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Optimization tool to improve the management of the leakages and recovered energy in irrigation water systems

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ABSTRACT

The use of pumps working as turbines is a new solution, which has been recently analysed to improve the water management in the different water systems. The improvement of sustainability involved with this use should be considered in these networks, and it focuses on the reduction of the consumption energy as well as the reduction of leakages. Both variables have a great influence on the rest of economical, technical and environmental indicators of network behavior, becoming key in their improvement. In this line, the research develops a methodology, which includes the estimation of the leakages in the different junctions and pipes as a function of the injected and registered volume data in the water. The present methodology proposes different operation scenarios according to leakages and it develops a double optimization procedure to locate and select the best recovery machines considering different objective functions. The methodology is applied to a real case study, which has serial data of water registered volume since 2001. The research shows the leakages influence in the operation points as well as the recovered energy. Different sustainable indicators are analysed for the different scenarios according to optimized procedures: The IRLGP index was defined as the ratio between reduction of the leakage volume for each installed power and it reached the annual value of 11,280.8 m^3/kW; The optimized procedure establishes the significance to consider the leakages when the hydraulic machines are selected. Their best efficiency points increase to 195% and 205% compared to the ideal scenario without leakages.

1. Introduction

Hydroelectric micro-energy can be a valuable answer to the need for low-cost and long-lasting electrical energy, using natural or artificial waterfalls, which do not harm environmental damage. Unconventional solutions are at the forefront of many developing countries to achieve energy self-sufficiency (Ramos and Borga, 1999). The need for research ideas on the field of reducing wastage of water can save a great amount of water, money, time or energy. Water leakages is an essential problem in the field of supply systems (Giustolisi et al., 2008), wastewater and desalination systems (Panagopoulos, 2021a, 2021b, 2021c). Water distribution networks are low-energy efficiency systems since they need high energy levels to satisfy consumption in terms of pressure. These high values cause a high leakages level increasing the energy consumption and decreasing the performance and sustainability indexes of the system (Morani et al., 2020).

The growth of the energy demand, the increase of its price as well as the limitation of access to exploitation sites due to environmental limitations caused new challenges to appear, addressing new technologies to improve the management of the water systems. These technologies are focused on hydraulic recovery and These technologies are focused on hydraulic recovery and they try to reduce the investment and exploitation costs compared to traditional machines try to reduce the investment and exploitation costs compared to traditional machines (Ebrahimi et al., 2021). In such a scenario, microhydraulic solutions for energy recovery can play a key role in exploiting small water resources (Manzano-Agugliaro et al., 2017). This energy recovery, which is defined as a process in which energy is recovered from the residual supply pressure (Kramer et al., 2018) when it is applied in water systems, the use of micro-hydropower technology can enhance the sustainability of the water industry (Gallagher et al., 2015).

The new strategies of water management are focused on the

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improvement of sustainable indexes. In this line, the leakages reduction in water distribution networks is an absolute priority and many pressure management strategies have been proposed in the literature to tackle this issue (Cavazzini et al., 2020). These new trends join the pressure management with the use of micro-hydropower systems, mainly pumps working as turbines (PATs) (Bonthuys et al., 2020) in which they play a key role to increase the self-consumption of the energies communities (Alberizzi et al., 2018). PATs are standard water pumps, which operate in reverse mode (Stepanoff, 1957). Although these machines show low-efficiency values compared to traditional machines, their low-cost technology could help to expand hydropower exploitation, decreasing the greenhouse gas emissions (Novara et al., 2019).

The efficiency analysis was analyzed for different researches over time. The main published researches were: Childs (1962) developed a comparative study between efficiencies the machines operate as pump or turbine. Grover (1980) proposed linear equations to estimate the best efficiency point of the machine operate as a turbine. Williams (1994) presented a study on the comparison of different calculation methods for turbine performance prediction (Sharma, 1985) using the best efficiency value (Alatorre-Frenk et al., 1994). Derakhshan and Nourbakhsh (2008) tried to estimate hydraulic parameters (i.e., head, flow and efficiency) in turbine mode using pump data by CFD techniques. Páscoa et al. (2012) proposed a new approach for the PAT power plant, which is a design based on a constant head, instead of a traditional operation, in constant flow rate. Rossi and Renzi (2018) evaluated both best efficiency points (BEP) and performance of PATs in an accurate way using the artificial neuronal networks. Pérez-Sánchez et al. (2020a) defined new approach equations to estimate the BEP of the PAT and the characteristic curves using an experimental database of 181 different PATs. Previously studies considering the machine operate under fixed rotational speed. Carravetta et al. (2014a) studied the efficiency when the affinity laws are modified, considering variable rotational speed and improving the energy estimation. Ávila et al. (2021) defined new analytical expressions, which enable the estimation of the best efficiency head, best power head and best power flow when the machine operated under rotational speed, showing the need to incorporate these expressions in the energy analyses, improving the predictions (Fecarotta et al., 2016b; Novara and McNabola, 2018; Tahani et al., 2020).

Fecarotta and McNabola (2017) presented an investigation focused on the optimal location of PATs within a water distribution network to produce energy and reduce leakage. Avoiding using pressure reducing valves (PRV) where only energy is lost and not recovered (Ebrahimi et al., 2021). Jain and Patel (2014) showed extensive information on the historical development, methods, selection criteria and the results of the installation of PATs in water distribution networks as an energy recovery system. Bonthuys et al. (2020) developed an efficient optimization process for energy recovery and reduction of water leaks. The procedure proved to be more cost-effective and realistic compared to others proposed in the literature. A nonlinear programming (NLP) algorithm for the optimal setting of PATs within WDNs was extended to the case of leakage reduction (Cimorelli et al., 2020). A multi-objective optimization methodology is presented to minimize leakage and minimize the difference between pumping operating costs and revenues generated through energy recovery by strategically locating PATs in the network, which can act analogously to conventional PRVs (Tricarico et al., 2014). Morani et al. (2020) established a study to define the optimal location of a PAT within a distribution network, in order to minimize installation costs and maximize the production of energy and water savings. Moazeni and Khazaei (2021) developed two mixed integer nonlinear programming models to find the optimal number and location of PATs and to minimize the cost of power generation in water and power systems. The results showed that it is feasible to replace PRV by PATs, the installation of three PATs generates a total power of 479.65 kW, which is more than 30% of the daily electricity demand of the water network.

Traditionally, pressure management was developed by using pressure reduction valves, which allow the reduction of leaks but dissipate excess energy. Lima et al. (2017) compared the use of PATs versus PRVs, indicating that it is possible by installing PATs to recover up to 169,360 kWh/year as well as reducing leaks. These leakages decrease, increasing the volumetric performance of the system from 0.73 to 0.9. (Lima et al., 2017) proposed a method that replaces a PRV with a PAT to produce electrical energy and reduce pressure. This method was improved by adding variable speed pumps to control the dynamic operation of networks, in order to improve energy recovery and reduce leakage (Lima et al., 2018). This solution enables the recovery above 40% of the gross power potential of an existing PRV could be converted to electrical energy using a PAT while also controlling pressure (Lydon et al., 2017).

To increase this recovery, other researchers developed Particle Swarm Optimization (PSO) selection algorithm, incorporating the model into a network that allows a total daily energy of 182 kWh (Ebrahimi et al., 2021). In this line, Rossi et al. (2016) defined the economic feasibility of installing a PAT in an aqueduct in the city of Merano. The results show a nominal power of 19.18 kW and a daily electrical energy production of 338 kWh. Bonthuys et al. (2019) conducted an analysis within the Polokwane Central District Metered Area in which it identified a recoverable energy potential of 2.3 GWh, resulting in a 3.3% and 4.2% annual reduction in water leakage. Patelis et al. (2017) studied the energy recovery in Kozani (Greece). The possibility of installing 7 PATs in different districts of the city with flow rates ranging between 14 l/s and 79 l/s and pressures between 55 and 71 m w.c. was evaluated. Using this hypothesis, annual energy recovery of 328500 kWh possible, decreasing the leakages between 18% and 65%. Nguyen et al. (2020) evaluated a water system that operates with a flow rate of 350 l/s and a pressure of 45 m w.c. The installation of PATs under these operating conditions enables the annual generation of 714670 kWh and the leakages decrease of 3%. This reduction saved 248, 504 m^3.

These contributions improved the different sustainability indicators. They can help to analyze the management of the water systems. Sustainability indicators are necessary to determine the efficiency of a system concerning criteria such as (i) annual energy consumption and cost for each cubic meter of water injected into the network, (ii) the percentage of energy recoverable in the network by energy excesses and (iii) the reduction of energy consumption for each cubic meter of water leaked. The recommended indicators that are analyzed in the water distribution networks are shown in Table 1.

Several sustainability indicators for pressurized water systems were proposed by (Mejía et al., 2012). Rosado et al. (2020) developed a proposal for a recovery system based on the installation of PATs in different points. It enables the annual theoretical generation of 847,301 kWh. In this case study, some results of the sustainability indicators mentioned in Table 2 are shown. Macias Ávila et al. (2021) defined some results of the sustainability indicators. IAAE, IER, ERP, IEFW and IRLGP are shown for 10 water distribution networks in which there are installed PATs recovery systems. In these studies, the annual energy consumption in the analyzed distribution networks ranges from 141,794 to 1583,106 kWh, the annual energy recovery varies from 28,470 to 714,670 kWh and the energy recovery values were found between 3% and 58%. Telci and Aral (2018) demonstrated the economic and environmental impacts when energy recovery systems are installed in water distribution networks in which the savings can support the electricity use of more than 20 average American households, corresponding to an annual reduction of 177 tons of CO_2 emissions. The indicators depend on the network topology and therefore, there are different between them. It implies one indicator cannot be adapted exclusively.

Sustainable Development Goals (SDGs) acknowledge the interlinkages between human wellbeing, economic prosperity, and a healthy environment and, hence, they are associated with a wide range of topical issues that include the securities of water, energy and food resources, poverty eradication, economic development, climate change, health, among others (Mabhaudhi et al., 2021). The implementation of PATs in water distribution systems is related to objective 9 (Kynčlová

Table 1
Sustainability indicators in PATs systems.

Indexes	Abbreviation	Units	Indicator	Definition
Energy (Mejía et al., 2012; Rosado et al., 2020)	**IED**	Dimensionless	Energy dissipation	Ratio between friction energy and input energy
	IAE	kWh/year	Annual consumed energy	Sum of the total active energy consumed in the network
	IEFW	kWh/m^3	Consumed energy per unit volume	Ratio between the active energy consumed and the total volume of water introduced in the system
	IER	kWh/year	Energy recovered	Sum of total energy recovered in the network
	ERP	%	Recoverable energy percentage	Recoverable energy percentage used of the total energy consumed in the system
	IAAE	kWh/year	Absolute annual consumed energy	Sum of the total active energy consumed in the network subtracted by the sum of the total energy recovered in the network
	IAEFW	kWh/m^3	Absolute consumed energy per unit volume	Ratio between IAAE and the total volume of water introduced in the network
	IRLGP	m^3/kW	Water recovery per unit volume per installed energy.	Ratio between reduction of the leakage volume for each installed power.
Economic (Macias Ávila et al., 2021; Rosado et al., 2020)	**REC**	€	Cost of recoverable electrical energy per installation of PATs	Product of the cost of the electricity tariff per kWh of energy produced
	IEC	€/m^3	Energy cost per unit volume introduced	Ratio between energy cost and the total volume of water introduced in the system
	CWSBRL	€/m^3	Cost of water saved by reducing leaks when installing PATs	Product of the cost of each cubic meter of water for each covered meter of water saved.
Environmental (Telci and Aral, 2018)	**CDRPE**	CO_2/kWh	Carbon Dioxide reduced by produced energy	Ratio between the reduction of CO_2 emission by the production of each kWh of renewable energy
	CDRBL	CO_2/m^3	Carbon dioxide reduced by each cubic meter of water saved by leaks	Ratio between the reduction of CO_2 emission for each cubic meter of water saved by leaks.

Table 2
Expressions to develop the energy balance.

Expression	Equation	ID
Total Energy (E_{T_j})	$\gamma Q_j (z_o - z_j) \Delta t/3600$	(13)
Friction Energy (E_{FR_j})	$\gamma Q_j (z_o - (z_j + P_j)) \Delta t/3600$	(14)
Theoretical Energy Necessary (E_{TN_j})	$\gamma Q_j P_{min_j} \Delta t/3600$	(15)
Energy Required E_{RS_j}	$\gamma Q_j P_{minS_j} \Delta t/3600$	(16)
Theoretical Available Energy (E_{TAj})	$\gamma Q_i (P_j - P_{min_j}) \Delta t/3600$	(17)
Theoretical Recoverable Energy (E_{TRj})	$\gamma Q_i (P_j - \max f() (P_{min_j}; P_{minS_j})) \Delta t/3600$	(18)
Theoretical Recovered Energy (E_{TRmj})	$\gamma Q_j H_i \eta_i \Delta t/3600$	(19)

et al., 2020) of the sustainable development objectives called "Industry, innovation and infrastructure" due to the introduction of promotion of new technologies that allow the efficient use of water resources as indicated by objective 6 (Nhamo et al., 2019) called "Clean water and sanitation". The installation of PATs makes cities more inclusive, safe, resilient and sustainable (Diaz-Sarachaga and Jato-Espino, 2019) allowing the generation of electricity in a renewable, affordable, reliable and modern way as indicated by goal 7 (Nhamo et al., 2019) "Affordable and clean energy" and reducing environmental indices emissions, contributing to the objective 13 (Bruce et al., 2018) of the SDG.

This research aims to establish a methodology, which optimizes the location and selection of the machine considering the influence of the leakages in the selection of the machine as well as its influence on the location when leaks are considered. The novelty focuses on the characterization of the operation points for different leakages values as well as the double application of the simulated annealing to optimize the location as well as the selection of the recovery systems. To develop the study, the methodology proposes an internal iterative procedure, which allows the estimation of the leakages in each line and consumption point according to measured volume data (i.e., injected and registered) by the water managers. The methodology was applied to the real irrigation network. It is located on the township called Vallada in the province of Valencia (Spain).

2. Methodology

The proposed optimization procedure is divided into six different phases in which each one contains different steps (Fig. 1). The model needs different inputs to develop the optimization procedure and there are two simulated annealing procedures includes in this methodology. These optimization procedures are applied on localization of the recovery systems in the different ones and define the best machine and its regulation control.

2.1. Optimization stages

Fig. 1 shows the proposed methodology, which is divided into five different stages: Network model (I), Leakages calibration (II), Energy Balance (III), Location Optimization (IV), Selection Optimization (V) and Definition of the best solution (VI).

2.1.1. Network model

The first stage is a preliminary phase in which the network model is developed according to the available information. This should define both the topology of the water systems as well as the demand base and the consumption patterns. The model is simulated to check the flow and pressure in all lines and nodes. When the model is correct, the model is ready to be calibrated, considering leaks. The model uses the calibrated methodology, which estimates the flow over time considering the consumed volume in the irrigation points as well as the irrigation needs and consumption trends of the farmers (Pérez-Sánchez et al., 2016, 2017).

2.1.2. Leakages calibration

The second step proposes a calibration strategy to consider the leakages in the water systems. The method is applied when the water managers have information on the water meters of the consumption. Therefore, the proposed method establishes a balance of the water volumes. The first step is the development of the implemented volume analysis, establishing the following continuity balance (Step II.A):

$$V_I = V_M + V_L \quad (1)$$

where V_I is the injected volume in the network in m^3; V_M is the total measured volume by water meters in the consumption nodes in m^3; and

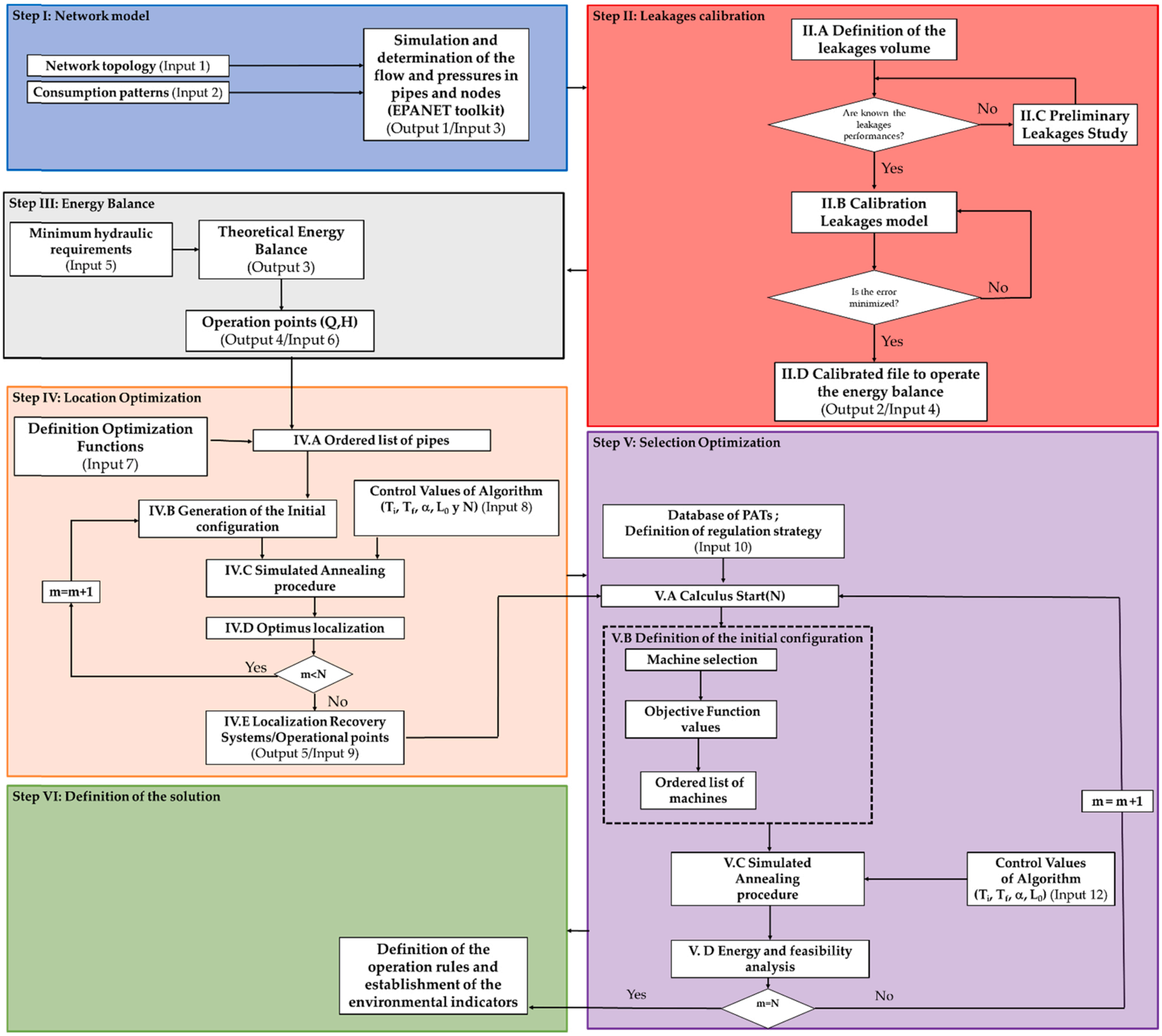

Fig. 1. Optimization procedure.

V_L is the total leakages volume in the water system in m^3.

If this data volume is known, the different volume performance of the network can be defined according to the following equations:

$$\eta_L = \frac{V_L}{V_I} \tag{2}$$

$$\eta_M = \frac{V_M}{V_I} \tag{3}$$

where η_L is the leakage performance of the water system and η_M is the measured volume performance of the water system.

The leaks can be divided into two types, which are called apparent and real losses (Almandoz et al., 2005) in which the real leakages are assigned in the distribution lines while the apparent losses are assigned to the irrigation consumption points. These leakages enable the definition of the following ratio

$$\eta_{AL} = \frac{V_{AL}}{V_L} \tag{4}$$

$$\eta_{RL} = \frac{V_{RL}}{V_L} \tag{5}$$

where η_{AL} is the ratio between apparent leakages and total leakages; V_{AL} is the total volume of the apparent losses in m^3; η_{RL} is the ratio between real leakages and total leakages; V_{RL} is the total volume of the real losses in m^3. The apparent losses are the uncontrolled leakeages in the water systems, which cannot be measured (Almandoz et al., 2005).

The calibration model distributes the leakages once the performances (i.e., η_{AL}, η_{RL}, and η_L) are known. This distribution establishes the different criteria as a function of the leakage type (Step II.B). The model determines the different emitter coefficients assigned to the lines and consumption points in different iterations, minimizing the error between simulated leakage volume and leakage volume of the water system. The model considers the following equation to evaluate the leakage in each element (i.e., line or tap).

$$q_{L,ij} = K_j (P_{ij})^N \tag{5}$$

where $q_{L,ij}$ is the leakage flow for the element *j* (i.e., line or consumption point) at the time *i; P_{ij}* is the pressure in the element *j* at the time *i* (if the element is a line, the chosen pressure is the average pressure value of the line - $P_{ij} = \overline{P}_{ij}$-); *N* is the leakage exponent; and K_j is the global emitter coefficient.

Using Eq. (5), the leakage volume is estimated by the following expression:

$$V_{L,j} = \sum_{i=1}^{i=T} (q_{L,ij}\Delta t) = \sum_{i=1}^{i=T} (K_j (P_{ij})^N \Delta t) \tag{6}$$

where Δt is the interval time in s, $V_{L,j}$ is the leakage volume for the element in m^3, assuming the K_j is constant in all annual simulations. It is defined by the following expression through iterative procedure

$$K_j = \frac{V_{L,j}}{\sum_{i=1}^{i=T}\left((P_{ij})^N \cdot \Delta t \right)} \tag{7}$$

The definition of the calibration of the leakages is based on the estimation of the parameter, K_j, assuming that the total leakage volume is distributed between all elements of the network. It assumed the leakage volume of each element (i.e., line or tap) will be proportional to some variables, which are related to network characteristics. In this case, the leakage volume of each element ($V_{L,j}$) can be determined by the following expression:

$$V_{L,j} = \delta_j \quad V_L = \delta_j \quad \eta_L \quad V_I \tag{8}$$

where δ_j is the distributed coefficient assigned to each element of the network. The addition of all distributed coefficients is equal to 1.

δ_j is estimated by the following expressions, which difference if δ_j is for a line (Eq. (9)) or consumption point (Eq. (10)).

$$\delta_j = \frac{L_j \cdot \tau_j}{\sum_{j=1}^{j=k} (L_j \cdot \tau_j)} \tag{9}$$

where L_j is the length of the line j in m; τ_j is the weighted coefficient, which is novel concerning other published researches; k is the number of lines of the model. It depends on the material of the line.; k is the number of pipes.

Eq. (10) establishes the proposed expression to estimate the distributed coefficient, which weighs the apparent losses in the consumption points. In this case, the distribution coefficient is based on the ratio between consumed volume in the consumption point and total consumed volume.

$$\delta_j = \frac{V_{T,j}}{\sum_{j=1}^{j=m} (V_{T,j})} \tag{10}$$

where $V_{T,j}$ is the total consumed volume of the irrigation points (j), including both measured (invoiced) for irrigation as well as the leakage volume (no invoiced); m is the number of consumption points of the model.

The iterations to assign the different distributed coefficients finalizes when the error is minimized in this distribution. When this error is minimum, compared between simulated and measured volume, the model is ready to be used in the optimization procedure (Step II.D).

When the water managers do not know the leakage performance, the proposed methodology develops a preliminary analysis of leaks (Step II.C). Step II.B develops a series of simulations to obtain ranges of values and define the scenarios correctly. The model supposes the calculus of the real leakages in the lines. It enables the estimation of the real leakage performance (η_{RL}) and establish the N exponent. In this hypothesis, the leaked volume is not known and the methodology assigned different leakage parameters to the lines, following the alignment of the other published researches (Germanopoulos, 1985; Giustolisi et al., 2008). The following expression is used:

$$q_{L,ij} = \beta_j \cdot L_j \cdot (\overline{P}_{ij})^N \tag{11}$$

where β_j is the leakage coefficient, which characterizes the pipe in terms of age, diameter, material, thickness, among others. In this case, the model does not need to iterate since the used emitter coefficient in EPANET is:

$$K_j = \beta_j L_j \tag{12}$$

β_j varied between 10^{-4} and 10^{-7} as a function of the material (cement, steel or PVC) (Maskit and Ostfeld, 2014). It grows over time and this increase depends on the material. Different scenarios are defined in this case, which weighted the β_j value. Besides, N exponent is defined in the calibration model, estimating the value through of normalized valued, which oscillates between 0.5 and 1.5 according to published researches (Maskit and Ostfeld, 2014). Step II.B enables the estimation of the η_{RL} and N exponent.

2.1.3. *Energy balance*

Once phases I and II occour, the energy balance can be established to know the energy audit and therefore, the available operational points in each line and consumption point. This energy balance is crucial since it should consider the minimum hydraulic requirements. Table 2 shows the equations used to establish the energy balance and define the operation points (i.e., flow and theoretical head), which are the main input to develop the first optimization procedure (Step IV).

The different variables of Table 1 are: γ is the specific weight of the fluid in kN/m^3, which is equal to the ratio 9.81/3600; E_{T_j} is the total energy supplied in the system in kWh; E_{FR_j} is the friction energy, which is lost in the water system in kWh; E_{TN_j} is the minimum energy required in a hydrant or line to ensure the minimum pressure of irrigation in the more unfavorable point in kWh; E_{TAj} it is the available energy for recovery in a tap or line in kWh; E_{RS_j} is the minimum energy required in a point to ensure the quality in the service in kWh; E_{TRj} it is the maximum theoretical recoverable energy in an irrigation point, hydrant or line of the network in kWh; E_{TRmj} is the recovered energy by a recovery system considering the efficiency of the PATs systems; Q_j is the circulating flow in an element (i.e., line or consumption point) over time in m^3/s; z_o is the head level of the reservoir in m w.c.; z_j is the geometry level in m; P_j is the pressure in the element j (line or node); P_{min_j} is the minimum pressure in the element to guarantee the pressure in the more unfavorable point in m w.c.; P_{minS_j} is the minimum service pressure in any consumption point in m w.c.; H_i is the recovered head by the recovery system (i) in m w.c.; η_i is the efficiency of the recovery system for this flow Q_j; Δt is the considered interval time in s.

2.1.4. *Location optimization*

Once the available operation points are known when the energy balance is developed (Input 6), the objectives functions (Input 7) are defined to develop the first optimization procedure. The proposed objective functions are: (i) Theoretical Recovered energy ($\psi_1 = E_{TR}$), which establishes the maximization of the theoretical recovered energy in the system; (ii) Reduction of the leakages in the network ($\psi_2 = \Delta V_L$); and (iii) Net Present Value (NPV) represents the cumulative sum of all revenues minus all costs, expected over the life of the project.

Input 6 and Input 7 enable the development of Step IV.A. This step establishes an ordered list of the elements according to each objective function. Once the ordered list is established, the procedure is ahead to Step IV.B. The optimization procedure is based on simulated annealing defined by (Pérez-Sánchez et al., 2018). The installation of different recovery systems provides a significant number of possible combinations. In this situation, the simulated annealing method is particularly suitable, since it satisfies the basic requirements for its application (Dougherty and Marryott, 1991). These requirements are (i) clear configuration of the decision variables, (ii) definition of the target variables, (iii) procedure for generating new system configurations, (iv) control parameters and analogous cooling scheme, and (v) algorithm completion criteria. In this case, the algorithm searches for the best locations for the recovery systems based on the defined objective functions, as well as the number of established recovery systems.

The optimization process maximizes the established objective functions; this process is shown in Steps IV.B and IV.C. Once, the objective function to be considered is selected, generating a list in descending order of the elements that enter the optimization according to the energy balances performed and the chosen objective function. The control parameters of the algorithm are defined and they are: the initial temperature (T_i); the final temperature (T_f); cooling ratio (α) and number of transitions for each temperature step (L_0). These parameters can be set by a previous sensitivity analysis. The transition temperature (T_t) is calculated according to a geometrical relation according to:

$$T_t = \alpha \quad T_{t-1} \tag{20}$$

When the control parameters are defined, the maximum number of recovery systems (N) should be determined. The range of this parameter is between 2 and the maximum number of elements (i.e., lines and nodes) of the water system. In the initial step of the procedure (Step IV.B), the initial configuration should be considered. This configuration begins by considering two recovery systems (m) in the two first elements of the list. Hereafter, the simulated procedure (Steps IV.C) develops a new combination between different elements for each value of the *m* recovery system. When the optimization process finishes, the methodology establishes the best location for this value of m (Step IV.D). If the m value is lower than N, then the procedure comes back from Step IV.B in which the new configuration for the *m+1* recovery system is developed. The final result of this stage (Step IV.E) is the knowledge of the optimum configuration for the N recovery system (Output 5). This output is input 9, which is used in Step V.

2.1.5. Selection optimization of the machines

The main goal of this stage is the definition of the most suitable machine or machines. It implies the selection of the machine, the definition of the maximum number of machines in each recovery system (if needed) and the best strategy to regulate according to the chosen objective variables. These inputs are previously defined, and the methodology used a database that used 110 different PATs. The machines are defined according to specific speed (n_{st}), head number and discharge number. These values allow the definition of the dimensionless parameters of the machines included in the database. To define the machine the dimensionless best efficiency point (BEP) is used, through the 110 tested machines. It considers different values of impeller diameter and rotational speed. Both values enable the definition of the generated best efficiency point of the theoretical machine. When the BEP is known, the characteristic curves are defined by the methodology proposed by (Pérez-Sánchez et al., 2020b). Once, the characteristic curve is estimated, the variable operation strategy zone is defined. The machine operates under variable rotational speed and the best efficiency head (BEH), best power head (BPH) and best power flow (BPF) is estimated. This prediction of the variation of the rotational speed is developed according to the proposed methodology by (Ávila et al., 2021). Considering these curves, the algorithm developed the optimization by iterations using different regulation strategies (RS). These strategies can be (i) nominal rotational speed (NR); (ii) BEH; (iii) BPH; (iv) BPF; and (v) operational area considering the maximum and minimum recoverable head.

The use of an optimization procedure is necessary because there are different variables: (i) the possibility to use a different number of machines, which can be installed in serial or parallel in the same recovery system; (ii) different regulation strategies; (iii) and different possible number of recovery systems installed in the network. It implies a high number of combinations. In this case, the methodology proposes the use of the simulated annealing again. The initial step of this stage (V.A) includes the definition of the problem, which indicates the number of recovery systems and their location in the water network as a function of the objective function (Input 9, which is the result of the previous optimization procedure, Step IV). Besides, the water managers should be defined the different regulation strategies.

Defined the inputs, the procedure continues to Step V.B in which the definition of the initial configuration is established. In each recovery system, an ordered list of the possible machines is developed, according to the objective function, establishing the initial operation rules. When the machine is chosen, an iterative procedure analyses whether there are other operation rules, which will be better to improve the objective function. Finally, Step V.B the best machine and operation rules, getting the initial configuration, which is used in the following Step V.C. Step V.B repeated the procedure for each recovery system.

Step V.C includes the definition of the control parameters, which are defined similarly to stage IV. A new configuration of the operation is developed in each iteration in which a recovery system is chosen randomly and another machine is checked in that recovery system. The beginning probability of the machine is proportional to the value of the objective function, keeping the ordered list. The beginning probability of the upstream recovery systems is greater than downstream systems in the first iterations. This probability decreases when the calculus procedure advances. Once, the machine and strategy are optimized the procedure continues to Step V.D, in which the energy and feasibility analysis is developed, developing iterations to reach the best solution in the combination of the N located recovery machines, the used database and the regulation strategy as well as considering the chosen scenario. The feasibility analysis is developed considering the recovered energy (E_{TR}), reduction of the leakages in the network (ΔV_L) and the Net Present Value (NPV) and the Internal Ratio Return (IRR)

$$NPV = -IC_0 + \sum_{i=1}^{i=n} \frac{AI_i - AC_i}{(1+k)^i} + RI_n \tag{21}$$

where: IC_0 is the initial investment in year 0; AI_i is the annual income in the year i; AC_i is the annual costs in the year i; RV_n is the recovered residual value in the year n; AI_0 is the annual income by the sale of energy and reduction of leakages; k is the discount rate. The internal return ratio (IRR) is the discount rate that makes NPV equal to zero.

The initial investment cost (IC_o) includes the initial investment for the implementation, installation and operation of the recovery systems (Carravetta et al., 2014b; García et al., 2019). The annual costs (*AC*) refer to the annual operating costs of the recovery systems over the life of the system (Giudicianni et al., 2020). The annual incomes (*AI*) refer to the annual incomes generated by the facility through the sale of energy or self-consumption benefits. The incomes also consider the reduction of leakages and therefore, the benefit for the water saving. In addition, they may include other types of benefits due to reduced leakage and reduced CO_2 emissions. The residual income (*RI*) is a concept that takes into account the possible income from the sale of the different elements once their function in the facility has ended.

2.1.6. Best solution

The final step is the development of the best solution through an iterative procedure in which the different sustainable indicators are analysed to consider the best recovery system. These indicators are shown in Table 1 and the optimization procedure calculates them in each iterative procedure of the selection of the machine.

2.2. Materials and case study

The proposed methodology was applied using a database of a total number of 110 pumps working as turbines. The dimensionless best efficiency point, characteristic of the machine and rotational speed is shown in (Rosado et al., 2020). Using this database, which classifies the recovery systems considering their specific speed, 7826 synthetic machines are generated through turbine generators published by (Pérez-Sánchez et al., 2018). When the simulated annealing is applied, a previous selection is developed considering the available operational points in this line. This first selection enables the decrease of computational times and an improvement of the final selected machine.

The research applies the proposed methodology to a real water system. The case study is located on Vallada (Spain) and it is an irrigation pressurized system, which was built in 2001. The network supplies around 230 ha. The crop is citric tree mainly and the water resources are got from a well, which is pumped to a reservoir. The pipelines of the network are built on asbestos cement pipes (10,780 m) and polyvinyl chloride (11015 m). The diameter oscillated between 90 and 450 mm and the total length of the main pipes and branches is around 22 km. There are 222 irrigation consumption points. The base demand was assigned considering the different farms facilities. The adopted plantation frame was 4×6 squared meter plantation frame and the flow rate of the dripper used was 4 l/h, applying the irrigation needs of the citric tree for each (Fig. 2).

Table 3 shows the recorded data of the water consumption (injected to the grid and measured) as well as the leakages of the system from 2001 to 2020. The present research proposes the establishment of four different scenarios to group the years in similar ranges of leakages. These scenarios are S0 from 2001 to 2005; S1 from 2006 to 2010; S2 from 2011 to 2015; S3 from 2016 to 2020. S0 is considered the ideal situation, which has no leakages. S1 considers an average of leakages of 4.98%, therefore, it considers a total leakage performance equal to 5%. S2 has an average of leakages of the 13.75%. This scenario was approached to 15%. Finally, S3 approaches the leakages at 25%, since the real data operated between 2016 and 2020 the average leakages was 22.61%. The serial data shows the lack of maintenance in the network, and therefore, the increase of the potential leaks in the system.

EPANET-Toolkit (Rossman, 2000) was used fot the modeling, with consumption patterns, which were applied in each irrigation point were defined considering both consumed volume as well as the irrigation area of each tap and defining the base demand of the irrigation point according to irrigation needs of the crop. The model calibration was developed establishing different leakages scenarios. These scenarios were considering the previous scenario in Table 3. They consider leakages equal to 0% (S0), 5% (S1), 15% (S2), 25% (S3), 35% (S4) and 50% (S5). S4 and S5 are future scenarios considering the water managers will not be maintained and the leakages increase according to the observed trend between 2001 and 2020. S4 and S5 are hypothetical and they showed the trend of the systems if the water managers will not apply corrective actions to improve the water systems and reduce the leakages. S4 and S5 are included to analyse the influence of the leakages in the recovery energy and the selection of the hydraulic systems.

3. Results

Once the model is developed used EPANET Toolkit (Step I), the methodology established a preliminary leakages model (Step II. C). It defines the real and apparent leakages performance since there is not this information registered by the water managers. This analysis enabled the estimation of the real and apparent losses. It enables the assignment of the exponent N both lines and irrigation consumption points considering the scenario (Step II.B) as a function of the registered volume data and total leakages performances (Step II.A, Table 3). The η_R and η_A values are defined through an iterative procedure in which the

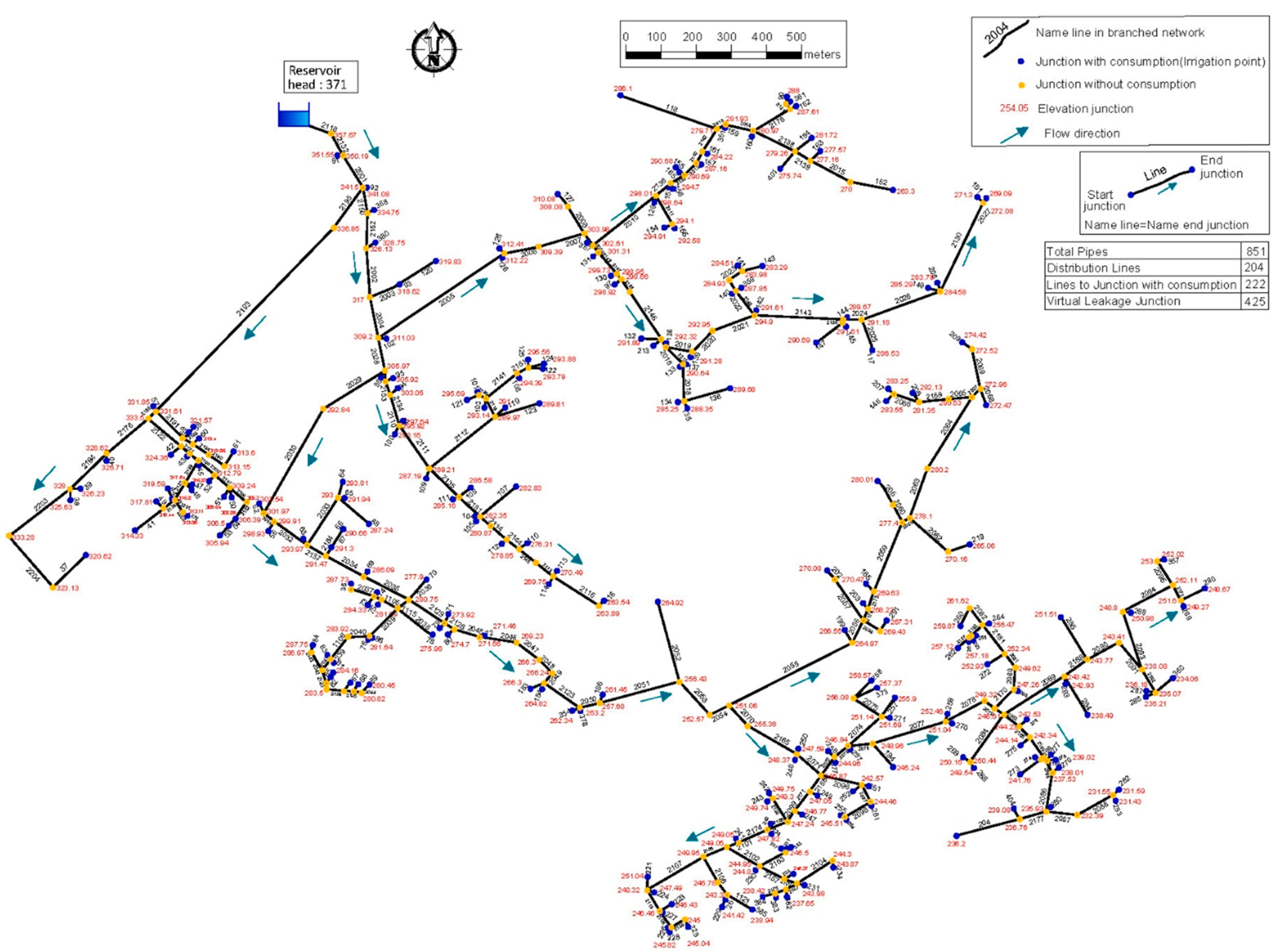

Fig. 2. Case study located on Vallada (Spain).

Table 3
Data volume registered between 2001 and 2020.

Scenario	Year	V_I (m^3)	V_M (m^3)	V_L (m^3)	η_L (%)	Scenario	Year	V_I (m^3)	V_M (m^3)	V_L (m^3)	η_L(%)
S0	2001	771142.49	768539.61	2602.87	0.33	**S2**	2011	1070160.52	1067961.52	107330.13	10.03
	2002	696169.69	693631.39	2538.3	0.36		2012	1005378.64	1002970.67	96084.59	9.56
	2003	752974.67	750504.16	2470.51	0.33		2013	1232688.42	1230339.22	179383.46	14.55
	2004	922877.16	920514.31	2362.85	0.26		2014	1451824.95	1449490.97	267431.08	18.42
	2005	922291.83	919865.51	19501.15	2.11		2015	1389921.12	1387603.13	223265.34	16.06
S1	2006	961511.76	959145.83	30213.09	3.14	**S3**	2016	1534154.5	1531843.67	208024.37	13.56
	2007	863520.55	861238.69	21789.34	2.52		2017	1423403.57	1421049.06	286341.39	20.11
	2008	810901.29	808680.1	63481.39	7.83		2018	1594029.8	1591736.33	421810.13	26.46
	2009	902655.86	900243.85	37540.17	4.16		2019	1707971.14	1705668.59	477246.07	27.94
	2010	880879.19	878638.1	61856.12	7.02		2020	1663597.31	1661358.24	413179.79	24.83

methodology analyse different values of N and compare with the real losses in Step II.C. These N values were obtained to adjust the leakages volume in each scenario by an iterative procedure in which the N and β are calibrated to minimize the error between registered data and simulated values. Table 4 shows the calibration values, which were obtained for this case study.

Fig. 3a shows the different values of the energies balance in taps as a function of the analysed scenario, previously to analyse the optimization procedure. The figure shows the annual total energy values for friction, theoretical recoverable and required energy. All energy values were considered and there is no direct relationship between different values, since the theoretical recoverable energy, required energy, as well as friction energy, depending on topology and characteristic of the network (i.e., length, the diameter of pipes, level of the consumption points, level of nodes and head of the reservoir, among others). The annual friction energy oscillates between 10,255 and 13,426 kWh. This increase is trivial since when the flow increases, the friction losses increase on squared growth. In this case, the annual friction energy increased 4.1% in the most unfavorable scenario (S5) compared to the ideal situation (S0). The annual required energy, which is necessary to satisfy the minimum pressure requirements, is also increased to compensate for the flow and friction losses. It oscillated between 78,968 and 94,716 kWh for the S0 and S5 respectively. This increase represented around 20% compared to S0 (ideal scenario without leakages). Finally, the annual theoretical recoverable energy, which is available to be recovered partially when the recovery system is installed and their efficiency is considered was between 152,906 and 182,264 kWh for S0 and S5 respectively. The annual energy recoverable also increased 26.2% when S5 is analysed.

Fig. 3b shows the analysis of the percentage of leakages reduction as a function of the number of recovery machines installed. These results were obtained when the objective function was the reduction of the leakages. It is observed the reduction oscillated between 0.15 and 0.37 when the number of recovery machines changed between 1 and 10 respectively. The figure shows not much difference in the reduction of the leakages when the different scenarios are considered. When simulations are extended increasing the number of recovery machines, the maximum decrease of leakages was 0.41 for S1, 0.44 for S2 and S3, and 0.43 for S4 and S5. The hypothetical number of recovery systems was 204 for these results.

The optimization procedure was developed for the three objective functions (i.e., theoretical recoverable, reduction of leakages and net present values). Table 5 shows the different results when these functions were optimized. The optimization procedure considered the following combinations: 204 when N was 1; 20,706 for N equal to 2; 1394,204 when N was 3; 70,058,751 when N was 5, the possible combinations were 2802,350,040; 9.2945 10^{10} for N equal to 6; 2.62910^{12} when N was 7; 6.4739 10^{13} for N equal to 8; 1.409910^{15} for N equal to 9; and 2.7493 10^{16}. The iterations oscillated between 140 and 2640 depending of the combinations and the simulated parameters for the optimization of the locations were: Initial temperature was 10; final temperature was 0.001, the cooling rate was 0.9 and the transition change was 10. These parameters were defined previously through sensitive analysis. The simulated parameters were changed when the optimization of the selection was applied. The following parameters were used: Initial temperature was 10; final temperature was 0.001, the cooling rate was 0.5 and the transition change was 10.

Table 5 shows that the use of three number of recovery systems (N) allows the potential recovery of around 0.8 of the available energy in all scenarios, in which the theoretical recoverable energy increases proportionally with the leakages values. If the objective function is the reduction of the leakages, the reduction range oscillates between 0.37

Table 4
Calibration results for each scenario.

Scenario	η_L (%)	η_R (%)	η_A (%)	N	$\beta_{PVC}/\beta_{asbestos}$
S1	5	65	35	0.5	100
S2	15	75	25	0.55	59
S3	25	75	25	0.55	36
S4	35	75	25	0.55	14
S5	50	80	20	0.6	10

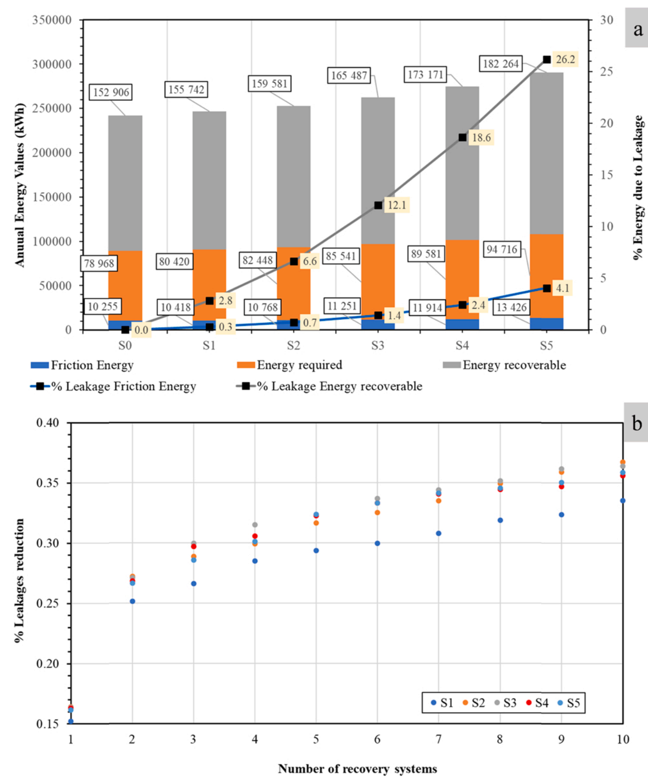

Fig. 3. (a) Annual Energy Values for the different scenarios. (b) Reduction of the leakages as a function of the number of recovery systems.

Table 5
Location results for the optimization procedure for each leakages scenario.

N	S0		S1		S2		S3		S4		S5	
	E_{TR} (kWh)	$\frac{E_{TRn}}{E_{TRmax}}$	E_{TR} (kWh)	$\frac{E_{TRn}}{E_{TRmax}}$	E_{TR} (kWh)	$\frac{E_{TRn}}{E_{TRmax}}$	E_{TR} (kWh)	$\frac{E_{TRn}}{E_{TRmax}}$	E_{TR} (kWh)	$\frac{E_{TRn}}{E_{TRmax}}$	E_{TR} (kWh)	$\frac{E_{TRn}}{E_{TRmax}}$
1	36,957	0.46	38,924	0.45	43,539	0.45	49,347	0.44	56,817	0.44	73,449	0.43
2	57,963	0.72	61,287	0.72	69,206	0.71	79,099	0.71	91,664	0.71	119,992	0.70
3	64,799	0.80	68,326	0.80	76,643	0.79	87,079	0.78	100,417	0.78	130,235	0.76
4	67,054	0.83	70,753	0.83	79,501	0.82	90,475	0.81	104,550	0.81	136,069	0.80
5	68,696	0.85	72,455	0.85	81,330	0.84	92,467	0.83	106,743	0.82	138,663	0.81
6	70,017	0.87	73,856	0.86	82,917	0.85	94,289	0.85	108,869	0.84	141,470	0.83
7	71,007	0.88	74,910	0.87	84,125	0.87	95,689	0.86	110,503	0.85	143,648	0.84
8	71,933	0.89	75,952	0.89	85,475	0.88	97,410	0.88	112,679	0.87	146,935	0.86
9	72,345	0.89	76,452	0.89	86,213	0.89	98,431	0.88	114,038	0.88	149,141	0.87
10	73,544	0.91	77,644	0.91	87,350	0.90	99,513	0.89	115,063	0.89	149,923	0.88
204	80,848	1.00	85,626	1.00	97,020	1.00	111,273	1.00	129,474	1.00	170,558	1.00
N	S0		S1		S2		S3		S4		S5	
	ΔV_L (m^3)	$\frac{\Delta V_L}{\Delta V_{Lmax}}$	ΔV_L (m^3)	$\frac{\Delta V_L}{\Delta V_{Lmax}}$	ΔV_L (m^3)	$\frac{\Delta V_L}{\Delta V_{Lmax}}$	ΔV_L (m^3)	$\frac{\Delta V_L}{\Delta V_{Lmax}}$	ΔV_L (m^3)	$\frac{\Delta V_L}{\Delta V_{Lmax}}$	ΔV_L (m^3)	$\frac{\Delta V_L}{\Delta V_{Lmax}}$
1	0	–	7777	0.37	28,206	0.38	53,173	0.38	85,440	0.38	157,130	0.37
2	0	–	12,838	0.62	40,607	0.54	76,560	0.54	123,092	0.54	227,658	0.54
3	0	–	13,592	0.65	49,253	0.66	92,748	0.66	148,429	0.65	273,333	0.65
4	0	–	14,557	0.70	52,569	0.70	98,998	0.70	158,500	0.70	291,536	0.70
5	0	–	14,999	0.72	54,135	0.72	101,964	0.72	163,345	0.72	300,565	0.72
6	0	–	15,290	0.74	55,246	0.74	104,081	0.74	166,878	0.74	307,444	0.73
7	0	–	15,711	0.76	56,870	0.76	107,082	0.76	171,316	0.76	315,413	0.75
8	0	–	16,277	0.78	58,929	0.78	110,995	0.78	177,795	0.78	327,867	0.78
9	0	–	16,533	0.80	59,824	0.80	112,684	0.80	180,522	0.80	332,856	0.79
10	0	–	17,128	0.82	62,005	0.83	116,778	0.83	186,964	0.82	344,855	0.82
204	0	–	20,762	1.00	75,084	1.00	141,468	1.00	226,777	1.00	419,160	1.00
N	S0		S1		S2		S3		S4		S5	
	NPV (€)	IRR (years)	NPV (€)	IRR (years)	NPV (€)	IRR (years)	NPV (€)	IRR (years)	NPV (€)	IRR (years)	NPV (€)	IRR (years)
1	-25,038	–	15,163	21.83	118,934	6.68	246,326	3.64	410,875	2.31	776,680	1.28
2	-20,636	–	19,870	19.97	124,172	6.65	252,298	3.69	417,773	2.35	785,112	1.31
3	-22,607	–	17,217	21.05	123,054	7.01	251,924	3.89	418,319	2.49	787,494	1.39
4	-29,361	–	16,908	24.27	119,446	7.65	250,980	4.21	420,584	2.68	797,616	1.49
5	-30,333	–	10,545	25.05	115,689	7.60	244,875	4.15	411,647	2.63	781,774	1.46
6	-38,067	–	5369	29.24	111,073	8.38	242,899	4.53	412,872	2.85	790,596	1.58
7	-39,309	–	3139	30.00	102,916	8.03	227,765	4.26	383,620	2.70	742,135	1.48
8	-45,724	–	-6494	–	96,663	8.68	221,655	4.53	377,690	2.85	736,575	1.55
9	-51,069	–	-11817	–	91,423	9.18	216,501	4.71	372,627	2.94	731,783	1.60
10	-57,484	–	-18180	–	85,170	9.91	210,391	4.99	366,697	3.10	726,222	1.67
204	-4183,255	–	-3796,038	–	-3490,233	–	-3202,062	–	-2829,678	–	-1994,308	–

and 0.66 when the N varies between 1 and 3. The leakages decrease is around 0.8 when the procedure is optimized using ten recovery systems. Although this solution is not feasible if the NPV values are analysed. Finally, when the NPV function is analysed it shows feasibility between S1 and S5, although this feasibility reduces according to N and it increases when there is a high percentage de leakages in the network since the circulating flow is higher. Besides, the NPV function considers both recovered energy as well as the reduction of the leakages for the decrease of the pressure when PATs operate in the network. The installations of PAT systems enable the reduction of the leakages and therefore, there is a benefit by the cost of the water that does not leak due to recovery systems. Therefore, the third function considers economic, energy and technical indicators to locate the recovery systems in the network.

The optimization procedure enables the preselection of the machine according to theoretical operational points to develop the second procedure of the optimization (Step V). In this case, the machine is chosen to optimize its operating in terms of flow, head and efficiency. The procedure chooses the best machine for each scenario in one of the defined lines, which were established by the location optimization procedure. The model develops an iterative procedure to define the best regulation strategy (RS) to evaluate the recovered energy, reduction of leakages and NPV values. The recovery never reaches 100% of the theoretical recoverable energy because the efficiency of the recovery systems is less than 1 since this study did not consider ideal machines.

Fig. 4 shows the influence map in which the selection optimization operates to locate the best machine. The color gradient shows the ratio between the variable value and the maximum value. Therefore, the red areas are the best to improve the variable objective. Fig. 4a and b show the results for line 2004 of the network when the recovered energy is maximized in both S1 and S5. All figures show a black cross, which indicates the selected machine. In each case, the selected machines are different, showing the regulation strategy, specific speed, rotational speed of the machine as well as the best efficiency point of the machine. This variability of the machine shows the importance of considering the leakages when the recovery systems want to be chosen. For example, when the S1 is analysed, the best efficiency point of the machine is 24.4 l/s and 14.21 m w.c. If S5 is analysed, the best efficiency point of the machine increases 195% and 205% particularly, 47.7 l/s and 30.64 m w.c., respectively.

Fig. 4c and d show the optimized solution to select the best machine both S1 and S5 when the optimized variable is the leakages reduction. Similar results were obtained in the selection, where the BEP of the machine varied from 9.27 to 18.65 l/s. The head in the BEP changed from 53 to 35 m w.c. The regulation strategy (RS) established on S1 it was NR, while the S2 operated under BPH. Fig. 4e and f defined the best machine when the NPV value was optimized. In both scenarios shown (S1 and S5), the best regulation strategy was NR. In S1, the best efficiency point was 24.42 l/s and 19.61 m w.c., while it increases for S5. In this case, the BEP was 37.71 l/s and 33.94 m w.c.

In addition, the analysis of each scenario, as well as of each combination of installed recovery systems (N), allows to know the recovered energy, the reduction of leaks as well as the NPV analysis as a function of the number of machines installed in each recovery system (N_m) and their

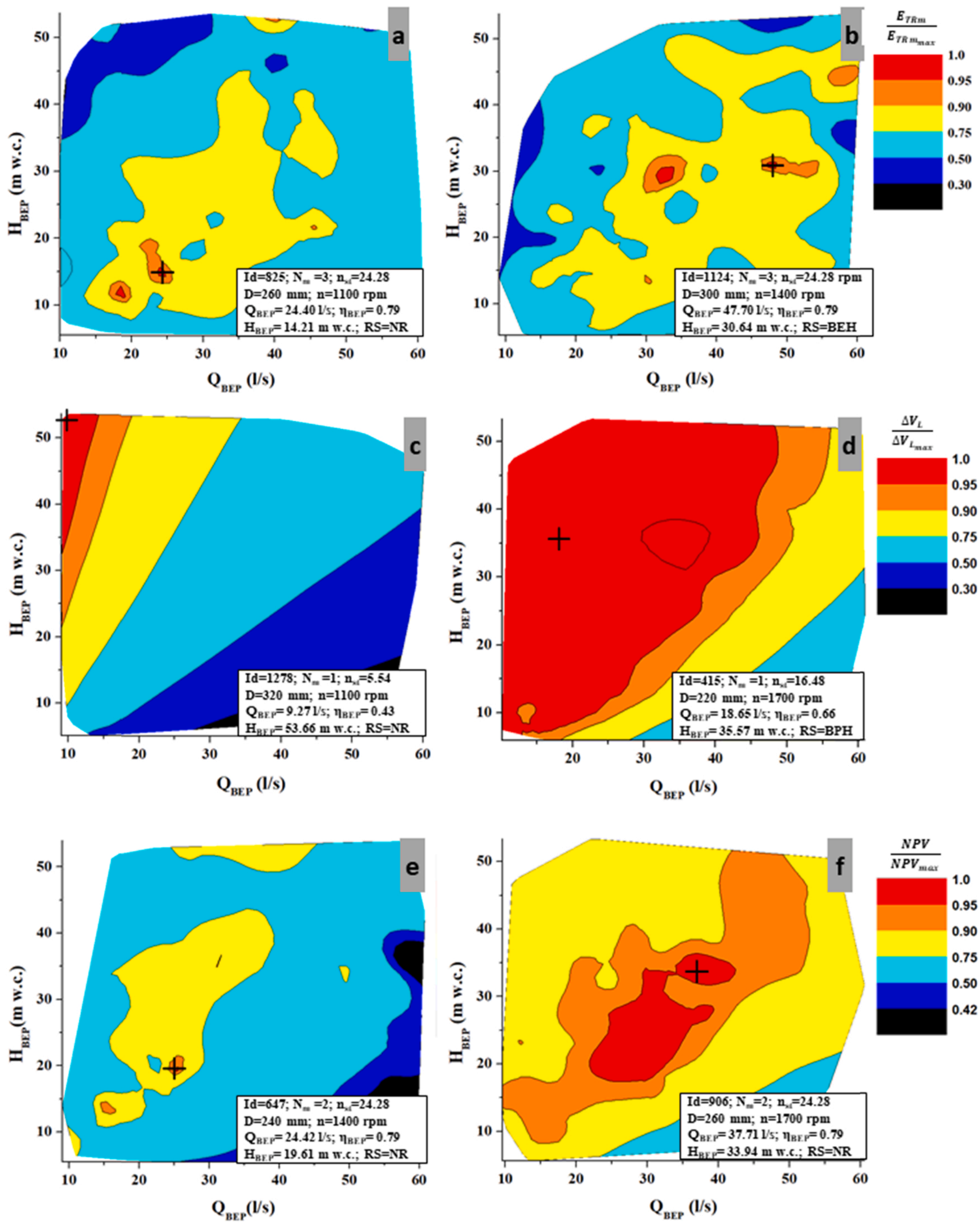

Fig. 4. Recovery system installed in line 2004. (a) Recovered energy for S1; (b) Recovered energy for S5; (c) Reduction leakages for S1; (d) Reduction leakages for S5; (e) NPV for S1; (f) NPV for S5.

characterization of them using specific speed (n_{st}), impeller diameter (D), rotational speed (n) and best efficiency point. Table 6 shows an example of the information selection obtained in the optimized procedure when the S2 was analysed under the hypothesis of the NPV function. The table shows annual recoverable energy values above 32,000 kWh and annual leakages decrease above 18,000 m^3 in some configurations with different recovery systems (N).

The inclusion of the PATs in water systems is developed to improve the sustainability indicators. Fig. 5 shows the influence of the PATs in the improvement of these indicators defined in Table 1 depending on the scenario analysed. Fig. 5a shows four indexes. IED showed values between 0.042 and 0.046, increasing in the S5 mainly. IEC decreased 40% between S0 and S5. It shows the decrease of unit cost when PATs are used in the irrigation system. IEFW and IAEFW showed similar trends with decreases equal to 40.1% and 45.4%.

IER showed annual values between 29,010 and 57,543 kWh (Fig. 5b). Another index, which is related to IER is the IRLGP. This index shows the reduction of leaks in the system considered the installed recovery power. If IRLGP is observed in Fig. 5b, the zero value is defined for the ideal situation (S0). The rest values for the different scenarios were 265.3 (S1), 1207.6 (S2), 7584.5 (S3), 7584.6 (S4) and 11,280.8 (S5) m^3/kW. This index is too significant since it shows the influence of

Table 6
Example of optimized selection of PAT for S2 when the chosen objective function is NPV.

N	1	2		3		
ID Location	2004	2004	2092	2004	2092	2138
n_s (rpm)	24.28	18.59	9.3	18.59	9.3	5.54
N_m	2	2	2	2	2	1
D (mm)	240	220	134	220	134	260
n (rpm)	2000	1400	3100	1400	3100	800
Q_{BEP} (l/s)	34.89	17.45	3.85	17.45	3.85	3.62
H_{BEP} (l/s)	40.02	22.38	59.38	22.38	59.38	18.74
RS	BEH	NR	BEH	RN	BEH	NR
Annual E_{TR}(kWh)	32,456	28,570	1932	28,570	1932	1179
P (kW)	11.55	7.14	1.41	7.14	1.41	0.55
Leakage Reduction (m^3)	13,947	17,004	206	17,004	206	708
NPV (€)	44,421.31	51,421.4	1531.7	51,421.4	1531.7	48,896.28
IRR (years)	11.83	10.36	12.27	10.36	12.27	11.4

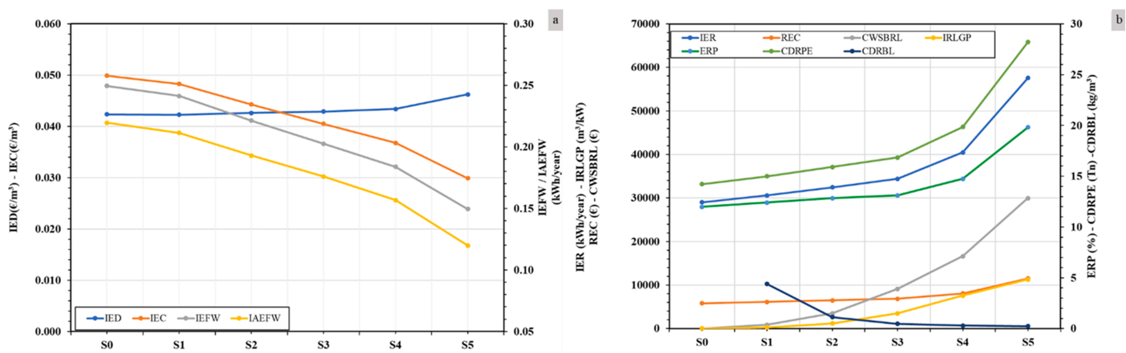

Fig. 5. (a) IED, IEC, IEFW and IAEFW indexes according to analysed scenario; (b) IER, IRLGP, REC, CWSBRL, ERP, CDRPE and CDRBL indexes in each analysed scenario.

leakage reduction when recovery systems are installed and therefore, it demonstrates the advantage of incorporating micro hydropower systems in the network. Related to environmental indexes, CDRPE and CDRBL were applied considering the conversion parameter from kWh to kgCO_2 reduction. In this case, the research considered the value 0.49 kg/kWh defined by (Marchis et al., 2016). CDRPE showed the same trend of ERP and CDRBL decreased from 4.38 to 0.24 kgCO_2 emissions for each cubic meter of water saved by leakages.

4. Conclusions

The present research represents a new step forward in improving the sustainability of irrigation systems. The new optimized procedure was developed in which three novelties were introduced. A double simulated annealing procedure was introduced to determine the location of the recovery system, considering three different objective functions and the selection of the best machine, as well as the best regulation strategy. The regulation strategy considered the operation of the machines in different work modes between them, the recovery systems can operate under BEH, BPF and BPH using the modified affinity laws. The methodology uses a database in which there are 7826 PATs which were defined using the dimensionless numbers generated by 110 tested machines.

The second novelty shown in this research is the need to consider, evaluate and estimate the leaks in the network to carry out a correct selection of the machines in the different recovery systems. Leaks can cause significant variations of the best efficiency point to choose the machine, mainly in terms of flow. The particular case study in which the methodology was applied showed a variation around 200% in terms of flow and head related to the best efficiency point of the machine. These values show the significance of the leakages consideration in the new future energy balances. There are no published studies that consider the variation of the operating points of the machines. Besides, tool is presented that combines all aspects of analysis within the water distribution systems that affect the efficiency of the system, developing a novel methodology applicable to any type of network.

As a third novelty, the research allows the characterization of the sustainability indicators in the selection of the machines and therefore, includes the analysis of the sustainability indicators in each iteration. Besides, the methodology operates with different scenarios in which different leakages values could be considered as a function of the serial data and future scenarios. The methodology enables the fit of the calibrated leakages model. The applicability enables the use of this tool by water managers, improving the efficiency of the water systems. The leakages management as well as the use of renewable energies system will open new research trends, which are focused on reach new targets of the sustainable development goals inside of the water systems.

Finally, the proposal was applied to a real irrigation system. The calibration model was developed considering serial data of twenty years in which five different scenarios were developed defining different leakages levels in one of them. The application of the methodology shows the great influence of the leakages reduction when the recovery systems were installed in the water networks. The annual recoverable energy values above 32,000 kWh and annual leakages decrease above 18,000 m^3 in the best configurations, using three recovery systems, which are configurated with three PAT each one. The IRLGP index was defined as the ratio between reduction of the leakage volume for each installed power and it reached the annual value of 11,280.8 m^3/kW and CDRBL decreased from 4.38 to 0.24 kgCO_2 emissions for each cubic meter of water saved by leakages. Future works should be focused on apply the measurement of sustainable indicators to the different supply systems and develop new optimization procedures, which support to the sustainable management of the hydraulic systems.

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CRediT authorship contribution statement

Modesto Pérez-Sánchez, Francisco-Javier Sánchez-Romero: Conceptualization, Methodology, Software. **Carlos Andrés Macías Ávila, Modesto Pérez-Sánchez, Francisco-Javier Sánchez-Romero**: Validation, Formal analysis. **P. Amparo López-Jiménez, Modesto Pérez-Sánchez, Carlos Andrés Macías Ávila**: Writing – original draft preparation, Writing – review & editing. **P. Amparo López-Jiménez**: Supervision. **Modesto Pérez-Sánchez, P. Amparo López-Jiménez**: Final review. All authors have read and agreed to the published version of the manuscript.

Declaration of Competing Interest

There are no conflict of interest.

References

A.J. Stepanoff, P.D., 1957, Centrifugal and Axial Flow Pumps: Theory, Design, and Application.

Alatorre-Frenk, C., MI, K., Karin, A., 1994. Cost Minimisation in Micro-Hydro Systems Using Pumps-as-Turbines. Univ. Warwick, Coventry, UK (Ph.D. Thesis).

Alberizzi, J.C., Renzi, M., Nigro, A., Rossi, M., 2018. Study of a Pump-as-Turbine (PaT) speed control for a Water Distribution Network (WDN) in South-Tyrol subjected to high variable water flow rates. Energy Procedia 148, 226–233. https://doi.org/10.1016/j.egypro.2018.08.072.

Almandoz, J., Cabrera, E., Arregui, F., CabreraJr, E., Cobacho, R., 2005. Leakage assessment through water distribution network simulation. J. Water Resour. Plan. Manag. 131, 458–466. https://doi.org/10.1061/(ASCE)0733-9496(2005)131:6(458).

Ávila, C.A.M., Sánchez-Romero, F.-J., López-Jiménez, P.A., Pérez-Sánchez, M., 2021. Definition of the operational curves by modification of the affinity laws to improve the simulation of PATs. Water Vol. 13, 1880. https://doi.org/10.3390/W13141880.

Bonthuys, G.J., van Dijk, M., Cavazzini, G., 2020. The optimization of energy recovery device sizes and locations in municipal water distribution systems during extended-period simulation. Water (Switz.) 12. https://doi.org/10.3390/w12092447.

Bonthuys, G.J., van Dijk, M., Cavazzini, G., 2019. Leveraging water infrastructure asset management for energy recovery and leakage reduction. Sustain. Cities Soc. 46, 101434 https://doi.org/10.1016/j.scs.2019.101434.

Bruce, M.C., James, H., Janie, R., Clare, M.S., Stephen, T., Eva, (L.) W., 2018. Urgent action to combat climate change and its impacts (SDG 13): transforming agriculture and food systems. Curr. Opin. Environ. Sustain 34, 13–20. https://doi.org/10.1016/j.cosust.2018.06.005.

Carravetta, A., Conte, M.C., Fecarotta, O., Ramos, H.M., 2014a. Evaluation of PAT performances by modified affinity law. Procedia Eng. 89, 581–587.

Carravetta, A., Fecarotta, O., Sinagra, M., Tucciarelli, T., 2014b. Cost-benefit analysis for hydropower production in water distribution networks by a pump as turbine. J. Water Resour. Plan. Manag. 140, 04014002. https://doi.org/10.1061/(ASCE)WR.19435452.0000384.

Cavazzini, G., Pavesi, G., Ardizzon, G., 2020. Optimal assets management of a water distribution network for leakage minimization based on an innovative index. Sustain. Cities Soc. 54, 101890 https://doi.org/10.1016/j.scs.2019.101890.

Childs, S., 1962. Convert pumps to turbines and recover HP. Hydro Carbon Proces- sing Pet. Refine 41, 173–174.

Cimorelli, L., D'Aniello, A., Cozzolino, L., Pianese, D., 2020. Leakage reduction in WDNs through optimal setting of PATs with a derivative-free optimizer. J. Hydroinf. 22, 713–724. https://doi.org/10.2166/hydro.2020.142.

Derakhshan, S., Nourbakhsh, A., 2008. Theoretical, numerical and experimental investigation of centrifugal pumps in reverse operation. Exp. Therm. Fluid Sci. 32, 1620–1627. https://doi.org/10.1016/j.expthermflusci.2008.05.004.

De Marchis, M., Milici, B., Volpe, R., Messineo, A., 2016. Energy saving in water distribution network through pump as turbine generators: economic and environmental analysis. Energies 9 (11), 877.

Diaz-Sarachaga, J.M., Jato-Espino, D., 2019. Development and application of a new Resilient, Sustainable, Safe and Inclusive Community Rating System (RESSICOM). J. Clean. Prod. 207, 971–979. https://doi.org/10.1016/j.jclepro.2018.10.061.

Dougherty, D.E., Marryott, R.A., 1991. Optimal groundwater management: 1. Simulated annealing. Water Resour. Res. 27 (10), 2493–2508.

Ebrahimi, S., Riasi, A., Kandi, A., 2021. Selection optimization of variable speed pump as turbine (PAT) for energy recovery and pressure management. Energy Convers. Manag. 227, 113586 https://doi.org/10.1016/j.enconman.2020.113586.

Fecarotta, O., Carravetta, A., Ramos, H.M., Martino, R., 2016b. An improved affinity model to enhance variable operating strategy for pumps used as turbines. J. Hydraul. Res 1686, 1–10. https://doi.org/10.1080/00221686.2016.1141804.

Fecarotta, O., McNabola, A., 2017. Optimal Location of Pump as Turbines (PATs) in water distribution networks to recover energy and reduce leakage. Water Resour. Manag. 31, 5043–5059. https://doi.org/10.1007/s11269-017-1795-2.

Gallagher, J., Harris, I.M., Packwood, A.J., McNabola, A., Williams, A.P., 2015. A strategic assessment of micro-hydropower in the UK and Irish water industry: identifying technical and economic constraints. Renew. Energy 81, 808–815. https://doi.org/10.1016/j.renene.2015.03.078.

García, I.F., Novara, D., Nabola, A.M., 2019. A model for selecting the most cost-effective pressure control device for more sustainable water supply networks. Water Vol. 11, 1297. https://doi.org/10.3390/W11061297.

Germanopoulos, G., 1985. A technical note on the inclusion of pressure dependent demand and leakage terms in water supply network models. Civ. Eng. Syst. 2, 171–179. https://doi.org/10.1080/02630258508970401.

Giudicianni, C., Herrera, M., di Nardo, A., Carravetta, A., Ramos, H.M., Adeyeye, K., 2020. Zero-net energy management for the monitoring and control of dynamically-partitioned smart water systems. J. Clean. Prod. 252, 119745 https://doi.org/10.1016/J.JCLEPRO.2019.119745.

Giustolisi, O., Savic, D., Kapelan, Z., 2008. Pressure-driven demand and leakage simulation for water distribution networks. J. Hydraul. Eng. 134, 626–635. https://doi.org/10.1061/(ASCE)0733-9429(2008)134:5(626).

Grover, K.M., 1980. Conversion of Pumps to Turbines. GSA Inter Corp., Katonah, New York.

Jain, S.V., Patel, R.N., 2014. Investigations on pump running in turbine mode: a review of the state-of-the-art. Renew. Sustain. Energy Rev. 30, 841–868. https://doi.org/10.1016/j.rser.2013.11.030.

Kramer, M., Terheiden, K., Wieprecht, S., 2018. Pumps as turbines for efficient energy recovery in water supply networks. Renew. Energy 122, 17–25. https://doi.org/10.1016/j.renene.2018.01.053.

Kynčlová, P., Upadhyaya, S., Nice, T., 2020. Composite index as a measure on achieving Sustainable Development Goal 9 (SDG-9) industry-related targets: the SDG-9 index. Appl. Energy 265, 114755. https://doi.org/10.1016/j.apenergy.2020.114755.

Lima, G.M., Luvizotto, E., Brentan, B.M., 2017. Selection and location of Pumps as Turbines substituting pressure reducing valves. Renew. Energy 109, 392–405. https://doi.org/10.1016/j.renene.2017.03.056.

Lima, G.M., Luvizotto, E., Brentan, B.M., Ramos, H.M., 2018. Leakage control and energy recovery using variable speed pumps as turbines. J. Water Resour. Plan. Manag. 144, 04017077. https://doi.org/10.1061/(asce)wr.19435452.0000852.

Lydon, T., Coughlan, P., McNabola, A., 2017. Pressure management and energy recovery in water distribution networks: development of design and selection methodologies using three pump-as-turbine case studies. Renew. Energy 114, 1038–1050. https://doi.org/10.1016/j.renene.2017.07.120.

Mabhaudhi, T., Nhamo, L., Chibarabada, T.P., Mabaya, G., Mpandeli, S., Liphadzi, S., Senzanje, A., Naidoo, D., Modi, A.T., Chivenge, P.P., 2021. Assessing progress towards sustainable development goals through nexus planning. Water (Switz.) 13, 1–13. https://doi.org/10.3390/w13091321.

Macias Ávila, C.A., Francisco-javier, S., Amparo, P.L., Pérez-Sánchez, M., 2021, Leakage Management and Pipe System Efficiency. Its Influence in the Improvement of the Efficiency Indexes.

Manzano-Agugliaro, F., Taher, M., Zapata-Sierra, A., Juaidi, A., Montoya, F.G., 2017. An overview of research and energy evolution for small hydropower in Europe. Renew. Sustain. Energy Rev. 75, 476–489. https://doi.org/10.1016/j.rser.2016.11.013.

Maskit, M., Ostfeld, A., 2014. Leakage calibration of water distribution networks. Procedia Eng. 89, 664–671. https://doi.org/10.1016/J.PROENG.2014.11.492.

Mejía, A., Hubner, M.N., Sánchez, E.R., Doria, M., 2012, Water and sustainability. A review of targets, tools and regional cases.

Moazeni, F., Khazaei, J., 2021. Optimal energy management of water-energy networks via optimal placement of pumps-as-turbines and demand response through water storage tanks. Appl. Energy 283, 116335. https://doi.org/10.1016/j.apenergy.2020.116335.

Morani, M.C., Carravetta, A., D'Ambrosio, C., Fecarotta, O., 2020. A new preliminary model to optimize PATs location in a water distribution network. Environ. Sci. Proc. 2, 57. https://doi.org/10.3390/environsciproc2020002057.

Nguyen, K.D., Dai, P.D., Vu, D.Q., Cuong, B.M., Tuyen, V.P., Li, P., 2020. A MINLP model for optimal localization of pumps as turbines in water distribution systems considering power generation constraints. Water (Switz.) 12. https://doi.org/10.3390/w12071979.

Nhamo, G., Nhemachena, C., Nhamo, S., 2019. Is 2030 too soon for Africa to achieve the water and sanitation sustainable development goal? Sci. Total Environ. 669, 129–139. https://doi.org/10.1016/j.scitotenv.2019.03.109.

Novara, D., Carravetta, A., McNabola, A., Ramos, H.M., 2019. Cost model for pumps as turbines in run-of-river and in-pipe microhydropower applications. J. Water Resour. Plan. Manag. 145, 04019012. https://doi.org/10.1061/(asce)wr.1943-5452.0001063.

Novara, D., McNabola, A., 2018. A model for the extrapolation of the characteristic curves of Pumps as Turbines from a datum Best Efficiency Point. Energy Convers. Manag. 174, 1–7. https://doi.org/10.1016/j.enconman.2018.07.091.

Panagopoulos, A., 2021a. Water-energy nexus: desalination technologies and renewable energy sources. Environ. Sci. Pollut. Res. 2817 (28), 21009–21022. https://doi.org/10.1007/S11356-021-13332-8.

Panagopoulos, A., 2021b. Techno-economic assessment of minimal liquid discharge (MLD) treatment systems for saline wastewater (brine) management and treatment. Process Saf. Environ. Prot. 146, 656–669. https://doi.org/10.1016/J.PSEP.2020.12.007.

Panagopoulos, A., 2021c. Beneficiation of saline effluents from seawater desalination plants: fostering the zero liquid discharge (ZLD) approach - A techno-economic evaluation. J. Environ. Chem. Eng. 9, 105338 https://doi.org/10.1016/J.JECE.2021.105338.

Páscoa, J.C., Silva, F.J., Pinheiro, J.S., Martins, D.J., 2012. A new approach for predicting PAT-pumps operating point from direct pumping mode characteristics. J. Sci. Ind. Res.

Patelis, M. ciudad de K. (Grec), Kanakoudis, V., Gonelas, K., 2017. Combining pressure management and energy recovery benefits in a water distribution system installing PATs. J. Water Supply Res. Technol. - AQUA 66, 520–527. https://doi.org/10.2166/aqua.2017.018.

Pérez-Sánchez, M., Sánchez-Romero, F., Ramos, H., López-Jiménez, P., 2017. Calibrating a flow model in an irrigation network: case study in Alicante, Spain. Span. J. Agric. Res 15, e1202. https://doi.org/10.5424/sjar/2017151-10144.

Pérez-Sánchez, M., Sánchez-Romero, F., Ramos, H., López-Jiménez, P., 2016. Modeling irrigation networks for the quantification of potential energy recovering: a case study. Water 8, 1–26. https://doi.org/10.3390/w8060234.

Pérez-Sánchez, M., Sánchez-Romero, F.J., López-Jiménez, P.A., Ramos, H.M., 2018. PATs selection towards sustainability in irrigation networks: simulated annealing as a water management tool. Renew. Energy 116, 234–249. https://doi.org/10.1016/J.RENENE.2017.09.060.

Pérez-Sánchez, M., Sánchez-Romero, F.J., Ramos, H.M., López-Jiménez, P.A., 2020a. Improved planning of energy recovery in water systems using a new analytic approach to PAT performance curves. Water Vol. 12, 468. https://doi.org/10.3390/W12020468.

Pérez-Sánchez, M., Sánchez-Romero, F.J., Ramos, H.M., López-Jiménez, P.A., 2020b. Improved planning of energy recovery in water systems using a new analytic approach to PAT performance curves. Water 12, 468. https://doi.org/10.3390/w12020468.

Ramos, H., Borga, A., 1999. Pumps as turbines: an unconventional solution to energy production. Urban Water 1, 261–263. https://doi.org/10.1016/s1462-0758(00)00016-9.

Rosado, L.E.C., López-Jiménez, P.A., Sánchez-Romero, F.J., Fuertes, P.C., Pérez-Sánchez, M., 2020. Applied strategy to characterize the energy improvement using PATs in a water supply system. Water (Switz.) 12, 1–22. https://doi.org/10.3390/w12061818.

Rossi, M., Renzi, M., 2018. A general methodology for performance prediction of pumps-as-turbines using Artificial Neural Networks. Renew. Energy 128, 265–274. https://doi.org/10.1016/J.RENENE.2018.05.060.

Rossi, M., Righetti, M., Renzi, M., 2016. Pump-as-turbine for energy recovery applications: the case study of an aqueduct. Energy Procedia 101, 1207–1214. https://doi.org/10.1016/j.egypro.2016.11.163.

Rossman, L.A., 2000, EPANET 2: User's manual, U.S. EPA. ed. Cincinnati.

Sharma, K., 1985. Small Hydroelectric Projects-use of Centrifugal Pumps as Turbines. Kirloskar Electr. Co. Ltd., Bangalore, India.

Tahani, M., Kandi, A., Moghimi, M., Houreh, S.D., 2020. Rotational speed variation assessment of centrifugal pump-as-turbine as an energy utilization device under water distribution network condition. Energy 213, 118502. https://doi.org/10.1016/j.energy.2020.118502.

Telci, I.T., Aral, M.M., 2018. Optimal energy recovery fromwater distribution systems using smart operation scheduling. Water (Switz.) 10. https://doi.org/10.3390/w10101464.

Tricarico, C., Morley, M.S., Gargano, R., Kapelan, Z., De Marinis, G., Savić, D., Granata, F., 2014. Optimal water supply system management by leakage reduction and energy recovery. Procedia Eng. 89, 573–580. https://doi.org/10.1016/j.proeng.2014.11.480.

Williams, A., 1994. The turbine performance of centrifugal pumps: a comparison of prediction methods. J. Power Energ. Proc. Inst. Eng. 208, 59–66. https://doi.org/10.1243/PIME.