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Multi-objective design of water distribution systems based on the fuzzy reliability index

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ABSTRACT

This paper reports the application of a multi-objective evolutionary algorithm to the design of water distribution systems. The objective functions are the minimization of the capital costs and the maximization of the hydraulic reliability of the network so as to identify the tradeoff between cost and reliability. Furthermore, a new deterministic reliability index named fuzzy reliability index is introduced utilizing fuzzy logic and the definition of hydraulic reliability. The multi-objective honey-bee mating optimization (MOHBMO) algorithm is developed to achieve the design of two well-known water distribution networks. Results show that the proposed reliability measure is able to produce appropriate hydraulic reliability in the system and the MOHBMO algorithm calculates desirable Pareto-optimal solutions.

Key words | fuzzy reliability index, multi-objective HBMO, water distribution systems

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INTRODUCTION

Many recent investigations have been conducted in many aspects of water resources systems such as reservoir operation (Fallah-Mehdipour *et al.* 2011, 2012a, 2013a; Aboutalebi *et al.* 2015; Garousi-Nejad *et al.* 2016a), hydrology (Orouji *et al.* 2013; Aboutalebi *et al.* 2016), project management (Bozorg-Haddad *et al.* 2010a; Fallah-Mehdipour *et al.* 2012b), cultivation rules (Bozorg-Haddad *et al.* 2009; Fallah-Mehdipour *et al.* 2013b), pumping scheduling (Bozorg-Haddad *et al.* 2011), hydraulic structures (Bozorg-Haddad *et al.* 2010b), water distribution networks (Solgi *et al.* 2015, 2016; Bozorg-Haddad *et al.* 2016), operation of aquifer systems (Bozorg-Haddad & Mariño 2011), site selection of infrastructures (Karimi-Hosseini *et al.* 2011), and algorithmic developments (Shokri *et al.* 2013; Garousi-Nejad *et al.* 2016b). However, only a few of these works dealt with the fuzzy multi-objective design of water distribution systems (WDSs).

The use of optimization methods to design a WDS began about 30 years ago. Before that time, WDS design was usually performed based on trial and error by experienced engineers and, as a result, because of the complexity of these problems and also their large decision space, those designs were far from optimal. Thus, development of design methods with the aid of optimization techniques was inevitable. Alperovits & Shamir (1977) applied linear programming (LP) for the optimal design of WDS. Subsequently, Quindry *et al.* (1981), Goulter *et al.* (1986), and Kessler & Shamir (1989) complemented and further developed the method introduced earlier by Alperovits & Shamir (1977). Fujiwara & Kang (1990) suggested a two-phase decomposition method based on a nonlinear programming (NLP) gradient procedure. LP and NLP consider pipe diameters as continuous parameters while they are discrete commercial diameters. Thus, a modification is needed on the final continuous solutions obtained by LP or NLP methods. Furthermore, optimal solutions found by these methods usually contain one or two

pipe segments with different diameters between each pair of nodes and this split-pipe design must be altered into only one diameter (Savic & Walters 1997). These modifications may impact the final optimal solution and may introduce constraint violations (Cunha & Sousa 1999). Therefore, it is advantageous to develop methods that can overcome these problems or at least lessen them.

Savic & Walters (1997) suggested the application of evolutionary algorithms to overcome the aforementioned shortcomings in the least-cost design of WDSs. Evolutionary and meta-heuristic methods are efficient tools in solving nonlinear problems and do not involve linearization or calculation of partial derivatives. Moreover, because of the global sampling of these methods, the probability of reporting local optima as the final answer decreases significantly and also the impact of a starting solution on the final solution is negligible. Other investigators suggested the application of simulated annealing (Cunha & Sousa 1999), taboo search (Lippai *et al.* 1999), shuffled frog leaping algorithm (Eusuff & Lansey 2003; Seifollahi-Aghmiuni *et al.* 2011), ant colony optimization (Maier *et al.* 2003), harmony search (Geem 2006), particle swarm optimization (Suribabu & Neelakantan 2006), and honey-bee mating optimization (HBMO) (Soltanjalili *et al.* 2010; Ghajarnia *et al.* 2011), in the optimal design, the rehabilitation, and the calibration of WDSs (Bozorg-Haddad *et al.* 2008; Sabbaghpour *et al.* 2012). Those algorithms have been able to report more flexible and realistic designs for WDSs in comparison with traditional mathematical methods. Evolutionary algorithms permit the search for discrete commercial diameters easily in the optimization procedure. In addition, because of their global sampling for solutions these methods are more reliable than traditional methods in finding near-global optima of complex problems.

WDS design is beset by the trade-off between cost and reliability. Mays (1996) considered two types of failures in WDSs: mechanical (such as pipe breakage, pump failure, power outages, control valve failure, etc.) and hydraulic (such as changes in demand or in pressure head, aging of pipes, inadequate pipe sizing, insufficient pumping capacity, insufficient storage capability). Several investigators have tried to combine these two types of failures to define a measure of reliability (Todini 2000). However, there are no universally accepted definitions for risk and reliability for WDSs. Moreover, Walski *et al.* (1987) pointed out that a reliability measure should reflect the way in which water users are affected. There are various viewpoints on how to apply reliability in WDS design (Rowell & Barnes 1982; Kettler & Goulter 1983; Morgan & Goulter 1985; Goulter & Coals 1986; Goulter & Bouchart 1990; Ostfeld & Shamir 1996; Xu & Goulter 1999; Tabesh *et al.* 2004, 2009; Geem 2015).

The necessity of building cost-effective WDSs while ensuring consumers' satisfaction with supply during any operation period leads us to consider the design of a WDS as a multi-objective model with the following objectives: (1) minimization of the cost and (2) maximization of the efficiency factors. Walski (2001) lamented that in spite of numerous papers on optimal design of WDS in the past 15 years none has managed to take a leading role in the design of water distribution networks. The former author lamented the common emphasis on minimizing the cost of WDS without enough attention paid to the WDSs' efficiency, this being the main reason that these methods have not gained widespread acceptance. Focusing on the minimization of WDS costs neglects the efficiency factors, such as the reliability in delivering demand with a desired pressure. Hence, the optimal design of WDS must aim at cost effectiveness and achieving maximum system reliability. This explains the pre-eminence taken by the multi-objective design of WDS.

Several researchers implemented multi-objective optimization to the design of WDSs (i.e. Farmani *et al.* 2005; Fu & Kapelan 2011; Wang *et al.* 2014; Geem 2015). Todini (2000) stated that if the WDS design is performed based on the complete satisfaction of the hydraulic constraints it may not be capable of delivering water with sufficient pressure and discharge during failures. Therefore, the probability of delivering water with a desirable pressure increases if each node is provided with more power (energy per unit time) than required so as to have a sufficient surplus to be dissipated internally in the case of failures (Todini 2000). This surplus was considered as a reliability measure by Todini (2000) and is named resilience (I_r). The latter author considered the two objective functions of cost minimization and maximization of (I_r) for the multi-objective design of two water networks.

According to Prasad & Park (2004), by maximizing Todini's (2000) resilience index some surplus pressure can

be provided in the network and this does not have any influence on the redundancy of the network loops. They indicated that by having a high I_r index in a tree-shaped network is not enough to guarantee a high level of reliability since any failure, and, particularly, a pipe failure, in a tree-shaped or cost-optimized network can have severe consequences in terms of reliability. Thus, resiliency alone is not enough for assessing the reliability of a network and a modification is needed to assess the reliability of the network loops. Prasad & Park (2004) modified the resilience index in a way to be capable of ensuring the network with reliable loops and named the improved index as network resilience (I_n). Neither the I_r index nor the I_n index consider the maximum allowable pressure in their calculations. In fact, as the I_r or I_n reliability indices increase, the nodal pressures of the network increase without any restriction, which may lead to uncontrollable leakage of the pipes in failure conditions.

This paper proposes a new deterministic reliability index based on fuzzy logic. In addition, the multi-objective MOHBMO algorithm is presented to perform multi-objective WDS design. The results are assessed based on the final Pareto front obtained after applying the algorithm on two well-known and benchmark networks. The effectiveness of the introduced reliability measure is also examined by assessing the final solutions from the viewpoint of nodal pressures and having reliable loops. Identification of the payoff between cost and reliability is also another aim of this study, which is obtained by applying the MOHBMO algorithm in complex, nonlinear, and discrete networks.

THE FUZZY RELIABILITY INDEX

All WDSs have a value for minimum allowable pressure due to the regional topography and their nodal demands. The network suffers failures whenever the supplied nodal pressures during the operational period fall below the minimum required level, in which case rehabilitation alternatives must be taken. Thus, by having higher values of nodal pressures, the network is more capable of facing hydraulic failures and its reliability in supplying required pressure will increase. On the other hand, nodal pressure in each network has a maximum permissible value which is defined

based on the resistance of network components. Nodal pressures greater than the maximum permissible value cause undesirable leakage and breakage, which lead to a considerable decrease in the useful life of the network. Hence, the optimal value of the design nodal pressure in the network should fall between the minimum and maximum permissible values. This study introduces a fuzzy function in the range between the minimum and maximum permissible pressure heads and defines the fuzzy reliability index (*FRI*) as follows:

$$MemF_j = \begin{cases} 0 & If\ h_j \leq h_{j*} \\ \dfrac{2}{h_j^{**} - h_{j*}}(h_j - h_{j*}) & If\ h_{j*} < h_j \leq \dfrac{h_{j*} + h_j^{**}}{2} \\ \dfrac{2}{h_{j*} - h_j^{**}}(h_j - h_j^{**}) & If\ \dfrac{h_{j*} + h_j^{**}}{2} < h_j \leq h_j^{**} \\ 0 & If\ h_j > h_j^{**} \end{cases}$$

$$(1)$$

in which $MemF_j = $ fuzzy membership value for node j; $h_j = $ pressure head in node j; $h_{j*} = $ minimum required pressure head for node j; and $h_j^{**} = $ maximum permissible pressure head for node j. The fuzzy membership value for each node in the WDS is calculated with Equation (1) and this equals the *FRI* index for that node. Thus, due to the definition of $MemF_j$, the reliability of the network nodes increases if their pressure values are close to the average value of minimum and maximum permissible values. Figure 1 provides insight into the definition of fuzzy membership function. It is shown in Figure 1 that the optimal value of fuzzy membership (equal to one) is achieved when the pressure head is equal to the average of the minimum and maximum of permissible values.

Each network node has a specific water-demand value which determines its importance from the viewpoint of water supply in the network. Clearly, nodes with higher levels of water demand have more importance in comparison with nodes with lower consumption rates. Thus, to consider this importance in the reliability calculations, C_j^1 is denoted as the demand coefficient and is defined as follows:

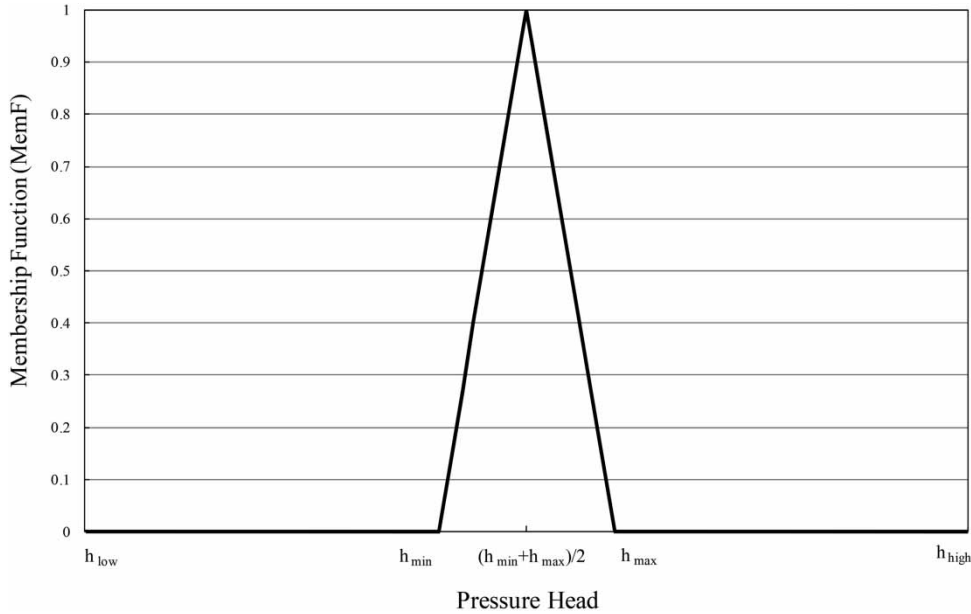$$C_j^1 = 1 - \frac{q_{j*}}{\sum_{j=1}^{Nj} q_{j*}}$$

$$(2)$$

Figure 1 │ Fuzzy membership function applied in the *FRI* formula.

where C_j^1 = demand coefficient in each node j; q_{j*} = nodal demand in node j; and N_j = number of network nodes. By multiplying C_j^1 in $MemF_j$, the membership value of high consumption nodes decreases and the membership value of low consumption nodes increases.

The importance of high consumption nodes is considered in a reverse order here since the *FRI* index is defined to be used in an optimization model. In an optimization model intending to maximize an index, solutions with values lower than the index are restrictive. As a result, the model improves solutions with lower values of the desired index. That is, the optimization model focuses on improving the condition of high-consumption nodes over those of other junctions. The sensitivity of high-consumption nodes is increased by decreasing their membership values, which is a desirable feature of WDSs. Thus, by defining the objective function to maximize the *FRI* index it is possible to improve the value of critical (high-consumption) nodes. This assures that the final optimal answer cannot have low *FRI* values in high consumption nodes. It is noteworthy that there are other considerations in the design of WDSs. For example, there may be low-demand nodes which are critical and strategically important, e.g. supplying hospitals and other essential facilities. Thus, one must consider site-specific requirements that are implemented in the FRI equations.

The Prasad & Park (2004) coefficient is applied in the *FRI* index to improve the redundancy in network loops. Prasad & Park (2004) claimed that network loop reliability is improved when the diameters of the pipes in each loop are as similar to each other as possible. The proposed coefficient, C_j^2, is given by:

$$C_j^2 = \frac{\sum_{i=1}^{NP_j} D_{ij}}{NP_j \times D_{Max_j}} \qquad (3)$$

where C_j^2 = coefficient introduced by Prasad & Park (2004) to ensure redundancy in network loops, calculated at each node j; D_{ij} = diameter of pipe i which is connected to node j; NP_j = number of pipes connected to node j; and D_{Max_j} = diameter of the largest pipe connected to node j. Equation (3) produces a C_j^2 equal to one when the diameters of all the pipes connected to a node are equal to each other; otherwise, it is less than its optimal value. Reliance on Equations (1)–(3) yields the *FRI* index:

$$FRI_j = MemF_j \times C_j^1 \times C_j^2 \qquad (4)$$

The final value of the *FRI* index for each node takes into account the magnitude of pressure reliability achieved in supplying the total network water demand and also considers the redundancy of the network loops.

THE MULTI-OBJECTIVE OPTIMIZATION MODEL

The aim of this study is to minimize the cost of WDSs and maximize the *FRI*. Letting *Cost* and *Reliability* denote the cost of network pipes and system's reliability, respectively, the following objective function takes into account the minimization of the network capital costs and the maximization of the *FRI* index.

Minimize cost, where cost is given by:

$$Cost = \sum_{i=1}^{Ni} C(D_i) \cdot L_i + \sum_{j=1}^{Nj} PF_j^1 \qquad (5)$$

where $C(D_i)$ = unit length cost of pipe *i* with diameter D_i; PF_j^1 = penalty function on minimum allowable pressure constraints; L_i = length of pipe *i*; and *Ni* = number of network pipes; and maximize reliability, where reliability is expressed as follows:

$$reliability = \left(\sum_{j=1}^{Nj} FRI_j \right) \times Min(FRI_j) \qquad (6)$$

The reliability objective function in Equation (6) considers the sum and the minimum values of *FRI* indices at all nodes in the calculations. Thus, by maximizing *Z* all the *FRI* indices in all nodes are maximized and the *FRI* index of any probable critical node (the node with the lowest *FRI* value) is maximized.

Equation (7) is a penalty function added to the cost objective function. That is:

$$PF_j^1 = \begin{cases} \alpha_1 (h_{j*} - h_j)^{\alpha_2} & \text{if } h_j < h_{j*} \\ 0 & \text{if } h_j \geq h_{j*} \end{cases} \qquad (7)$$

where α_1 and α_2 = constant coefficients whose values depend on the problem being considered.

Let h_1 and h_2 = pressure heads; V_1 and V_2 = water velocities; Z_1 and Z_2 = elevation of points 1 and 2 in one stream flow; $h_f^{1,2}$ = head loss between points 1 and 2 along a flow path; $Q_{i,j}$ = discharge of the *i*th inflow or outflow pipe connected to node *j*; h_{fi} = head loss in pipe *i*; ω = constant coefficient in the Hazen–Williams formula; C_i^{HW} = Hazen–Williams coefficient of pipe *i*; Q_i = discharge in pipe *i*; *g* = earth's gravity; and *NIn* and *NOut* = number of pipes with incoming or outgoing flow, respectively. Three hydraulic constraints stated in Equations (8)–(10) are imposed in the design of a WDS:

$$h_1 + \frac{V_1^2}{2g} + Z_1 - h_f^{1,2} = h_2 + \frac{V_2^2}{2g} + Z_2 \qquad (8)$$

$$\sum_{i=1}^{NIn} Q_{i,j} = \sum_{i=1}^{NOut} Q_{i,j} \ \forall \, j = 1, 2, \ldots, Nj \qquad (9)$$

$$h_{f_i} = \omega L C_i^{HW^{-1.852}} D_i^{-4.871} Q_i^{1.852} \ \forall \, i = 1, 2, \ldots, Ni \qquad (10)$$

The hydraulic simulation of WDS in this study is performed with the EPANET 2.0 software (Rossman 1993), which satisfies constraints (8)–(10) automatically.

THE MOHBMO ALGORITHM

MOHBMO is the multi-objective version of HBMO algorithm presented by Bozorg-Haddad *et al.* (2006). The superiority of the MOHBMO over the multi-objective genetic algorithm and multi-objective particle swarm optimization has been demonstrated in other fields of study (i.e. Niknam *et al.* 2011), although it has not been applied to design water distribution networks. MOHBMO is inspired by the natural life of honey-bees. Each bee hive can contain one or more queens. The queens exit the hive during the mating season and perform the mating flight by attracting drones. Successful drones which mate with the queen do not necessarily belong to the queen's hive. In other words, the queen might mate with drones belonging to other hives. In addition, two queens might not live in the same hive. Therefore, if a hive contains two queens, one of them leaves the hive and migrates to another bee

hive which does not contain a queen. It is possible for the migratory queen to mate also with drones of a new hive, leading to the replacement of honey-bee genes between different bee hives. This mating ritual inspired the development of the multi-objective version of the HBMO algorithm.

In MOHBMO, at first two hives with two (or more) different queens are generated. Each hive performs a single objective optimization with one objective function and attempts to improve its queen after a predefined number of iterations. In a multi-objective problem, the final Pareto solutions found by the algorithm do not extend beyond the area defined by the solutions obtained by solving the single objective problem with each objective function. Thus, to obtain a proper multi-objective Pareto it is necessary for its two extreme points to be as near as possible to the solutions found by the single objective solutions of the problem. To ensure the aforementioned Pareto condition a warm up (WU) period is added to the MOHBMO algorithm (Fallah-Mehdipour *et al.* 2011). During the WU period, each hive attempts to improve the queen through the global optimum of its own objective function by performing a considerable number of iterations. This produces two different solutions; one having optimal conditions related to the first objective function and the other having optimal conditions related to the second objective function. These solutions are compared with each other. If one of them dominates the other, it is then added to the non-dominated list, otherwise both of them are added to the non-dominated list. The queens are then replaced in the hives. This means that the best solution for first objective function moves to the hive which improves the second objective function, and vice versa. Thereafter, each hive starts evolving once more through its own objective function using a new queen, while at this stage the number of iterations is much less than that in the WU period. After conducting a predefined number of iterations the final solutions are compared and moved to the non-dominated list. Each new member which is added to the non-dominated list is compared with older ones and at the end of the iterations only the non-dominated solutions remain in the list.

After updating the non-dominated list the solution having a better value of the first objective function moves into the second hive (which improves the second objective function), and vice versa. Once more, each hive starts

evolving to improve its own objective function and this repetitive procedure continues until the stopping criterion, which is usually a predefined number of iterations, is reached. If the WU period performs well and the number of each hive's iterations during the repetitive procedure and the stopping criterion is chosen correctly, one can expect a well distributed and expanded Pareto solution. Figure 2 shows a flowchart of the MOHBMO algorithm, in which NWU1 and NWU2 are the number of iterations in the WU periods for the first and second hives, respectively. Also, Itt1 and Itt2 define the numbers of each hive's iterations during the repetitive procedure and Rep is the repetition number of the repetitive procedure (stopping criterion).

RESULTS

MOHBMO is applied to the design of two well-known benchmark problems for the design of WDSs. The following sections present the results of these applications.

Case 1: The two-loop network

The proposed algorithm with the two considered objective functions is applied in two benchmark problems. The first problem is the network introduced by Alperovits & Shamir (1977), which has been considered by many investigators (Savic & Walters 1997; Cunha & Sousa 1999; Lippai *et al.* 1999; Eusuff & Lansey 2003; Geem 2006). This two-loop network is a simple gravity-fed WDS consisting of eight pipes (each 1,000 m long with Hazen–Williams value, C, of 130 and ω value of 10.6744 which are the considered value in the EPANET 2.0 software), seven nodes, and a single reservoir (Figure 3). The minimum and maximum permissible pressure heads are 30 and 60 m for each node, respectively ($P_{j*} = 30$ and $P_j^{**} = 60$). The commercially available pipe sizes and corresponding cost per unit length and the network nodes data are given in Alperovits & Shamir (1977).

Multi-objective design of the two-loop network was performed by making the pipe diameters the decision variables, applying the MOHBMO algorithm so that the first hive performs cost minimization and the second hive performs *FRI* maximization. Ten different runs of the MOHBMO
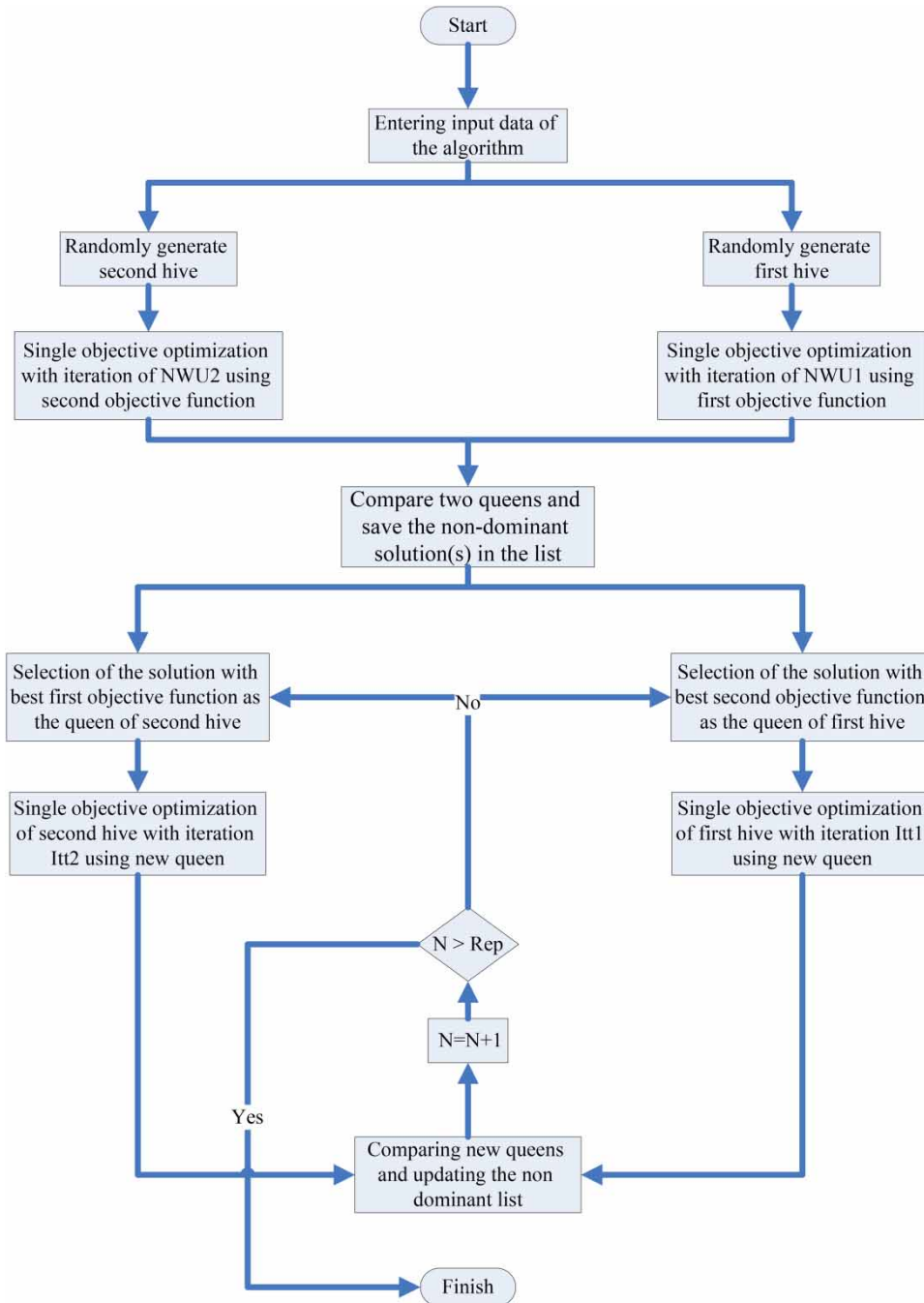
Figure 2 │ Flowchart of the MOHBMO algorithm. NWU1 and NWU2 are the number of iterations in the WU periods for the first and second hives, respectively.

algorithm were conducted to obtain a sample of optimal Paretos. The 10 different Pareto solutions were mixed to arrive at the final Pareto shown in Figure 4. All the elements of this Pareto are feasible solutions. Moreover, the hyper volume index of this Pareto set, which is a performance

metric of Pareto front and evaluates the density of the Pareto front (Deb 2001), was calculated and its value was equal to 0.86.

Two extreme points in the Pareto of Figure 4 (points A and B) are obtained by a single objective design of the
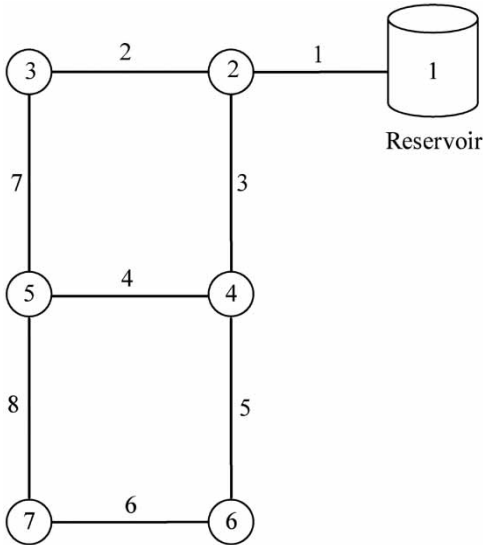
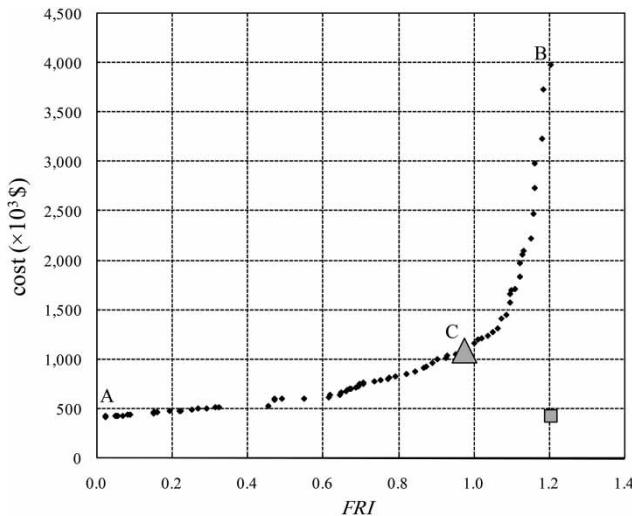**Figure 3** | Schematic of the two-loop network.

Figure 4 | Pareto solution of two-loop network problem and selected points.

two-loop network, using each objective function separately (WU period). It is seen in Figure 4 that the MOHBMO algorithm was able to cover the area between these two boundary points.

The main aim of the multi-objective design of a WDS is to find a solution which is optimal with respect to the single objective functions. Hence, it is necessary to select one of the solutions on the Pareto set to report it as the final result of the multi-objective design. In this regard, there are different conflict resolution methods to achieve this

selection. This study implements the method of Young (1993), in which a desirability or utility function is distributed for each objective function and one of them is chosen by maximizing a mathematical equation based on the gradient of different points of the Pareto (Young 1993). By using this method, point C (Figure 4) is chosen and differentiated by a triangle in Figure 4. The minimum cost solution, maximum FRI solution, and the selected point by Young's (1993) model have been named A, B, and C, respectively, in Figure 4. Their corresponding pipe diameters, pressure head, and FRI values are reported in Tables 1 and 2. Also, the values of both objective functions are shown in these tables. By comparing these values it is seen that the reliability of solution C is 40 times that of solution A, while its cost is only 2.5 times of the cost associated with solution A. A similar

Table 1 | The pipe diameters for solutions A, C, and B in the two-loop network

Point Pipe no.	A D (cm)	C D (cm)	B D (cm)
1	45.72	45.72	45.72
2	25.40	50.80	69.96
3	40.46	50.80	69.96
4	10.16	35.56	69.96
5	40.64	45.72	69.96
6	25.40	45.72	69.96
7	25.40	50.80	69.96
8	2.54	45.72	69.96
Cost ($)	419,000	1,090,000	3,980,000

Table 2 | The nodal pressure heads and FRI indices for solutions A, C, and B in the two-loop network

Point Node	A FRI	A Head (m)	C FRI	C Head (m)	B FRI	B Head (m)
2	0.34	53.25	0.40	53.25	0.38	53.25
3	0.04	30.46	0.76	42.41	0.79	42.93
4	0.60	43.45	0.66	47.19	0.73	47.78
5	0.10	33.81	0.36	51.88	0.37	52.74
6	0.02	30.44	0.31	36.55	0.36	37.64
7	0.02	30.55	0.63	41.55	0.69	42.64
FRI obj. fun.	0.0234		0.9749		1.2055	

comparison on points C and B indicates that solution C achieves 80% of the reliability of solution B while its cost is only a third (0.33) of that of B.

Clearly, the best point on a Pareto set is the point whose objective functions' values are close to the optimal values of each single objective function. In other words, the best design for the two-loop network is the one whose cost is equal to $419,000 and its *FRI* reliability index is 1.2055. Obviously, such a network does not exist. Showing this point with a rectangle in Figure 4 helps evaluating the Pareto set. It can be seen in Figure 4 that the Pareto set obtained by the MOHBMO algorithm has a proper convexity towards the rectangle. This means that some of the non-dominant solutions have close proximity to this hypothetical optimal point, and even the point selected with the method of Young (1993) fall within that area too.

Figure 5 depicts the change of nodal pressure heads for solutions A, C, and B. The first noticeable point in this figure is that the nodal pressure heads of solution A, which is obtained from minimum cost design of the two-loop network, is very close to the minimum allowable pressure head (30 m of water). Yet, in solutions C and B the nodal pressure heads are close to the average value of the minimum and maximum permissible values (45 m of water). Figure 5 demonstrates that the second objective function was able to successfully bring the nodal pressures close to the considered optimal value, which is the average of h_j^{**} and less than h_{j*} consistent with the definition of the *FRI* index (Figure 1).

Figure 6 shows the pipe diameters of all three solutions in a bar diagram. There are eight scaled bars in this diagram,
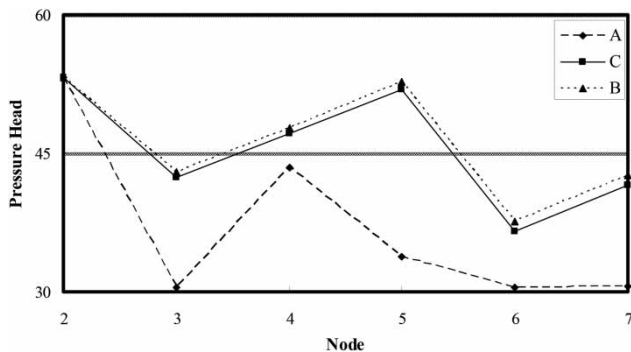
each of them being related to one pipe. A geometrical diagram is obtained by defining the pipe diameter on these bars and connecting the points. The more this geometrical diagram is close to a square, the more reliable are the network loops, according to the criterion of Prasad & Park (2004). It is seen in Figure 6 that the solution B which is obtained from maximum design of the two-loop network has the most uniform pipe diameters as its geometric diagram is very close to a square. Thus, it can be concluded that the *FRI* index is able to bring the nodal pressures to the proposed optimum value and is capable of producing reliable loops.

Case 2: The Hanoi network

The second problem concerns a water distribution network of Hanoi city in Vietnam (Fujiwara & Kang 1990). Figure 7 shows the schematic of Hanoi network. This network contains 32 nodes and 34 pipes organized in three loops. No pumping facilities are considered for the network since only a single fixed head reservoir at an elevation of 100 m is available. The minimum and maximum permissible pressure heads are 30 and 60 m for each node, respectively ($P_{j*} = 30$ and $P_j^{**} = 60$). The Hazen–Williams C coefficient and ω value are considered to be 130 and 10.5088, respectively. Other relevant data are presented by Fujiwara & Kang (1990).

Figure 5 │ Nodal pressure heads for solutions A, C, and B (meters of water) in the two-loop network.
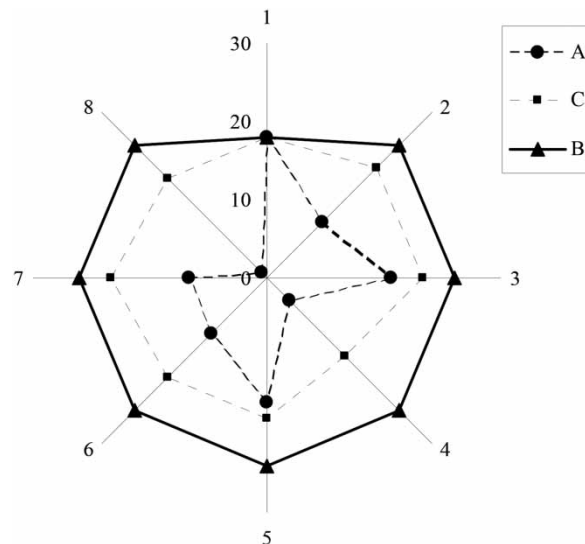

Figure 6 │ Pipe diameters of solutions A, C, and B (inches) in the two-loop network.
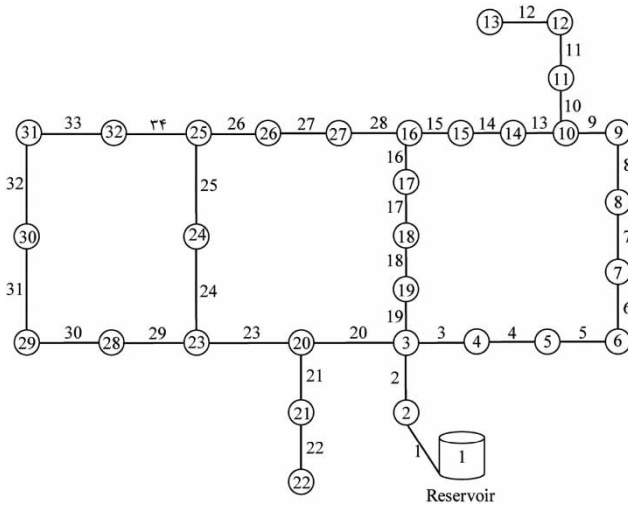
Figure 7 | Schematic of the Hanoi network.

The final Pareto set in the multi-objective design of the Hanoi Network was obtained by combining 10 different Pareto sets resulting from 10 different MOHBMO runs. Figure 8 shows the final non-dominant solutions which are all feasible. Moreover, the hyper volume index for this Pareto set was calculated to equal 0.72.

Point H was selected in this Pareto set with the method of Young (1993), and is shown by a triangle in Figure 8. Capital cost and *FRI* values for this solution are $7,244,479 and 0.17, respectively. Solution H is able to supply 80% of the reliability of solution G while its cost is
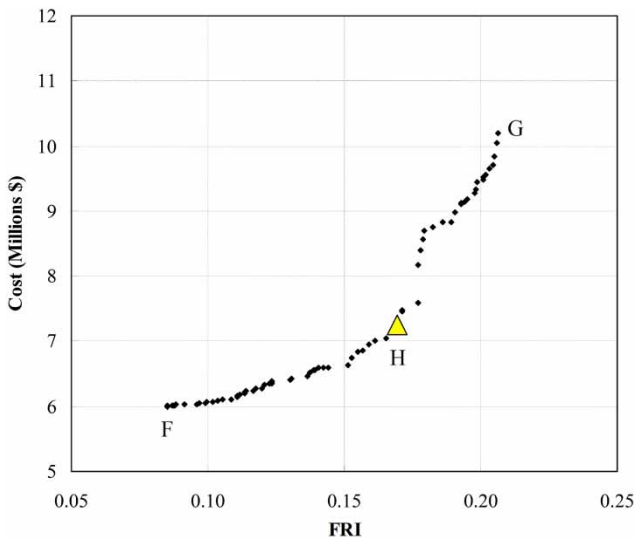

Figure 8 | Pareto solution of the Hanoi network problem and selected points.

only 0.7 of that. By a similar comparison between points H and F it is concluded that although the cost of solution H is 1.2 times higher than solution F, its reliability is 13 times higher. Furthermore, Table 3 shows the diameters of solution H, while the *FRI* index data for this solution is reported in Table 4. It is seen in Table 4 that Node 2 appears to have a high head. The model chooses pipes' diameters such that the pressure of the nodes immediately downstream the reservoir is relatively high in order to cope with the head losses throughout the gravity network.

CONCLUSIONS

This study presented a new deterministic fuzzy reliability index named *FRI* for the design of WDSs. Another goal of this study was the multi-objective design of WDS. The multi-objective version of the HBMO (MOHBMO) algorithm was developed and applied to the bi-objective design of two benchmark problems with one objective function for cost minimization and the other for reliability maximization. This paper's results demonstrated that the *FRI* index is

Table 3 | Pipe diameters for solution H in the Hanoi network

Pipe	D (cm)	Pipe	D (cm)
1	101.60	18	60.96
2	101.60	19	101.60
3	101.60	20	50.80
4	101.60	21	50.80
5	101.60	22	101.60
6	101.60	23	101.60
7	101.60	24	101.60
8	101.60	25	50.80
9	76.20	26	50.80
10	101.60	27	60.96
11	101.60	28	50.80
12	60.96	29	50.80
13	40.64	30	30.48
14	30.48	31	40.64
15	30.48	32	40.64
16	60.96	33	101.60
17	60.96	34	101.60

Table 4 │ Nodal pressure heads and FRI indices for solution H in the Hanoi network

Node	Head (m)	MemF	*FRI*	Node	Head (m)	MemF	*FRI*
2	97.21	0.0092	0.0087	18	52.23	0.5227	0.4874
3	62.55	0.0099	0.0089	19	61.01	0.0100	0.0090
4	58.56	0.1051	0.1045	20	52.19	0.5252	0.4097
5	53.63	0.4305	0.4149	21	43.06	0.8718	0.8311
6	48.51	0.7681	0.7294	22	42.64	0.8928	0.7050
7	47.35	0.8449	0.7877	23	46.62	0.8928	0.7050
8	46.04	0.9312	0.9055	24	45.47	0.9690	0.9292
9	45.04	0.9976	0.8499	25	44.77	0.9845	0.8134
10	42.16	0.8126	0.5670	26	42.16	0.8127	0.7760
11	41.78	0.7878	0.7680	27	42.15	0.8121	0.7306
12	41.51	0.7694	0.5982	28	44.18	0.9461	0.9323
13	37.39	0.4980	0.4745	29	42.99	0.8672	0.6813
14	39.50	0.6371	0.5403	30	42.80	0.8548	0.7344
15	39.57	0.6416	0.6326	31	42.97	0.8659	0.8613
16	42.26	0.8189	0.6718	32	44.61	0.9745	0.6546
17	45.41	0.9730	0.9308	–	–	–	–

able to bring the nodal pressures close to their optimal values (those defined as the average of minimum and maximum permissible values in this study), and is capable of producing redundant loops. The results indicated acceptable performance of the *FRI* index and MOHBMO algorithm that produced a set of optimal non-dominant solutions for decision makers.

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