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Enhancing sustainability in irrigation networks: A multicriteria method for optimizing flow distribution and reducing environmental impact

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A B S T R A C T

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.

1. Introduction

Irrigation systems are crucial in developing new agricultural practices to guarantee feasibility [1]. The correct operation of these water systems is mandatory to guarantee the pressure and flow at each irrigation point [2]. Both terms (i.e., feasibility and pressure guarantee) imply the need to consider climate change [3] since water management is key to optimizing the available water resources, which is very important in deficit areas [4]. Improving the management of irrigation systems starts with the correct design of irrigation systems [5]. For this reason, the study of flow frequency distributions is more significant than ever [6], 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 [7].

Water scarcity is present strongly in Mediterranean areas [8], which should be considered when managing irrigation communities. These structures should satisfy the water demand [1], guarantee the water resources [9] and improve the evaluation of the different targets of the sustainable development goals (SDGs) [10]. 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 [11]. Its water requirements depend partly on the quality of the water [12].

The water demand of the different crops in irrigation systems depends on the irrigation requirements by soil water balance [13], which are new trends to get new volume resources [14], soil type and climatic factors involved in the system [15]. These different approaches were reviewed by Ref. [16], 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

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topology but also the distribution (i.e. gravity or pumped) [17]. 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 [18]. Currently, using decision support systems and artificial intelligence supported with digital twins helped improve the networks' management once they are designed [19]. However, management comes at a later stage than design and implementation [20]. 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 [21].

Water scarcity has led system managers to develop better water management within the framework of intensive agriculture in recent decades [22]. Intensive agriculture implied the irrigation transformation from gravity to pressurised irrigation systems to increase the water efficiency [23]. 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 [24].The improvement of water efficiency solved the water scarcity problems [25]. However, the increase in profitability led and the food needs of the population to cover its needs caused an increase in the volumes demanded [26]. The rise in water consumption, coupled with the reduction of water resources during drought periods due to climate change [27], necessitates that water managers establish new strategies to introduce additional water sources to balance irrigation demands with available water [14]. This volume increment could get from water reuse volume from wastewater treatment plants, which is currently discharged to sea [28]. 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 % [24]. This increase in energy was offset by the use of renewable systems (mainly photovoltaic and micro hydropower systems) in past years [29]. It contributed to reducing the carbon footprint of the irrigation systems [30], considering a potential of 2.8 Wh/m^3 for each meter of difference in elevation [31] 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 [32]. 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 [33].

[34] 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 [35]; (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 [36]; (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 [37]; 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 [38]. 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 [34].

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 [39]. The novelty of the study is focused on developing a tool that allows to characterize 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).

2. Methodology

The proposed procedure is divided into five different phases, each containing different steps (Fig. 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.

2.1. Optimization stages

Fig. 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).

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 [40] in step A. MATLAB is a desktop software and a programming language that directly expresses mathematic expressions as matrices and arrays (vectors or arrays) [41]. The developed tool is divided into five main steps, as shown in Fig. 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.

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 [42–44].

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

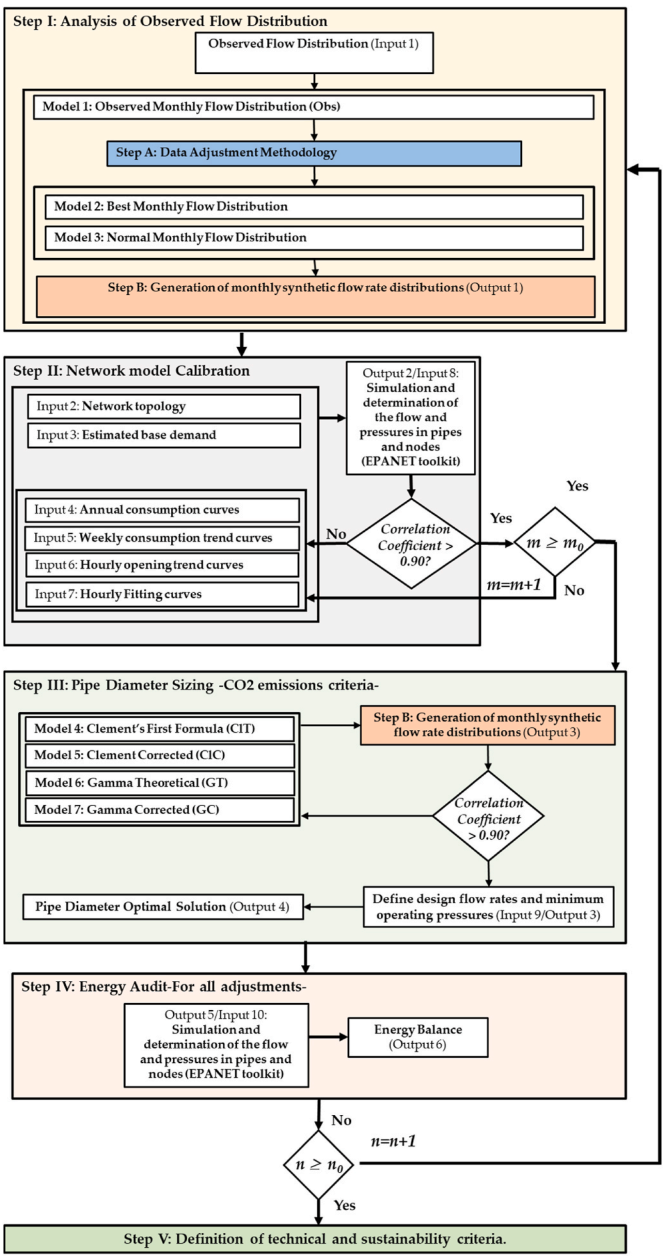

Fig. 1. Optimization procedure.

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 [45,46]. 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 (1) [45,46]:

$$AIC = 2 \cdot LL + 2 \cdot n_{param} \tag{1}$$

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 [47,48]. 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 [47,48].

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 [49,50]. MATLAB's Statistics and Machine Learning Toolbox provide the 'chi2gof' and the 'kstest' functions for calculating the goodness of fit tests [51,52].

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 [49,50]. 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 (2) is developed and evaluated for the four criteria for each year according to the research proposal:

$$FP_{criterion} = \sum_{i=0;j=1}^{i=12;j=10} \frac{n_{repi}}{12} \frac{\left(11 - p_j\right)}{10} \tag{2}$$

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) 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.

$$FP_{distribution} = FP_{LL} + FP_{AIC} + FP_{Chi2} + FP_{KS} \tag{3}$$

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. Fig. 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 B: 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

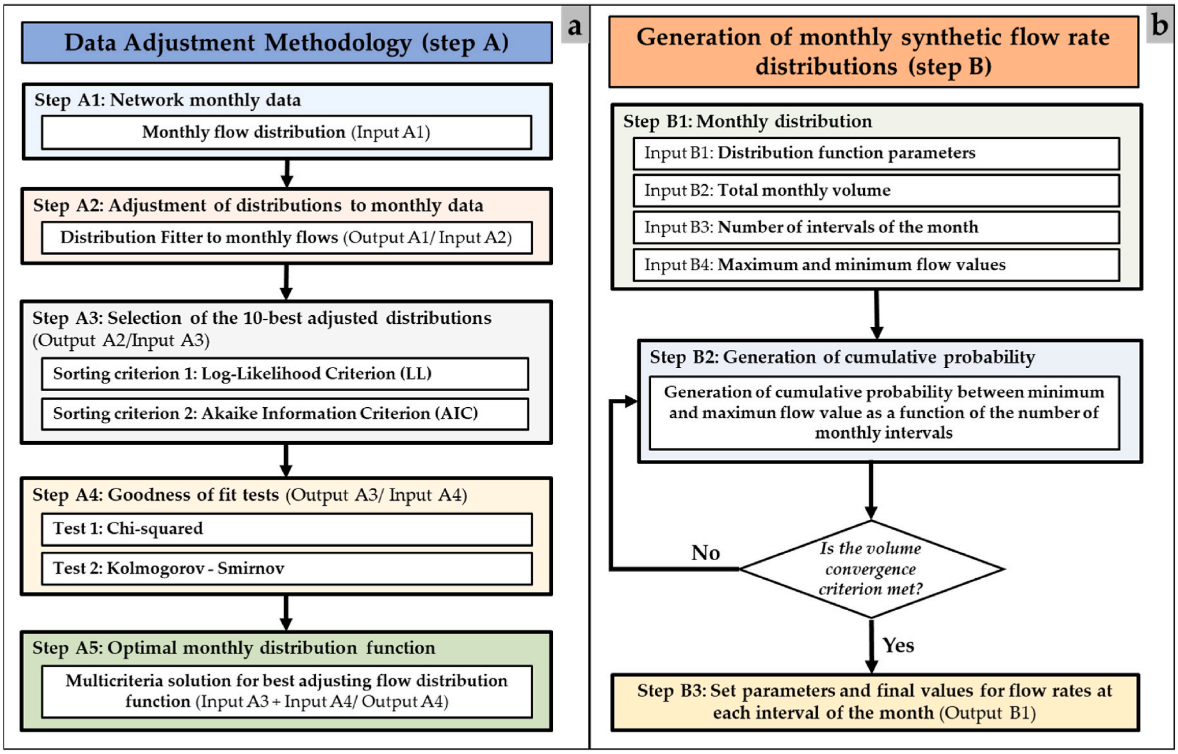

Fig. 2. Proposed methodology for the data adjustment. (a) Step A. (b) Step B.

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 [53,54]. 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 [55,56]. This network will be calibrated with the available datasets following different scenarios, generating three main calibrated models [57]. 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 [58] 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 Ref. [59]. Water distribution systems rely on consumption trend curves to efficiently manage and optimize water usage across various temporal scales, including annually, weekly, and hourly [60,61]. *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 [62,63]. *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 [64].

The previous step enables the simulation and determines the flow and pressures in pipes and nodes by EPANET [55]. 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 (4) [56]. Also, Q-Q plots are generated for each model and then compared with the observed data.

$$CC(Q_s, Q_c) = \frac{\sum (Q_s - \overline{Q_s})(Q_c - \overline{Q_c})}{\sqrt{\sum (Q_s - \overline{Q_s})^2 \sum (Q_c - \overline{Q_c})^2}} \tag{4}$$

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 Ref. [65], 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 coefcient 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 -CO2 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 [66,67]: 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 [68]. 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 (5) [21,68,69]:

$$Q_d = \mu_{clement} + U \cdot \sigma_{clement} \tag{5}$$

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 (6) [21] and Equation (7) [21] respectively:

$$\mu_{Clement} = \sum_{i=1}^{i=n} p_i \cdot q_i \tag{6}$$

$$\sigma_{Clement} = \sqrt{\sum_{i=1}^{i=n} p_i(1-p_i) q_i^2} \tag{7}$$

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 (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 $R^2 = 0.9568$. The corrected standard deviation was obtained with Equation (9):

$$R_\sigma = 0.87818 \cdot \mu_{Clement}{}^{0.25} \tag{8}$$

$$\sigma_{Corrected} = R_\sigma \cdot \sigma_{Clement} \tag{9}$$

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 (10):

$$Q_{Corrected} = \mu_{clement} + U \cdot \sigma_{Corrected} \tag{10}$$

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 (11) [49] and Equation (12) [47,70]. After determining the parameters, the design flows can be calculated.

$$\alpha_{Theoretical} = \frac{\mu_{Clement}^2}{\sigma_{Clement}^2} \tag{11}$$

$$\lambda_{Theoretical} = \frac{\mu_{Clement}}{\sigma_{Clement}^2} \tag{12}$$

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 (11) and (12), proposing Equation (13) and Equation (14).

$$\alpha_{Corrected} = \frac{\mu_{Clement}^2}{\sigma_{Corrected}^2} \tag{13}$$

$$\lambda_{Corrected} = \frac{\mu_{Clement}}{\sigma_{Corrected}^2} \tag{14}$$

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.

2.1.1. 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 [71,72]. For this method, instead of a cost per meter and material curve, the CO2 emission per meter criteria was used [73], as shown in Fig. 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.

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 [74], the energy balance equations relative to different types of energy within the network were described and summarized in Equations (15) to (20), as shown in Table 1.

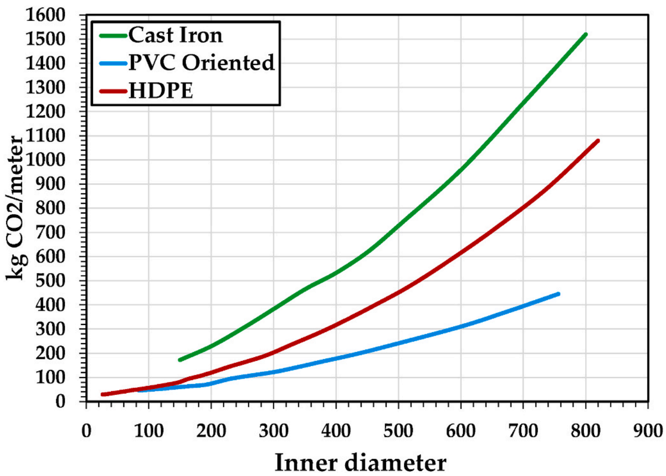

Fig. 3. Curve inner diameter and kg of CO2/meter for evaluated materials.

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 (Fig. 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.

2.1.2. Sustainability indicators

Once the optimal material is determined, the sustainability indicators are obtained. Following the works of [73], 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.

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 ha. Irrigation uses water resources from wells. The water volume is regulated using a reservoir with enough

Table 1
Expressions to develop the energy balance defined by Ref. [74].

Annual Energy (kWh)	Equation	Id
Total Energy ($\mathbf{E}_{\mathbf{T}_j}$)	$\gamma Q_j(z_o - z_j)\Delta t/3600$	(15)
Friction Energy ($\mathbf{E}_{\mathbf{FR}_j}$)	$\gamma Q_j(z_o - (z_j + P_j))\Delta t/3600$	(16)
Theoretical Necessary Energy ($\mathbf{E}_{\mathbf{TN}_j}$)	$\gamma Q_j P_{min_j}\Delta t/3600$	(17)
Required Energy ($\mathbf{E}_{\mathbf{RS}_j}$)	$\gamma Q_j P_{minS_j}\Delta t/3600$	(18)
Theoretical Available Energy (E_{TAj})	$\gamma Q_i(P_j - P_{\min j})\Delta t/3600$	(19)
Theoretical Recoverable Energy (E_{TRj})	$\gamma Q_i(P_j - \max(P_{min_j}; P_{minS_j}))\Delta t/3600$	(20)

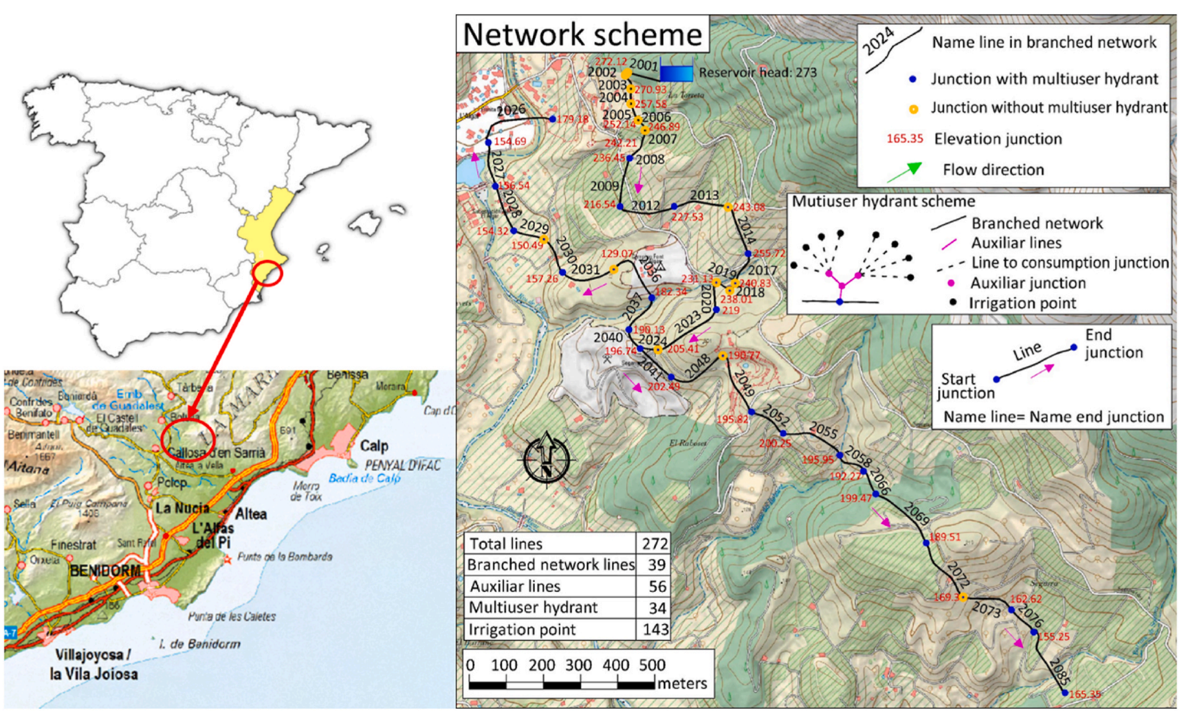

Fig. 4. Case study scheme.

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 512,369 and 552,699 m^3, while the maximum flow varied between 72.63 and 94.26 l/s Fig. 4 shows the case study network topology.

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 Fig. 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 62,339 and 66,718 m^3. Fig. 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 Fig. 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 (2) in step A5. Table 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.

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 Fig. 2b, was also executed to prepare a Gamma model and a Normal model. After completing the

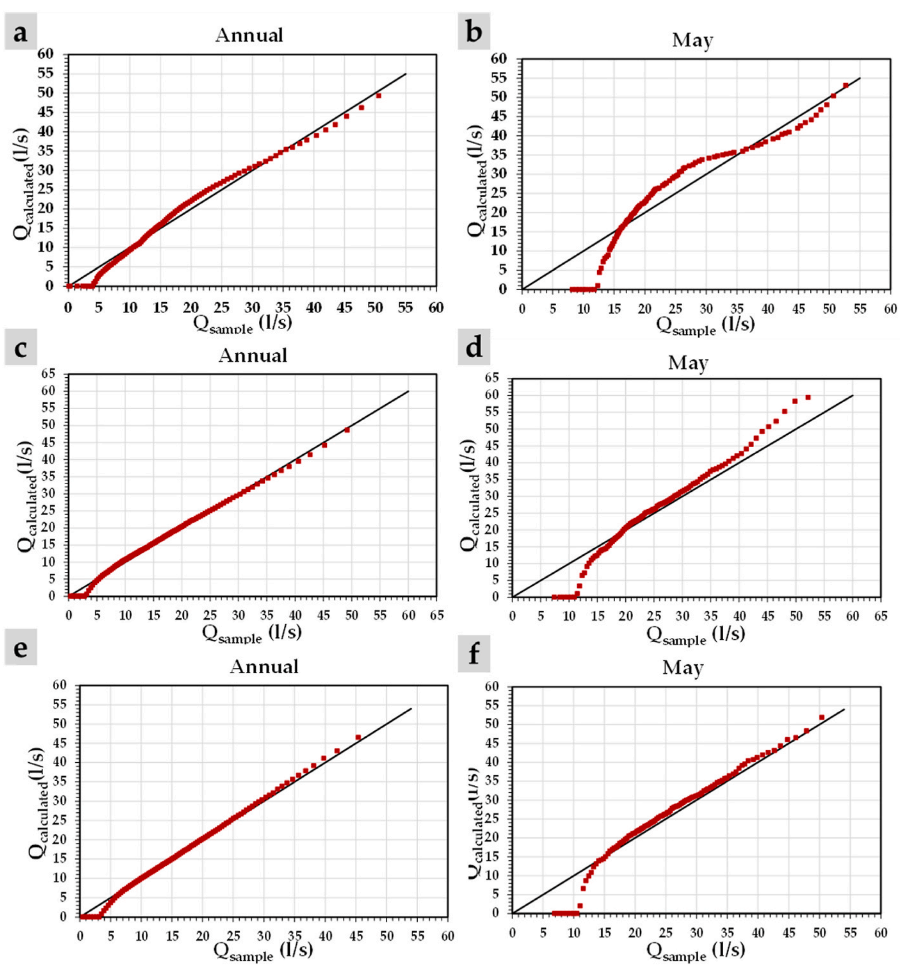

Fig. 5. (a) Q-Q plots for Annual Observed_Calibrated in 2015; (b) Q-Q plots for Observed_Calibrated in May 2015; Q-Q plots for Annual Gamma_Calibrated in 2015 (c); (d) Q-Q plots for Gamma_Calibrated in May 2015; (e) Q-Q plots for Annual Normal_Calibrated in 2015; (f) Q-Q plots for Normal_Calibrated in May 2015.

Table 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

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. Fig. 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 (Fig. 5b).

Table 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 Ref. [65], 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 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. Fig. 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 (Fig. 5d). Table 2A 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 [65].

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 (Fig. 5e) and May 2015 were compared to the observed data in Fig. 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.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 Ref. [65].

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 Fig. 5, the results obtained show a better fit for the gamma distribution in the case study. The development of the methodology allows this characterization 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 4.A (Appendix I) shows the characteristic values of May, which were get in the proposed model. Fig. 2A (Appendix I) shows the different flow distribution for observed (Fig. 2Aa), Gamma distribution function (Fig. 2Ab) and Normal distribution function (Fig. 2Ac).

Table 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.

Table 4
Sustainability indicators for the evaluated models using the PVC-O material solution.

Model code	Model	Total network enviromental cost *(Tn CO_2)*	CO_2 emissions per network meter *(Tn CO_2/m)*	CO_2 emissions per hectare *(Tn CO_2/ha)*	CO_2 emissions from supplied water *($kgCO_2/m^3$)*
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

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 Fig. 2b. These years are compared only with the observed data from the main line. Fig. 6 shows the maximum and minimum values for the Correlation Coefficient as well as the average values for each month and annually.

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 (see Fig. 4). 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. Fig. 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 (Gcal), overestimating 1.12 % of the design flow on average for the month of May.

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. Fig. 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

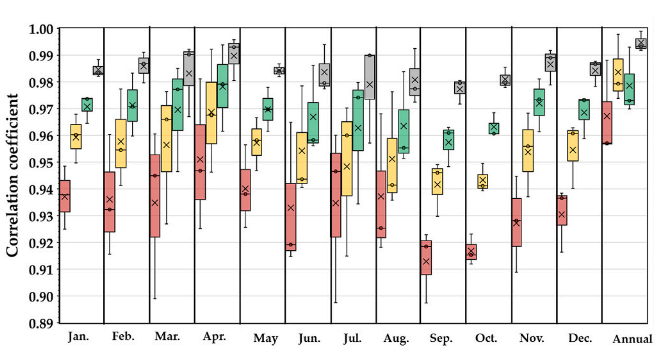

Fig. 6. Correlation Coefficients for the theoretical and corrected Clement and Gamma models.

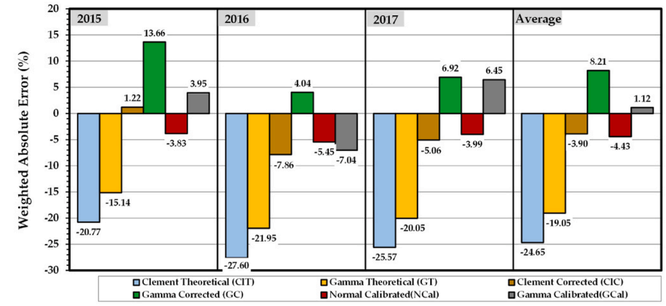

Fig. 7. Weighted absolute error for the design flow in May for the evaluated models.

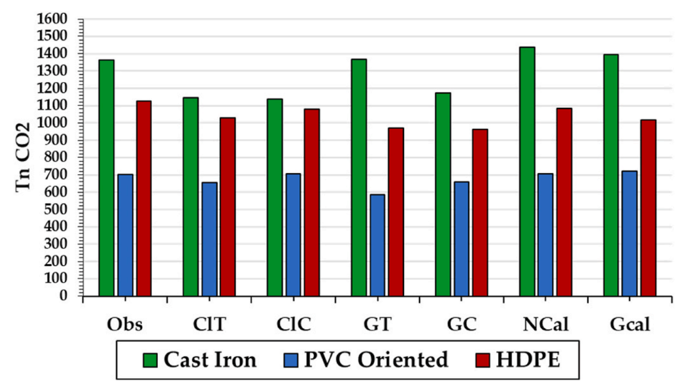

Fig. 8. Tons of CO2 emissions for the different models and materials.

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.

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 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.

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 5.A (Appendix I). These annual recovered values oscillated between 32,838 and 34,798 kWh, representing around 27.5 % of the annual total energy injected in the gravity system (Table 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 Ref. [75]) were similar to those defined by Ref. [76], 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 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.

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 [76]: (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 Ref. [34], 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 [77]. 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 [78].

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.

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CRediT authorship contribution statement

Melvin Alfonso Garcia-Espinal: Writing – original draft, Formal analysis. **Francisco-Javier Sanchez-Romero:** Data curation. **Modesto Perez-Sanchez:** Writing – original draft, Methodology, Conceptualization. **P. Amparo Lopez-Jimenez:** Visualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

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

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