Check for updates

Water Supply

© 2022 The Authors

Water Supply Vol 22 No 12, 8972 doi: 10.2166/ws.2022.413

A new multi-objective evolutionary algorithm for the optimization of water distribution networks

Nikita Palod *, Vishnu Prasad and Ruchi Khare
Department of Civil Engineering, MANIT, Bhopal, MP, 462003, India
*Corresponding author. E-mail: npalod@gmail.com

NP, 0000-0002-8955-2375

ABSTRACT

This work introduces a new bi-objective optimization model for the design of a water distribution network (WDN). Reliability and design cost are two contradicting objectives that are optimized. The evolutionary technique multi-objective (MO) Jaya, hereafter referred as MO-JAYANET, is developed for the optimal design of WDN. EPANET is used as a hydraulic network solver in this study. The concept of constraint violation, dominance, non-dominance and crowding distance is used to develop MO-JAYANET. As the Jaya algorithm is a parameter-less technique, and with the concept of constraint dominance involved in the MO model, the penalty parameter required to penalize the non-feasible solution is also dropped. This makes MO-JAYANET a completely parameter-less technique, requiring no tuning at all. MO-JAYANET is applied on two benchmark networks from the literature using three different reliability indices that are Resilience Index, Network Resilience Index, and Modified Resilience Index. MO-JAYANET is found to be very easy and efficient for WDN optimization. The present work obtains a smooth Pareto Front (PF) that overlaps the best-known PF. The maximum reliability diameters obtained by the MO-JAYANET for the three indices are also simulated for both hydraulic and mechanical failures under different scenarios to identify a better-performing index.

Key words: evolutionary algorithm, Jaya, multi-objective optimization, reliability, water distribution networks

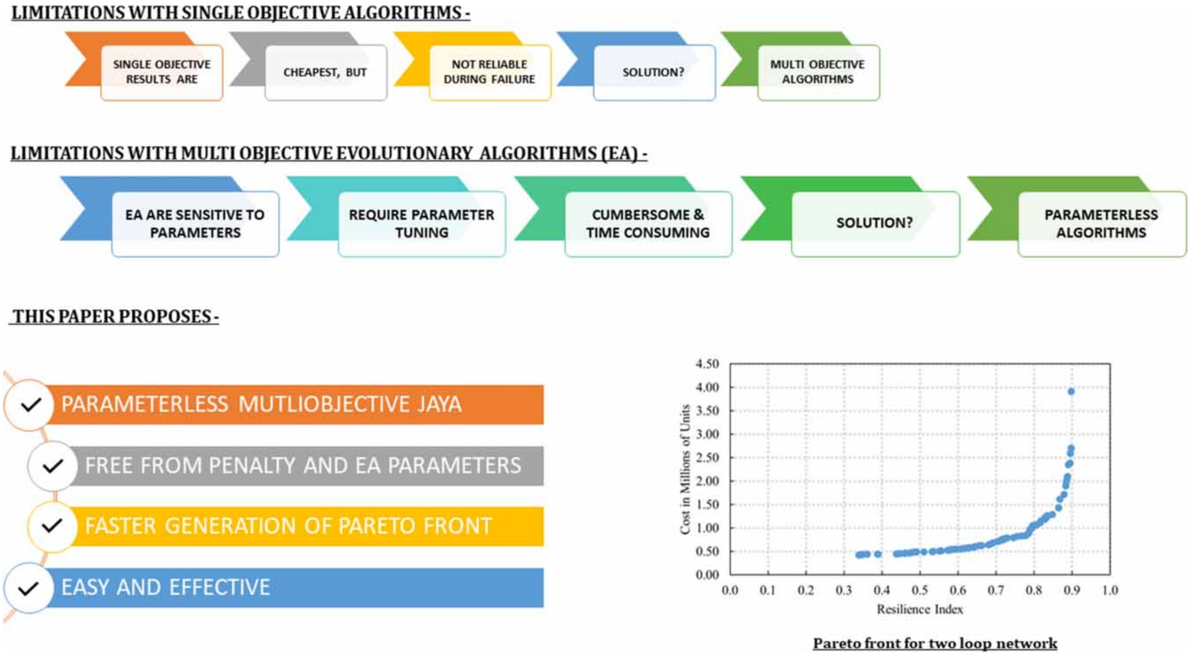
HIGHLIGHTS

- A parameter-less multi-objective optimization technique for the design of Water Supply is developed.
- Three well-known Reliability Indexes (RIs) are used.
- The parameter-less Jaya technique is developed for the multi-objective optimization of water distribution.
- Smooth Pareto fronts that overlap the best-known Pareto front are obtained.
- The RIs are checked for hydraulic and mechanical failures to identify the better performing index.

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (http://creativecommons.org/licenses/by/4.0/).

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

GRAPHICAL ABSTRACT



INTRODUCTION

Previous research on the optimization of the water distribution network (WDN) focuses only on reducing the network cost, i.e. single-objective optimization. This optimization leaves us with a least-cost solution that saves a lot of capital when compared with other options. However, the least-cost solution may not be reliable during failure, which may lead to a sudden increase in the pressure in the distribution network, due to the choice of diameters that are selected just to satisfy the minimum pressure requirement. Also, WDN is not only an expensive but complex engineering problem due to the involvement of non-linear relations between discharge and head, its discrete nature, and various constraints of the problem. Thus, redesign is not possible as well as not feasible at any stage of the design. This is where the need for multi-objective optimization of WDN is felt, i.e. designing the network with various objectives such that the design is not only cheap but also reliable. Such networks can function under different failure scenarios. The failure in WDN occurs either due to hydraulic or mechanical reasons. Hydraulic failure refers to the deficiency in the pressure head due to the uncertainty or sudden increase in the nodal demand or pipe roughness. Mechanical failure occurs due to the failure of WDN components such as pipe, valves, etc. To record the response of the network toward these failures, reliability is determined. However, there is not a universally accepted definition for the reliability of WDN. Broadly, it is defined as the ability of the network to meet demand under different failure scenarios. Many authors have defined and determined the reliability of WDN, both hydraulic and mechanical, by determining the ratio of available flow to the flow required, taking into consideration the probability of failure in each scenario (Creaco *et al.* 2016). The minimum cut-set method was used by Su *et al.* (1987) which was later used by other authors (Sirsant & Reddy 2017) to determine the mechanical reliability. Bhave & Gupta (2004) incorporated the fuzziness in demand for determining the hydraulic reliability of WDN. Monte Carlo simulation is also used for generating the various random samples that are later used for determining the hydraulic reliability (Sirsant & Janga Reddy 2018) of the WDN. However, such techniques are not only complex but require a large number of hydraulic computations when implemented. This adds to the computational efforts required by the optimization technique. To ease the process of determining the reliability of WDN various surrogate measures are proposed and have been used extensively over the last decade. Todini (2000) was given the credit for proposing the first-ever reliability surrogate measure (RSM) called resilience index (RI). Thereafter many indices such as the network resilience index (NRI) (Prasad & Park 2004), modified resilience index (MRI) (Jayaram & Srinivasan 2008), minimum surplus head index, and flow uniformity index (Moosavian & Lence 2020) have been proposed and implemented to different problems. Many studies compared the different reliability indices under various failure

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

scenarios. Raad *et al.* (2010) compared four reliability indices namely RI, NRI, flow entropy, and mixed reliability index for three WDN using the AMALGAM optimization algorithm. They compared the solutions obtained by different reliability indices for demand satisfaction and found RI to be a better performer. Baños *et al.* (2011) incorporated the Strength Pareto Evolutionary Algorithm 2 (SPEA2) for the multi-objective design of Two Loop and Hanoi networks using RI, NRI, and MRI. Various over-demand scenarios are used for comparison of the indices and concluded RI to be a better performer for Two Loop network and NRI for Hanoi network. Greco *et al.* (2012) found that, unlike entropy, the robustness of any network is better represented by its resilience. Anytown benchmark network was optimized by Atkinson *et al.* (2014) for both hydraulic and mechanical reliability. According to them the solutions with high entropy are found to be better performers under mechanical failures. Liu *et al.* (2017) developed two new reliability surrogate measures, Pipe Hydraulic Resilience Index (PHRI) and Available Power Index (API), and compared them with four available reliability indices. Demand uncertainty is simulated using stochastic sampling that is distributed normally. PHRI and API outperform RI, MRI, NRI, and diameter-sensitive flow uniformity. Most recently a detailed comparative analysis was carried out by Jeong & Kang (2020). The authors addressed the most complicated issue faced by water engineers, i.e., which reliability index should be selected for the different hydraulic scenarios. They developed various correlations between hydraulic measures and reliability index so that the correct reliability index is chosen for the different hydraulic measures, for example, PHRI index performed better for the single pipe failure scenario, for fire flow scenarios RI, MRI and API performs better, and so on. Thus researchers can select the hydraulic scenarios and choose the relevant reliability index accordingly. This may prove very efficient for hydraulic engineers.

Multi-objective (MO) optimization leads to the generation of various non-dominated solutions, which when spread across the objectives, and is termed as Pareto Front (PF), unlike in single-objective optimization the result of which for the design of WDN is a single solution with minimum cost. The designer can choose any solution from the non-dominated set based on the requirements, as all the solutions present in the Pareto front are feasible and satisfy all the constraints of the problem. Various multi-objective evolutionary algorithms (MOEA) have been applied to the design of WDN. Farmani *et al.* (2005) applied Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and SPEA2 to Newyork Tunnel and Hanoi network. Minimum cost and maximum head deficiency were two objectives that were considered. The authors found SPEA2 slightly better than NSGA-II. Ostfeld *et al.* (2014) applied MOGA to three WDNs and reconfirms that the reliability of network increases with its cost. RI and network costs were optimized using MOGA. A memetic algorithm (MA) for two objectives for reducing cost and pressure deficit was applied by Barlow & Tanyimboh (2014). The algorithm outperformed NSGA-II when tested on two benchmark problems. Wang *et al.* (2015) developed the best-known Pareto Fronts (BKPF) using cost and NRI for different water supply networks using five MOEAs. Monsef *et al.* (2019) tested three MOEAs, namely NSGA-II, Multi-objective Differential Evolution (MODE), and Multi-objective Particle Swarm Optimization (MOPSO), on four WDNs. Minimum cost and maximum NRI were considered as two objectives of the problem. All three algorithms were able to produce the PF, however, the PF obtained by MODE was found to be more accurate. Fuso *et al.* (2020) incorporated the GALAXY algorithm for generating the PF. The author also developed various performance indices (PI) to access the network performance under different failure scenarios. Moghaddam *et al.* (2021) used the GANetXL (an excel tool for optimization using a Genetic Algorithm) for optimizing the network and used statistics to determine the critical pipes and analyze the failure of these pipes for three networks. The author finds the NRI to be a poor performer when compared with other indices. All the above-mentioned MOEA are sensitive to the parameters and required extensive fine-tuning of the parameters for their proper convergence which further enhances the complexity of the MO design. Fine-tuning is a rigorous exercise that needs to be done ‘n’ times for ‘n’ different problems since the algorithm once tuned cannot be directly used for another problem. Jaya optimization algorithm has been used widely in different fields. Therefore it will be interesting and novel to test this parameter-less algorithm for a non-linear polynomial hard discrete multi-objective design problem. Hence the main objective of the present work is to introduce the MO-JAYANET, a completely parameter-less multi-objective optimization model for the design of WDN. The algorithm does not require any algorithm-specific parameters as required by other meta-heuristic techniques, in addition to this, it is also free from penalty parameters. Only common parameters like population size and iteration numbers are required that need to be tuned. These parameters are required for any of the evolutionary algorithms in addition to its algorithm-specific parameters. The MO-JAYANET algorithm is developed and tested on two benchmark networks using three reliability indices. PFs are plotted and the maximum reliability solution of the three indices is checked for various failure scenarios.

The present work is divided into two parts. Part one describes the modeling and development of the MO-JAYANET for the WDN, and its application for obtaining the set of non-dominated solutions, i.e the spread of the solutions in the Pareto front.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

The second part of the paper is structured to study the performance of the three reliability indices under different failure scenarios. Efforts are made to include both hydraulic and mechanical reliability. The detailed flow chart of the present work is shown in Figure 1.

FORMULATION OF OPTIMIZATION MODEL

The bi-objective optimization model for WDN consists of minimizing the network cost as the first objective and maximizing the reliability in form of RSM as the second objective. The mathematical equations of the objective functions are as follows:

$$Min\ cost = \sum_{i=1}^{np} C_i(D_i)*L_i \tag{1}$$

$$Max\ RSM \tag{2}$$

where L_i = length of pipe i in the network (m); $C_i\ (D_i)$ = cost per meter run of a given diameter; D_i = diameter of the selected pipe (m); np = number of pipes; RSM is any reliability surrogate measure. The objective functions represented by Equations (1) and (2) are contradicting in nature since to improve the reliability of the network larger diameter pipes must be used which in turn increases network cost and vice-versa. Since the design of WDN is a constrained problem, the following set of constraints are to be satisfied for its design:

$$\sum Q_I - \sum Q_O = q_k, \quad \forall\ k \in nn \tag{3}$$

$$\sum_{i\ \in loopl} hf_i = 0, \quad \forall\, l \in nl \tag{4}$$

$$h_{avl} \geq h_{min}, \quad \forall\, k \in nn \tag{5}$$

$$D_i = \{D\}, \quad \forall\, i\ \in np \tag{6}$$

Equation (3) defines the continuity at any node, where Q_I, Q_O, q_k are the inflow, outflow, and demand at any node k, nn are total nodes in the network. The constraint of energy conservation in any loop is defined by Equation (4), where nl are total loops in the network, hfi is frictional head loss. For any design in the distribution network, the pressure available at any node must be greater than the prescribed minimum pressure head and this constraint is defined by Equation (5) where h_{avl} and h_{min} are available and minimum pressure head required. The diameters for the design of WDN must be selected from the set of commercially available diameters, i.e. $\{D\}$, as defined in Equation (6).

The second objective of the optimization model is to maximize the reliability of the network, which is achieved by maximizing the RSM. The present work uses the following reliability surrogate measures as the second objective.

Resilience Index (RI)

RI (Todini 2000) has been used extensively over the last two decades for determining the reliability of the network. It is defined as the internal capacity of the network to meet the demand under both normal and abnormal situations. RI gives a measure of the surplus power that is present within the network to the total power available. Surplus power is the extra energy within the system that can be dissipated during any failure without affecting the user demand. RI as given in Equation (7) ranges anywhere between 0 and 1 for feasible solutions:

$$RI = \frac{\sum\limits_{j=1}^{N} q_i(h_{avl,j} - h_{min,j})}{\left(\sum\limits_{i=1}^{R} Q_r h_{res,i} + \sum\limits_{b=1}^{B} \dfrac{P_b}{v}\right) - \sum\limits_{j=1}^{N} q_j h_{min,j}} \tag{7}$$

where q_i is the demand at node i, h_{avl} and h_{min} are the available and minimum head respectively at any j, Q_r and h_{res} are the discharge and head available at the reservoir, P_b is pump capacity which is taken as 0 for gravity-fed reservoirs, v is the specific weight of water, N is the total number of demand nodes present in the network.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

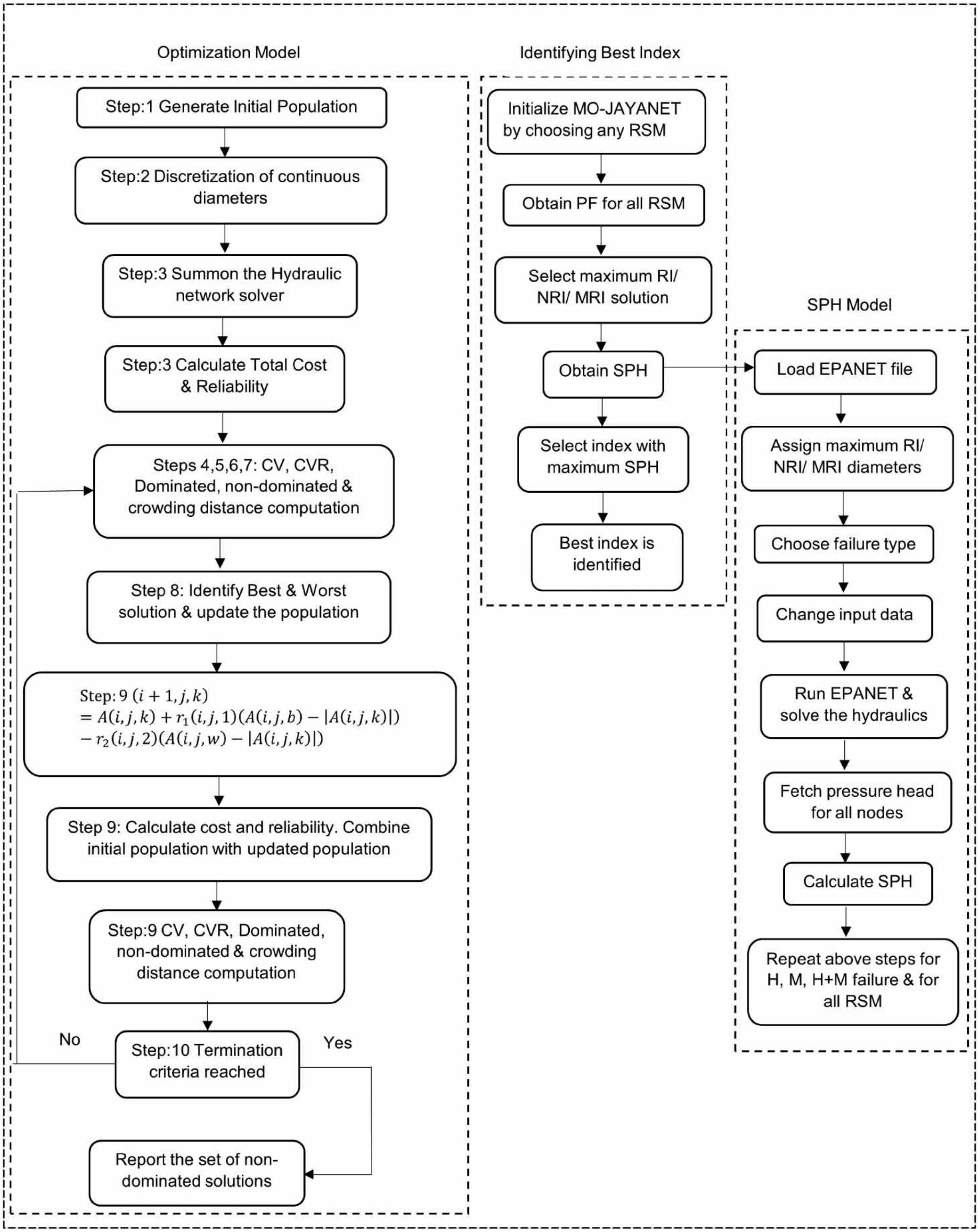


Figure 1 | Flow chart of the proposed methodology.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

Network Resilience Index (NRI)

NRI (Prasad & Park 2004) is a modification over RI by considering the concept of uniformity in pipe diameters along with the surplus power available within the system. Prasad & Park (2004) introduced a factor C_j to consider the reliable loops in the network such that the pipes connected to a node do not vary largely in diameter and thus allow pipes that are practical if implemented. For the same set of diameters, NRI is slightly lesser than RI due to the involvement of C_j. If $D_1, D_2, D_3, \ldots D_{np}$ (where $D_1 \geq D_2 \geq D_3 \geq \ldots \geq D_{np}$) are the diameters of pipes connected to node i, C_j is calculated as:

$$C_j = \frac{\sum_{i=1}^{np} D_i}{np * \max(D_i)} \tag{8}$$

where np is the number of pipes connected to node i. The value of $C_j < 1$, for different pipe diameters connected at a node. However, if only one pipe or the same diameter pipes are connected to a node the value of C_j becomes 1:

$$NRI = \frac{\sum_{j=1}^{N} C_j q_i (h_{avl,j} - h_{min,j})}{\left(\sum_{i=1}^{R} Q_r h_{res,i} + \sum_{b=1}^{B} \frac{P_b}{v} \right) - \sum_{j=1}^{N} q_j h_{min,j}} \tag{9}$$

where C_j is the uniformity index.

Modified Resilience Index (MRI)

MRI (Jayaram & Srinivasan 2008) gives a measure of the surplus power that is present with the network to the power present at the demand nodes. This surrogate measure does not consider the power supplied by the reservoir to the network. The range of MRI can be greater than 1:

$$MRI = \frac{\sum_{j=1}^{N} q_i (h_{avl,j} - h_{min,j})}{\sum_{j=1}^{N} q_j h_{min,j}} \tag{10}$$

METHODOLOGY

The optimization technique Jaya was introduced by Rao (2016). Like any other meta-heuristic technique, Jaya begins its implementation by generating a random initial population. The main advantage behind choosing the Jaya technique for the development of a multi-objective optimization model for WDN is its simple structure along with the parameterless nature of the Jaya. Being parameterless, Jaya skips all the computational efforts that are otherwise required to fine-tune any Evolutionary Algorithm (EA). The formulation of the MO-JAYANET model is explained below.

1. The random initial population is generated within the lower and upper bound of the decision variable:

$$x_{ij} = d_i^L + rand_{ij} * (d_i^U - d_i^L) \tag{11}$$

   where the random value of the decision variable is represented by x_{ij}, $rand_{ij}$ is any random number generated between 0 and 1 that is distributed uniformly. d_i^L and d_i^U are the lower and upper limits, respectively of the decision variable.
2. Since the generated initial population is continuous, thus it is converted to the discrete initial population by applying the average discrete constraint rule as given in Equation (12):

$$x_{ij} = \begin{cases} x_i(k) & \text{if } x_{ij} \leq \dfrac{x_i(k) + x_i(k+1)}{2} \\ x_i(k+1) & \text{otherwise} \end{cases} \tag{12}$$

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

where x_i is commercially available pipe diameters. The available pipe diameters are arranged in increasing order of magnitude and the nearby diameters between which the value of x_{ij} lies are selected. x_i (k) is the diameter smaller than x_{ij} and x_i $(k+1)$ is the diameter larger than $x_{ij.}$ Thus, if the value of x_{ij} is less than the average of the selected diameters (smaller and larger), x_{ij} becomes x_i (k) else x_i $(k+1)$. If the value of x_{ij} is smaller than the least value among the commercially available diameters then it is replaced by the least commercially available diameter. Similarly, if the value of x_{ij} is greater than the largest value among the commercially available diameter, it is replaced by the largest commercially available diameter. The discretization of the continuous diameter is explained with the help of an example. Consider the Hanoi network, its commercially available diameters are given in Table 1.

i. Arrange the commercially available diameters in increasing order i.e., 304.8, 406.4, 508, 609.6, 762, 1016.
ii. Suppose the continuously generated diameter is 931.81.
iii. When compared with the available diameters we can say that 931.81 lie in between 762 and 1,016.
iv. Calculate an average of 762 and 1016 which is 889.
v. 931.81 (continuously generated diameter) is greater than the average value of 889, thus 931. 81 is replaced by 1016. If the continuously generated value is less than the average of two commercially available diameters then it will be replaced by the smaller of the two chosen commercially available diameters.
vi. If the continuously generated diameter is 300, then this value is less than the least available commercial diameter, hence it is replaced by 304.8. The same applies to the value generated greater than 1016, it will be replaced by 1016.

3. After the discretization of the initial population, these discrete diameters are passed to the simulation software, EPANET 2.0 (Rossman 2000), and discharge, head, and pressure values at all demand nodes are determined and noted. Once these parameters are known, the reliability of the network can be calculated using the reliability indices described in Equations (7), (9) and (10) (applying one at a time). The total cost of the network is also determined using Equation (1). However, no penalty is imposed on infeasible solutions in this methodology, thus fitness value includes only the cost of the network.
4. The next step is to calculate the constraint violation (CV) for each solution in the population using Equation (13):

$$CV = \begin{cases} \sum_{j=1}^{nc} h_{min} - h_{avl} & if\, h_{avl} < h_{min} \\ 0 & if\, h_{avl} \geq h_{min} \end{cases} \quad \forall \, \mathrm{nn} \tag{13}$$

Table 1 | Commercially available pipe diameters with the unit cost for Two Loop and Hanoi Network

Two Loop Network		Hanoi Network	
Diameter (mm)	**Cost (units)**	**Diameter (mm)**	**Cost ($/m)**
25.4	2	304.8	45.73
50.8	5	406.4	70.40
76.2	8	508.0	98.38
101.6	11	609.6	129.33
152.4	16	762.0	180.80
203.2	23	1016.0	278.30
254.0	32		
304.8	50		
355.6	60		
406.4	90		
457.2	130		
508.0	170		
558.8	300		
609.6	550		

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

where nc is the number of nodes for which $h_{avl} < h_{min}$ and nn is the number of demand nodes. For example, if there are 10 nodes at which pressure is less than the minimum pressure requirement, then CV is the summation of all the 10 nodes pressure differences from the minimum pressure requirement. A CV tells about the total violation a solution has in terms of pressure. It is obvious to state that the solution with less CV value is superior to the solution with more CV value.

5. The constraint violation ratio (CVR) is next determined for every solution in the population using Equation (14):

$$CVR = \frac{CV_i}{(CV_{max})_N}\ ,\ \ if\ (CV_{max})_N = 0\ \ then\ (CV_{max})_N = 1 \tag{14}$$

where CV_i is the constraint violation of solution i, $(CV_{max})_N$ is the maximum constraint violation among the population N. In the initial stage of the algorithm almost all the solutions may violate the minimum pressure requirement constraint. However, as the algorithm advances the count of such solutions decreases, and the algorithm may reach a point with zero constraint violation solutions. In such a case $(CV_{max})_N$ is taken as 1, as it is in the denominator and cannot take zero as a value.

6. The solutions are then sorted and ranked based on their respective *CVR* values. This ratio is chosen to sort the solutions because the solution with higher CV values will require larger diameters to satisfy the pressure. Hence such solutions will be costly, and thus will be less probable to be picked up for the next iteration for a minimization cost problem.

Thus the chance of a solution performing better than others depends on its CV value and hence solutions are sorted based on the CVR. The solution with minimum and maximum *CVR* is ranked 1 and N (N is the population size) respectively. However, different solutions may have the same CVR since for some solutions the CV_{max} comes out to be very large as compared to individual CV values. Hence when divided, the CVR values come out to be nearly the same.

So we can say that the solutions are divided into different fronts based on their CVR and the solution with the same CVR lies on the same front.

7. After getting sorted into different fronts, solutions in the same front are sorted based on the concept of dominance and non-dominance. One solution is said to dominate other solutions if it is better in at least one objective. However, if no solution is found to dominate a solution then the latter is categorized as a non-dominant solution. This creates two distinct sets, one of non-dominated and the other of dominated solutions within a front. Similar front non-dominated and dominated solutions are again sorted based on the crowding distance (CD) (Deb *et al.* 2002).
8. After sorting the solutions, the first front non-dominated solution with maximum CD is selected as the best solution (Deb *et al.* 2002) and the last front last solution is selected as the worst.
9. Once the best and worst solutions are identified, the population is updated using Equation (15). Steps 2, 3 and 4 are repeated for the newly generated population. At this stage the initial population is combined with the new population, making the population size twice the initial population, i.e. $2N$. Steps 5–8 are repeated for $2N$ population $\{(CV_{max})_{2N}$ is determined from the entire $2N$ population for step 5}:

$$A(i+1, j, k) = A(i, j, k) + r_1(i, j)(A(i, j, b) - |A(i, j, k)|) - r_2(i, j)(A(i, j, w) - |A(i, j, k)|) \tag{15}$$

r_1 and r_2 are the random numbers generated between 0 and 1. The best and worst solution is represented by index b and index w respectively. i,j,k are the indices of iteration, variable, and candidate solution respectively. $A(i+1, j, k)$ denotes the new value of the variable j, which is determined by using the old value of variable j, the best and the worst values from the population represented by $A(i, j, k)$, $A(i, j, b)$, and $A(i, j, w)$respectively.

10. Top N solutions are selected from $2N$ solutions and become the initial population for the next iteration. The process is continued till the termination criteria are met.

Including the constraint violation domination in the above methodology eliminates the use of penalty function for penalizing the non-feasible solutions, making the MO-JAYANET a completely parameter-less optimization technique. The code for MO-JAYANET is written in Python by linking it with EPANET 2.0 (Rossman 2000) for performing all the hydraulic simulations.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

COMPUTATIONAL RESULTS

Two loop network

The schematic sketch of the Two Loop network is shown in Figure 2(a). This hypothetical network taken from Alperovits & Shamir (1977) consists of eight pipes, each 1000 m long with a Hazen-William coefficient of 130, and a gravity-fed reservoir kept at an elevation of 210 m. The search space of the network is 1.48×10^{-9} which is large due to the availability of 13 commercial pipe diameters as given in Table 1. The minimum pressure head requirement at all the nodes of the network is 30 m. All the network hydraulic data can be found in Alperovits & Shamir (1977). The optimal cost of the network is reported as 419,000 (Sirsant & Janga Reddy 2018) when only minimizing the network cost is considered with the optimal diameters as given in Table 2. The PF obtained for this network using MO-JAYANET by considering RI, NRI, and MRI as the second objective is shown in Figure 3(a)–3(c) respectively. A single-trial run is performed for the MO-JAYANET for the Two Loop network for three reliability indices by considering 100 population size and 100 iterations as the termination criteria. The cost and reliability ranges from 424,000 to 3,910,000 and 0.3391 to 0.8980 for RI, from 427,000 to 3,260,000 and 0.3213 to 0.8666 for NRI, from 457,000 to 3,472,000 and 0.0449 to 0.1077 for MRI. MO-JAYANET located 101, 106 and 96 different non-dominated solutions for RI, NRI and MRI respectively. All the solutions reported above and plotted in the PF are feasible, i.e. pressure at all nodes is above the minimum pressure requirement thus any solution from the PF can be selected. The PF for NRI obtained by MO-JAYANET is also overlapped with the BKPF obtained by Wang *et al.* (2015) and is found to cover the BKPF. Since many trials with different population sizes are used to obtain the BKPF, MO-JAYANET was able to overlap the maximum portion of the BKPF in a single trial run with one set of population sizes but has undergone a slight diversion at a higher cost solution due to this.

Hanoi network

Figure 2(b) shows the second benchmark network which is a 3-looped real network of Hanoi city taken from Fujiwara & Khang (1990). The network consists of 34 pipes with a Hazen-William coefficient of 130, connecting 31 demand nodes and a reservoir kept at an elevation of 100 m. The diameter for 34 pipes can be chosen from six commercially available diameters given in Table 1 which leads to a total search space of 2.85×10^{-26}. A minimum of 30 m pressure head is required at all the nodes of the network. All the hydraulic data for the Hanoi network is given in Fujiwara & Khang (1990). The optimal network cost reported in the literature is 6.081 M$ (Siew & Tanyimboh 2012) when only minimizing the cost is considered and the corresponding optimal diameters are given in Table 3. Multi-objective optimization using MO-JAYANET for the Hanoi network is carried out using RI, NRI and MRI as the second objective. To obtain the PF shown in Figure 3(d)–3(f)

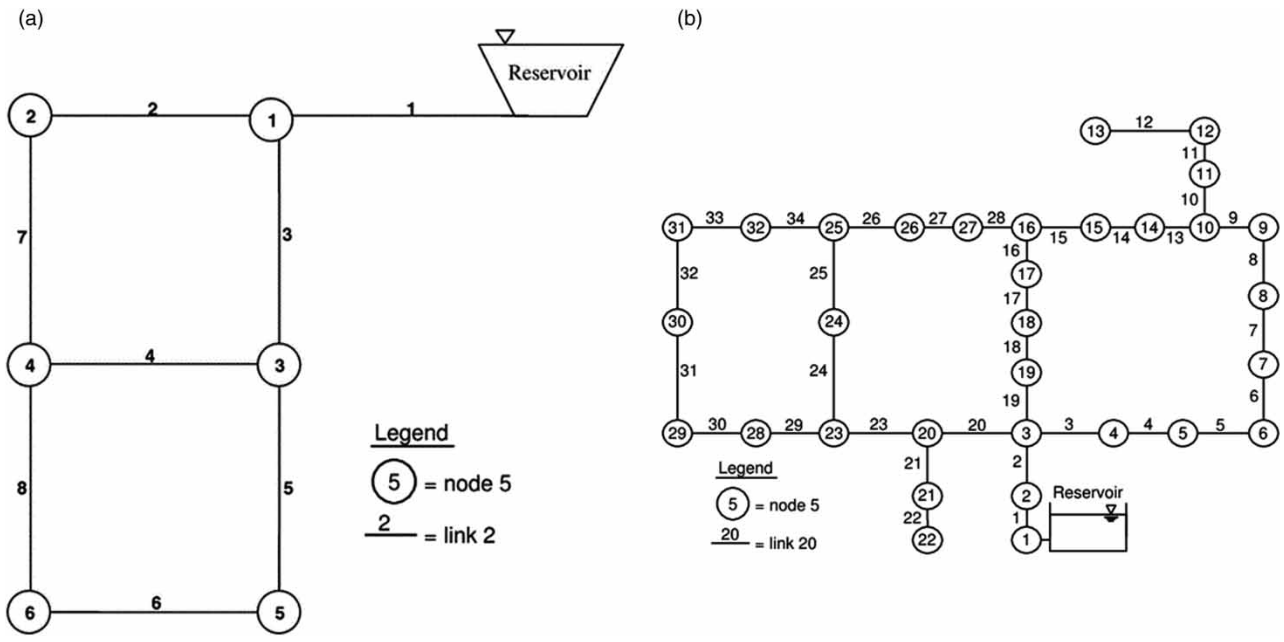


Figure 2 | (a) Schematic sketch for Two Loop network; (b) Schematic sketch for Hanoi network.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

Table 2 | Maximum RI, NRI and MRI diameters for the Two Loop network obtained by MO-JAYANET

Pipe No.	Optimal Diameters	Maximum RI Diameters	Maximum NRI Diameters	Maximum MRI Diameters
1	457.2	609.6	609.6	609.6
2	254.0	609.6	609.6	609.6
3	406.4	609.6	508.0	609.6
4	101.6	609.6	508.0	508.0
5	406.4	355.6	508.0	609.6
6	254.0	609.6	609.6	25.4
7	254.0	609.6	609.6	609.6
8	25.4	609.6	609.6	609.6
Total Cost	419,000	3,910,000	3,260,000	3,472,000

for RI, NRI and MRI respectively, 10 trial runs are performed with a population size of 150 and 1000 iterations as the termination criteria. The PF for Hanoi network ranges from 6,403,449.4 $ to 9,590,894 $ and 0.2186 to 0.3502 for RI, 6,186,046 $ to 9,390,643.8 $ and 0.1985 to 0.3339 for NRI & 6,714,648 $ to 84,66,717 $ and 0.4833 to 0.7902 for MRI. The PF of three reliability indices RI, NRI and MRI reports a total of 180, 163 & 124 feasible and distinct solutions respectively. Among the three indices, solutions with NRI as the second objective report proximity to the optimal solution by obtaining a solution from 163 with a cost of 6.18 M$. PF obtained by MO-JAYANET for NRI is overlapped with the BKPF for the Hanoi network as shown in Figure 3(e) indicating the feasibility of the solutions. The shape of the PF for RI and MRI obtained by MO-JAYANET also matches the PF obtained by Moghaddam *et al.* (2021).

HYDRAULIC AND MECHANICAL RELIABILITY

The maximum reliability solution as given in Table 2 for the Two Loop network and Table 3 for the Hanoi network is selected for all three indices and is checked for the different failure scenarios that are given in Table 4. The solutions are tested for Hydraulic (H), Mechanical (M) and combined Hydraulic and Mechanical (H + M) failures. Table 4 gives the detail about

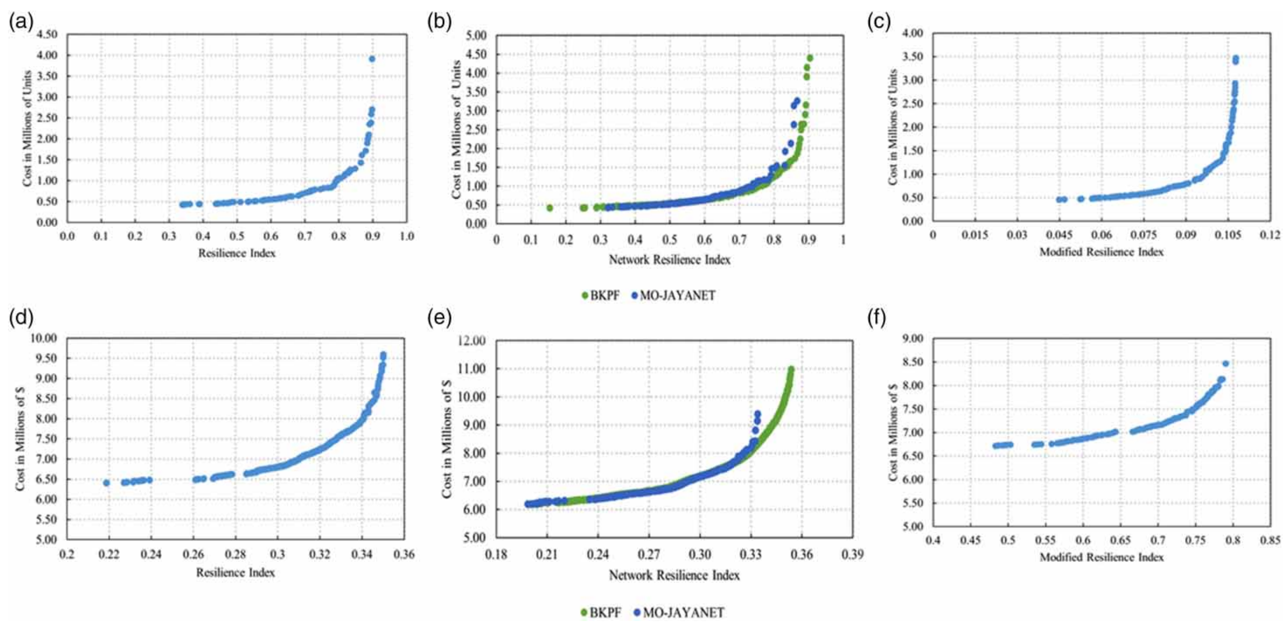


Figure 3 | (a) PF of RI for Two Loop; (b) PF of NRI for Two Loop; (c) PF of MRI for Two Loop; (d) PF of RI for Hanoi; (e) PF of NRI for Hanoi; (f) PF of MRI for Hanoi.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

Table 3 | Maximum RI, NRI and MRI diameters for the Hanoi network obtained by MO-JAYANET

Pipe No.	Optimal Diameters	Maximum RI Diameters	Maximum NRI Diameters	Maximum MRI Diameters
1	1016.0	1016.0	1016.0	1016.0
2	1016.0	1016.0	1016.0	1016.0
3	1016.0	1016.0	1016.0	1016.0
4	762.0	1016.0	1016.0	1016.0
5	609.6	1016.0	1016.0	1016.0
6	609.6	1016.0	1016.0	1016.0
7	508.0	1016.0	762.0	1016.0
8	406.4	1016.0	762.0	1016.0
9	304.8	1016.0	762.0	762.0
10	304.8	1016.0	1016.0	762.0
11	406.4	1016.0	1016.0	762.0
12	609.6	1016.0	1016.0	762.0
13	508.0	1016.0	609.6	1016.0
14	1016.0	1016.0	1016.0	1016.0
15	508.0	1016.0	1016.0	1016.0
16	304.8	1016.0	1016.0	1016.0
17	1016.0	1016.0	1016.0	1016.0
18	762.0	1016.0	1016.0	1016.0
19	762.0	1016.0	1016.0	1016.0
20	508.0	1016.0	1016.0	1016.0
21	304.8	1016.0	1016.0	762.0
22	304.8	304.8	762.0	508.0
23	406.4	1016.0	1016.0	1016.0
24	304.8	1016.0	609.6	609.6
25	304.8	762.0	609.6	609.6
26	406.4	304.8	609.6	304.8
27	406.4	762.0	609.6	1016.0
28	609.6	1016.0	609.6	1016.0
29	1016.0	762.0	1016.0	762.0
30	1016.0	762.0	1016.0	762.0
31	1016.0	406.4	762.0	304.8
32	762.0	304.8	406.4	1016.0
33	609.6	304.8	406.4	406.4
34	609.6	1016.0	609.6	508.0
Total Cost (M$)	6.081	9.591	9.391	8.467

the different scenarios for both Two Loop and Hanoi networks for a single reliability index. Thus, for a reliability index, 11 failure scenarios are tested for the Two Loop network and 14 failure scenarios for the Hanoi network. The difference in the failure scenarios between the two networks is due to the difference in pipe failure. Thus, the three reliability indices are tested for the same scenarios. Only a single pipe failure is considered at a time since multiple pipe failures are rare incidents and are hence neglected (Tabesh *et al.* 2001). Mechanical failure, i.e pipe fail, is simulated by closing a pipe in EPANET 2.0 while simulation of hydraulic failure is done by increasing the demand at all nodes. Demand is increased by incorporating a Demand Multiplier (DM) of 1.5 and 2 for the three indices for both networks. This value of DM is included since it

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

Table 4 | Different hydraulic and mechanical scenarios for the Two Loop and Hanoi networks

		Two Loop			Hanoi			
Case Type	**DM**	**Pipe 2**	**Pipe 3**	**Pipe 5**	**Pipe 4**	**Pipe 5**	**Pipe 6**	**Pipe 20**
M	1	Fail	–	–	Fail	–	–	–
M	1	–	Fail	–	–	Fail	–	–
M	1	–	–	Fail	–	–	Fail	
M	1	NIL			–	–	–	Fail
H	2	No Failure						
H + M	2	Fail	–	–	Fail	–	–	–
H + M	2	–	Fail	–	–	Fail	–	–
H + M	2	–	–	Fail	–	–	Fail	–
H + M	2	NIL			–	–	–	Fail
H	3	No Failure						
H + M	3	Fail	–	–	Fail	–	–	–
H + M	3	–	Fail	–	–	Fail	–	–
H + M	3	–	–	Fail	–	–	Fail	
H + M	3	NIL			–	–	–	Fail

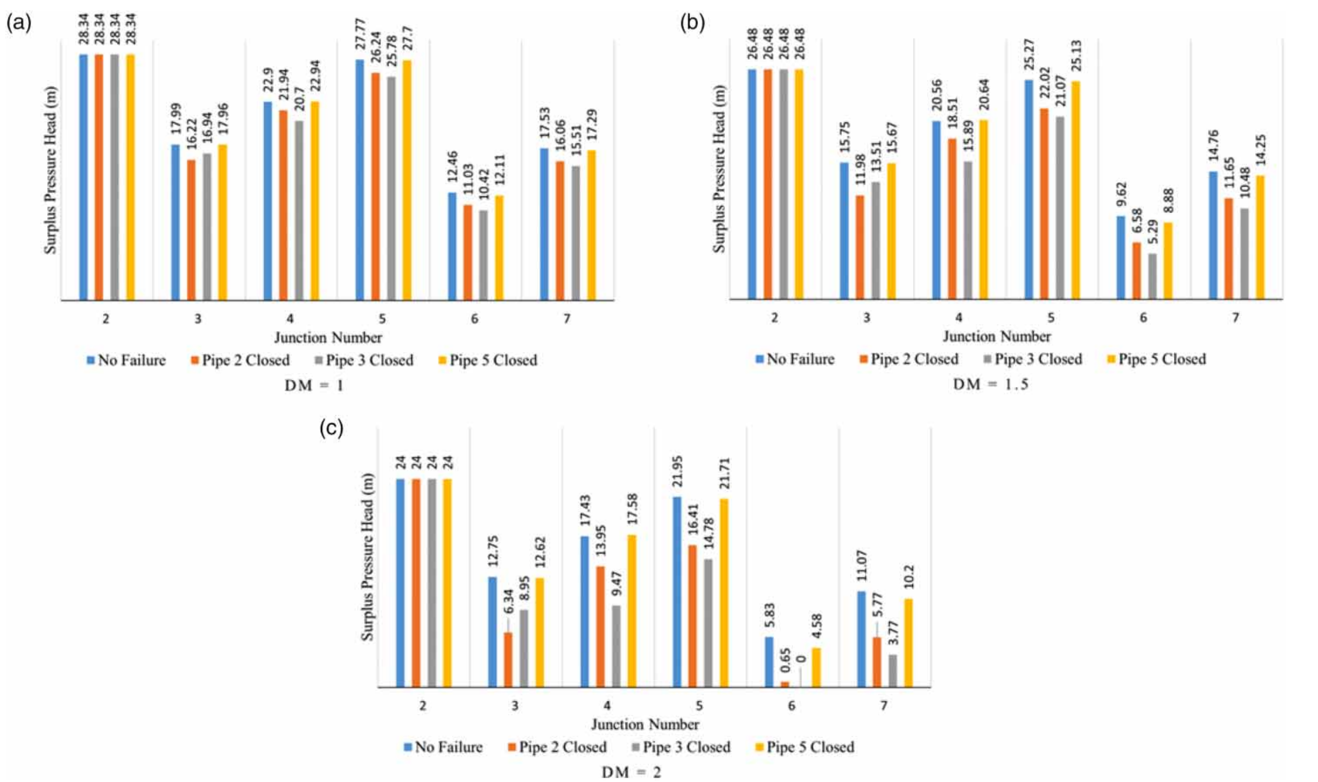


Figure 4 | Surplus pressure head (SPH) for Two Loop network: (a) SPH for RI with DM = 1; (b) SPH for RI with DM = 1.5; (c) SPH for RI with DM = 2.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

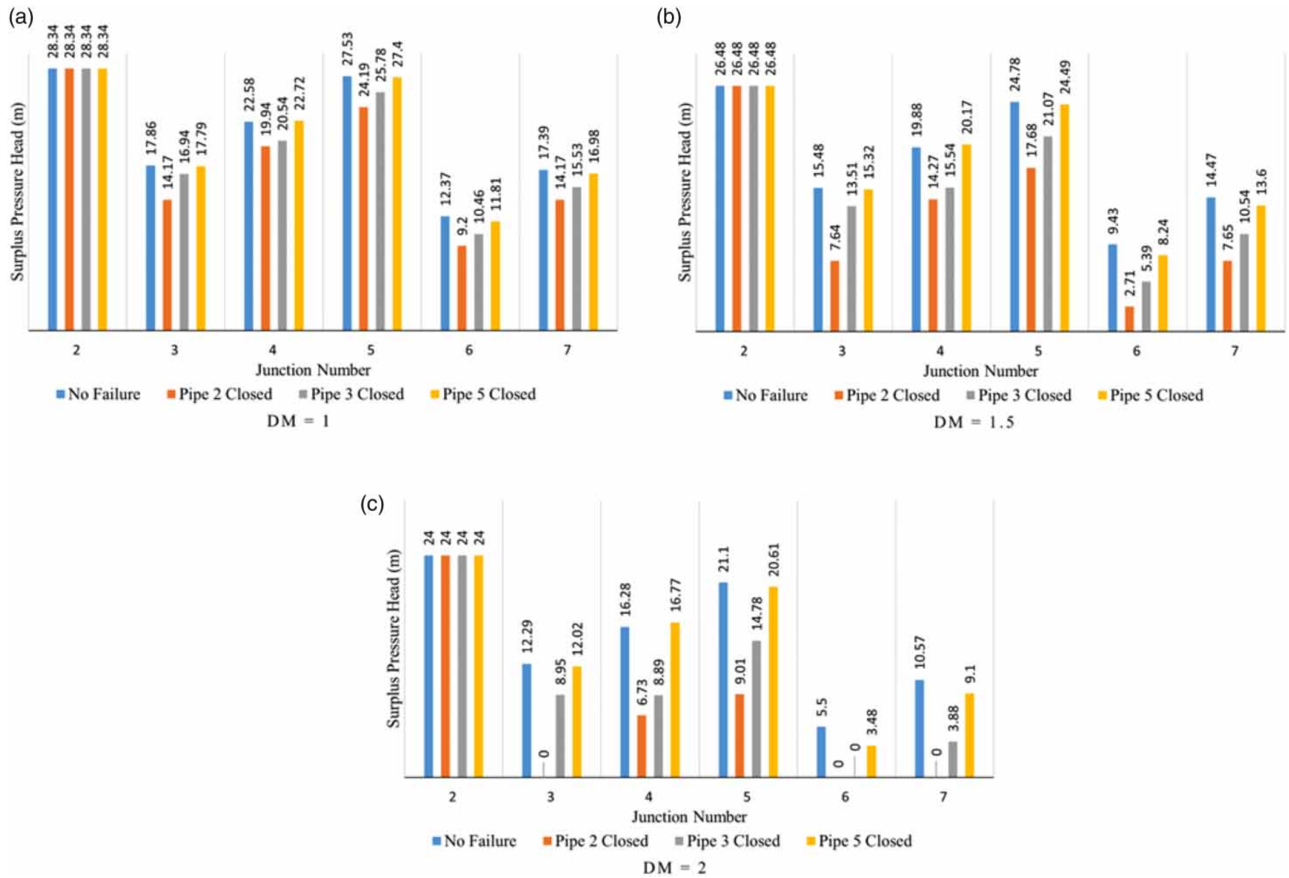


Figure 5 | Surplus pressure head (SPH) for Two Loop network: (a) SPH for NRI with DM $=1$; (b) SPH for NRI with DM $=1.5$; (c) SPH for NRI with DM $=2$.

covers a large range of demand scenarios. Hence if a solution performs satisfactorily at these demands it will be obvious that similar performance can be expected for demands less than this. Network simulated to closed pipe along with increased demand at all nodes is categorized in H + M failure. Moghaddam *et al.* (2021) performed a statistical analysis of the vulnerable pipes in the Two Loop and Hanoi networks and found that pipes 2, 3 and 5 are most vulnerable to failure in the Two Loop network and pipes 4, 5, 6, and 20 are the most vulnerable to failure in the Hanoi network. Thus, the three reliability indices are tested on the failure of the above-mentioned pipes for the two benchmark networks. Surplus Pressure Head (SPH) indicates the pressure above the minimum head requirement at any node. SPH is calculated and plotted for the networks for different failure scenarios. Figures 4–7 show the SPH obtained under different failure scenarios for the Two Loop and Hanoi networks respectively. The SPH graph of the Hanoi network for DM $=1.5$ and 2 are not given as maximum nodes depicted negative pressure at this hydraulic condition and thus leaves very few nodes with a positive SPH.

For the three indices, the summation of the SPH at all nodes for the three DM and failure of pipes 2, 3 and 5 for the Two Loop and DM $=1$ and failure of pipes 4, 5, 6 and 20 for the Hanoi network is determined. SPH tells about the extra pressure head that is available at any node after the minimum pressure head is satisfied. Hence, the higher the value of SPH, the higher is the power available within the network which can be dissipated during any failure (Todini 2000). All the RSM discussed in the present work are based on the surplus power available within the network. Thus, the index having the maximum SPH indirectly tells about the reliability of the network. However, much research is needed to comment on the best-performing index but based on the value of SPH, Todini's RI can be seen as a better performer when compared with NRI and MRI. From Table 5 it is clear that for both the networks, Todini's RI has the highest SPH value of 1216 m for Two Loop and 2223.69 m for the Hanoi network).

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

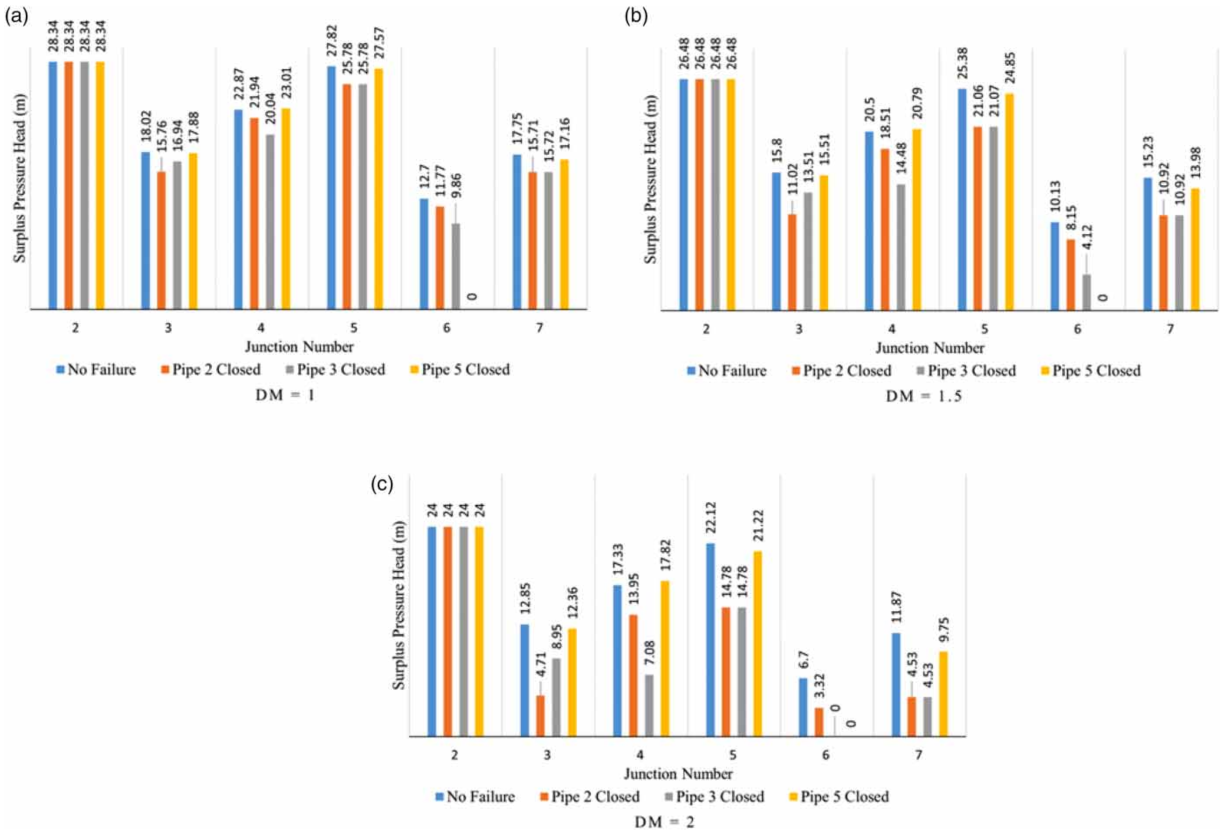


Figure 6 | Surplus pressure head (SPH) for Two Loop network: (a) SPH for MRI with DM = 1; (b) SPH for MRI with DM = 1.5; (c) SPH for MRI with DM = 2.

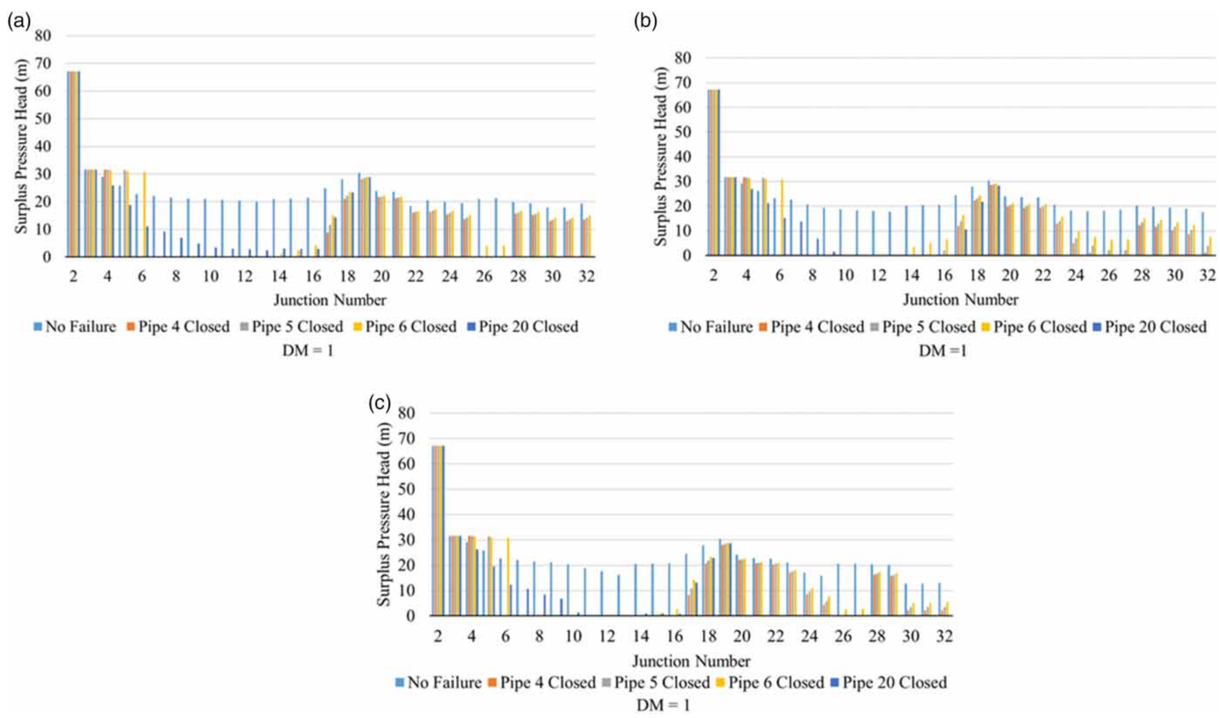


Figure 7 | Surplus pressure head (SPH) for Hanoi network: (a) SPH for RI with DM = 1; (b) SPH for NRI with DM = 1; (c) SPH for MRI with DM = 1.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

Table 5 | Summation of SPH values for Two Loop and Hanoi networks

Index	Summation SPH (m) - Two Loop	Summation SPH (m) – Hanoi
RI	1216.00	2223.69
NRI	1142.45	2096.33
MRI	1183.94	2056.56

CONCLUSIONS

Single objective optimization for WDN searches for a solution with minimum cost only. However least-cost solutions are less reliable and thus cannot sustain failures. The above problem can be solved by multi-objective optimization with reliability being one of the objectives. However, multi-objective optimization is a complex process and the complexity of it increases more when solved using evolutionary algorithms due to the involvement of various parameters in the algorithm. Optimal parameters must be found which is a tedious task.

The above mentioned problem is solved in the present work with the introduction of a new multi-objective evolutionary technique, MO-JAYANET, for the optimal design of water distribution networks. MO-JAYANET is found to be free from any algorithm-specific parameters and penalty parameters, thus skipping all the efforts that are otherwise required to tune the algorithm. MO-JAYANET is developed and tested on two well-known benchmark networks from the literature using three different extensively used RSMs as the second objective. PF for the three indices RI, NRI and MRI are developed and the PF of NRI is also overlapped with the BKPF from the literature for both the networks and found to cover the maximum curve area with single population size and fewer iterations. Thus the major achievement on application of Jaya algorithm for optimal design of WDN are:

(i) No algorithm parameters are involved and thus no need of their synchronization for optimal solution.
(ii) It is more efficient as the optimal solution is obtained in less function evaluations.

Efforts are made to test the maximum reliability solution obtained by MO-JAYANET under different hydraulic and mechanical failures. SPH graph for the maximum reliability solution is plotted and the index with maximum summation of SPH is selected as a better performing index. Based on the results obtained from the SPH analysis for both the hydraulic and mechanical failures it is concluded that Todini's RI performs slightly better for both the distribution networks under 11 different failure scenarios for the Two Loop network and 14 different failure scenarios for the Hanoi network. When compared between NRI and MRI, NRI is found to be a better performer for the Two Loop network and for the Hanoi network MRI performs better. These results are based on the SPH value, however extensive research is needed to comment on the best-performing index.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Alperovits, E. & Shamir, U. 1977 Design of optimal water distribution systems. *Water Resources Research* **13** (6), 885–900. doi:10.1029/WR013i006p00885.

Atkinson, S., Farmani, R., Memon, F. A. & Butler, D. 2014 Reliability indicators for water distribution system design: comparison. *Journal of Water Resources Planning and Management* **140** (2), 160–168. doi:10.1061/(ASCE)WR.1943-5452.0000304.

Baños, R., Reca, J., Martínez, J., Gil, C. & Márquez, A. L. 2011 Resilience indexes for water distribution network design: a performance analysis under demand uncertainty. *Water Resources Management* **25** (10), 2351–2366. doi:10.1007/s11269-011-9812-3.

Barlow, E. & Tanyimboh, T. T. 2014 Multiobjective memetic algorithm applied to the optimisation of water distribution systems. *Water Resources Management* **28** (8), 2229–2242. doi:10.1007/s11269-014-0608-0.

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest

Bhave, P. R. & Gupta, R. 2004 Optimal design of water distribution networks for fuzzy demands. *Civil Engineering and Environmental Systems* **21** (4), 229–245. doi:10.1080/10286600412331314564.

Creaco, E., Franchini, M. & Todini, E. 2016 The combined use of resilience and loop diameter uniformity as a good indirect measure of network reliability. *Urban Water Journal* **13** (2), 167–181. doi:10.1080/1573062X.2014.949799.

Deb, K., Pratap, A., Agarwal, S. & Meyarivan, T. A. M. T. 2002 A fast and elitist multiobjective genetic algorithm: *NSGA-II*. *IEEE Transactions on Evolutionary Computation* **6** (2), 182–197. doi:10.1109/4235.996017.

Farmani, R., Savic, D. A. & Walters, G. A. 2005 Evolutionary multi-objective optimization in water distribution network design. *Engineering Optimization* **37** (2), 167–183. doi:10.1080/03052150512331303436.

Fujiwara, O. & Khang, D. B. 1990 A two-phase decomposition method for optimal design of looped water distribution networks. *Water Resources Research* **26** (4), 539–549. doi:10.1029/WR026i004p00539.

Fuso, F., Cunha, M. C. & Becciu, G. 2020 Functional feasibility in optimal evaluation of water distribution network performances. *Water* **12** (12), 3404. doi:10.3390/w12123404.

Greco, R., Di Nardo, A. & Santonastaso, G. 2012 Resilience and entropy as indices of robustness of water distribution networks. *Journal of Hydroinformatics* **14** (3), 761–771. doi:10.2166/hydro.2012.037.

Jayaram, N. & Srinivasan, K. 2008 Performance-based optimal design and rehabilitation of water distribution networks using life cycle costing. *Water Resources Research* **44** (1). doi:10.1029/2006WR005316.

Jeong, G. & Kang, D. 2020 Comparative analysis of reliability indices and hydraulic measures for water distribution network performance evaluation. *Water* **12** (9), 2399. doi:10.3390/w12092399.

Liu, H., Savić, D. A., Kapelan, Z., Creaco, E. & Yuan, Y. 2017 Reliability surrogate measures for water distribution system design: comparative analysis. *American Society of Civil Engineers* doi:10.1061/(ASCE)WR.1943-5452.0000728.

Moghaddam, A., Peirovi-Minaee, R., Rezaei, H., Faridhosseini, A. & Ziaei, A. N. 2021 The evaluation of reliability indices in water distribution networks under pipe failure condition. *Drinking Water Engineering and Science Discussions* **1**, 29. doi:10.5194/dwes-2020-37.

Monsef, H., Naghashzadegan, M., Jamali, A. & Farmani, R. 2019 Comparison of evolutionary multi objective optimization algorithms in optimum design of water distribution network. *Ain Shams Engineering Journal* **10** (1), 103–111. doi:10.1016/j.asej.2018.04.003.

Moosavian, N. & Lence, B. J. 2020 Flow-uniformity index for reliable-Based optimal design of water-distribution networks. *Journal of Water Resources Planning and Management* **146** (3), 04020005. doi:10.1061/(ASCE)WR.1943-5452.0001161.

Ostfeld, A., Oliker, N. & Salomons, E. 2014 Multiobjective optimization for least cost design and resiliency of water distribution systems. *Journal of Water Resources Planning and Management* **140** (12), 04014037. doi:10.1061/(ASCE)WR.1943-5452.0000407.

Prasad, T. D. & Park, N. S. 2004 Multiobjective genetic algorithms for design of water distribution networks. *Journal of Water Resources Planning and Management* **130** (1), 73–82. doi:10.1061/(ASCE)0733-9496(2004)130:1(73).

Raad, D. N., Sinske, A. N. & Van Vuuren, J. H. 2010 Comparison of four reliability surrogate measures for water distribution systems design. *Water Resources Research* **46** (5). doi:10.1029/2009WR007785.

Rao, R. 2016 Jaya: a simple and new optimization algorithm for solving constrained and unconstrained optimization problems. *International Journal of Industrial Engineering Computations* **7** (1), 19–34. doi:10.5267/j.ijiec.2015.8.004.

Rossman, L. A. 2000 *EPANET 2: Users Manual*. USA Environmental Protection Agency, Washington, DC.

Siew, C. & Tanyimboh, T. T. 2012 Penalty-free feasibility boundary-convergent multi-objective evolutionary algorithm for the optimization of water distribution systems. *Water Resour. Manage* **26** (15), 4485–4507. doi:10.1007/s11269-012-0158-2.

Sirsant, S. & Janga Reddy, M. 2018 Reliability-based design of water distribution networks using self-adaptive differential evolution algorithm. *ISH Journal of Hydraulic Engineering* **24** (2), 198–212. doi:10.1080/09715010.2017.1408038.

Sirsant, S. & Reddy, M. J. 2017 Reliability-based design of water distribution networks considering mechanical failures. *European Water* **58**, 407–414.

Su, Y. C., Mays, L. W., Duan, N. & Lansey, K. E. 1987 Reliability-based optimization model for water distribution systems. *Journal of Hydraulic Engineering* **113** (12), 1539–1556. doi:10.1061/(ASCE)0733-9429(1987)113:12(1539).

Tabesh, M., Tanyimboh, T. T. & Burrows, R. 2001 Extended period reliability analysis of water distribution systems based on head driven simulation method. In: *Bridging the Gap: Meeting the World's Water and Environmental Resources Challenges*. pp. 1–11. doi:10.1061/40569(2001)385.

Todini, E. 2000 Looped water distribution networks design using a resilience index based heuristic approach. *Urban Water* **2** (2), 115–122. doi:10.1016/S1462-0758(00)00049-2.

Wang, Q., Guidolin, M., Savic, D. & Kapelan, Z. 2015 Two-objective design of benchmark problems of a water distribution system via MOEAs: towards the best-known approximation of the true pareto front. *Journal of Water Resources Planning and Management* **141** (3), 04014060. doi:10.1061/(ASCE)WR.1943-5452.0000460.

First received 3 September 2022; accepted in revised form 28 November 2022. Available online 5 December 2022

Downloaded from http://iwaponline.com/ws/article-pdf/22/12/8972/1260264/ws022128972.pdf
by guest