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Multi-objective optimization of water distribution networks: An overview

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ABSTRACT

Optimization methods are extensively required and applied to solve problems from almost all disciplines, whether engineering, sciences, or economics. The distribution network is an essential part of all urban water supply systems that require efficient design and operation, which may be achieved through the effective application of optimization methods. This article provides a brief overview of the most approached method, models, and numerical examples for multi-objective optimization of water distribution networks (WDNs) design and operation. The main deterministic and heuristic optimization techniques are synthesized and presented, a single-and multi-objective optimization problem is generally formulated, and the main optimization objectives, decision variables, and constraints for the design, rehabilitation, and operation of WDNs are discussed. Additionally, some deterministic and heuristic multi-objective optimization models for WDN design/rehabilitation is included and numerically exemplified. Finally, the advantages and disadvantages of the optimization techniques and models used for designing WDNs are presented along with some recommendations on future research directions in this domain.

1. Introduction

Distribution system costs within any water supply scheme may be equal to or greater than 60% of the entire cost of the project (Walski et al., 2003; Sarbu and Tokar, 2018). These observations highlight the need for an efficient and safe water distribution network (WDN). The reduction of the cost and energy consumption of the WDN can be achieved through its design and operational optimization.

An important stage of network design is to find the optimum network layout which satisfies requirements such as pressure, power consumption, and demands at different nodes and also to minimize cost while meeting a performance criterion.

The development of WDNs without the use of optimization provides non-optimal structures, based essentially on the immediate response to the growing water demand of population and industry (Walski et al., 2003). These non-optimal structures are translated into non-efficient systems in terms of design and operation. The unpredictability of growing water demand also creates a challenge for optimization techniques. For these reasons, recourse to the optimization tools is crucial. For the optimal design of WDNs, both steady and transient states must be taken into consideration.

Optimization problems can be solved using conventional trial and error methods or more effective optimization methods. However, in WDNs, the optimization process by trial and error methods can present difficulties due to the complexity of these systems such as multiple pumps, valves and reservoirs, head losses, large variations in pressure values, several demand loads, etc. For this reason, innovative linear (Sarbu and Ostafe, 2016), non-linear (Samani and Naeeni, 1996; Djebedjian et al., 2000; Sarbu and Kalmar, 2002) and heuristic (Simpson et al., 1994; Cunha and Sousa, 2001; Zecchin et al., 2005; Vasan and Simonovic, 2010; Babu and Vijayalakshmi, 2013; Yazdi et al., 2017; El-Ghandour and Elansary, 2018) optimization algorithms are becoming more widely explored in optimization processes of the WDNs. In the solution procedure, each algorithm is linked with a hydraulic analysis solver of WDNs to obtain the optimum solution. Consideration of reliability in WDNs also has been drawing increasing attention over the past few years (Gargano and Pianese, 2000; Todini, 2000; Chandramouli, 2015). WDN design requirements have been shifting from a single objective of

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economic considerations in early years to a comprehensive multi-objective design in recent years (Zheng et al., 2016).

This article provides a survey of the most approached method, models and numerical examples for multi-objective optimization of WDNs design and operation. The main deterministic and heuristic optimization techniques are synthesised, a single- and multi-objective optimization problem is generally formulated, and the main optimization objectives, decision variables and constraints for the design, rehabilitation and operation of WDNs are discussed. Additionally, some deterministic and heuristic multi-objective optimization models for WDN design and rehabilitation is included and numerically exemplified. Finally, the advantages and disadvantages of the optimization techniques and models used for designing WDNs are presented along with some recommendations on future research directions. The main purpose of this survey is to facilitate the rapid knowledge of the field and insight in the overwhelming amount of publications available and implementation of the future research directions.

2. Methods and techniques of optimization

Due to the complexities in the optimal design of WDNs, many researchers have applied diverse suitable calculation methods to solve the problem. The optimization methods and techniques can be classified into two main categories: (1) deterministic methods, based essentially on the computation of the objective function gradient and/or function evaluations, and (2) heuristic techniques, based essentially on exploratory search and natural phenomena or even on artificial intelligence. Heuristic searches that use the heuristic function in a strategic way are referred to as meta-heuristic techniques.

The deterministic methods most applied in WDN optimization comprise linear programming (LP), integer linear programming (ILP), non-linear programming (NLP), integer non-linear programming (INLP), and dynamic programming (DP). Optimization problems that combine continuous and integer values are referred to as mixed-integer programming (MIP). These kinds of algorithms enable finding the exact position of an optimal solution. However, they usually converge to local optimal solutions which may not be the global optimum. In addition, the need of derivative evaluations can, in some cases, complicate the optimization process.

The heuristic techniques usually provide only suboptimal solutions because they do not attempt to escape from local optimum. These drawbacks have led to the introduction of meta-heuristics. In fact, the prefix "meta," which means "upper level methodology," indicates that meta-heuristic algorithms can be viewed as "higher level" heuristics. A number of meta-heuristic algorithms have been developed and extensively applied, including genetic algorithms (GAs), evolutionary algorithms (EAs), differential evolution (DE), cross-entropy (CE), simulated annealing (SA), tabu search (TS), particle swarm optimization (PSO), ant-colony optimization (ACO), harmony search (HS), shuffled complex evolution (SCE), shuffled frog leaping algorithm (SFLA), etc. These techniques provide the advantages of not requiring derivatives calculations and do not rely on the initial choice of values for the decision variables. Due to the exploratory nature of the heuristic algorithms, the probability of finding global optimal solutions using these advanced techniques is higher than in the case of deterministic methods. The main disadvantage of these techniques is related to the higher computational effort (Coelho and Andrade-Campos, 2012).

The previously described existing meta-heuristic techniques can be divided into three classes (Sorensen and Glover 2013) summarised in Table 1. Local search meta-heuristics operate on a single complete solution and iteratively improve it by making small adjustments called moves. Population-based meta-heuristics operate on a set of solutions and find better solutions by combining solutions from that set into new ones. Finally, constructive meta-heuristics build a solution by working with a single, unfinished, solution and adding one solution element at a time.

3. Objective of optimization

A general optimization problem is defined as the minimisation (or maximisation) of an objective function F subject to equality and/or inequality constraints and can be expressed as (Coello et al., 2007):

$$F(\mathbf{X}) \to \min\ (or\ \max)$$

subject to: (1)

$$\varphi_i(\mathbf{X}) \le 0; \quad i = 1,2,\dots p$$
$$\varphi_j(\mathbf{X}) = 0 \quad j = 1,2,\dots m$$

where X={x_1, x_2,...,x_n} is the vector of decision variables (continuous or discrete) with dimension n; p is the number of inequality constraints φ_i, and m is the number of equality constraints φ_j.

An objective function to which optimization is performed consists of a mathematical function with real values that expresses a linear or non-linear relationship between the decision variables

The goal of a multi-objective problem (MOP) is to optimise (minimise and/or maximise) a number of objective functions simultaneously. The general formulation of a MOP can be stated as:

$$F(\mathbf{X}) = F(f_1(\mathbf{X}),\dots,f_k(\mathbf{X})) \to \min\ (or\ \max)$$

subject to: (2)

$$\varphi_i(\mathbf{X}) \le 0; \quad i = 1,2,\dots p$$
$$\varphi_j(\mathbf{X}) = 0 \quad j = 1,2,\dots m$$

where k is the number of objective functions.

Table 1: Classification of meta-heuristic methods

Local search meta-heuristics		Population-based meta-heuristics		Constructive meta-heuristics	
Methods	Authors	Methods	Authors	Methods	Authors
SA	Kirkpatrick et al. (1983)	GA	Holland (1975), Goldberg (1989)	PSO	Kennedy and Eberhart (1995)
TS	Glover (1986; 1989)	DE	Storn and Price (1997)	ACO	Dorigo and Gambardella (1997)
		CE	Rubinstein (1999)	HS	Geem et al. (2001)
		SCE	Liong and Atiquzzaman (2004)		
		SFLA	Eusuff and Lansey (2003)		

Multi-objective optimization methods have the advantage of providing a set of optimal solutions, called Pareto front (Coello et al., 2007), which shows the trade-offs between the different objectives, especially the conflicting ones, and after their analysis, only one solution is selected based on an additional criterion. EAs are usually the most used to solving MOPs.

Optimization problem for WDNs arises when it is desired to solve the design, rehabilitation/extension or operation problem based on an optimization criterion expressed by the objective function, subject to a set of practical constraints.

Many aspects related to the application of the multi-objective heuristic techniques for optimal design or rehabilitation of WDNs were investigated, such as: GA (Bi et al., 2015; Diogo et al., 2018), PSO (Mora-Melia et al., 2015), ACO (Tong et al., 2011), and SFLA (Mora-Melia et al., 2016).

Objectives of a general optimization model of WDN design can be divided into four groups: (1) economic objectives such as total costs (capital and operation) (Ostfeld, 2005; Wu et al., 2012b) and rehabilitation costs (Kim and Mays, 1994), (2) performance objectives, reflecting the pressure deficit at demand nodes (McClymont et al., 2014) and reliability and resilience of the system (Basupi and Kapelan, 2015), (3) community objectives, which include a benefit function of the solution (i.e., rehabilitation, expansion) (Halhal et al., 1997), water quality deficiencies (Kanta et al., 2012), and hydraulic failure of the system (Fu et al., 2013), (4) environmental objectives namely greenhouse gas (GHG) emissions consisting of capital and operating emissions (Wu et al., 2012a).

Typically, in design optimization problem of WDNs, the objective function is expressed as a function of costs that can be associated to distinct water supply components or even costs associated to energy consumption. Annual total cost (capital and energy costs) (ATC) can be defined by a single-objective function expressed with equation (Sarbu and Tokar, 2018):

$$\mathrm{ATC} = \beta_0(C_n + C_p) + C_{op} \tag{3}$$

in which,

$$C_{op} = p_1 C_n + p_2 C_p + C_e \tag{4}$$

where $\beta_0=1/T_r$ is the discount (amortisation) rate of the operation period T_r; C_n is the network investment cost, obtained by adding the capital costs of each compound pipe; C_p is the pumping station capital cost, proportional to the installed power; C_e is the pumping energy cost; C_{op} is the annual operation cost; p_1 and p_2 are the service and maintenance rates for network pipes and pumping stations, respectively.

Recently, more focus has been laid on the life cycle cost (LCC) defined as:

$$\mathrm{LCC} = C_n + C_p + u_r C_{op} \tag{5}$$

in which u_r is the update rate (present value factor or discount factor).

- Rehabilitation of an existing pipe network consists of the replacement of pipes with the same or larger diameter, cleaning, or cleaning and lining of existing pipes. To formulate a network rehabilitation problem (Kim and Mays, 1994) some studies consider only a single economic objective, while other investigations apply a multi-objective optimization framework considering the network benefit (Halhal et al., 1997), violations of pressure at network nodes (McClymont et al., 2014), velocity constraints in pipes (Jin et al., 2008), and water quality deficiencies at network nodes (Morrison et al., 2013).
- The objective function of the operational optimization problem of WDNs can assume various forms. For example, the objective can be to maintain the minimum pressure on the network or to minimise the pumping costs through the use of pumps with variable speeds (Lingireddy and Wood, 1998) or to maximise energy efficiency of a supply system that uses water and wind turbines for power generation (Vieira and Ramos, 2009).
- Reliability and resilience of the system represent performance characteristics of a WDN in relation to current and most importantly future uncertain conditions.

As a measure of reliability can be considered hydraulic availability (Cullinane et al., 1992) or hydraulic performance indices (Gargano and Pianese, 2000). Numerous researchers proposed indirect reliability indices as surrogate reliability measures (SRMs). Two of the most employed SRMs are the resilience index (Todini, 2000), related to the WDN energy surplus and the entropy index (Tanyimboh and Templeman, 2000) related to the flow path uniformity within the WDN.

The resilience can be defined in broadest terms as the ability of a WDN to adapt to or recover from a significant disturbance, which can be internal (e.g., pipe failure) or external (e.g., natural disaster). Prasad and Park (2004) used the network resilience index (NRI) proposed by Todini (2000), whose maximisation can be considered one of the objectives of multi-objective optimization in WDN design (Piratla, 2016).

4. Decision variables and constraints

The decision variables define the characteristics of each hydraulic component in the design such as pipe diameters (Lansey and Mays, 1989), pipe lengths (Sarbu and Ostafe, 2016), pipe roughness (Giustolisi et al., 2009), pressure heads at nodes (Bragalli et al., 2012), number of pumps (Kang and Lansey, 2012), pump head (Goncalves et al., 2014), tank volumes or elevations and valve settings (Dandy et al., 2009).

In a looped pipe network in steady state, the objective function is conditioned by hydraulic constraints given by physical laws governing the water flow (mass and energy conservation) and minimum pressure head requirements at the demand nodes (Sarbu and Tokar, 2018). Additional constraints can be the operational constraints (e.g., minimum/maximum pressure at nodes (Ostfeld and Tubaltzev, 2008), minimum/maximum water velocity in pipes (Geem and Cho, 2011), and minimum/maximum allowable residual chlorine concentration at nodes (Broad et al., 2005) and constraints on decision variables (e.g., minimum pipe diameters and use of a discrete set of commercially available diameters (Kanta et al., 2012), limits on pipe segment lengths (Sarbu and Ostafe, 2016) and pump station capacities (Kang and Lansey, 2013). Additionally, in transient state the continuity and momentum equations (Chaudhry, 2014) are considered as constraints.

5. Overview of the multi-objective optimization models in literature

In most researches, optimal design, operation and rehabilitation of WDNs have been investigated at a specific time (statically) regardless of the relationship between them (separately). Some of researches are focused on optimal design of WDNs (Banos et al., 2010) and some of them focus on optimal operation scheduling of WDNs (Kurek and Ostfeld, 2013). Additionally, some of researches have focused on rehabilitation of WDNs (Shin et al., 2016).

In literature, most MOPs applied to WDN optimization are represented by combinations of two objectives such as: Minimising design cost and maximising hydraulic benefits (Halhal et al., 1997); minimising rehabilitation cost and transient impacts (through a surge damage potential factor-SDPF) (El-Ghandour and Elansary, 2018) or combinations of three objective, such as minimising LCC and life cycle GHG emissions (LCE), and maximising NRI (Piratla, 2016). Cenedese and Mele (1978) applied a mathematical approach based on the reduced gradient (RG) with multi-objective analysis to select the optimal solution for the hydraulic networks.

Walski et al. (1988) were the first to use multi-objective evolutionary optimization to solve a WDN design problem. They dealt with minimisation of network costs and pressure. Several other multi-objective optimisations for least-cost design (LCD) and maximum resilience of WDNs were approached in the literature (Todini, 2000; Prasad and Park, 2004; Creaco and Franchini, 2012; Wang et al., 2015a; Zheng et al., 2014; Wang et al., 2015b; Beygi et al., 2019).

Wu et al. (2012b) considered the use of variable-speed pumping during the optimization of network design using multi-objective GA for the reduction of total costs and GHG emissions and concluded that variable-speed pumps are effective for achieving the multiple objectives.

Chandramouli (2015) provided a detailed methodology on the development of an optimization model including reliability for design of WDNs using GAs and hydraulic simulator EPANET in MATLAB. A new parameter was proposed to determine the overall network reliability using network nodal demands and their corresponding satisfaction indices. The proposed methodology was tested on a Hanoi network.

Yazdi et al. (2017) developed a hybrid algorithm for multi-objective design of WDNs. This method combines the global search schemes of DE with the local search capabilities of HS to enhance the search proficiency of EAs. This method was compared with other multi-objective EAs and the results showed that the proposed hybrid method provided better optimal solutions and outperformed the other algorithms.

El-Ghandour and Elansary (2018) recently investigated the problem of optimal rehabilitation of WDNs for both steady and transient state. Two objectives are considered: Minimising rehabilitation cost by considering pipe diameters as decision variables and minimising the transient impacts by minimising a SDPF. A multi-objective ACO model was developed to solve this problem. This model was verified using the well-known New York tunnels network.

In general, there are few researches in WDNs, which consider the relationship between the design and renovation planning of WDN during its life cycle. Ghajarnia et al. (2012) introduced multi-objective dynamic design of WDNs. The first objective was to minimise the total cost of dynamic design and rehabilitation of the network and the second objective was to maximise the network fuzzy reliability index. The developed method was tested on two sample networks. Results showed that the dynamic design method had a positive performance on more decreasing the design costs and increasing reliability of the network.

Siew et al. (2014) presented penalty-free multi-objective evolutionary optimization approach for the phased whole-life design and rehabilitation of WDNs. An external hydraulic analysis model based on EPANET 2 called EPANET-PDX (pressure-dependent extension) was used. Results for two sample networks showed that the algorithm was stable and could find optimal and near-optimal solutions for reliably and efficiently.

Shirzad et al. (2017) used an approach for simultaneous optimization of initial design and rehabilitation scheduling of WDNs during their life cycle. The optimization model consists of a multi-objective ACO algorithm linked to a pressure-analysis model. The first objective is to minimise the total cost of dynamic design and renovation of the network and the second objective is to maximize the network reliability index. To evaluate the dynamic design in comparison to the static design, a small sample network and a real WDN have been used. The results showed that the dynamic design produces more reliable and lower costs in comparison to the static design or rehabilitation scheduling separately.

Dini and Tabesh (2019) developed a multi-objective ACO meta-model by the combination of ACO algorithm, hydraulic simulator EPANET and an artificial neural network (ANN) within MATLAB. Comparison of the results in the sample network showed that the design and rehabilitation planning of the network during its life cycle can create lower costs and higher reliability.

Huang et al. (2020) developed a multi-objective optimization model of WDN design that includes four objectives: Minimising transient adverse impacts (for two objectives), minimising network cost and maximising hydraulic reliability. The non-dominated sorting genetic algorithm III (NSGA-III) was adopted to solve this multi-objective optimization problem.

Table 2 summarises the main researches developed in the last two decades for multi-objective optimization of WDNs.

Table 2: Previous multi-objective optimization studies

Authors (year)	Multi-objectives	Method	Optimization
Walski et al. (1988)	Minimum cost Minimum pressure	EA	Design
Halhal et al. (1997)	Minimum total cost Maximum hydraulic benefit	Messy GA	Design
Todini (2000)	Minimum cost Maximum resilience	GA	Design
Prasad and Park (2004)	Minimum cost Maximum resilience	GA	Design
Creaco and Franchini (2012)	Minimum total cost Maximum resilience	GA and LP	Design
Wu et al. (2012b)	Minimum total cost Minimum GHG emissions	GA	Design
Ghajarnia et al. (2012)	Minimum total cost Maximum network fuzzy reliability index	Honey-bee mating optimization algorithm	Dynamic design
Wang et al. (2015a)	Minimum cost Maximum resilience	Multi-objective EAs (MOEAs)	Design
Zheng et al. (2014)	Minimum cost Maximum resilience	Self-adaptive multi-objective DE	Design
Siew et al. (2014)	Minimum total cost Maximum demand satisfaction ratio	NSGA-II and EPANET-PDX	Design and Rehabilitation
Wang et al. (2015b)	Minimum cost Maximum resilience	NSGA-II	Design
Chandramouli (2015)	Minimum total cost Maximum resilience	GAs and EPANET	Design
Piratla (2016)	Minimum LCC Minimum LCE Maximum NRI	GANetXL	Design
Yazdi et al. (2017)	Minimum cost Maximum resilience	DE and HS	Design
Shirzad et al. (2017)	Minimum cost Maximum resilience	ACO and EPANET-PDX	Design and Rehabilitation
El-Gahandour and Elansary (2018)	Minimum cost Minimum SDPF	ACO	Rehabilitation
Beygi et al. (2019)	Minimum total cost Maximum resilience	NSGA-II and EPANET	Design and Operation
Dini and Tabesh (2019)	Minimum total cost Maximum com-bined network reliability index	ACO, EPANET and ANN	Design and Rehabilitation
Huang et al. (2020)	Minimum cost Minimum transient adverse impacts Maximum hydraulic reliability	NSGA-III	Design

6. Examples of WDN design optimization

6.1. Single-objective optimization

In this example, the optimal design problem of a distribution network, supplied by pumping or gravity from one or more node sources is formulated as a non-linear objective function subject to linear and non-linear constraints (Sarbu and Ostafe, 2010). A non-linear optimization technique is used in which the minimum total capital cost in terms of pipe diameters and reservoir elevations or pump heads is considered as a single-objective function. The minimum and maximum sizing of pipe diameters, pipe flow velocities and nodal pressures with the hydraulic analysis equations of the network are considered as constraints. This technique has the advantage that it uses a specialised optimization algorithm which minimises directly an objective multivariable function without constraints. Additionally, the optimization technique is coupled with a hydraulic analysis performed by the iterative Newton–Raphson method (Sarbu, 2014).

6.1.1. Optimization model

Total capital costs of the distribution network consist of: (a) Cost of the pipes and their installations and (b) Cost of the pressure generating facilities. The objective function Fc with constraints, that express the minimum total capital costs, can be written as follows (Sarbu and Ostafe, 2010):

$$F_c(D_{ij}, Z_{\mathrm{IP},k}) = f_1(D_{ij}) + f_2(Z_{\mathrm{IP},k}) \tag{6}$$

and is subject to

$$\begin{aligned} &D_{\min} \le D_{ij} \le D_{\max}(ij = 1,\dots,T)\\ &V_{\min} \le V_{ij} \le V_{\max}\ (ij = 1,\dots,T)\\ &H_{\min} \le H_j \le H_{\max} \quad (j = 1,\dots,N)\\ &Z_{\mathrm{IPmin}} \le Z_{\mathrm{IP},k} \le Z_{\mathrm{IPmax}}\ \ (k = 1,\dots,N_{RP}) \end{aligned} \tag{7}$$

where, $Z_{\mathrm{IP},k}$ is the reservoir piezometric head or pump dynamic head; V_{ij} is the flow velocity in pipe ij; H_j is the pressure head at node j; $V_{\min}$, $V_{\max}$ are the minimum and maximum allowable flow velocities in pipes, respectively; $H_{\min}$, $H_{\max}$ are the minimum and maximum allowable nodal pressure heads, respectively; Z_{IPmin}, Z_{IPmax} are the minimum and maximum allowable reservoir piezometric heads/pump dynamic heads, respectively; T is the total number of pipes in the network; N is the total number of nodes; N_{RP} is the number of pressure generating facilities.

Discharge continuity and energy must be also conserved for the network. The objective function F_c can be changed to unconstrained optimization problem by using the following transformation (Box, 1966):

- for pipe diameters:

$$D_{ij} = D_{\min} + (D_{\max} - D_{\min})\sin^2 d_{ij} \tag{8}$$

- for reservoir elevations:

$$Z_{\mathrm{IP},k} = Z_{\mathrm{IPmin}} + (Z_{\mathrm{IPmax}} - Z_{\mathrm{IPmin}})\ \sin^2 z_k \tag{9}$$

where d_{ij} and z_k are new transformed variables.

The concept of the penalty function (ω) was used and, hence, a generalised objective function can be introduced as:

$$\begin{aligned} &\Gamma(D_{ij}, V_{ij}, H_j, Z_{\mathrm{IP},k}, \omega) = f_1(D_{ij}) + f_2(Z_{\mathrm{IP},k}) + \\ &+\omega\left[\sum_{ij=1}^{T}\left(1 - \frac{V_{ij}}{V_{\max}}\right)^2 + + \sum_{ij=1}^{T}\left(\frac{V_{ij}}{V_{\min}} - 1\right)^2 + \right.\\ &\left. + \sum_{j=1}^{N}\left(1 - \frac{H_j}{H_{\max}}\right)^2 + \sum_{j=1}^{N}\left(\frac{H_j}{H_{\min}} - 1\right)^2\right] \to \min \end{aligned} \tag{10}$$

The objective function (10) can be minimised by the conjugate direction method (Powell, 1964). The coupled hydraulic and optimization analysis of pipe networks can be summarised as follows:

a. Assume pipe diameters and reservoir piezo-metric heads/pump dynamic heads (prelimi-nary design).
b. Do the hydraulic analysis by initially solving the non-linear system of equations at nodes via the Newton-Raphson method to get the piezometric heads at all nodes. Then, disc-harges, head losses of all pipes, and residual pressure heads at the nodes can be deter-mined easily.
c. Compute the objective function of Eq. 10.
d. Use Powell's conjugate direction method to minimise the total capital cost objective function. If the objective function is not minimal, pipe diameters and reservoir piezometric heads should be changed. Then, repeat the cycle from stage (b).

6.1.2. Numerical application

A complex network that consists of two fixed-head reservoirs, sixteen pipes, a booster pump and a check valve as shown in Fig. 1 is considered. It is supplied with a discharge of 0.165 m^3/s provided from two sources, and for all pipes use ductile iron material. The input data (L_{ij}, in m, q_j, in m^3/s, and ZT_j, in m) of pipe network is given in Fig. 1 and the constraints is imposed from Table 3.

Results of the numerical solution performed by means of a PC computer, referring to the hydraulic characteristics of the pipes (optimal diameter D_{ij}, discharge Q_{ij}, head loss h_{ij}, velocity V_{ij}) and the nodes (consumed discharge q_j, elevation ZT_j, piezometric head Z_j, and pressure head H_j) are presented in Table 4 and Table 5 (Sarbu and Ostafe, 2010). The value of the minimised function F_c=1.51×10^9.

The significance of the (–) sign of discharges and head losses in Table 4 is the change of flow sense in the respective pipes with respect to the initial sense considered in Fig. 1.

The mathematical model expressed by the objective function (10) based on unconditioned optimization techniques is capable of handling almost all standard and non-standard components of pipe networks (i.e. pipes, source and booster pumps, reservoirs, check and pressure-reducing valves).

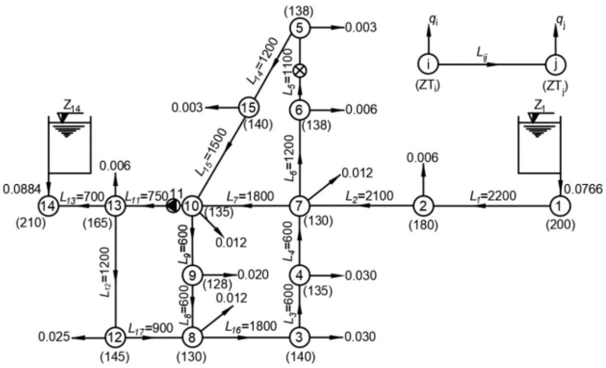

Fig. 1: Schematic of the designed network

Table 3: Constraints

Value	Allowable diameter (mm)	Allowable velocity (m/s)	Allowable pressure head (m)
Minimum	80	0.15	15.0
Maximum	750	2.50	95.0

Table 4: Hydraulic characteristics of the pipes (Optimal continuous solution)

Pipe i - j	L_{ij} (m)	D_{ij} (mm)	Q_{ij} (m³/s)	h_{ij} (m)	V_{ij} (m/s)
2 – 1	2200	381.0	0.07660	2.70	0.67
7 – 2	2100	361.2	0.07092	2.87	0.69
4 – 3	600	401.0	0.02003	0.08	0.16
7 – 4	600	254.6	−0.00997	−0.23	0.21
6 – 5	1100	424.6	0.03572	0.38	0.25
7 – 6	1200	287.8	0.04172	3.70	0.64
10 – 7	1800	128.7	0.00693	5.09	0.53
9 – 8	600	376.9	−0.12371	−3.37	1.11
10 – 9	600	309.0	−0.10371	−6.39	1.38
11–10	Pump	–	0.12836	37.79	–
13–11	750	352.5	0.12836	3.49	1.32
13–12	1200	384.0	0.21074	9.22	1.82
14–13	700	354.5	0.08840	1.59	0.90
15 – 5	1200	380.4	0.03272	0.50	0.29
10–15	1500	382.6	0.02972	0.51	0.26
8 – 3	1800	304.9	0.05003	4.82	0.69
12 – 8	900	310.8	0.18574	15.33	2.45

Table 5: Hydraulic characteristics of the nodes

Node j	q_j [m³/s]	ZT_j [m]	Z_j [m]	H_j [m]
1	−0.0766	200.0	230.58	30.58
2	0.006	180.0	197.39	17.39
3	0.030	140.0	194.36	54.36
4	0.030	135.0	194.28	59.28
5	0.003	138.0	190.44	52.44
6	0.006	138.0	190.82	52.82
7	0.012	130.0	194.52	64.52
8	0.012	130.0	199.18	69.18
9	0.020	128.0	195.82	67.82
10	0.012	135.0	189.43	54.43
11	0.000	135.0	227.23	92.23
12	0.025	145.0	214.52	69.52
13	0.006	165.0	223.73	58.73
14	−0.0884	210.0	225.32	15.32

6.2. Double-objective optimization

6.2.1. Optimization model

The optimal rehabilitation of WDNs under both steady and transient states is expressed as a double-objective optimization problem. The first objective, Eq. 11, is the least rehabilitation cost; while the second objective, Eq. 12, is to minimise the expected damage occurred by transient events by minimising the surge damage potential factor (SDPF). These two equations can be represented as follows (El-Ghandour and Elansary, 2018):

$$C_n = \sum_{ij=1}^{T} c_{ij}(D_k)L_{ij}; \quad (k = 1, \dots N_D) \quad \rightarrow \min \tag{11}$$

$$\text{SDPF} = \sum_{j=1}^{N} \begin{cases} \int (H_j(\tau) - H^*_{\max})d\tau & \text{if} \quad H_j(\tau) > H^*_{\max} \\ 0 & \text{if} \quad H^*_{\min} \le H_j(\tau) \le H^*_{\max} \\ \int (H^*_{\min} - H_j(\tau))d\tau & \text{if} \quad H_j(\tau) < H^*_{\min} \end{cases} \rightarrow \min \tag{12}$$

where, $c_{ij}(D_k)$ is the cost of unit length of pipe ij corresponding to diameter k; L_{ij} is the length of pipe ij; N_D is total commercially available diameters; N is total number of nodes; $H_j(\tau)$ is the pressure head at node j and instant τ; H^*_{max} is the maximum allowable pressure head; H^*_{min} is the minimum required pressure head. The network pipe-diameters are the decision variable and the hydraulic constraints suggested by Jung et al. (2011) are considered.

An ACO algorithm was used by El-Ghandour and Elansary (2018) to perform the double-objective optimization in this study. Both a steady state hydraulic analysis model, based on extended linear graph theory (Gupta and Prasad, 2000), and a developed transient analysis model (Watters, 1984) are linked with previous model to evaluate the potential solutions.

6.2.2. Numerical application

The case study of the New York tunnel network (Fig. 2) gravity-driven, given by Jung et al. (2011), was used to verify the developed model by El-Ghandour and Elansary (2018), and the results are compared. The network needs rehabilitation actions by adding new pipes parallel to the existing ones to increase the pressure heads at some demand nodes.

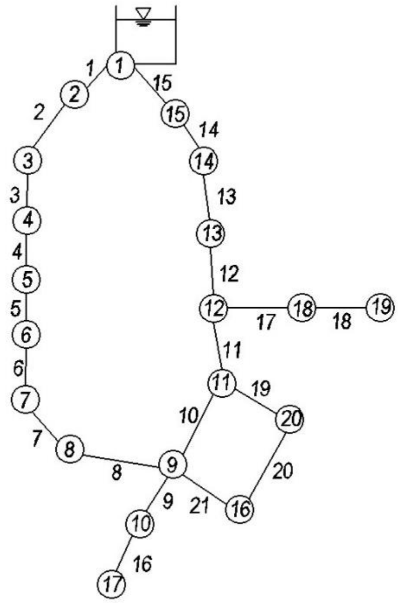

Fig. 2: New York tunnel network

The previous optimization model was applied to the New York tunnel network to determine which of the 21 existing pipes is needed to be duplicated and determining the size of each duplicated pipe from 15 available pipe sizes achieving both the least rehabilitation cost and the minimum SDPF. The layout of the network and the corresponding data are given by Dandy et al. (1996). A transient condition in the network is introduced by sudden demand increase (from 28.3 l/s to 4817.6 l/s) at node 10 during a time equal to 1 second. This increase in demand may be due to: A temporary increase in water consumption, a fire flow or a burst pipe. Table 6 shows the total cost of the pipes and the pipe sizes selected in the optimization corresponding to zero SDPF for both the model developed by El-Ghandour and Elansary (2018) and the corresponding one given by Jung et al. (2011).

Table 6: Total cost of the pipes and the selected pipe sizes corresponding to zero SDPF

Model	Total cost ($ millions)	Pipe size (mm) 7	9	15	16
Jung et al. (2011)	49.1	–	3,900	3,000	2,100
		Pipe size (mm)			
		17	18	19	21
		3,000	2,100	3,000	1,500
		Pipe size (mm)			
		7	9	15	16
El-Ghandour and Elansary (2018)	47.2	2,700	4,200	–	2,700
		Pipe size (mm)			
		17	18	19	21
		3,000	1,800	2,100	1,800

The results showed the rehabilitation strategy of the network satisfies the constraints with a cost $2 million lower than Jung et al. (2011). Both studies identified the same locations to be duplicated except for one location only. The transient pressure head profiles obtained using the results of the two Pareto optimal solutions summarised in Table 6 at most critical nodes 17 and 19 are shown in Fig. 3.

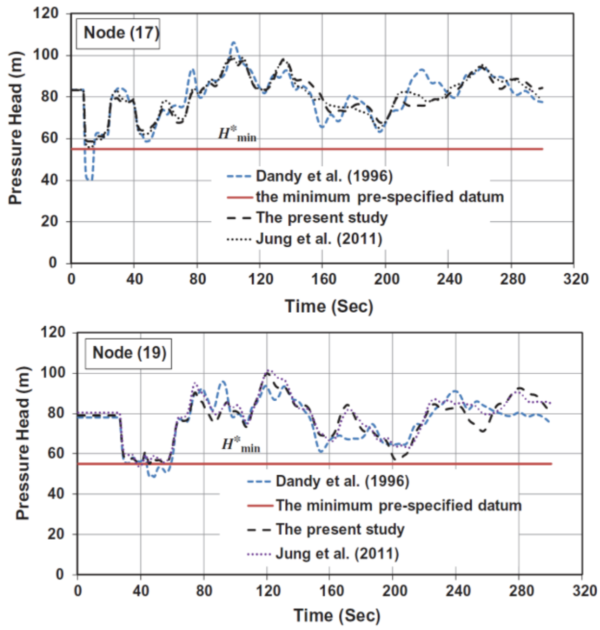

Fig. 3: Transient pressure head profile at nodes 17 and 19 (El-Ghandour and Elansary, 2018)

For the purpose of comparison with the optimal rehabilitation of the network in steady state only, the results given by Dandy et al. (1996) is adopted and the transient head profiles for the two nodes are calculated and drawn on the Fig. 3. From the results shown, the El-Ghandour and Elansary (2018) model seems perfectly able to determine pipe sizes with lower total rehabilitation costs and SDPF than those that were presented by Jung et al. (2011).

6.3. Three-objective optimization

This example presents a three-objective optimization model for the investigation of various sustainable and resilient design alternatives for water distribution networks (Piratla, 2016). This study combines three parameters such as life cycle cost, resilience and environmental impacts (CO_2 emissions) in a multi-objective model to obtain various sustainable and resilient design alternatives. The model is validated on a three-loop benchmark network that was previously studied.

6.3.1. Optimization model

A three-objective function is proposed to design WDNs by: (1) minimising LCC; (2) minimising life cycle CO_2 emissions (LCE); and (3) maximising NRI. The constraints are the discharge and pressure requirements. The decision variables are pipe diameters and pump sizes. The network topology and the operational parameters such as required pressures and water demands are assumed to be given (Piratla, 2016).

- Objective 1: Minimum LCC obtained by mini-mising Eq. 5, in which:

$$C_n = \sum_{ij=1}^{T} c_{ij} L_{ij}; \quad C_p = \sum_{i=1}^{NP} K_p Q_{p,i}^{0.7} H_{p,i}^{0.4}; \quad C_{op} = \sum_{i=1}^{NP} T_p e P_i \tag{13}$$

where c_{ij} is the pipe cost of diameter D_{ij} per unit length; L_{ij} is the length of pipe ij; K_p is a constant for pump capital cost with the value of 700,743 (Costa et al., 2000); $Q_{p,i}$ and $H_{p,i}$ are the rated discharge and head (i.e., the discharge and head at the best efficiency) of pump i; T_p is number of operating hours in a year (8760); e is the cost of electricity (0.12 $/kWh (Geem, 2009); P_i is the power expended by pump i.

- Objective 2: Minimum LCE:

$$\text{LCE} = CE_n + CE_{op} \rightarrow \min \tag{14}$$

where CE_n is the emissions related the embodied energy of network pipe materials estimated using an emissions coefficient g_e; CE_{op} is the emissions related to the operational pumping energy over the design life time. Emissions related to pumping energy are estimated using an emissions coefficient g_p=0.5566 kg/kWh (Piratla and Ariaratnam, 2012).

- Objective 3: Maximum NRI as proposed by Prasad and Park (2004):

$$\text{NRI} = \frac{\sum_{j=1}^{N} \psi_j q_j (H_j - H_{j,\min})}{\left[\sum_{k=1}^{NR} Q_k H_k + \sum_{i=1}^{NP} (P_i/\gamma)\right] - \sum_{j=1}^{N} q_j H_{j,\min}} \tag{15}$$

with

$$\psi_j = \frac{\sum_{ij=1}^{NT_j} D_{ij}}{NT_j \max\{D_{ij}\}} \tag{16}$$

where N is the number of nodes in the network; N_R is the number of reservoirs; N_P is the number of pumps; P_i is the operating power of the pump i; Q_k is the discharge from reservoir k; H_k is the pressure head supplied at the source node by reservoir k; q_j is the demand at node j; H_j is the pressure head in normal operating conditions at node j; $H_{j,\min}$ is the minimum pressure head constraint at node j; γ is the specific weight of water; ψ_j is the nodal uniformity coefficient; NT_j is the number of pipes connected to node j; D_{ij} is the diameter of pipe ij.

- Constraints: $H_j \geq H_{j,\min}$ ($\forall$ node j).
- Optimization algorithm: A GA based optimization tool called GANetXL, linked with EPANET software, initially developed by Savic et al. (2011) was used to perform the three-objective optimization.

6.3.2. Numerical application

The three-objective optimization model previously described was applied using a benchmark network, shown in Fig. 4 (Piratla, 2016), which was originally used by Costa et al. (2000) to demonstrate a SA model for the design of this network. The same network was later used by Geem (2009) to demonstrate a HS optimization model.

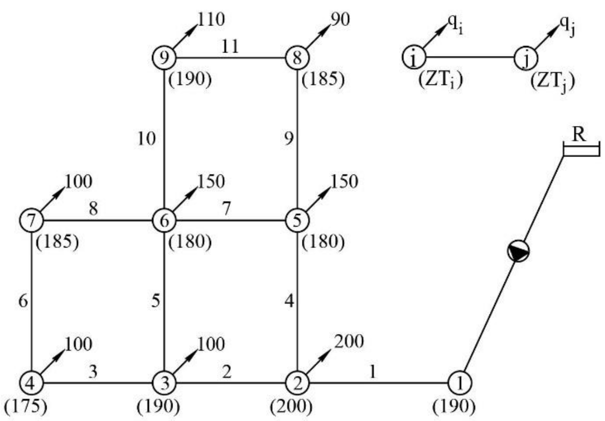

Fig. 4: Schematic of the benchmark WDN

This three-loop network has 9 nodes, 11 pipes, and is supplied by a reservoir and a pump. Each pipe is 2500 m long, and a value of 130 is chosen for the Hazen-Williams coefficient. The hydraulic constraints that need to be met are the demands q_j (m^3/h) at each node j as shown in Fig. 4 with a minimum allowable pressure head of 30 m at each node. The elevation heads ZT_j, in m, at each node are also presented in Fig. 4 (Piratla, 2016).

Ten candidate diameters for pipes and nine pump curves in addition to the option of "no pump" are considered as shown in Table 7. The candidate pipe diameters are adapted from the previous studies that used the same three-loop benchmark network.

The algorithm previously described was tested on the optimization presented by Geem (2009) for the design of pump-included WDNs by minimising LCC (for a 20 year period), and using a HP algorithm for obtaining the optimal solution. The same optimal solution was converged upon in approximately 875 generations (Geem, 2009) using the GANetXL algorithm. The solution which is called the "least cost solution" or "S_1" can be seen in Table 8. The corresponding LCC, LCE and NRI values are for a 50-year design period.

Table 7: List of candidate pipes for the decision variables

Candidate number, i	D_i (mm)	c_i (\$/m)	g_e (kg/m)	Break rate (break/(km·year))	Break repair cost (\$)
1	152.4	42	140.62	0.41	5000
2	203.2	58.4	185.44	0.25	5500
3	254	73.8	238.17	0.15	6000
4	304.8	95.8	305.84	0.10	6500
5	355.6	118.8	355.06	0.08	7000
6	406.4	143	433.28	0.06	7500
7	457.2	169	502.71	0.05	8000
8	508	197.2	593.23	0.04	8500
9	609.6	252.6	710.12	0.02	9000
10	762	346.1	1015.09	0.01	9500

Table 8: Comparison of solutions in several scenarios

Solution	S_1	S_3	S_{89}	S_{123}	S_{282}	S_{324}
1	609.6	609.6	609.6	609.6	609.6	762
2	254	355.6	406.4	406.4	457.2	457.2
3	152.4	254	254	254	304.8	254
4	457.2	406.4	457.2	406.4	457.2	457.2
5	152.4	152.4	254	254	254	304.8
6	152.4	203.2	203.2	203.2	254	254
7	355.6	254	254	254	254	304.8
8	254	152.4	254	203.2	254	254
9	254	304.8	304.8	304.8	304.8	304.8
10	254	152.4	152.4	152.4	203.2	203.2
11	152.4	254	254	203.2	203.2	203.2
Pump	4	4	4	5	5	4
LCC (million \$)	5.683	5.738	5.998	6.058	6.361	6.448
LCE (kilo tonne)	56.949	57.144	57.913	61.848	62.740	59.300
Resilience (NRI)	0.127	0.163	0.226	0.241	0.291	0.298

The use of either larger diameter pipes or larger capacity pumps improves redundancy in the system, and subsequently NRI values are expected to increase with LCC. The challenge however is to choose a solution that will provide the highest benefit to the user.

The comparison of the most beneficial solution (S_3) to the least-cost solution (S_1), presented in Table 6, shows that both LCC and LCE of S_3 are marginally greater than those of S_1, but the NRI of S_3 is significantly greater than of S_1. The benefits from such a significant rise in NRI outclassed the slight increase in cost and emissions.

This study along with several others point out the fact that capital costs should not be the sole criteria while making design decisions.

7. Conclusion

In this survey, the general optimal WDN design problem was presented with all the additional complexities and various successful models were reviewed.

The optimization of pipe networks under steady-state conditions has been studied and different researchers proposed the use of mathematical programming techniques (LP, NLP, DP) to identify the optimal solution for WDNs. However, these deterministic methods either use some gradient information or require restrictive assumptions such as linearity, convexity, and differentiability of the objective function, which cannot be generally satisfied and they usually converge to local optimal solutions that may not be the global optimum.

Recently, the focus of the research in this area has shifted to the meta-heuristic based optimization methods like GA, SA, ACO, PSO, SFLA, DE, HS, etc. As meta-heuristic optimization methods use only the values of the objective function in the search for optimal solutions, a large number of numerical simulations are required to reach these solutions. This is time consuming for small problems, but for larger problems it may be the only feasible way, and in that sense the required computational effort is actually the benefit of this approach.

Multi-objective optimization methods, based on different design criteria, have the advantage of providing a set of optimal solution, called Pareto front, instead of a unique optimal solution. Heuristic algorithms are usually the most used for solving MOPs. While the heuristic methods deal with a set of solutions during the search procedure, allowing to obtain a set of Pareto optimal solutions in a single run, the deterministic methods only lead to a single solution and cannot guarantee the generation of different points on the Pareto front.

Further research in heuristic optimization methods should focus on hybrid methods, which combine the specific advantages of different approaches. These studies should also contain the use of hyper-heuristic techniques for optimising WDNs, which are more general and can solve a wider series of problems compared to the current meta-heuristic methods specialised in a narrow class of problems.

Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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