to manage them more adequately and efficiently. In recent years, the use of renewable energy systems has increased, in which water distribution networks are no exception. Pumps operating as turbines (PATs) are an innovative solution with enormous potential to achieve these sustainable development goals. As a means of improving sustainability, in this research, an optimized regulation tool is developed to maximize the recovered energy in the system using PATs in water distribution networks (WDNs). This is possible due to the use of empirical methods for the estimation of the characteristic curves. The tool was developed in Simulink MATLAB, in which the optimization and iterative steps were carried out. It is based on the intended methodology and applied to a real case study. When implementing the tool, the results given are the hydraulic–electrical regulation strategies, where the number of machines working, the frequency inverter setpoint, and the degree of opening of the pressure-reducing valves (PRV) is defined for any given time. After the analysis in the case study, the tool recovered 28% of the supplied energy in the system. This daily recovered energy was above 7160 kWh, and it contributed to an increase in efficiency and sustainability.

Keywords

hydraulic regulation; electronic regulation; sustainability; pump working as turbine; water distribution network

4.1. Introduction

In the search for the sustainable development of society, various authors have carried out studies in which the use of energy recovery systems is proposed, with the so-called microgeneration systems being more commonly used (Corcoran et al., 2013). Population growth has been responsible for an increase in energy and water consumption since the industrial revolution (Del Borghi et al., 2020). This caused an increase in the energy cost in different hydraulic systems and the inclusion of management to make the water cycle more sustainable (Kanakoudis V et al., 2011). Renewable energy sources with little or no environmental impacts have led to a global proliferation of this hydropower technology (Kuriqi et al., 2021), particularly those of the run-of-river type (Kuriqi et al., 2019). To improve these sustainable indexes, several studies have shown that the use of microgeneration causes a decrease in pressure and an increase in renewable energy (Grubic et al., 2020) and its optimization in generation (Reigstad & Uhlen, 2020). Additionally, this pressure decrease guarantees the improvement of the leakage indexes of the supply network (Morani et al., 2018).

With the development of strategies focused on ensuring energy and hydraulic efficiencies, such as pressure control for leak reduction or energy recovery using microturbines, it is possible to increase sustainability (Eshra et al., 2021). In this way, the use of a pump in reverse mode, called a pump working as a turbine (PAT), is a real application that has been considered in recent years (Tahani et al., 2020). The use of microhydropower systems, joined with other renewable systems such as photovoltaic systems, enables an improvement in the use of clean energies in water distribution systems (Alhejji et al., 2021).

The major availability of pumps compared to available turbines improves the feasibility of these facilities, reducing investment and showing low payback, although PAT efficiency is lower than turbine efficiencies (Stefanizzi et al., 2020).

PATs analyses have been developed since the 1940s. Stepanoff (Stepanoff, 1957) was the first to establish a method to estimate the efficiency of the machine when it operates as a turbine, and Childs (Childs, 1962) developed a comparative study of efficiencies when the machines operate as pumps or turbines. Grover (Grover, 1980) proposed linear equations to estimate the best efficiency point of a machine operating as a turbine. Sharma (Sharma, 1985) developed a prediction method that uses relationships. These values depend on the efficiency of the pump. Alatorre-Frenk et al. (Alatorre-Frenk et al., 1994) proposed a method based on equations setting a limited number of PATs data, which improved the previous results, and Williams (Williams, 1994) presented a study on the comparison of different calculation methods for turbine performance prediction using the best efficiency value. Fernández et al. (Fernández et al., 2004) observed the influence of the rotational speed on efficiency and obtained the characteristics at constant head and runaway speed. Derakhshan and Nourbakhsh (Derakhshan & Nourbakhsh, 2008) tried to estimate hydraulic parameters (i.e., head, flow, and efficiency) in turbine mode using pump data with CFD techniques. Páscoa et al. (Páscoa et al., 2012) proposed a new approach for the PAT power plant, designed based on a constant head, instead of a traditional operation, at a constant flow rate. Rossi and Renzi (Rossi & Renzi, 2018) evaluated both the best efficiency points (BEP) and the performance of PATs in an accurate way using artificial neural networks. Macías Ávila et al. (2021) defined new approach equations to estimate the BEP of a PAT and the characteristic curves using an experimental database of 181 different PATs.

Estimating the characteristic curves and the best efficiency point in a PAT requires overcoming new challenges to improve the use of these systems in the future (Delgado et al., 2019). Systems of the future should be focused on taking advantage of the different regulation strategies and applying affinity laws (Carravetta et al., 2013). The use of these methods enables the hydraulic and electrical regulation of these recovery systems. Additionally, their implementation improves the optimization procedure and includes an increase in the generated energy (Kandi et al., 2021).

This regulation improvement should be supported by optimization tools, with water managers knowing the main constraints of the system (flow over time, upstream pressure, and downstream pressure) to guarantee the quality of service to the end-user (Crespo Chacón et al., 2019). There are only a few previous works that have developed a tool to select PATs or turbines (Rodríguez-Pérez et al., 2021). The tools were focused on defining the best efficiency point, but this analysis was not centered on the interface used to analyze alternatives and develop energy studies (Venturini et al., 2018), improving their operation (Reigstad & Uhlen, 2021). A MATLAB Simulink model was developed for simulating a branch of the WDN located in Laives (South-Tyrol) (Alberizzi et al., 2018) or for analyzing two different scenarios (Rossi et al., 2019). Simulink was also used to estimate leakages (Nabil et al., 2020), floods control (Hòa et al., 2017), or waste-water treatment modeling (Kuriqi, 2014), among others.

This research develops an interface using a dynamic model by Simulink MATLAB (Camilo Rosado et al., 2020). The optimization tool is focused on the selection of the pump, defining the best regulation strategies (the number of operating machines, rotational speed value, and opening degree valves) at any given time to guarantee the hydraulic constraints of the system and maximize the generated power, which could be supplied to the grid or self-consumed. The main goal of the manuscript is to develop an optimization tool that enables an improvement in PAT management in water systems. The novelty of our work is the focus on the integration of empirical methods, which can estimate the characteristic curves to optimize the operation and select machines based on flow over time as well as the frequency of these flows. The implementation tool is new and crucial to improving sustainability in water distribution systems.

4.2. Methods

This section proposes a methodology that enables the development of a tool for the analysis of the regulation of an energy-recovery system. As a starting point, there are flow input records and pressure setpoints established at a point in the distribution system, which establish the operating restrictions.

As the object of the application is water supply, this means that there is a variable operation system, and we seek to design a strategy in which energy recovery does not compromise the level of service of the network but can provide an improved solution to the study system.

As shown in Figure 4.1, the hydraulic model considers there will be a replacement between a pressure-reduction valve (PRV) and a recovery system.

The energy recovery equipment has two main groups of elements: PATs and PRVs. A parallel group of three PATs is considered, including two pressure-reducing valves (one in parallel to the machines and another at the outlet, connected in series). The function of these PRVs is the dissipation of the excess of the hydraulic head, which is not recovered by PAT since the downstream pressure is an established constraint, and it must guarantee the correct operation of the water system.

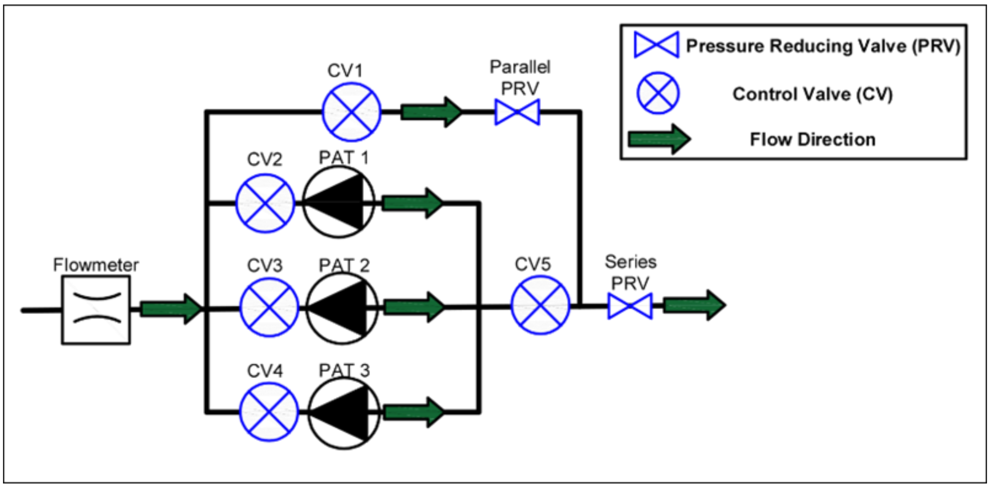

Figure 4.1. *Hydraulic model layout.*

A structured methodology was developed and executed in MATLAB Simulink. MATLAB is desktop software with a programming language that expresses the mathematics of matrices and arrays (vectors or arrays) directly. Simulink is one of the most important MATLAB complements; it allows users to combine textual and graphical programming to design systems in a simulation environment (Pérez-Sánchez et al., 2020). The tool searches the definition of the signal parameters to define the number of machines operating, their rotational speed, and the opening degree of the PRVs by reading the flow over time and the upstream pressure when the main constraint (the downstream pressure) is known.

4.2.1. Methodology

Figure 4.2 shows the proposed methodology, which is composed of three main blocks: A. Model preparation, B. Simulation of PAT system and hydraulic model, and C. Analysis and presentation of results. Each block is divided into different sections that contain the steps of the different developed actions.

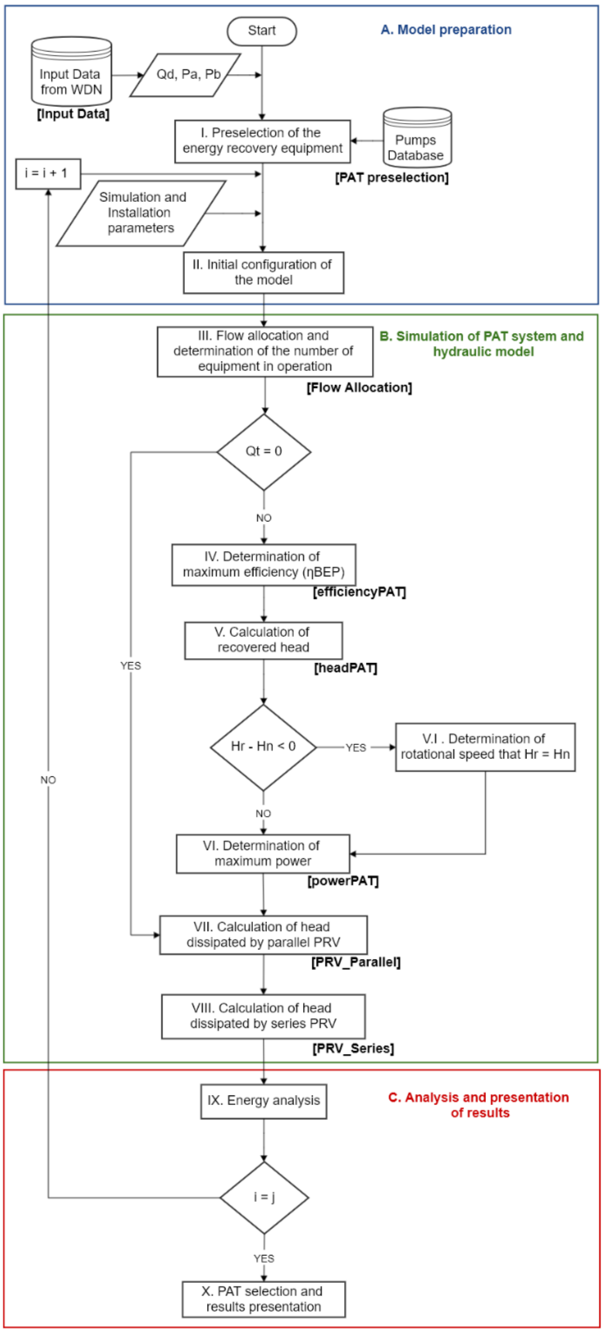

Figure 4.2. *Proposed methodology for the analysis of the regulation in an energy recovery system.*

The first block (A. Model Preparation) is focused on the establishment of the input parameters to develop the optimization operation of the recovery systems. Step I is focused on the preselection of the pump working as a turbine. For development, the programmed tool used two different databases. Firstly, the flow and upstream pressure, as well as the downstream pressure (restriction to guarantee the service operation of the system), should be known over time. The selection was developed using the methodology proposed by Camilo Rosado et al. (2020). This methodology contains the following steps: (a) statistical analysis of the data record (flow and upstream and downstream pressures) to define the flow and head more representative of the series. This point will establish the future of both flow and head at the best efficiency point of the machine (Q_{BEP_t} and H_{BEP_t}); (b) calculation of specific numbers in turbine mode (ns_t) and estimation of coefficients β_Q and β_H; (c) estimation of the best efficiency point (Q_{BEP_p}, H_{BEP_p}) operating as a pump; (d) selection of the pumps in manufacturer catalog; (e) calculation of specific number in pump mode (ns_p); (f) estimation of the characteristics of the equipment working in turbine mode, obtaining Q_{BEP_t}, H_{BEP_t}, and η_{BEP_t}; and lastly, (g) validation if the preselected PAT meets the criteria of ($C \leq 1$).

Step II develops the initial configuration of the tool to be implemented in the MATLAB algorithm. It defines the database established in step I and establishes the simulation time steps. The following setup parameters are defined:

1. Parameters of the installed PATs: number of units installed, np (between 1 to 3); nominal rotational speed, no (in rpm); minimum and maximum operating flows of the equipment, Q_{mint} and Q_{maxt} (in L/s), as well as the BEP (Q_{BEP_t}, H_{BEP_t}, and η_{BEP_t}).

2. The frequency inverter: where the minimum and maximum values of α are defined at which the equipment can work (α_{min} and α_{max}).

3. The efficiency of the electric generator: the efficiency of the electric generator is defined with a constant or variable value depending on the mechanical power of the output.

4. Limits for range determine maximum power: the values that will define the search space (lower bound, lb and upper bound, ub) are defined.

5. Pressure Reducing Valves (PRVs): Enter the diameter, $Diam$ (in mm), the valve curve, and the flow coefficient with the valve fully open, Kvo (in $m^3/h/\sqrt{Pa}$).

6. Relative fluid properties: where the density of the fluid is entered according to the operating temperature (in kg/m3) and the acceleration of gravity (in m/s2).

The second block (B. Simulation and hydraulic model), which contains the simulation of the PAT system and hydraulic model, is developed between steps

III and VII. It considers the optimization block to optimize the operation of the recovery system, maximizing the generated power by compliance with the constraints (flow and downstream pressure). Five sections comprise this block: B.1 flow allocation and number of equipment in operation (step III); B.2 determination of the maximum efficiency for the installed PAT (step IV); B.3 calculation of the recovered head (step V); B.4 determination of maximum power (step VI); B.5 calculation of head dissipated by the parallel PRV and the output PRV (steps VII and VIII).

Step III establishes the operation conditions of the recovery systems considering the constraints defined by Block A and determines the operating conditions under which the simulation will be carried out at that moment. Defined the number of installed PATs (np), this step establishes the flow range of the operation of PAT. The methodology considered its strategy to estimate the operating flow (Qt) for each PAT and the number of machines operating at each time (nf). The strategies proposed by (UNE, 2014) and the ratio between the maximum and minimum flows of the equipment to be evaluated were taken as a reference, obtaining two possible cases.

$$\mathrm{Q_{rt}}=\frac{\mathrm{Q_t}}{\mathrm{Q_{BEP_t}}} \tag{4.1}$$

where Q_{rt} is the ratio between Q_t and Q_{BEP_t}

The Q_{rt} value is obtained using Equation (4.1). It will define the flow strategy to be used with the equipment to be evaluated: 1. For a Q_{rt} value < 0.50, the machine is not operating, and the flow is bypassed for VRP. When $Q_{rt} > 2$, the flow excess is also bypassed by the VRP. When Q_{rt} is between 0.5 and 2, the system establishes the regulation strategy using the hydraulic machines. At the exit of this step, there is decision-making in which it is verified that flow is not null ($Q_t > 0$). If this condition is met, the order of the steps is continued, with the next step being the determination of the maximum efficiency.

Otherwise, the next step is the calculations of the heads dissipated by the PRV, meaning that the demanded flow is below the minimum operating flow of the PAT. When the flow of each PAT is known, the procedure estimates the maximum possible efficiency that each machine could reach. It is always sought to be able to work at the point of maximum efficiency (BEP). This point is estimated using dimensionless curves, which were published by Plua et al. (2021), as illustrated in the following expressions:

$$h = -0.31070\left(\alpha\frac{Q_t}{Q_{BEPt}}\right) + 0.1958\left(\frac{Qt}{Q_{BEPt}}\right)^2 - 0.0118\left(\frac{Qt}{Q_{BEPt}}\right) - 0.06429\alpha^2 + 1.8489\alpha - 0.2241 \quad (4.2)$$

$$e = 0.8271\left(\alpha\frac{Q_t}{Q_{BEPt}}\right) - 0.3187\left(\frac{Qt}{Q_{BEPt}}\right)^2 - 0.1758\left(\frac{Qt}{Q_{BEPt}}\right) - 1.035\alpha^2 + 1.1815\alpha - 0.5019 \quad (4.3)$$

Kuriqi (2014) found a root mean square error (RMSE) lower than 0.2, and these equations reduced the error values by between 30 and 50% compared with other published methods. The use of these equations enables the estimation of the characteristic curves of the hydraulic machines considering the variable rotational speed.

Reorganizing Equation (4.3), it is possible to determine the efficiency that the PAT would have at each moment, using the following expression:

$$\eta t = \eta_{BEPt}\left(0.8271\left(\alpha\frac{Q_t}{Q_{BEPt}}\right) - 0.3187\left(\frac{Qt}{Q_{BEPt}}\right)^2 - 0.1758\left(\frac{Qt}{Q_{BEPt}}\right) - 1.035\alpha^2 + 1.1815\alpha - 0.5019\right) \quad (4.4)$$

where h is the dimensionless ratio between recovered head and recovered head at the point of maximum efficiency of the PAT; e is the dimensionless ratio between efficiency and efficiency at the point of maximum efficiency of the PAT; H_{rt} is the head recovered by the PAT (in m w.c.); H_{BEPt} is the head recovered at the point of maximum efficiency (in m w.c.); Q_t is the flow rate turbinated by the machine (in L/s); Q_{BEPt} is the flow at the point of maximum efficiency (in L/s); η_t is the efficiency of the PAT (in %); η_{BEPt} is the efficiency of the machine at its optimum point (in %); and α is the rotational speed modifier set by the frequency inverter.

The latter is defined by the ratio between n and no, in which no is the nominal rotational speed of the machine in rpm and n is the rotational speed of the machine in rpm.

Step IV develops an iterative process, exploring the minimum speed of rotation allowed up to the maximum. The turning speed enables the selection of the best process based on which reaches the highest efficiency. Step V estimates the recovered head and compares it with the net available head (H_n), which is the difference between the pressures upstream and downstream of the evaluated point.

This pressure difference is a restriction of the model since it must guarantee the service quality of the users. Rearranging Equation (4.2), the expression to determine the head recovered at each moment is:

$$\mathrm{H_{rt}} = \mathrm{H_{BEPt}}\left(-0.31070\left(\alpha\frac{\mathrm{Q_t}}{\mathrm{Q_{BEPt}}}\right) + 0.1958\left(\frac{\mathrm{Qt}}{\mathrm{Q_{BEPt}}}\right)^2 - 0.0118\left(\frac{\mathrm{Qt}}{\mathrm{Q_{BEPt}}}\right) - 0.06429\alpha^2 + 1.8489\alpha - 0.2241\right) \quad (4.5)$$

$$\mathrm{H_n} = \mathrm{P_u} - \mathrm{P_d} \quad (4.6)$$

where H_n is the net head available in m w.c.; P_u is the upstream pressure at the point (in m w.c.), and P_d is the downstream pressure in m w.c.

At the end of step V, it must be checked that the difference between H_n and H_{rt} is equal to or greater than 0. If this condition is met, step VI is achieved, in which the generated power is optimized, determining a new α value. It should be determined within the established limits in step V. In step VI, a search range defined by the lower and upper limits (lb, ub) is established, where the rotation speed obtained in the recovered head block will be varied until the maximum power is obtained.

The optimization of the power tool enables the estimation of the mechanical power in the axis (MP), the electrically generated power (EP), and the torque (T) in the axis by the following expressions:

$$\mathrm{MP} = \gamma \cdot \mathrm{Q_t} \cdot \mathrm{H_{rt}} \cdot \eta_\mathrm{t} \quad (4.7)$$

$$\mathrm{EP} = \mathrm{MP} \cdot \eta_\mathrm{elec} \quad (4.8)$$

$$\mathrm{T} = \frac{30 \cdot \mathrm{MP}}{\mathrm{n}\,\pi} \quad (4.9)$$

where MP is the mechanical power of the machine in kW; γ is the specific weight of the fluid in kN/m^3; g is the acceleration of gravity in m/s^2; Q_t is the flow rate turbinated by the machine in m^3/s; H_{rt} is the head recovered by the machine (in m w.c.); η_t is the efficiency of the PAT; EP is the electrical power generated by the generator in kW, and η_{elec} is the efficiency of the generator (Camilo Rosado et al., 2020), which depends on rotational speed and power; T is the torque produced by the machine in Nm; and n is the rotational speed of the machine affected in rpm.

Once the instantaneous head recovered by the machine is known, the energy dissipated by the installed PRVs is calculated, in which one is in parallel with the PAT system, and the other is connected cited in series, at the outlet of the supply, as represented in Figure 4.1.

Steps VII and VIII define the opening degree of both valves that guarantees the downstream pressure restriction.

Finally, section C is focused on the analysis of results. Step IX develops an energy analysis of the installation with the proposed equipment, and step X defines the selection of final equipment, presentation of proposals, and report of results. These ten steps define the main structure of the optimization machine tool.

At the end of this step, decision-making is presented, in which the subscript i of the preselected machine that is being evaluated is verified, and it is compared with the value j of the number of models obtained in the preselection. If they are different, the results of the energy analysis are stored in memory; the value of i is increased, with $i = i + 1$, and returns to step II, performing a new simulation with the next machine on the list. This means that j different models must be evaluated, and the results obtained from each of these must be stored in memory to be able to compare and select the machine.

4.3. Results

4.3.1. Case Study Description

The particular case study to which this methodology was applied is located in Valencia (Spain). It is a supply system that distributes the supplied volume to different municipalities using pressurized water systems. The possibility of installing energy-recovery systems is proposed in the place of making an intermediate deposit to improve the sustainability and efficiency indicators of the distribution system. The main reservoir, called Tank A, is connected to the water network by a pipe. In this line, there is a reservoir, called Tank B, that will enable the installation of the recovery system to take advantage of the potential energy, installing the recovery system and supplying this generated energy in a pump system, which is near Tank B.

Figure 4.3 shows a schematic of the system between Tank A and Tank B. Their water levels are 113 and 75 m, respectively. Both tanks would be connected by a steel pipe. The length of this pipe is 1300 m, and the diameter is 1.4 m.

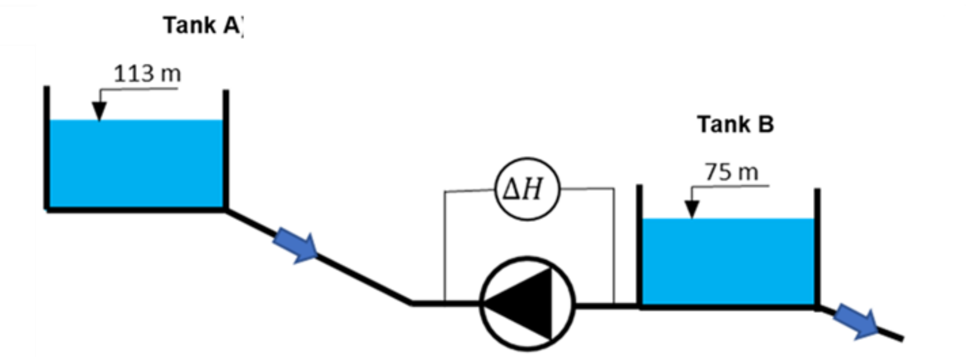

Figure 4.3. *The layout of the case study scenario. ΔH represents the net hydraulic jump available.*

Table 4.1 shows the demanded flow (Qd), upstream pressure (Pu), and downstream pressure (Pd) over time. The analysis only considered one day because the system connected two deposits, and the flow is established between them.

Table 4.1. *Data recovered from the case study.*

Time Interval (Δt = 60 min)	Q_d (L/s)	P_u (m w.c.)	P_d (m w.c.)
00:00–01:00	749.03	88.53	52.71
01:00–02:00	684.59	89.67	53.82
02:00–03:00	672.70	89.89	54.03
03:00–04:00	619.79	90.87	54.99
04:00–05:00	655.86	90.19	54.33
05:00–06:00	936.02	85.52	49.79
06:00–07:00	1758.97	77.47	42.36
07:00–08:00	1896.68	76.95	41.98
08:00–09:00	1825.87	77.18	42.14
09:00–10:00	1851.91	77.09	42.08
10:00–11:00	1809.20	77.25	42.19
11:00–12:00	1745.49	77.53	42.41
12:00–13:00	1648.52	78.05	42.84
13:00–14:00	1816.76	77.22	42.17
14:00–15:00	1736.82	77.56	42.44
15:00–16:00	1597.23	78.38	43.12
16:00–17:00	1439.17	79.59	44.20
17:00–18:00	1477.33	79.27	43.91
18:00–19:00	1599.64	78.37	43.11

Table 4.1. (Continuation)

Time Interval (Δt = 60 min)	Q_d (L/s)	P_u (m w.c.)	P_d (m w.c.)
19:00–20:00	1700.32	77.76	42.60
20:00–21:00	1751.77	77.50	42.39
21:00–22:00	1449.60	79.50	44.12
22:00–23:00	1151.92	82.59	46.99
23:00–24:00	979.29	84.89	49.18
Minimum value	619.79	76.95	41.98
Maximum value	1896.68	90.87	54.99
Mean Value	1398.10	81.20	45.83
Standard Deviation	455.89	5.08	4.77

4.3.2. PAT Selection for the Case Study

Following the methodology proposed by Camilo Rosado et al. (2020), for the selection of the most suitable PAT for the installation, the following steps must be carried out: (a) Statistical analysis of data record to determine Q_{BEP_t} and H_{BEP_t}; (b) calculation of specific numbers in turbine mode, ns_t and estimation of coefficients β_Q and β_H (Pérez-Sánchez et al., 2020); (c) calculation of $Q_{BEP_p}$and H_{BEP_p} using the coefficients from the previous step; (d) preselection of equipment that meets the previously calculated Q–H operating point, along with obtaining its optimal operating data; € calculation of specific number in pump mode, ns_p, and coefficients β_Q, β_H and β_η; (f) estimation of the characteristics of the equipment working in turbine mode, obtaining Q_{BEP_t}, H_{BEP_t}, and η_{BEP_t}; (g) calculation of C to verify that the preselected machines meet the established criteria of ($C \leq 1$) (Williams, 1994). An additional step is also included: (h) calculation of recovered energy for each preselected machine and final PAT selection.

Once the steps before the preselection are completed, the characteristics of the preselected machines are obtained, and the calculation of the flow and head error is carried out using Equation (4.10). The criteria used for acceptance or rejection of the selection were based on ellipse error. This ellipse, which was defined by (Williams, 1994), enables an error of $+/-30\%$ and $+/-10\%$ in the major and minor axis (flow and head, respectively) of the ellipse compared to the ideal selection point. It enables the determination of the C value, discarding the preselected machines that do not match the criterium of $C \leq 1$.

$$C^2 = \left(\frac{\frac{1}{2}(\Delta q + \Delta h)}{0.3}\right)^2 + \left(\frac{\frac{1}{2}\sqrt{\Delta q^2 + \Delta h^2 - 2\Delta q \Delta h}}{0.1}\right)^2 \quad (4.10)$$

where C is the error coefficient of the estimated values; Δq is the error of the estimated flow concerning the selection flow; Δh is the error of the estimated head for the selection head.

The results obtained from the preselected machines are presented in Table 4.2. Machine 3 was discarded for not meeting the error criterion, while machine 1 had an error very close to that of the maximum allowable (Table 4.2). The different expressions used were validated in other published research, which analyzed the different errors and validated them with another case study (Pérez-Sánchez et al., 2020; Plua et al., 2021). The optimization tool used these expressions and methodology to choose and operate the recovery systems.

Table 4.2. *Preselected machines in turbine mode and value of C.*

No.	Manufacturer	Model	Q_{BEP_t} (L/s)	H_{BEP_t} (m w.c.)	η_{BEP_t} (%)	ns_t (m, kW)	Δq (%)	Δh (%)	C
1	IDEAL	350–430	809.53	44.47	0.671	75.758	31.28	26.52	0.98
2	IDEAL	350–360	652.85	43.04	0.671	69.727	5.87	22.44	0.95
3	KSB	350–430	842.42	48.14	0.64	72.82	36.61	36.97	1.23
4	KSB	350–430	768.87	43.63	0.640	87.984	24.68	24.13	0.81

Figure 4.4a shows the results of the simulation with each machine, and the chosen PAT is highlighted once the different blocks described in the methodology section were programmed and integrated into the optimization tool (Figure 4.4b).

The selected machine was CPH 350–360 at 50 Hz from the manufacturer Bombas IDEAL, which considered the criterion of maximum daily recovered energy. Once the PAT group was selected, the characteristic was plotted for the nominal rotational according to the expressions defined in the methodology section (Figure 4.4c). The curves were constructed between the minimum and maximum flow ranges of the PAT.

The minimum operating flow was defined as the flow that resulted in the lowest head recovered at nominal speed, and for this specific case, the maximum flow was obtained by dividing the maximum inlet flow by the number of equipment installed. The recovered head oscillated between 41.53 and 43.64 m w.c. and the efficiency of the hydraulic machine was between 0.62 and 0.66.

To complete the optimization model (Figure 4.4b), the pressure-reducing valves to be installed in each case must be selected. A valve, whose size was DN150, was installed in parallel, and a valve, whose size was DN350, was installed in serial of the system. The model was Hydrobloc KXG-BELGICAS, and the flow coefficient was 388 and 1389 (m^3/h, 1 bar), respectively.

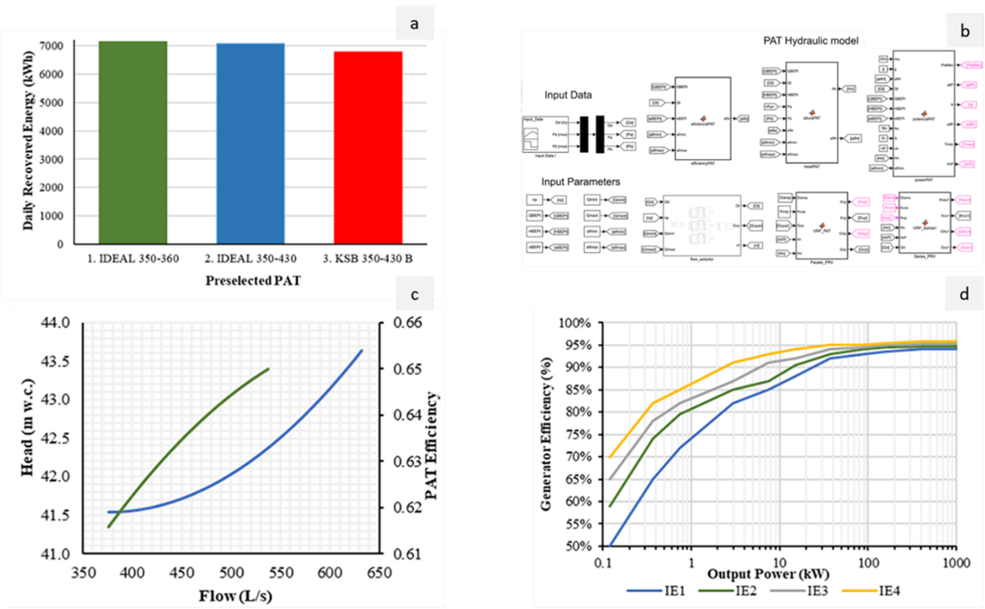

Figure 4.4. *(a) Total daily recovered energy for preselected machines; (b) block structure in Simulink MATLAB; (c) head and efficiency curve for preselected PAT; (d) efficiency generator curves according to the power to define the efficiency of the PAT generator adapted of the data from* (UNE, 2014).

To estimate the energy recovered by the recovery system, the efficiency of the electric motor was considered in the optimization tool. This consideration can be incorporated as a fixed value by (McNabola et al., 2014), or the optimization model enables the definition of this efficiency as a function of the rotational speed and resistive load of the system for isolated grid systems (Novara & McNabola, 2018). This energy analysis considered a conservative value, defining the class of generator as IE1 (Figure 4.4d). When the model considered a conservative value (IE1, Figure 4.4d), the daily recovered head was 6911 kWh.

Otherwise, if the generator efficiency is considered variable as a function of the rotational speed, the daily recovered energy increased by around 4%.

Figure 4.5a shows the operational flow of one machine during the entire simulation, in which instants are observed. Each PAT works between 468 and 632 L/s, considering that there are three machines connected in parallel. These machines operated with efficiency values between 0.61 and 0.65, and the recovered head oscillated between 33 and 35 m w.c.

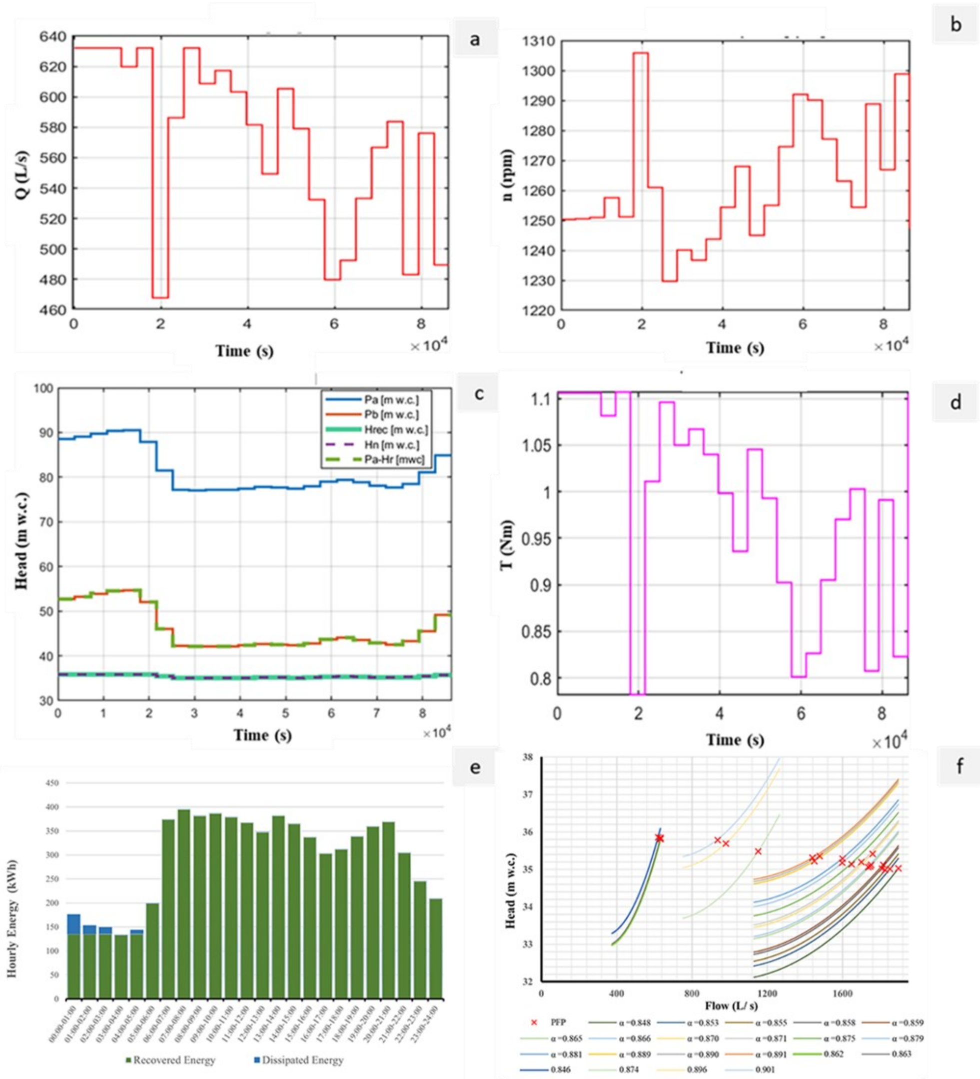

Figure 4.5. *(a) Flow over time; (b) rotational speed of the machine over time; (c) pressures and Head over time; (d) torque over time; (e) hourly energy; (f) regulation of the recovery system.*

Figure 4.5b shows the variation of the rotational speed to optimize the generated power over time. The rotational speed oscillated between 1229 and 1305 rpm over time. **Figure 4.5c** shows the temporal evolution of the heads during the optimization. These show the upstream (Pu) and downstream (Pd) pressures and the net head (H_n). Moreover, the figure shows the Hrt value, which never exceeded the net head value. Figure 4.5d shows the variation of the output torque value. It oscillates between 0.75 and 1.1 Nm over time, and this value is needed when the optimization of the generator is considered. The power on the shaft depends directly on the PAT's efficiency and affects the electric motor efficiency, as well as the power and energy recovered by the machine. The generated power for each machine is between 107 and 145 kW.

Figure 4.5e shows the hourly energy analysis of the recovered and dissipated energies. The lowest recoverable energy value was 133 kWh, and it was recorded at 3 a.m., while the highest value was 395 kWh and was located at 7 a.m.

Otherwise, most of the time, the recoverable energy values remained close to the average value, which was 286 kWh. The daily recovered value was 7160 kWh, with an average efficiency value of 0.61. The complete optimization simulation represented 27.33% of the available energy, which was used to improve the efficiency ratio in the water system. These results are aligned with research published in (McNabola et al., 2014). However, this research enables the discretized flow over time, developing the selection and regulation of the machine under empirical expressions, which enables operation at the best point of the machine. This research improved the selection of the machines according to these expressions, but it is able to use any empirical expression, such as the equations proposed by (Novara & McNabola, 2018).

Figure 4.5f shows the regulation strategy to guarantee the different operation points (PFP). It defines the recovered head curves as a function of the flow for the different values of α and their corresponding operating points for each of the PAT and their operating point for 1, 2, and 3 machines operating, respectively.

The analysis of the figure established the set values for the optimization of the hydraulic–electric regulation strategies. This set of regulations also defined the opening degrees of pressure-reduction valves (PRV), both serial and parallel. This last valve remained closed most of the time, and the highest degree of opening was 44.13%.

In the case of the serial PRV, it was always kept fully open because the recovery system optimization guarantees the downstream pressure defined by the operation restrictions.

The analysis considered the operation of the machine under steady conditions. The operation of the machine was not analyzed under unsteady conditions. However, when the flow change in water systems, the variation of the pressure is not significant if the flow does not totally stop. The operation and its consequences were analyzed by (Pérez-Sánchez et al., 2018).

Figure 4.5 only shows an example of the operation with the optimization tool. The main advantage of this optimized tool is focused on the selection, regulation, and definition of the operation. The optimization procedure can choose the best machine and optimize its regulation to maximize the recovered energy while only knowing the flow over time and the downstream pressure constraint. It is a step ahead since the optimization tool defines the rotational speed and torque at each moment. These two variables are crucial to establishing the best electrical regulation when the machine is operating off-grid (Capelo et al., 2017).

4.4. Conclusions

The lack of simulation and optimization tools for the management of recovery systems shows the need to implement models that enable the optimization of these energy facilities and the definition of setup regulation parameters for the electrical equipment. For this reason, this research proposes the implementation of an optimization model using the Simulink MATLAB code for its application.

This research defines an optimization strategy to establish the number of machines operating at any given time, the rotational speed, and the opening degree of the different PRVs to guarantee the hydraulic constraints of the system as well as maximize the recovered energy over time. The novelty of this research is focused on the integration of empirical methods, which could estimate the characteristic curves and optimize the operation and selection of the machines based on flow over time, as well as the frequency of these flows. The implementation tool is new and crucial to improving sustainability in water distribution systems. The proposed methodology is limited in terms of communication with the electronic regulation, which needs the output results of this methodology (i.e, torque and rotational speed in the axis of the machine) to develop optimization linked to electric loads and capacitance when the recovery system is installed off-grid. Future lines should be focused on integrating electric and water optimization into one tool.

The optimization management tool was applied in a real case in Valencia (Spain), and we showed the benefit of the model when variable flow occurs over time and under different constraints in terms of upstream and downstream pressure. The tool could be extrapolated for any water system when the water managers know the flow over time and the values of upstream and downstream pressure of the system. The model includes a preselection block to choose the pump necessary for operating as a turbine.

The implementation of hydraulic–electric regulation is a commitment to efficiency and sustainability. It should be incorporated into pressurized water systems to increase the generation of clean energy and improve the sustainability of the systems. The use of green or clean energies by the use of renewable systems allows us to reach different targets linked to the sustainable development goals and demonstrate the good practices of water managers in different supply systems.

Chapter 5
Results and Discussion

This chapter provides a comprehensive discussion of the findings from this thesis. The three publications have detailed and analyzed each stage of the research process. This chapter summarizes these results and presents a comprehensive discussion of the objectives outlined in section 1.2.

This thesis aims to develop a methodology that considers the distribution of flows and the optimization of technical, economic, and environmental sustainability indicators in the design of pressurized irrigation networks. The complete research process followed during this Ph.D thesis is shown in Figure 5.1, with the three main stages of research: contextualization, methodology development, and case study application. Each stage is briefly outlined below, along with their steps, their correspondence with the objectives, and the three publications included as Chapters 2, 3, and 4.

The **first stage *(contextualization)*** corresponds to objective 1. This significant stage sets the foundation for the following steps and the research process.

- An exhaustive review of the existing irrigation network design and analysis methods is conducted (***objective 1***), identifying the strengths and weaknesses of current approaches while establishing a solid theoretical foundation for developing a new analytical model. This review (***Publication I***) highlights the importance of agronomic variables, crop patterns, weather conditions, and user interactions in accurately forecasting irrigation. It also emphasizes the need for robust sustainability indicators in irrigation practices.

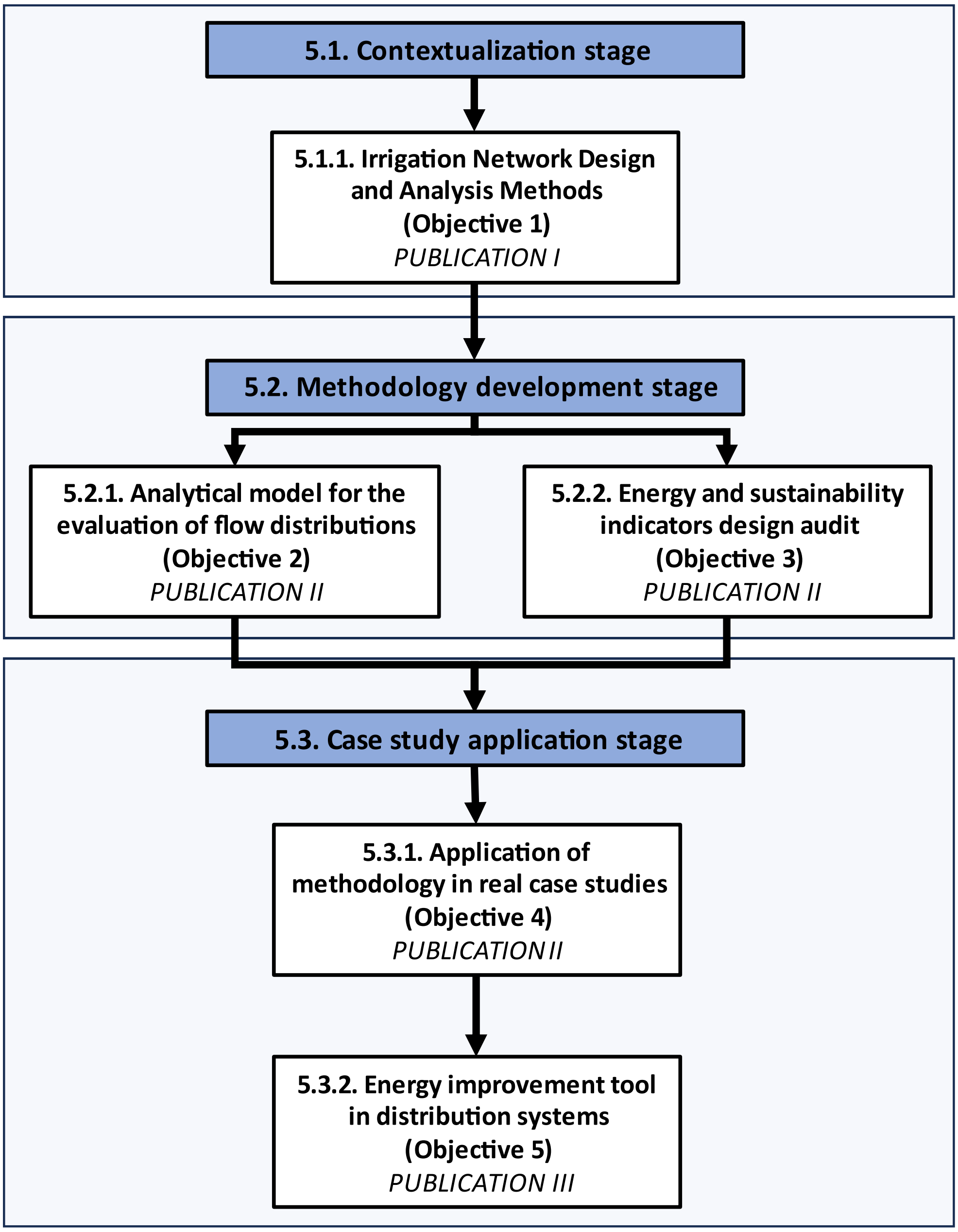

Figure 5.1. *Stages followed during this thesis to reach the research objectives.*

The **second stage** ***(methodology development)*** corresponds to ***objectives 2 and 3***, consisting of the following parallel steps:

- The first step was establishing an analytical model development methodology for evaluating flow distributions (***objective 2***). A multi-criteria approach was employed, incorporating various technical and environmental factors to ensure a sustainable design. The developed tool and methodology for the optimization of flow distributions in irrigation networks was presented in ***Publication II.***
- Additionally, in ***Publication II,*** a design audit was implemented ***(objective 3)***, assigning energy and sustainability indicators to measure the impact of design decisions. Identifying areas for improvement and measuring the impact of design decisions, ultimately leading to significant material savings and CO_2 emissions reduction.

The **third stage** ***(case study development)*** corresponds to ***objectives 4 and 5***, consisting of the following steps:

- Initially, the methodological development was applied to real cases (***objective 4***). The case study results were contained in ***Publication II.***
- Furthermore, in ***Publication III,*** a tool for energy improvement in distribution systems was developed and applied to the case studies ***(objective 5)***. This was used to increase efficiency and sustainability in the case study applied.

5.1. Contextualization stage

The contextualization stage corresponds to ***objective 1***, and the results obtained during this stage were published in ***Publication I.***

5.1.1. Irrigation Network Design and Analysis Methods

To meet ***objective 1***, a comprehensive review of the state of the art in irrigation network design and analysis methods was conducted, as detailed in ***Publication I,*** "*Irrigation distribution network design parameters and their influence on sustainability management*". This review identified several key strengths and weaknesses in current approaches. The existing methods were evaluated based on their ability to forecast irrigation demands accurately and manage water resources efficiently.

The design phase is essential for the investment of infrastructures and the estimation and evaluation of the different targets of the Sustainable Development Goals (SDGs). Moreover, using different methodologies to estimate flow rates can result in variations in the assessment of sustainability indicators and energy audits related to installing micro-hydro generation systems. The evaluation methodology followed in Publication I was divided into three main steps, as shown in Figure 5.2.

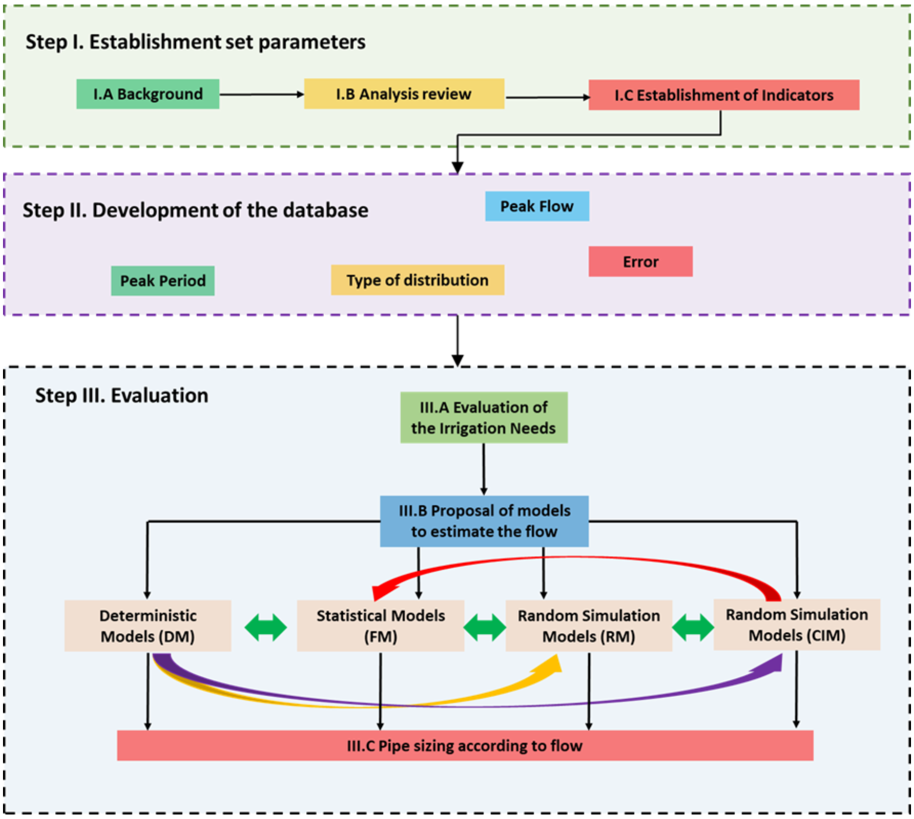

Figure 5.2. *Evaluation methodology of the models to estimate the circulate flow.*

Step I. A background review is conducted to search for the maximum number of proposal models that enable peak flow estimation. Additionally, during the analysis review, a parameter list was elaborated in which indicators or variables discretize the main variables and characteristics in the database.

Step II. A database was created using information and data from the consulted bibliographic sources. Indicators from various case studies were selected for the database, focusing on measurements, variables, and reference values. The main variables were peak flow, error between estimation and experimental data, peak period, and type of distribution, among others.

Step III. This third step is the core of the research. First, evapotranspiration and possible inputs for developing different models to determine peak flow were estimated (Step III.A). Then, a detailed analysis of four different typologies was carried out (Step III.B). Based on the literature review, 45 references were analyzed, resulting in 25 different models distributed across Europe and China, as shown in Figure 2.6.

According to their methodological approach and the data involved, the forecasting methods are classified into four groups:

Deterministic models assume that uncertainties are external and require extensive data collection. In contrast, Statistical models focus on determining the relative frequency of different flows during the irrigation season, aiming to predict the operation probability of hydrants.

Moreover, Random Simulation models adopt a random approach to variables influenced by uncertainties or assumptions. Computational Intelligence models utilize historical data to predict new values, proving to be the most adaptable and robust. In Tables 5.1 to 5.4, several of the most significant research works from each group are presented.

Table 5.1. *Deterministic models articles reviewed.*

ID	Title	Reference	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
D.1	Simulation and management of on-demand irrigation systems: a combined agrohydrological and remote sensing approach	(D'Urso, 2001)	Gromola (Southern Italy)	Underestimated by 9%	33 days	• The temporal variation of water demand at the district level was satisfactorily reproduced. • Irrigation efficiency was evaluated using indicators calculated from the real transpiration rate and irrigation values computed by SIMODIS. • The results of SIMODIS are exceptionally reliable at the primary unit scale while obtaining reliable results at the secondary unit level.
D.2	Crop And Irrigation Water Management Using High Resolution Remote Sensing And Agrohydrological Models	(Minacapilli et al., 2006)	Southern Sicily (Italy)	Overestimated by 2.33%	45 days	• Agrohydrological simulation models and remote sensing can be effectively combined to improve irrigation water management in semiarid regions. • The SIMODIS procedure predicted the water demand satisfactorily at district and secondary levels. • The distributed approach performed better than the lumped one at a large scale to define the upper boundary conditions.
D.3	Model to Forecast Maximum Flows in On-Demand Irrigation Distribution Networks	(Rodríguez Díaz et al., 2007)	Santaella, Córdoba (Southern Spain)	Overestimated by 11.6%	2 weeks	• Real demand tends to be concentrated at certain times of the day. • During peak demand periods, water requirements can exceed the design flow. • Demand is not uniform throughout the day; it increases in the morning until peaking, remains constant for several hours, and then decreases at midday. This process is repeated in the afternoon. • To be used in other districts, the gamma model should be applied considering local farmers' practices and network constraints. • Human behaviour affects uniform probability prediction.

Table 5.1. (Continuation)

ID	Title	Reference	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
D.4	A distributed agro-hydrological model for irrigation water demand assessment	(Minacapilli et al., 2008)	Southern Sicily (Italy)	Scenarios 1 thru 4, overestimated by 25%, 8%, 32% and 36% respectively	45 days	• Differences between simulated and measured irrigation volumes were attributed to different management behaviours. • The threshold value of the soil water pressure head in the root zone (h_m) and the fraction of soil water deficit to be refilled (Δ) can be tuned adequately to reproduce the spatial and temporal evolution of crop water use. • Depends on water availability and farmers' subjectivity to recognise the crop water requirement. • This approach can be effectively used to support the decision-making process in managing irrigation water resources and improving the efficiency of irrigation systems.

Table 5.2. *Statistical models articles reviewed.*

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
S.1	Water Delivery System Planning Considering Irrigation Simultaneity	(Pulido-Calvo et al., 2003b)	Statistical	Fuente Palmera, Córdoba (Southern Spain)	Non specified	10 days	• Probability operation is not a constant due to cost energy discrimination. Farmers prefer low- and medium-cost hours and avoid high-price hours. • Human behaviour is influenced by time discrimination rate costs. • The recommendations of optimum pump combination produced significant reductions in energy costs.

Table 5.2. (Continuation)

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
S.2	Analysis of Clement's First Formula for Irrigation Distribution Networks	(Monserrat et al., 2004)	Frequentist	Ebro River basin (Northeast Spain)	Clément underestimated the real flows by 2.9% to 9.4%	1 month	• Hypothesis 1: Only two possible states of the hydrants (open/closed). Not fulfilled. CV = 25%. • Hypothesis 2: Uniform hydrant opening throughout the day. • Not fulfilled. CV = 5.7% daily and CV = 13% hourly. • Hypothesis 3: The hydrants function randomly and independently. - Random functioning is rejected since the Kolmogorov–Smirnov p-value = 0. - Independent operation is fulfilled. • The normal distribution hypothesis is not fulfilled. • Moreover, the model with Clément's first formula seems robust enough in the conditions studied, so using more complicated models is unnecessary
S.3	Model to Forecast Maximum Flows in On-Demand Irrigation Distribution Networks	(Rodríguez Díaz, Camacho Poyato, et al., 2007)	Deterministic	Santaella, Córdoba (Southern Spain)	Clément's distribution mean value was overestimated by 18%, and the distribution variance value was underestimated by 81%	2 weeks	• The generated distribution tends towards a normal distribution only in the peak demand month (July) and will not coincide with Clément's distribution. • Because the standard deviation is higher, a greater probability of higher flows exists. • Although most of Clément's hypotheses were not fulfilled, his formula is a valid design criterion. • The formula used to determine Clément's design flow adjusts better to demand behaviour than Mavropoulo's does, particularly for a small number of outlets.
S.4	Validity of the Theory of Probability in On-Demand Irrigation Networks	(Mavropoulos & Lotidi, 2016)	Statistical	Customized Networks	Clément overestimated the proposed method by 18% (P=0.95) and 25.5% (P=0.99)	Not considered	• The validity of the probability theory in on-demand irrigation networks was largely verified on the study network. • The goodness of fit test results shows that the same crop in a plain area with the same climate, and general slope and high territorial homogeneity can significantly alter the irrigation water demand, favouring the randomisation of demand over time.

Table 5.2. (Continuation)

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
S.5	New Methodology to Evaluate Flow Rates in On-Demand Irrigation Networks	(Moreno, Planells, et al., 2007)	Random Simulation	Tarazona de La Mancha (Spain)	Clément underestimated measured flows by 27% (2003) and 17% (2004)	1 week	• Normal distribution fit hypothesis: the Kolmogorov–Smirnov test with a p-value lower than 0.05. Therefore, it cannot be assumed to be a better approximation to a gamma distribution for 2003 and a Weibull for 2004. • Daily and hourly opening hydrant probability hypothesis: The analysis of a variance p-value was lower than 0.05. Thus, it is concluded that there are significant differences between the peak period days for each season. • In the peak period week of the first season, farmers used weekends to irrigate because they had more time and lower costs. In the following one, the behaviour of the network was not the same, which may be due to some breakdown in the network or weather conditions. • The underestimation caused by the Clément methodology is due to using the average opening hydrant probability concept.
S.6	Comparison between Clément's first formula and other statistical distributions in a real irrigation network	(Pérez-Sánchez et al., 2018)	Statistical	Callosa d'en Sarrià (Alicante, Spain)	Clément underestimated the frequency of calculated flows compared to the expected values	1 month	• Data were not distributed in the network under CTD (in which the mean and standard deviation were calculated under Clément's parameters) in any of the months of the year. • Normal distribution does not satisfactorily explain the behaviour of the random variables. • Other distributions were proposed, obtaining a better fit for distributions of the observed flows in each month.

Table 5.3. *Random models articles reviewed.*

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
R.1	Performance analysis of on-demand pressurized irrigation systems	(Lamaddalena et al., 2000)	Random Simulation	Sinistra Ofanto, Foggia (Southern Italy)	For peak scenarios 1 and 2, the r parameter became 0.86 and 0.90, respectively.	10 days	• A good fit exists between the theoretical Gaussian curve and the histogram of frequencies obtained using field data. This means the population of the discharges during this period is well represented by CFF. • The r coefficient should be intended only as a calibration coefficient aiming to understand the farmer's behaviour. • Using field calculations, the Clément operation quality corresponded to 97.6% (exceeding the designed value of 95%). This implies a lower probability of exceeding the maximum discharge.
R.2	Modelling the Irrigation Demand Hydrograph in a Pressurized System	(Calejo et al., 2005)	Deterministic - Random	Lucefeci, Alentejo (Southern Portugal)	Regression coefficient is very close to 1, and the average relative error is <10 %	10 days	• The IRDEMAND model was able to generate hourly discharge hydrographs of pressurised irrigation systems operating on demand. • This methodology considers the deterministic component (crop irrigation requirements) and the uncertainty associated with farmers' decisions on crops, farm irrigation systems, seeding dates, irrigation performances, and scheduling.
R.3	A Simulation Model to generate the Demand Hydrographs in Large-scale Irrigation Systems	(Khadra & Lamaddalena, 2006)	Deterministic - Random	Sinistra Ofanto, Foggia (Southern Italy)	Underestimation by 13% (1990 to 1995 seasons) and overestimation from 1% to 46% (1996 to 1999 seasons)	10 days	• The comparison has shown good correspondence, particularly for daily withdrawn volumes. • A stochastic approach simulated the farmers' management strategy. • The simulated hourly discharges showed, sometimes, hourly peaks higher than the measured ones. • Model results show good agreements between the registered and simulated values for both the daily and hourly irrigation volumes.

Table 5.3. (Continuation)

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
R.4	New Methodology to Evaluate Flow Rates in On-Demand Irrigation Networks	(Moreno, Planells, et al., 2007)	Random Simulation	Tarazona de La Mancha (Spain)	RDDC underestimated measured flows by 0.8% (2003) and overestimated 17.4% (2004)	1 week	• RDDC has a better fit with the measured data compared to the Clément methodology. • Considering a normal flow distribution in each line, Clément's underestimation is due to the use of opening hydrant probability. • The proposed methodology avoids the problem of using average opening hydrant probability.
R.5	Simulation of peak-demand hydrographs in pressurized irrigation delivery systems using a deterministic – stochastic combined model.	(Zaccaria et al., 2013)	Deterministic - Random	Taranto (Southern Italy)	Overestimations from 0,67% to 0,33%	10 days	• The HydroGEN model was conceived based on a methodology consisting of deterministic and stochastic components. • The model's short approach cannot simulate the hourly configurations of hydrants in simultaneous operations. • The model applicability varies from system design and redesign to the analysis of operation and evaluation of the performance of on-demand irrigation networks.
R.6	Alternative Method to the Clément's First Demand Formula for Estimating the Design Flow Rate in On-demand Pressurized Irrigation Systems	(Soler et al., 2016)	Random Simulation	Customized Networks	The alternative method underestimated the measurements by 12.5% (P=0.95) and 9% (P=0.99)	Not considered	• The alternative methods proposed work well in the analysed scenarios, mainly because the normality hypothesis is not required. • The programs allow the applicability of Clément's method to be checked and provide two alternative solutions when the CFF fails.
R.7	Generating Hydrants' Configurations for Efficient Analysis and Management of Pressurized Irrigation Distribution Systems	(Fouial et al., 2020)	Deterministic - Random	Southern Italy	Underestimated by 31%	10 days	• DESIDS module (Decision Support for Irrigation Distribution Systems) • The model proved to be a crucial tool for decision making, providing information, flexibility, and the ability to predict PID operation.

Table 5.4. *Computer Intelligence models articles reviewed.*

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
CI.1	Demand Forecasting for Irrigation Water Distribution Systems	(Pulido-Calvo et al., 2003a)	Computational Neural Networks (CNNs)	Córdoba (Spain)	SEP = 25.5%, R^2 = 0.82 and E=0.82	Not considered	• The CNN model predicted daily water demand better than multiple regression and univariate time series analysis. • The best results were obtained when inputting the water demands and maximum temperatures from the two previous days. • The model is well suited for real-time operations when the system’s state is continuously monitored.
CI.2	Linear regressions and neural approaches to water demand forecasting in irrigation districts with telemetry systems	(Pulido-Calvo et al., 2007)	Linear Regressions and Computational Neural Networks (CNNs)	Genil Cabra Irrigation District, Córdoba (Spain)	R^2 = 0.92 and E = 0.91	Not considered	• The best demand predictions were obtained when using the water demands from the two previous days as inputs. • Results could indicate that rainfall factors and other climatic variables are implicitly considered in water demand observations. • The CNN performed better than the regressions when water demand and climatic variables were considered as input data. • Short-term demand modelling can be used as input in real-time methods and/or programs for managing water delivery systems.

Table 5.4. (Continuation)

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main Results
CI.3	Improved irrigation water demand forecasting using a soft-computing hybrid model	(Pulido-Calvo & Gutiérrez-Estrada, 2009)	Hybrid Computational Neural Networks + Fuzzy Logic + Genetic Algorithm (CNNs + FL + GA)	Fuente Palmera, Córdoba (Spain)	SEP = 20.27%, R^2 = 0.89 and E = 0.89	Not considered	• The hybrid methodology was designed to forecast one day ahead of daily water demands at irrigation districts. • Fuzzy inference was used to estimate the correction of forecasts obtained from an autoregressive neural network to find the optimal values of the parameters of the fuzzy system. • This model, with not very large data requirements, can be very suitable for decision-making strategies in networks.
CI.4	Irrigation Demand Forecasting Using Artificial Neuro-Genetic Networks	(González Perea et al., 2015)	Artificial Neuro-Genetic Networks (ANGNs)	Bembézar Irrigation District, Andalusia (Southern Spain)	Best CNN model: SEP=12.63% and R^2=0.93	2 months	• The model was applied to predict water demand one day ahead in the network. • The genetic algorithm was used to find the optimal neural network settings to explain the maximum water demand variance with minimal error estimation. • Without an extended dataset and time requirements, the model can be a powerful tool for developing management strategies.
CI.5	Forecast of irrigation water demand considering multiple factors	(X. Wang et al., 2015)	Principal Component Analysis (PCA) + Regression Analysis Methods	Haihe River Basin (China)	Average error 1.32%	Not considered	• The irrigation water demand forecasting method, considering multiple factors, can achieve higher modelling accuracy. • The PCA method was used to identify the main influencing factors (precipitation, irrigation area, water-saving technology) • The water-saving improvement coefficient (α) concept is introduced into the water demand forecasting model based on the dual characteristic of “artificial-natural”. • The predicted irrigation water requirements of the Haihe River basin are lower than the present situation at the moment of the study.

Table 5.4. (Continuation)

ID	Title	Reference	Model Type	Network Data Set / Study Area	Accuracy	Peak Period	Main results
CI.6	Prediction of applied irrigation depths at farm level using artificial intelligence techniques	(González Perea et al., 2018)	Hybrid Computational Neural Networks + Fuzzy Logic + Genetic Algorithm (CNNs + FL + GA)	Canal de Zujar Irrigation District (Southwest Spain)	R^2 values for rice, maise and tomato models were 0.72, 0.87 and 0.72 and SEP values were 22.20%, 9.80% and 23.42%, respectively	Not considered	• Farmers' behaviour and cultural practices differ depending on the crop, even when the irrigation system is the same for different crops. • When several crops were trained together, the model's representativeness and accuracy were worse than those trained independently. • Irrigation district managers can determine the amount of water to apply at each hydrant beforehand, thus making it possible to manage the pumping station in advance and maximise its efficiency. • In the event of a pumping station failure, these models allow scheduling repairs and managing the time required to fix pumps, repair equipment, and purchase materials.
CI.7	Prediction of irrigation event occurrence at farm level using optimal decision trees	(González Perea et al., 2019)	Decision Trees + Genetic Algorithm (DTs + GA)	Canal de Zujar Irrigation District (Southwest Spain)	Predicted between 68% and 100% of the positive irrigation events and between 93% and 100% of the negative events.	Not considered	• DTs were successfully used as classification models to forecast when farmers irrigate. • The model focuses on the prediction of when irrigation events occur. • The optimal classification model predicted between 99.16% and 100% for the given dataset. • The model also allows the user to know each operational zone of the irrigation network one day ahead.

The review underscored the importance of considering agronomic variables, crop patterns, water and energy requirements, weather conditions, and user interactions in forecasting models. Integrating these factors is crucial for developing robust and efficient irrigation management systems that enhance sustainability by saving water and energy and improving planning and operation.

Additionally, Step III.C (Pipe sizing according to flow) from the evaluation methodology presented in Figure 5.2 was addressed. Utilizing different methodologies and examining opening probabilities based on flow assessments and estimation models enables water managers to derive different flow distributions over time. These distributions, which vary depending on the selected method, are illustrated schematically in Figure 5.3. Establishing the design value and the most accurate estimate is essential for the effective design and ongoing management of water infrastructure.

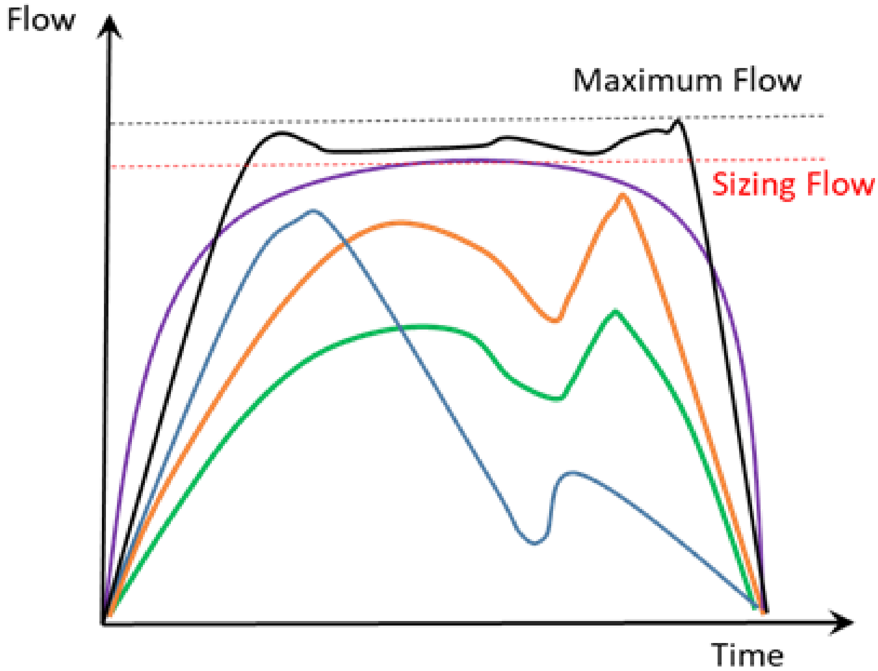

Figure 5.3. *Distribution of flow over time.*

Table 5.5 includes 20 different distribution networks; the network's uniqueness and topology imply that the values of flow, leakage, and energy consumed (and thus CO_2 emitted) are different. Therefore, analyzing flow distributions is crucial to address the design and subsequent management of distribution systems.

Table 5.5. *Variation of the flow, leakage, and annual consumed energy in irrigation networks.*

No.	Reference	Country	Average Flow (L/s)	Average Leakage (L/s)	Annual Energy Consumed (MWh)	Annual Carbon Emission ($TnCO_2$)
1	(Ramos & Ramos, 2009)	Portugal	17.36	3.47	139.09	257
2	(Perez-Sanchez et al., 2019)	Spain	31.17	6.23	2949.01	2.98
3	(Pérez-Sánchez et al., 2016b)	Spain	29.34	5.87	2776.28	2.81
4	(Pérez Urrestarazu et al., 2009)	Spain	4012	802.40	379,567.30	383.97
5	(Daccache et al., 2009)	Italy	1200	240.00	113,529.60	114.85
6	(Pardo et al., 2020)	Spain	17.81	3.56	1685.21	13
7	(Pérez-Sánchez, et al., 2018)	Spain	10	2.00	946.08	0.96
8	(Rodríguez Díaz et al., 2009)	Spain	479.8	95.96	45,392.92	1140.2
9	(Rodríguez Díaz et al., 2009)	Spain	1428	285.60	135,100.22	136.67
10	(Cabrera et al., 2019)	Spain	221.80	6.76	20,984.58	21.23
11	(Cabrera et al., 2019)	Spain	0.036	0.01	1245.95	1.26
12	(Cabrera et al., 2019)	Peru	250	50.00	23,652.00	23.93
13	(Cabrera et al., 2014)	Spain	76.27	2.32	7215.78	7.3
14	(Stamouli et al., 2017)	Greece	774	154.80	73,226.59	74.08

Table 5.5. (Continuation)

No.	Reference	Country	Average Flow (L/s)	Average Leakage (L/s)	Annual Energy Consumed (MWh)	Annual Carbon Emission ($TnCO_2$)
15	(Karimov et al., 2012)	Uzbekistan	619.61	123.92	58,620.00	59.29
16	(García Morillo et al., 2018)	Spain	4800	960.00	454,118.40	459.39
17	(Adhau et al., 2012)	India	6.3	1.26	596.03	0.6
18	(Moreno et al., 2007)	Spain	120	24.00	11,352.96	11.48
19	(Al-Smairan, 2012)	Jordan	520.8	104.16	49,271.85	49.84
20	(Cabrera et al., 2015)	Italy	215.04	43.01	20,345.10	20.58

Flow distributions impact energy consumption and the CO_2 water footprint, while the network's construction also contributes to CO_2 emissions for each meter of pipeline installed. This includes emissions from the creation, excavation, transport, and execution of irrigation system works. Figure 5.4 demonstrates that CO_2 emissions vary between 50% and 150% depending on the diameter and material of the pipelines.

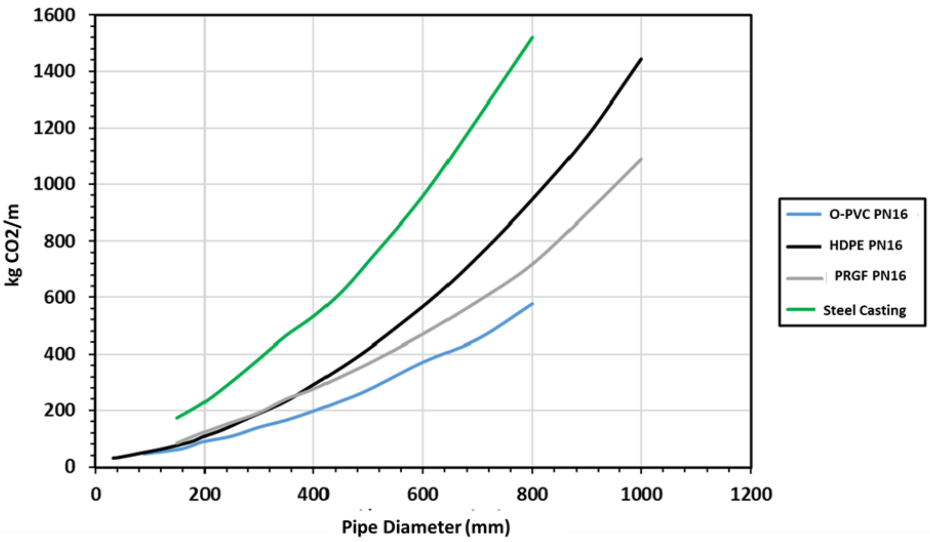

Figure 5.4. *Distribution of the different analyzed models.*

The review identified computational intelligence models as particularly effective for forecasting irrigation demands, highlighting their potential to integrate human behavior and weather conditions into predictive models. The advantages and limitations of current methods have been identified, highlighting the need for greater consideration of sustainability and energy efficiency in designing irrigation networks.

The findings of the review indicate a significant gap in the existing literature in terms of methodologies that comprehensively address technical, economic, and environmental sustainability. This analysis justifies the need to develop a new methodology, as outlined in the objectives of this thesis.

5.2. Methodology development stage

The methodology development stage corresponds to ***objectives 2 and 3***, and the results obtained during this stage were published in ***Publication II***.

5.2.1. Analytical Model for the Evaluation of Flow Distributions

In the methodology development stage, an analytical model was developed to evaluate and optimize flow distributions in irrigation networks for reaching ***objective 2***, as detailed in ***Publication II***, "*Enhancing Sustainability in Irrigation Networks: A Multicriteria Method for Optimizing Flow Distribution and Reducing Environmental Impact*". This model employs a multicriteria approach to determine the optimal flow distribution based on system needs, aiming to enhance sustainability by optimizing pipe diameters and reducing CO_2 emissions.

The novelty of the proposed methodology is the development of a tool to characterize flow distributions that deviate from the traditional Clement's formulation used in irrigation systems while incorporating goodness-of-fit tests such as log-likelihood, AIC values, Chi-squared, and Kolmogorov-Smirnov tests to validate the flow distributions. The methodology also emphasizes material savings and potential energy recovery, contributing to a holistic approach to sustainable network design.

The methodology aimed to allow the development of a tool that, considering the consumption patterns according to the crop, can estimate the best distribution and establish the sustainable design of the network.

The proposed optimization process is divided into five blocks and presented in Figure 5.5. Methodology steps I to III corresponded to the development of the analytical model. Such a model needed different inputs and iterative procedures, which established the energy requirements and the infrastructure sizing to supply the water irrigation demand according to available volume.

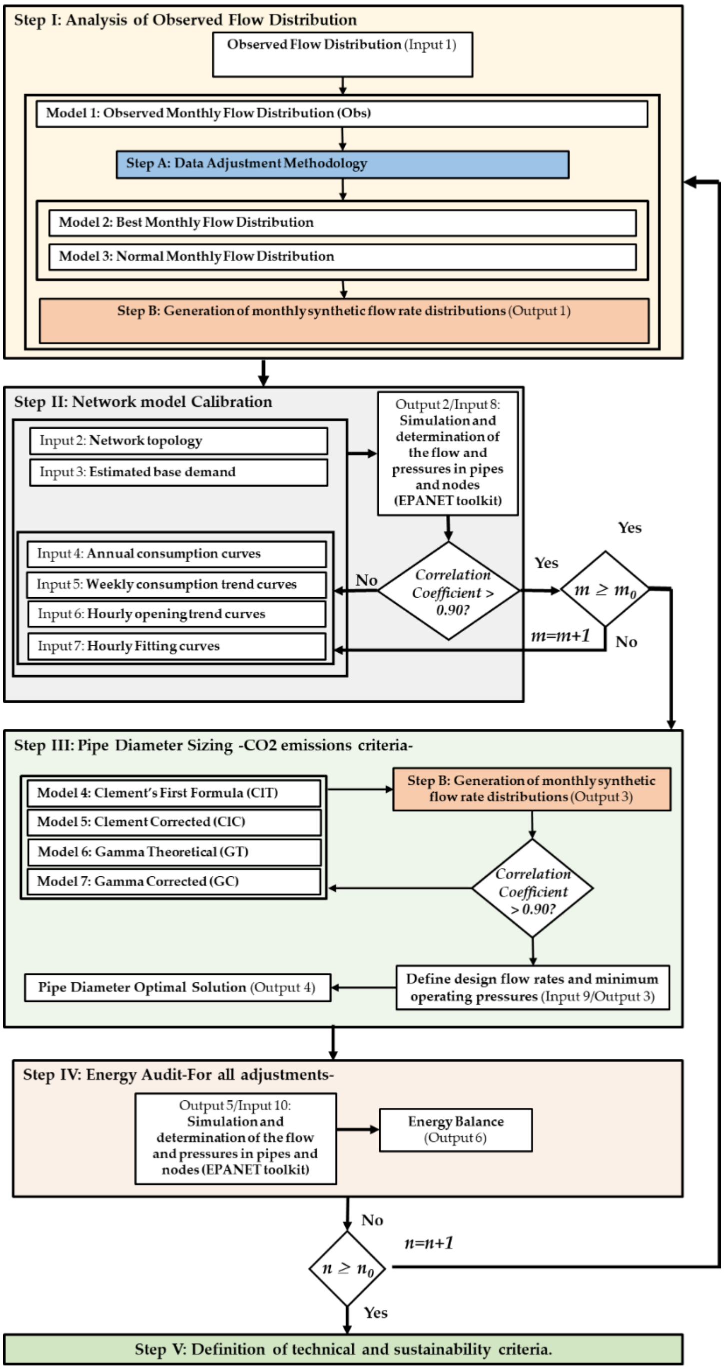

Figure 5.5. *Optimization procedure*

The first adjustment consisted of determining the distribution function that better fit the data for each month. However, the established methodology allows for replication in any case study as well as irrigation typology. Only the data inputs described above in the methodological process are necessary.

Following the characterization of the observed data, a structured methodology for data adjustment was developed and executed in MATLAB using the Statistics and Machine Learning Toolbox in step A. The data adjustment methodology is shown in Figure 5.6a. It receives the monthly flow data as input and fits it with all the available distributions supported by MATLAB. Subsequently, the results are sorted following defined criteria, selecting the best 10 for each month evaluated with their corresponding parameters. Lastly, goodness of fit tests are applied, and the multicriteria process is executed to select the optimal distribution for the data.

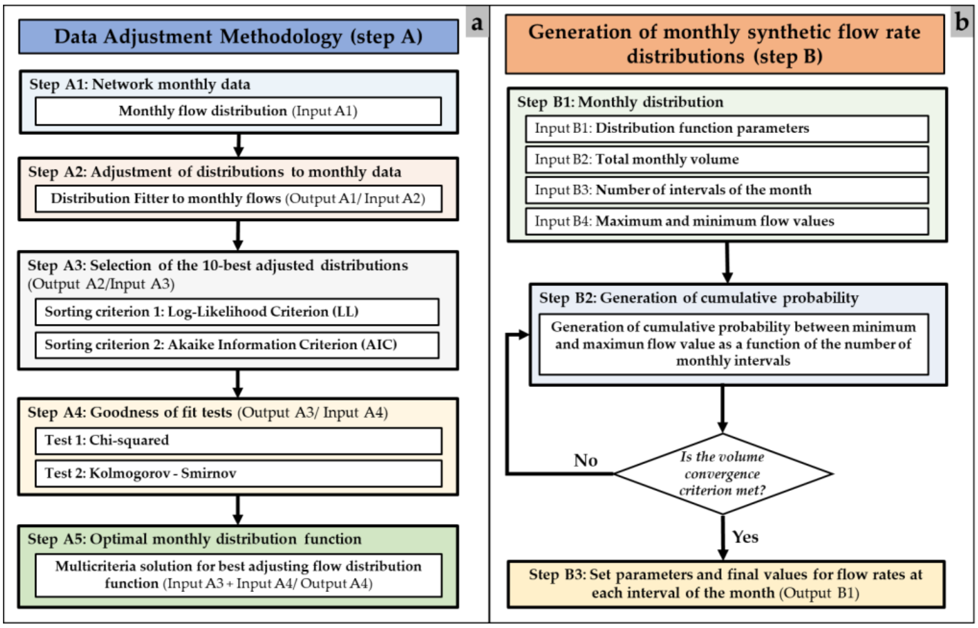

Figure 5.6. *Proposed methodology for the data adjustment. (a) Step A. (b) Step B*

In the last step of the data adjustment methodology (Step A5), the optimal monthly distribution for each year was selected following a multicriteria function (FP), using the log-likelihood (LL), the AIC, the Chi-squared test statistic, and the Kolmogorov-Smirnov statistic as inputs. FP is a proposed criterion of the methodology as a novelty, whereby mathematical definition, the value closest to one, establishes that the type of distribution is repeated more times throughout the year, and, therefore, its behavior can be attributed to it. Equation (5.1) is developed and evaluated for the four criteria for each year according to the research proposal:

$$FP_{criterion} = \sum_{i=0;j=1}^{i=12;j=10} \frac{n_{repi}}{12} \frac{(11 - p_j)}{10} \quad (5.1)$$

Where $FP_{criterion}$ is the FP value for the evaluated criterion; i is the number of the month; j is the index of the position the distribution occupies in that month; n_{rep_i} is the number of months the distribution repeats in that position in a year, and p_j is the position of the distribution in that month. FP values closer to 1 represent the best-fitted function for that year.

This function handles additional considerations, such as benefiting the distributions that repeat more in higher positions, dealing with log-likelihood ties, and providing more detailed output for selecting the optimal distribution. After calculating the FP values for each distribution and criterion in a year, Equation (5.2) determines the total FP value of every distribution. It selects the distribution with the highest value as the best-adjusting distribution function for the flow data in that year.

$$FP_{distribution} = FP_{LL} + FP_{AIC} + FP_{Chi2} + FP_{KS} \quad (5.2)$$

where $FP_{distribution}$ is the total FP value for the distribution function in that year; FP_{LL} is FP value for the log-likelihood criterion; FP_{AIC} is the FP value for the Akaike Information Criterion; FP_{Chi2} is the FP value for the Chi-squared test statistic; FP_{KS} is the FP value for the Kolmogorov-Smirnov statistic. The output of this function is an array containing the best distribution for each year and the parameters for each month for that distribution. After the data adjustment process results, creating a synthetic year generator that follows the selected optimal monthly distribution was necessary.

The resultant methodology and function continued from step B. Figure 5.6b shows the process for generating synthetic monthly data described below. The function created uses as inputs the distribution function parameters for each month and the number of intervals for each month and generates a vector with a set of values that follows the distribution function, ensuring the total volume is the same as the input of that original month.

In the second stage (Step II), calibrating the network model in this study was a crucial step to ensure the accuracy and reliability of the simulations. By using three distinct datasets (observed data, synthetic data following a Gamma distribution, and synthetic data following a Normal distribution), the model was tested against varied conditions. This comprehensive approach allowed for a more robust validation, ensuring the model could handle real-world variability in water flow patterns.

The model simulated realistic flow and pressure scenarios using the EPANET Toolkit by incorporating detailed network topology and base demand inputs. This detailed approach, which included an inventory of pipes and nodes and considered irrigated areas and crop characteristics, ensured that the model was grounded in the practical realities of the studied network.

Calculating consumption trend curves using WaterPAT software was a significant aspect of this study. These curves provided vital insights into water usage patterns over annual, weekly, and hourly timescales. Understanding these patterns was essential for optimizing water distribution and management. For instance, recognizing the increased water demand during warmer months helped plan and ensure sufficient water supply during peak periods.

Using the Correlation Coefficient (CC) to measure the model's accuracy was a well-established method. The study's threshold of CC > 0.90 for a well-calibrated model indicated a high standard for model accuracy. This criterion ensured that the model fit the observed data closely and reliably predicted future scenarios. The iterative process of recalculating trend curves and re-simulating until satisfactory CC values were achieved demonstrated a commitment to precision and reliability.

The condition that the number of simulations (m) must meet or exceed a predefined threshold (m_0) before advancing ensured that the model had been sufficiently tested. This requirement added another layer of rigor, ensuring the design parameters were robust and the model was resilient to variations in input data.

Finally, the developed model significantly improves upon traditional methods, offering a more robust and adaptable tool for various conditions. Initial validation suggests it is a solid basis for practical applications. The calibration process ensured high accuracy and reliability, which is essential for effective water management. Using diverse datasets, detailed hydraulic modeling, and rigorous validation criteria created a practical tool for optimizing water distribution and enhancing efficiency and sustainability while adapting to real-world conditions and variability.

5.2.2. Energy and Sustainability Indicators Design Audit

A design audit was conducted to assign design and management indicators that measure the impact of design decisions on energy efficiency and environmental sustainability. This audit corresponds to ***objective 3*** and is also detailed in Publication II, “Enhancing Sustainability in Irrigation Networks: A Multicriteria Method for Optimizing Flow Distribution and Reducing Environmental Impact”, which evaluated the influence of flow distribution on energy consumption and the feasibility of installing micro-hydraulic generation systems.

The third step involves determining pipe diameter sizing based on CO_2 emissions criteria. Design flow rates are calculated using various models, including *Clement_Theoretical, Clement_Corrected, Gamma_Theoretical, and Gamma_Corrected*. These models are validated using correlation coefficients, ensuring they meet the required standards. Lastly, the optimal pipe size and material that minimized CO_2 emissions per meter of installed network was selected. From the methodology described in Figure 5.5, steps III to V correspond to this section.

The transition to determining pipe diameter sizing based on CO_2 emission criteria represents a crucial advancement in sustainable water management. Traditional methods often focused on hydraulic efficiency and cost but incorporating environmental impact (specifically CO_2 emissions) aligns with contemporary sustainability goals. The model’s emphasis on minimizing CO_2 emissions per meter of installed pipe underscores a commitment to reducing the environmental footprint of irrigation networks.

The various models (*Clement_Theoretical, Clement_Corrected, Gamma_Theoretical, and Gamma_Corrected*) each offer a unique approach to calculating design flow rates. The use of Clément’s First Formula and the subsequent adjustments for standard deviations reflect a detailed understanding of flow distribution. By comparing theoretical and corrected models, the study can determine if the flow rates are accurate and reflect real-world conditions.

The validation process, which requires a correlation coefficient (CC) greater than 0.90, ensures reliable models. This rigorous validation criterion means that the simulated flow rates closely match observed data, enhancing the model's credibility. The iterative process of recalculating and re-simulating until the desired CC is achieved further emphasizes the commitment to precision.

Using the *Economic pipe size selection method* focusing on minimizing CO_2 emissions per meter (as presented in Figure 5.7) is innovative in selecting the solution with the least emissions generated. This approach not only considers the economic aspects but also integrates environmental sustainability into the decision-making process.

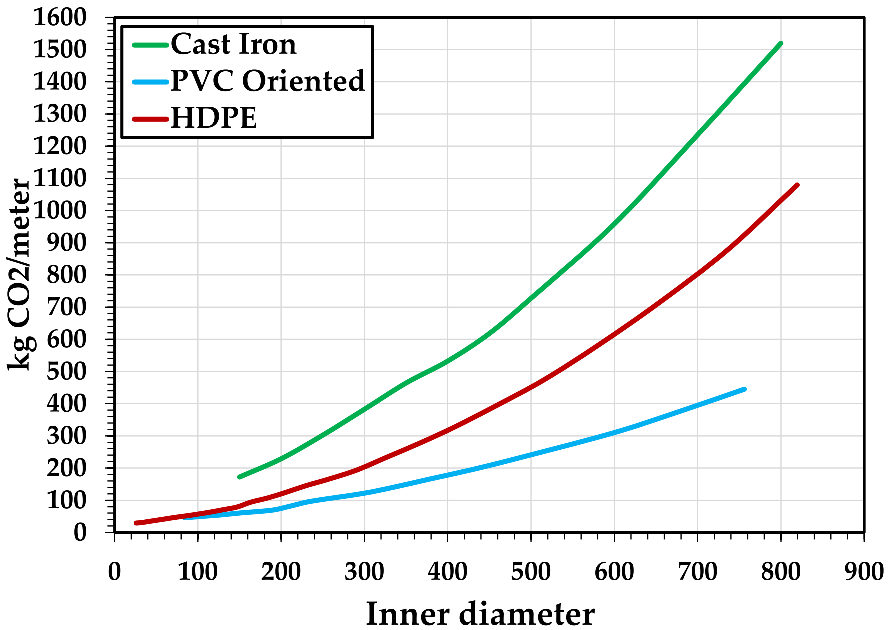

Figure 5.7. Curve inner diameter and kg of CO_2/meter for evaluated materials (Rubio Sánchez, 2022)

The subsequent energy audit for each model using the optimal material solution highlights the importance of understanding energy dynamics within the network. By simulating flow and pressure in pipes and nodes, the study ensures that the chosen solutions are not only environmentally sustainable but also energy efficient. Then, the design flow rates were calculated for all the available models for the month of maximum demand, May. The detailed energy balance equations used further validate the model's reliability are presented in Table 5.6.

Table 5.6. Expressions to develop the energy balance defined by (Pérez-Sánchez et al., 2016a).

Annual Energy (kWh)	Equation	Id
Total Energy *(E_{T_j})*	$\gamma Q_j(z_o - z_j)\Delta t/3600$	(5.3)
Friction Energy *(E_{FR_j})*	$\gamma Q_j\left(z_o - (z_j + P_j)\right)\Delta t/3600$	(5.4)
Theoretical Necessary Energy *(E_{TN_j})*	$\gamma Q_j P_{min_j}\Delta t/3600$	(5.5)
Required Energy *(E_{RS_j})*	$\gamma Q_j P_{minS_j}\Delta t/3600$	(5.6)
Theoretical Available Energy *(E_{TA_j})*	$\gamma Q_i(P_j - P_{\min j})\Delta t/3600$	(5.7)
Theoretical Recoverable Energy *(E_{TR_j})*	$\gamma Q_i\left(P_j - \max\left(P_{min_j}; P_{minS_j}\right)\right)\Delta t/3600$	(5.8)

Where γ is the specific weight of the water; Q_j is the demanded flow in the irrigation point or line *j*; z_o is the elevation concerning the reference plane of the water level at the supply point or line; z_j is the elevation of the irrigation point or line *j*; Δt is the timestep; P_j is the pressure at the irrigation point or line *j*; P_{min_j} is the minimum pressure at the irrigation point or line *j*; P_{minS_j} is the minimum service pressure in the irrigation point or line *j* to guarantee the demanded flow.

An additional condition is verified to determine which is the next step, $n \geq n_0$, where n represents the number of loops of the main methodology (Figure 5.5), n_0 represents the number of years of the evaluated period, this means that steps I to IV should be run three times for each model.

The final step of defining technical and sustainability criteria based on pipe sizing and energy evaluation results ensures that the model's outcomes are both practical and aligned with sustainability goals. By standardizing the assessment of energy consumption and CO_2 emissions, the study provides a clear framework for decision-making that balances technical efficiency with environmental responsibility.

The sustainability indicators derived from the optimal material selection (such as total network environmental cost, CO_2 emissions per linear meter of pipe, per hectare, and per cubic meter of supplied water) provide concrete metrics for evaluating the environmental impact of the irrigation network.

The audit revealed that optimizing flow distribution can significantly reduce material use and CO2 emissions. By incorporating energy and sustainability indicators, the irrigation network design meets operational needs and promotes sustainable development. This comprehensive approach allows for detailed analysis and identification of opportunities to improve sustainability and efficiency in irrigation networks.

5.3. Practical application stage

The case study application stage consisted of two steps, corresponding to ***objectives 4 and 5,*** respectively, and the results obtained during this stage were published in ***Publications II and III***.

5.3.1. Application of Methodology in Real Case Studies

To validate the developed methodology, it was applied to real case studies with experimental data for ***objective 4***, as reported in Publication II. These case studies involved various existing networks, ensuring the results were representative and applicable in real-world contexts.

The application of the developed methodology to real-world case study is presented in ***Publication II***, "*Enhancing Sustainability in Irrigation Networks: A Multicriteria Method for Optimizing Flow Distribution and Reducing Environmental Impact*", demonstrating the model's effectiveness in optimizing flow distributions and improving system efficiency and sustainability in a Mediterranean irrigation system.

Applying the developed methodology to the irrigation network in Callosa d'en Sarrià, Alicante, Spain, effectively demonstrates its potential to enhance system efficiency and sustainability. The network, which spans 120 hectares and primarily supports loquat cultivation, relies on water sourced from wells and regulated by a gravity-fed reservoir system. This case study involved a comprehensive analysis of flow distributions, model calibration using observed data, and a comparison of various statistical distributions. The network topology from the case study is shown in Figure 5.8.

Step I analyzed the observed flows for each month during the studied period. For the three-year dataset, it was determined that the month of maximum needs was May, represented between the days 122 and 155 in Figure 5.9.

The analysis revealed that the Gamma distribution consistently provided the best fit for the observed flow data over three years. This conclusion was reached through a multicriteria approach and correlation analyses, which showed that the Gamma distribution outperformed other distributions, including Lognormal, Weibull, and Normal distributions. The superior fit of the Gamma distribution underscores its suitability for modeling irrigation network flows, capturing both seasonal and annual variations more accurately. Table 5.7 shows the results of the multicriteria approach (FP value) for each year of the studied period.

Table 5.7. *FP value for different Distribution functions during the studied period.*

Order	Distribution	2015	2016	2017
1	Gamma	3.1167	3.1583	3.0917
2	Lognormal	3.0083	3.0083	3.0917
3	Loglogistic	2.6000	2.9167	2.9833
4	Generalized Extreme Value	2.7167	2.6750	2.8667
5	Birnbaum-Saunders	2.6333	2.4583	2.4083
6	Weibull	2.4750	2.5667	2.3750
7	Inverse Gaussian	2.1333	2.0250	2.0167
8	Exponential	1.4833	1.6000	1.6500
9	Normal	1.2167	1.1417	1.0500
10	Uniform	0.6167	0.4500	0.4667

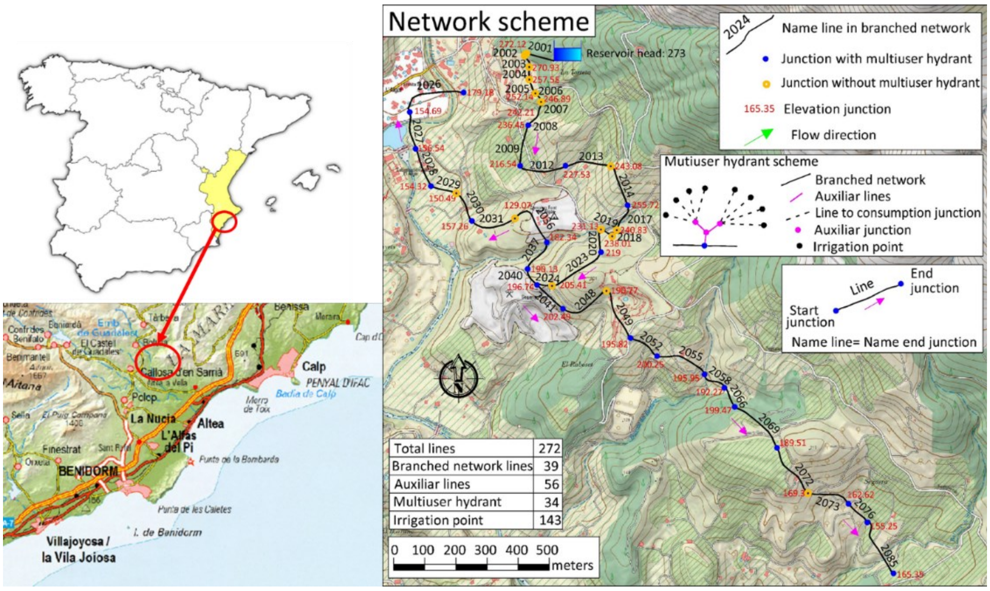

Figure 5.8. Case study scheme

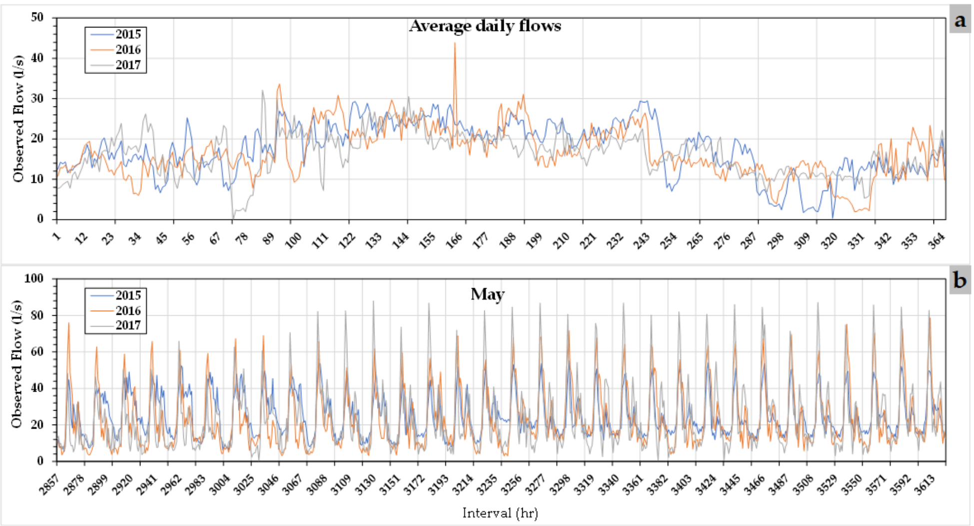

Figure 5.9. *Observed data (a) Average daily flows for years 2015, 2016, and 2017; (b) Hourly flows for May.*

Calibration of the observed data and synthetic models (Gamma and Normal) showed strong correlations, affirming the reliability of the proposed methodology. The Gamma_Corrected (GC) model demonstrated the highest accuracy in predicting flow patterns, with correlation coefficients indicating a very strong alignment between observed and modeled data (with values between 0.98 and 0.99 for May while having an average value of 0.995 for the annual series). Figure 5.10 shows minimum values for the Correlation Coefficient for the synthetic models.

The weighted absolute error analysis further supported this, as shown in Figure 5.11. The Gamma_Corrected (GC) model presented the second smallest error margin in design flow estimations (overestimating by 8.21% while compared to the observed data), and the best result comes from the Gamma_Calibrated (CCal), overestimating 1.12% of the design flow on average for May.

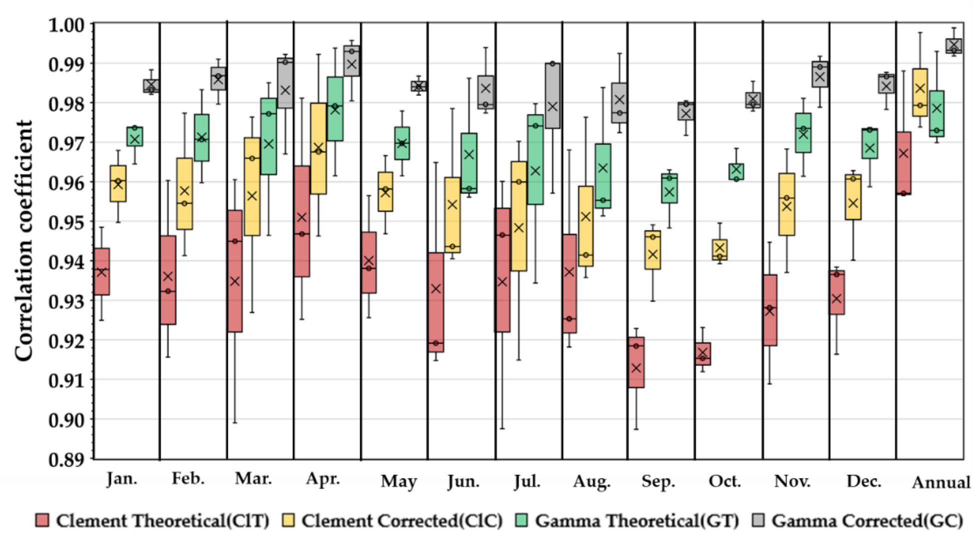

Figure 5.10. *Correlation Coefficients for the theoretical and corrected Clement and Gamma models.*

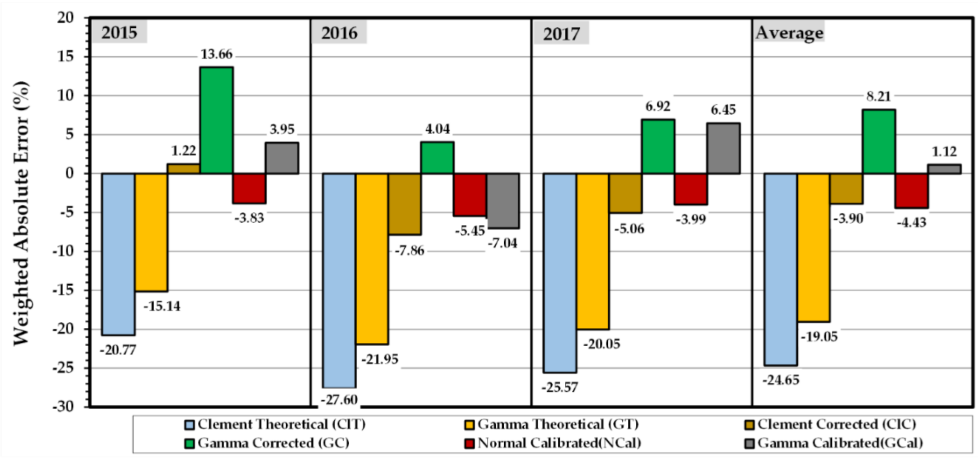

Figure 5.11. *Weighted absolute error for the design flow for the evaluated models in May.*

Environmental sustainability was a key focus of the methodology. The analysis showed that the Gamma models, especially the Gamma_Corrected model, resulted in the lowest CO_2 emissions per installation. This was consistent across different pipe materials, including HDPE, PVC-O, and cast iron. The PVC-O material, when combined with the Gamma_Corrected (GC) distribution, emerged as the optimal solution, offering the lowest environmental cost and significantly reducing the carbon footprint of the irrigation system. This reduction in CO_2 emissions aligns with sustainable development goals, specifically those aimed at mitigating climate change and promoting resource efficiency. Figure 5.12 shows the results for the six previous models as well as the Observed_Calibrated of the average cost for the three years, material, and model used.

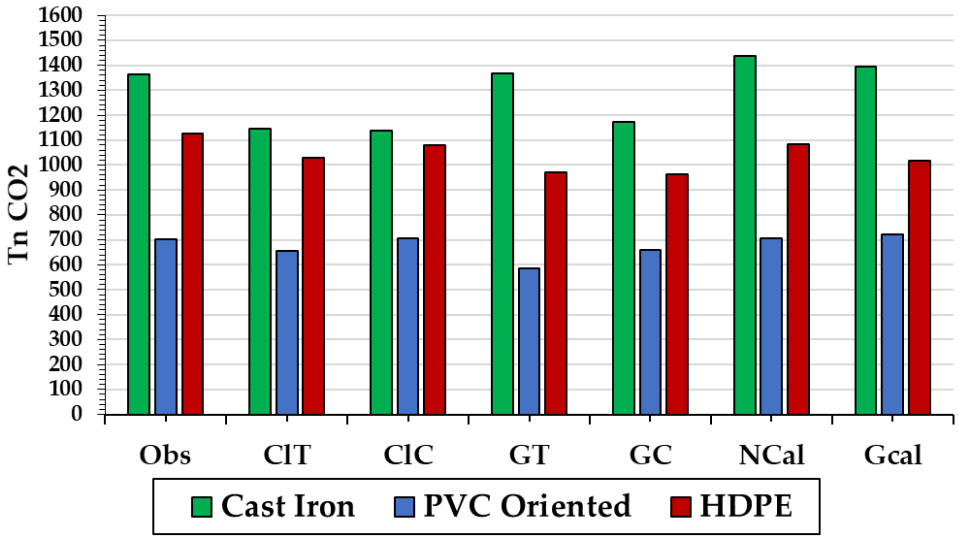

Figure 5.12. *Tons of CO_2 emissions for the different models and materials.*

Energy balance calculations highlighted the efficiency of the Gamma_Corrected (GC) model in optimizing energy use. This model achieved the highest theoretical available energy (63693.94 kWh) and the lowest friction energy losses (19408.06 kWh), contributing to an overall more energy-efficient system.

The proposed methodology offers a scalable framework for improving the design and renovation of irrigation networks, with a strong emphasis on sustainability. By incorporating flow distribution optimization, environmental cost analysis, and energy efficiency metrics, the methodology supports sustainable development goals, particularly those related to reducing greenhouse gas emissions (SDG-13) and promoting efficient water use (SDG-6) and clean energy (SDG-7).Furthermore, this approach encourages adopting more sustainable practices in agricultural water management.

It highlights the importance of selecting appropriate flow distribution models and materials to minimize environmental impacts and enhance resource efficiency. This methodology can be adapted and applied to various irrigation networks globally, ensuring that sustainability is integrated into the design and operation of these systems.

In conclusion, the developed methodology for optimizing flow distribution and reducing environmental impact in irrigation networks has been validated through its application to a real-world case study. The Gamma_Corrected (GC) model has proven to be highly effective in achieving sustainable and efficient water management, achieving material savings of 6.01% compared to the observed network, reducing CO_2 emissions between 5.61 and 5.72 TnCO2/ha over its lifecycle. The findings of this study emphasize the need for ongoing research and development in this area to further refine and expand the application of sustainable practices in agricultural water management.

5.3.2. Energy Improvement Tool in Distribution Systems

An energy improvement tool was developed to enhance irrigation distribution systems' energy, corresponding to ***objective 5*** and detailed in Publication III. This tool integrates hydraulic and electrical regulation strategies to maximize energy recovery and improve system efficiency.

This publication also discusses developing and implementing a tool for optimizing energy recovery in water distribution systems. ***Publication III,*** "Improvement of the Electrical Regulation of a Microhydropower System using a Water Management Tool", provides detailed insights into the tool's hydraulic-electrical regulation strategies and its successful application in a real case study, demonstrating significant efficiency and sustainability improvements. The implementation of this tool in a real case study in Valencia, Spain, highlights the practical benefits of the hydraulic-electrical regulation tool. The key outcomes were using empirical methods for estimating characteristic curves and developing a tool for hydraulic-electrical regulation in water distribution networks (WDNs). The tool, developed in Simulink MATLAB, optimized the number of machines operating, frequency inverter setpoints, and pressure-reducing valve settings to maximize recovered energy.

The proposed methodology is presented in Figure 5.13 and is composed of three main blocks:

A. Model preparation, where the input parameters are established, and preselect pumps operating as turbines (PATs).

B. Simulation of PAT system and hydraulic model, simulates the PAT system and optimizes the operation to maximize generated power.

C. Analysis and Presentation of Results: Analyzes the installation's energy and selects the final equipment.

This structure ensures a thorough and accurate optimization process. Each step, particularly the detailed preselection and validation of PATs, contributes to the tool's robustness and effectiveness.

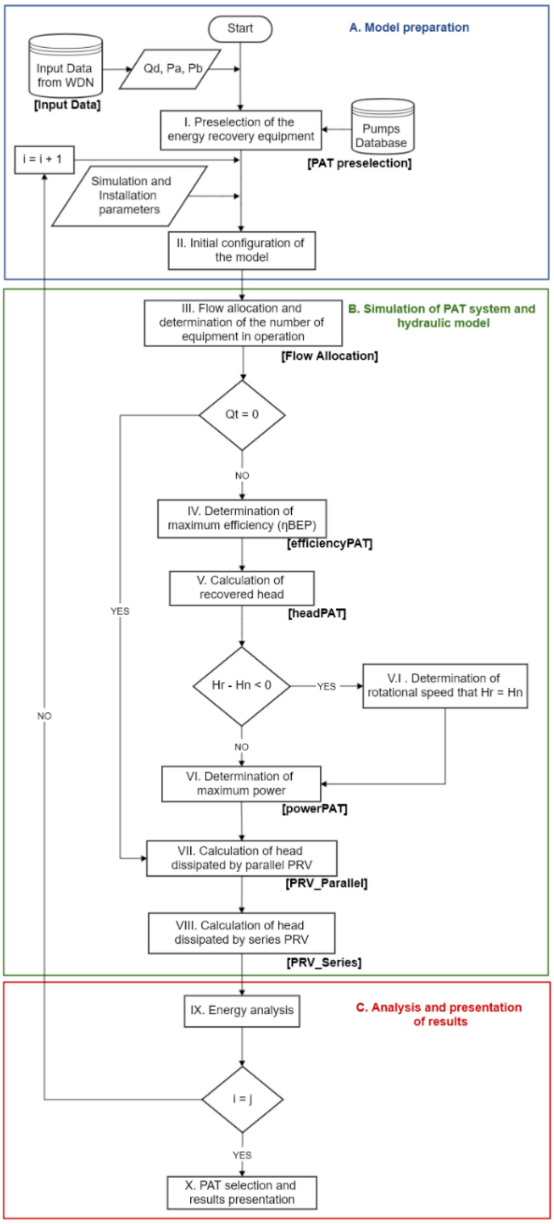

Figure 5.13. *Proposed methodology for the analysis of the regulation in an energy recovery system.*

The case study was in Valencia (Spain); the proposed system connected two tanks with a significant hydraulic jump, allowing energy-recovery systems to be installed. The analysis used data from a single day to simulate the flow and pressure conditions. Four machines were preselected based on specific criteria, and after simulations, one PAT model was chosen for its efficiency and energy recovery capabilities.

The schematic view of the system is presented in Figure 5.14.

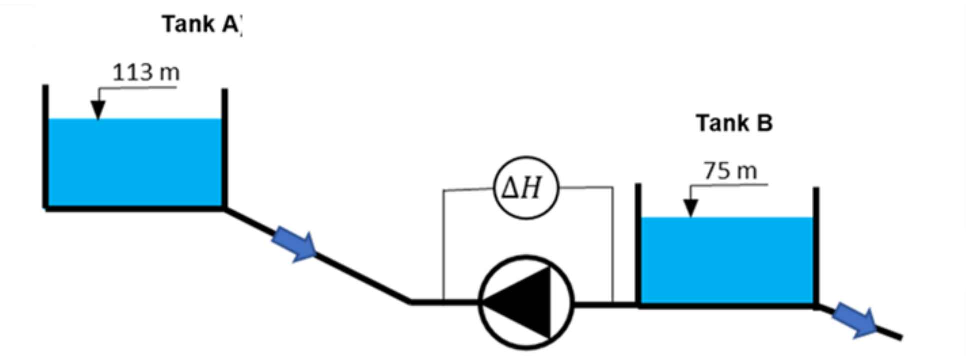

Figure 5.14. *The layout of the case study scenario. ΔH represents the net hydraulic jump available.*

The developed tool significantly improved energy recovery and efficiency within the water distribution system. Integrating hydraulic and electrical strategies in the tool allows for a comprehensive optimization approach, addressing both mechanical and electrical components of the energy recovery process.

The tool's ability to optimize the number of machines and their operational parameters ensures that the system operates at its highest efficiency. By adjusting the frequency inverter setpoints and PRV settings, the tool maximizes energy recovery, demonstrating the practical benefits in real-world scenarios.

The effectiveness of the tool was validated with the system recovering substantial energy and operating efficiently under varying flow conditions. The empirical methods used for estimating characteristic curves proved reliable, reducing error values significantly compared to other methods.

The selected machine model was a CPH 350–360 at 50 Hz from the manufacturer Bombas IDEAL, which considered the maximum daily recovered energy criterion. Each PAT operated with a minimum flow of 468 L/s and a maximum of 632 L/s (Figure 5.15a), with the rotational speed oscillating between 1229 and 1305 rpm over time (Figure 5.15b).

The system achieved efficiencies between 0.61 and 0.65 and a recovered head oscillating between 33 and 35 m w.c. (Figure 5.15c). Moreover, the output torque value is shown in Figure 5.15d, ranging between 0.75 and 1.1 Nm for the studied period. In addition, the generated power for each machine was between 107 and 145 kW.

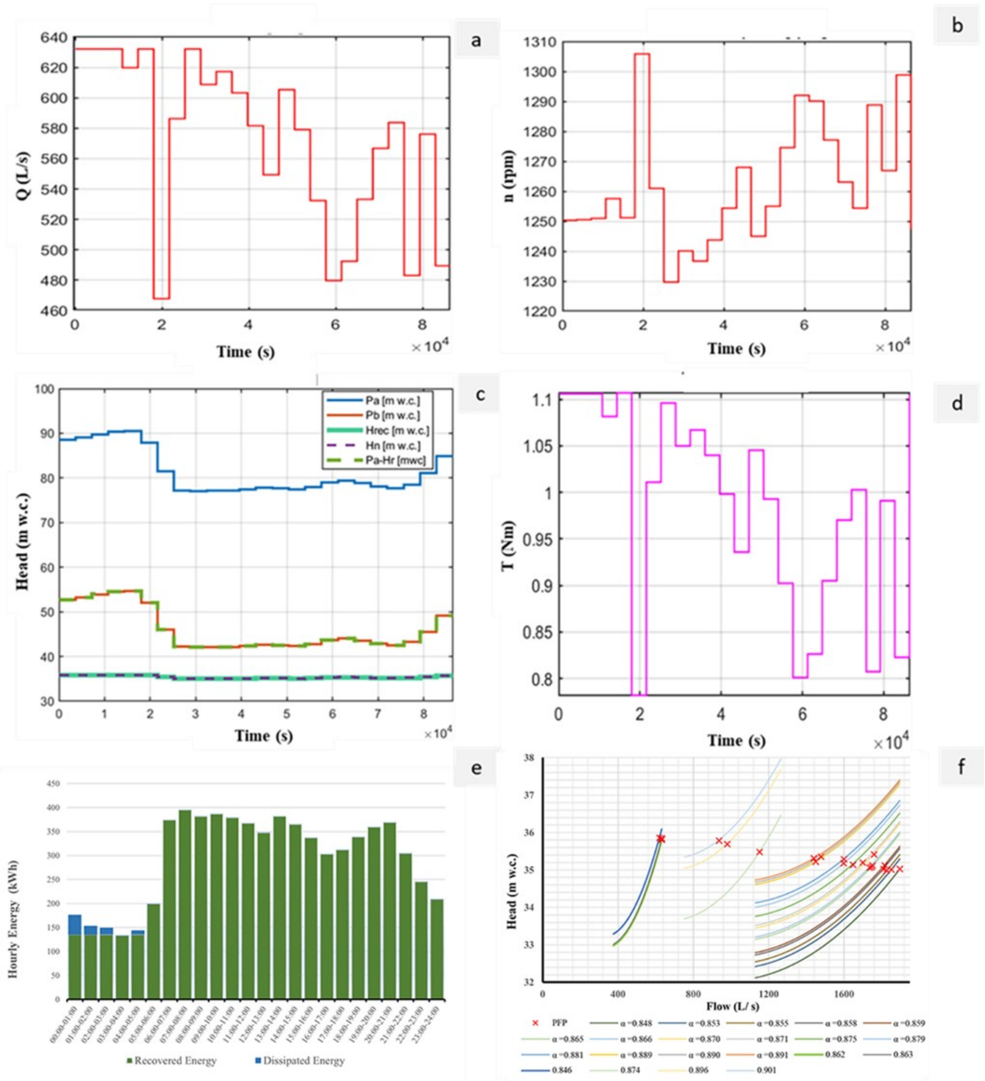

Figure 5.15. *(a) Flow over time; (b) rotational speed of the machine over time; (c) pressures and Head over time; (d) torque over time; (e) hourly energy; (f) regulation of the recovery system.*

The tool can choose the best machine and optimize its regulation to maximize the recovered energy while only knowing the flow over time and the downstream pressure constraint. It is a step ahead since the optimization tool defines the rotational speed and torque at each moment.

The successful application of this tool highlights its potential for broader implementation in similar water distribution systems. With a 28% recovery rate of supplied energy and an average efficiency value of 0.61, it translated to 7160 kWh of daily recovered energy for the case study

The improvements in sustainability and efficiency are critical for modern irrigation systems, where energy costs and environmental impacts are major considerations.

Moreover, developments could further enhance its capabilities. Incorporating more advanced predictive algorithms and real-time data integration could provide even more accurate and dynamic optimization, adapting to changing conditions instantaneously.

Chapter 6
Conclusions

Factors such as the constant growth of the world's population, water scarcity, and climate change increasingly threaten global agricultural sustainability, so irrigation stakeholders must have complete information to evaluate options to optimize irrigation networks. Improving water and energy efficiency is essential, so adopting sustainable solutions in the short term is essential. This thesis analyzed current methodologies for designing and managing irrigation networks, with a special focus on the practical application of these methodologies through real case studies. The main objective of the research was to develop a robust methodology that evaluates and optimizes the distribution of flows considering technical, economic, and environmental sustainability indicators. The integration of these indicators in the design process ensures that irrigation networks not only meet operational requirements but also contribute to sustainable development goals. The successful application of the methodology in real case studies demonstrates its practical viability and effectiveness, providing a valuable tool for engineers and water managers to enhance the sustainability and efficiency of irrigation systems. This chapter will present the main findings and conclusions resulting from the three stages of the development of this thesis and propose lines for future research.

6.1. Conclusions

The conclusions of this thesis summarize the general findings and implications of research on the optimization of pressurized irrigation networks for technical, economic, and environmental sustainability. The research aimed to develop a comprehensive methodology that addresses flow distribution and optimizing key sustainability indicators. Through an extensive literature review, development of analytical models, and practical case study applications, the research has established a robust framework to improve the design and management of irrigation networks. Key conclusions highlight the effectiveness of the proposed methods and their practical usefulness in achieving sustainable irrigation practices.

The ***review of the state of the art of irrigation network design and analysis methods*** was performed to accomplish ***objective 1***, obtaining the following conclusions:

O1.I. By reviewing the state of the art, the research identified the strengths and limitations of existing approaches, ranging from handling uncertainties and frequency-based predictions to leveraging historical data for advanced forecasting, and therefore, providing a solid theoretical foundation for the research.

O1.II. The agronomic variables are essential in accurately forecasting irrigation demands. Also, other factors, such as relationships between crop patterns, crop group stage, water and energy requirements, weather conditions, and user interactions, can be considered.

O1.III. Depending on the involved variables, the methods were classified into four different approaches: i) Deterministic models (D), being recognized for their reliance on extensive data collection, though limited by external uncertainties; ii) Statistical models (F), which can effectively predict operational probabilities and flows frequencies, providing valuable insights for network management; iii) Random Simulation models (R) offered flexibility in addressing uncertainties through variable relationships.; and iv) Computational Intelligence models (CI) proved to be the most effective in forecasting irrigation demands by integrating human behavior and weather conditions, emerging as the most promising due to their ability to learn from historical data and adapt to new information,

O1.IV. The importance of improving sustainability in irrigation systems is emphasized, while effective pipe sizing and network design are critical for reducing water waste and energy consumption.

O1.V. The ability to accurately predict and manage water demands helps in better planning and operation of irrigation systems, ultimately contributing to sustainable agricultural practices with the overall need for a methodology that accurately forecasts water demands in irrigation networks with more advanced methods.

O1.VI. The potential benefits of integrating micro hydrogeneration systems and optimizing flow distribution to enhance the overall sustainability of irrigation networks are highlighted.

An ***analytical model that allows the evaluation of flow distributions was developed*** following ***objective 2.*** The proposed methodology is robust and adaptable to different scenarios; key conclusions for this objective are:

O2.I. Successfully **developed a novel methodology to evaluate and optimize flow distributions in irrigation networks** while achieving high correlation coefficients (above 0.9), highlighting the model's effectiveness.

O2.II. The model's ability to use a multicriteria approach and adapt to various scenarios positions it as a valuable tool for sustainable irrigation network design and management.

O2.III. This model derives from the traditional Clements formulation and characterizes flow distributions, thus selecting the optimal flow distribution for each case.

O2.IV. Within the methodology, there is also a synthetic year generator, addressing the need for large datasets and a lack of information for irrigation demand forecasting, providing valuable tools for improved water management and environmental stewardship.

O2.V. The model was validated through statistical tests, achieving high accuracy and incorporating rigorous statistical tests such as log-likelihood, AIC values, Chi-squared, and Kolmogorov-Smirnov.

To meet ***objective 3***, ***developing a design audit that evaluates design and management indicators*** is essential for assessing and enhancing energy efficiency and environmental sustainability in irrigation networks. The main conclusions for this objective include:

O3.I. Conducted a design audit to assess the impact of design decisions on energy efficiency and environmental sustainability by integrating a multicriteria approach and a holistic network performance evaluation.

O3.II. The design audit provided valuable insights by optimizing pipe diameters to reduce CO_2 emissions, minimizing service pressure, and maximizing recoverable energy, demonstrating significant material and energy savings and promoting sustainability.

O3.III. The proposed methodology enhances the technical performance of irrigation networks and addresses the environmental impacts of irrigation systems.

O3.IV. Exploring the impact of climate change on irrigation demands and system efficiency could also provide additional insights for improving long-term network performance.

O3.V. Water managers can better assess and optimize their designs by applying the developed tools and approaches, leading to more sustainable and efficient irrigation practices.

Applying and ***validating the developed methodologies on existing pressurized networks*** is crucial to ensure their viability and effectiveness. Based on the insights from Publication II corresponding to ***objective 4***, the following conclusions can be outlined:

O4.I. The methodology developed was successfully applied to a real case study network, demonstrating its practical viability. The proposed multicriteria optimization model for flow distribution was validated using a Mediterranean irrigation system in Alicante, Spain.

O4.II. The methodologies proved adaptable to various operating conditions and scenarios. The Gamma function was identified as the most suitable for the case study among the analyzed distributions. The Gamma Corrected model provided a robust solution for optimizing flow distribution under different constraints.

O4.III. Significant energy efficiency and sustainability improvements are highlighted when applying the developed methodologies. It is demonstrated that careful design choices can lead to improvements in energy recovery and reductions in environmental impacts, such as a 6.01% material saving and reduced CO_2 emissions between 5.61 and 5.72 $TnCO_2$/ha.

O4.IV. The methodologies developed have the potential for broader application beyond the specific case studies. The tools and strategies can be adapted to various water systems, providing water managers with powerful tools for optimizing flow distribution and energy recovery.

O4.V. Publication II suggests directions for future research, emphasizing the need for further integration and refinement of the methodologies.

Developing a tool for energy improvement in irrigation distribution systems is essential for enhancing efficiency and sustainability. The findings from Publication III lead to the conclusions from ***objective 5***:

O5.I. The tool developed provides a comprehensive approach to managing irrigation networks by integrating hydraulic and electrical regulation strategies. This holistic approach ensures that all relevant factors are considered, leading to more efficient and sustainable system management.

O5.II. The tool's ability to define optimal regulation parameters for electrical equipment further enhances its utility for energy improvement. It significantly improves energy efficiency by recovering a considerable portion of the supplied energy in the system. It recovered 28% of the energy provided, equating to over 7160 kWh daily. This highlights the tool's effectiveness in enhancing energy efficiency and reducing overall energy consumption in distribution networks.

O5.III. The tool contributes to the sustainability of irrigation distribution systems. By optimizing hydraulic-electrical regulation strategies, the tool enhances energy recovery and reduces CO_2 emissions.

O5.IV. Empirical methods to estimate characteristic curves were utilized, which are critical for optimizing the operation of pumps working as turbines (PATs). The tool's optimization strategy ensures that the hydraulic constraints of the system are met while maximizing recovered energy over time. This innovative approach demonstrates the effectiveness of combining empirical data with advanced simulation and optimization techniques.

O5.V. The case study results indicate that the tool can be applied to any water system where the flow and upstream and downstream pressures are known over time. This adaptability is essential for addressing the diverse challenges different irrigation networks face and ensures that the tool can provide widespread benefits.

The final **contribution of this research** is threefold:

(i) Advanced understanding of methodologies for sustainable irrigation network design.

(ii) Developed practical tools and models for optimizing energy efficiency and reducing environmental impact. Although the criteria and results presented here are case-specific, the proposed approach can serve as a model for other regions.

(iii) Validated methodologies through real-world applications, providing actionable insights for industry practitioners and researchers.

6.2. Future Research

The culmination of this research has provided a robust methodology and practical tools for the design and optimization of pressurized irrigation networks, taking into account technical, economic and environmental sustainability. However, as with all research, the results obtained open the door to new questions and areas of study that deserve further exploration.

This section aims to identify and propose possible lines of future research that can expand and deepen the findings presented, further improving the efficiency and sustainability of irrigation systems. Various potential areas for future research are detailed below, based on the limitations encountered and the opportunities identified during the development of this thesis:

- While the current model provides significant improvements, incorporating more advanced computational techniques such as machine learning and artificial intelligence could further optimize the distribution of water and enhance predictive capabilities. These techniques can analyze large datasets to identify patterns and make real-time adjustments to irrigation systems.

- Exploring the integration of renewable energy sources, such as solar or wind power, into irrigation systems can address sustainability concerns. Future research can focus on developing hybrid systems that combine renewable energy with traditional power sources to reduce carbon footprints and operational costs.
- As climate change continues to affect water availability and agricultural practices, it is crucial to study its impact on irrigation systems. Future research should investigate adaptive strategies for irrigation management under varying climatic conditions, ensuring resilience and sustainability in the long term.
- Although a practical tool has been developed in this thesis, further refinement and user-testing can improve its usability and effectiveness. Research can focus on creating more intuitive interfaces, incorporating feedback from end-users, and ensuring that the tools meet the needs of diverse stakeholders.
- Investigating the role of policy and regulatory frameworks in promoting sustainable irrigation practices is another important area. Research can analyze existing policies, identify gaps, and propose new regulations that incentivize the adoption of efficient and sustainable irrigation technologies.

Chapter 7 References

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