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Intermittent Urban Water Supply with Protection of Consumers' Welfare

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Abstract: Intermittent operation of water networks is prevalent in many developing countries. It is a practical method to continue operation of water distribution networks (WDNs) during unexpected water shortages. Implementation of intermittent water supply compels consumers to withstand periods of interrupted water supply. Intermittent operation increases operating and maintenance costs attributable to the damage of pipes and valves caused by water pressure fluctuations. This paper considers consumers' welfare and system depreciation simultaneously in a multiobjective optimization model for intermittent water supply in WDNs. The objectives of the optimization model are the improvement of water supply resiliency and the maximization of the mechanical reliability of WDNs. The optimization model is solved by means of the honey-bee mating optimization (HBMO) algorithm linked to WDN hydraulic simulator software. The model's performance is tested with several shortage scenarios in two different WDNs. The calculated results show the optimization model's capacity to determine optimal values of water supply resiliency, and demonstrate that consumers' welfare may conflict with the objective of mechanical reliability, giving rise to an optimization possibility tradeoff frontier. **DOI: 10.1061/(ASCE)PS.1949-1204.0000231.** *© 2016 American Society of Civil Engineers.*

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Introduction

Water shortages due to hydrologic drought, natural disasters (e.g., earthquakes), conflicts (e.g., war) and intentional or accidental water pollution coupled with inadequate water-resources development may preclude the continuous operation of water distribution networks. One of the methods used to counteract urban water scarcity is intermittent water supply (Solgi et al. 2015). In addition, intermittent operation of water networks is common among developing countries (Ameyaw et al. 2013). A properly functioning water system is pressurized continuously and serves consumers without interruption. On the other hand, in an intermittent system the total amount of available water is less than consumers' demands, and operators have to cut the water supply to some parts of the network regularly (e.g., for a few hours daily). In intermittent water supply, customers' water needs are not fully satisfied. Most likely, the intermittent operation of distribution networks would cause adverse effects. When the intermittent operation of a network is inevitable, intermittent water supply must be implemented so that its adverse impacts are minimized.

Sashikumar et al. (2003) investigated the effect of initial filling of water pipes. Field experiments have shown that it may take even 1–2 h for air to be fully vented out of a water distribution system, after which hydraulic conditions stabilize. Andey and Kelkar (2009) conducted a study in four Indian cities to evaluate influence of intermittent water supply (IWS) and continuous water supply (CWS) on domestic water consumption. Soltanjalili et al. (2013) proposed intermittent water supply as a way to avoid severe water shortages. Solgi et al. (2015) developed an optimization model to consider the equanimity and justice of the water supply among consumers with the intermittent operation of water distribution networks.

Water distribution systems are essential components of urban water supply. Their design, operation, and calibration have been the subject of extensive research aiming at optimization their cost of operation and maximize serviceability (see recent work by Bozorg Haddad et al. 2008; Fallah-Mehdipour et al. 2011; Seifollahi-Aghmiuni et al. 2011, 2013; Sabbaghpour et al. 2012; Suribabu 2012; Babu and Vijayalakshmi 2013; Ezzeldin et al. 2014).

The Honey Bee Mating Optimization (HBMO) algorithm was developed by Bozorg Haddad et al. (2006). This algorithm has the ability to solve different engineering optimization problems with accuracy and efficiently. Many researchers have used the HBMO algorithm in various fields of water resources, e.g., water distribution networks, and they have proved that the HBMO algorithm has better performance than other algorithms, e.g., the genetic algorithm (GA) (Bozorg Haddad et al. 2006, 2008, 2011; Jahanshahi and Bozorg Haddad 2008; Karimi et al. 2013). Recently, the HBMO algorithm has been used for the optimal utilization of intermittent systems, and its good performance in solving such problems has been established (Soltanjalili et al. 2013; Solgi et al. 2015).

In intermittent systems, the pipes are empty during several hours of the day and hold water and air simultaneously. For this reason intermittent systems suffer from such problems as drastic pressure changes that cause damage to the network infrastructure, leading to

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failure to meet fire demands in some areas where water is absent, variations of the Hazen-Williams coefficient due to air mixing with water in the pipes, malfunction of water measurement equipment, and consumer dissatisfaction (Batish 2003; Sashikumar et al. 2003; Tushuka et al. 2004; Soltanjalili et al. 2013; Solgi et al. 2015).

Several studies have focused on intermittent operation of WDNs in recent years. Yet, there is not an efficient optimization model to decrease the operating and maintenance costs in intermittent operation. The implementation of intermittent water supply compels consumers to withstand periods of interrupted water supply. Prolongation of periods of interruption causes dissatisfaction of consumers. Therefore, water supply resiliency is one of the key issues to be considered in the intermittent operation of water distribution networks to protect consumers' welfare. In addition, intermittent operation increases operation costs associated with intermittent control and maintenance costs attributable to damage of pipes and valves caused by water pressure fluctuations. For these reasons another issue to be considered in scheduling of intermittent supply is mechanical reliability. This study considers simultaneously water supply resiliency and mechanical reliability as objectives of a multiobjective optimization model to determine the optimal scheduling of intermittent supply. The optimization model is applied to a benchmark and a real distribution network under different water-shortage scenarios. Finally, the trade-off curve, or optimization possibility frontier, of the two objectives is determined.

Methodology

In intermittent water supply mode, a node's demand is sometimes fully supplied and sometimes no water is supplied in a simulation period. When a node's demand is met, the water supply is considered a success. When no water is supplied on a node, it is considered as a WDN failure. Hashimoto et al. (1982) defined the return probability from a failure status to the success status as resiliency. According to this definition, the supply resiliency is equal to the number of times the WDN returns from failure to the success status divided by the number of times the system fails to meet water demands. A small value of resiliency in a WDN indicates frequent failures. On the other hand, in order to switch on and off the water supply at a node, the valves must be opened and closed intermittently. A WDN operating without failure (the ideal situation) is expected to remain on after turning on the system at the start of operation until the end of the operation period. Hashimoto et al. (1982) defined the reliability as the probability of success in a system. Therefore, the mechanical reliability is defined as the probability of not switching off a WDN. An ideal system implies a mechanical reliability is equal to one, which implies the WDN is never turned off during the operation period. WDNs that have reliability less than one undergo on and off cycles. The valves of a WDN are opened and closed, causing damage to the network infrastructure and increasing the cost of operation. Also water consumers are forced to endure longer periods of interrupted water supply when a WDN's resiliency decreases. Therefore, this work considers as objectives the maximization of water supply resiliency and the improvement of mechanical reliability in the intermittent operation of a WDN. The HBMO algorithm is herein linked to the hydraulic simulator software *EPANET 2.0* (Rossman 2000) to solve single-objective and dual-objective optimization of WDN operation.

Optimization Objectives

Eqs. (1) and (2) optimize, respectively, the water supply resiliency and the mechanical reliability of a WDN

$$\text{Max } f_1 = \prod_{i=1}^{Nnode} \left(\frac{\sum_{j=1}^{Nperiod} M_{i,j}}{Nperiod - \sum_{j=1}^{Nperiod} x_{i,j}} \right) \quad \text{where}$$
$$M_{i,j} = \begin{cases} 1 & \text{if } x_{i,j} \text{ and } x_{i,j+1} = 1 \\ 0 & \text{elseif} \end{cases} \tag{1}$$

$$\text{Max } f_2 = \frac{1}{\sum_{i=1}^{Nnode} (\sum_{j=1}^{Nperiod} K_{i,j})} \quad \text{where}$$
$$K_{i,j} = \begin{cases} 1 & \text{if } x_{i,j} + x_{i,j+1} = 1 \\ 0 & \text{elseif} \end{cases} \tag{2}$$

in which f_1 = supply resiliency; f_2 = mechanical reliability; $x_{i,j}$ = decision variable of cut-flow and on-flow for the ith node in the jth simulation period; $M_{i,j}$ = number of times an on-flow condition is reached immediately after a cut-flow at the ith node in the jth simulation period; $Nperiod$ = total number of simulation periods in the operation period; $Nnode$ = number of network nodes; $K_{i,j}$ = number of consecutive cut-flow and on-flow occurrences for the ith node in the jth simulation period; i = node index; and j = simulation period index.

In Eq. (1), the sum of $x_{i,j}$ means the number of on-flow periods over the operational period. For example if the network has six on-flow periods and four cut-flow periods in 2 days, then $x_{i,j}$ is equal to 6. The denominator in Eq. (1) defines the number of failures (cut-flow) in an operational duration for each node. The sum $M_{i,j}$ means the number of victories in the operational duration for each node. A victory is defined as the achievement of an on-flow period immediately after a cut-flow period. This definition of victory underlies the concept of resiliency, which means the probability of exiting from a failure situation. A victory ranges between 0 and 1, i.e., 0 when no on-flow is obtained after a cut-flow, and 1 when all the cut-flow periods lead to on-flow periods in each node. Thus, a victory multiplier is between 0 and 1 for all nodes. In Eq. (2), $K_{i,j}$ is the number of openings and closures of the valves at each node. When an opening occurs (from cut-flow to on-flow) the value of the decision variable changes from 0 to 1, and vice versa.

Eqs. (3)–(10) describe the constraints of the optimization problem. Soltanjalili et al. (2013) defined Eq. (3) to represent the consumers' welfare and increased consumers' satisfaction in providing intermittent supply. Repetitive cut-flow at the same hours on any day is highly disruptive to customers' lifestyles. The constraint in Eq. (3) is used to protect the consumer's welfare so that at a specific node customers do not have to endure cut-flow during the same hours every day. Based on Eq. (3), a simulation period (for example 8:05 a.m. through 12:55 p.m.) is on-flow during 2 days minimally, and it cannot be cut-flow on those 2 days

$$x_{i,p} + x_{i,p+Np} \geq 1 \tag{3}$$

where p = simulation period counter; and Np = number of simulation periods in a day (five in this paper)

Eq. (4) expresses the hourly water consumption coefficients at demand nodes where water flow has a constant value during all hours of the jth simulation period

$$R_{De_{i,p}} = \beta_p \times D_{De_i} \tag{4}$$

where $R_{De_{i,p}}$ = demand flow for ith node in the pth simulation period (design flow) (m^3/h); β_p = coefficient of hourly fluctuation of consumption in the pth simulation period of day; and D_{De_i} = base demand flow for ith node (m^3/h).

Eq. (5) is a restriction to have nonnegative pressure in each node in every simulation period

$$P_{i,j} \geq 0 \tag{5}$$

where $P_{i,j}$ = water pressure for ith node in the jth simulation period (m).

Eqs. (6)–(10) define the calculation of the initial reservoir storage [Eq. (6)], and storage volume constraints in each simulation period. The reason for inserting a regulating reservoir in the WDN is to ensure water supply during emergency situations.

$$S_0 = \begin{cases} 0, & \text{if } S_{\max} - (2 \times (Lp \times Q_{\text{in}}) - Lp \times \text{Min}R_{De}) < 0 \\ S_{\max}, & \text{if } S_{\max} - (2 \times (Lp \times Q_{\text{in}}) - Lp \times \text{Min}R_{De}) > S_{\max} \\ S_{\max} - (2 \times (Lp \times Q_{\text{in}}) - Lp \times \text{Min}R_{De}), & \text{if } 0 \leq S_{\max} - (2 \times (Lp \times Q_{\text{in}}) - Lp \times \text{Min}R_{De}) \leq S_{\max} \end{cases} \tag{6}$$

where S_0 = initial storage volume of reservoir at the beginning of operational period (m^3); Lp = duration of each simulation period (h); Q_{in} = input flow to the reservoir, which has a fixed amount during different hours of the day (design inflow) (m^3/h); S_{Max} = maximum reservoir storage capacity (m^3); and $\text{Min}R_{De}$ = minimum demand flow of the network among different simulation periods of a day (m^3/h).

The value of 2 used in Eq. (6) accounts for two consecutive simulation periods that are considered whereby the first is without water supply and the second is a low-demand period in any given day, which results in maximum storage volume.

Eq. (7) describes water balance in the reservoir

$$S_{p+1} = S_p + Lp \times \left(Q_{\text{in}} - \sum_{i=1}^{Nnode} Q_{i,p}\right) \tag{7}$$

where S_p = reservoir storage volume at the beginning of the pth simulation period (m^3); S_{p+1} = reservoir storage volume at the end of the pth simulation period (beginning of the $p+1$th simulation period) (m^3); and $Q_{i,p}$ = out flow of the reservoir at the ith node in the pth simulation period (m^3/h).

Eq. (8) states minimum and maximum reservoir storage capacity in every simulation period p

$$0 \leq S_p \leq S_{\text{Max}} \tag{8}$$

Eq. (9) indicates the carryover constraint in the operation of the WDN

$$S_{Nperiod+1} \geq S_1 \tag{9}$$

where S_1 = reservoir storage at the beginning of the first simulation period (m^3); and $S_{Nperiod+1}$ = reservoir storage volume at the end of the last simulation period (m^3).

Eq. (10) prescribes maximum reservoir storage considering average hourly water flow

$$S_{\text{Max}} \geq \text{NHR} \times \sum_{i=1}^{Nnode} \sum_{p=1}^{Np} R_{De_{i,p}} \tag{10}$$

in which NHR = number of hours by which one must multiply the hourly average water use to equal the reservoir storage capacity.

The number of simulation periods in a day is defined in such a way that the hourly fluctuation of water use is captured most accurately. Herein, five simulation periods were found suitable.

Table 1 shows the coefficients that specify hourly fluctuations of water use during five periods every day. The HBMO algorithm is used to solve the optimization model. The flowchart of the HBMO algorithm is presented in Fig. 1.

After performing single objective optimization in which each objective is evaluated independently, multiobjective optimization is carried out by applying weighing coefficients and priorities for each objective, and the best solution is selected. The summation of all the weighing coefficients equals 1. The weighting method is described by Eq. (11) (Gass and Saaty 1955) as follows:

$$\text{Max. or Min. } Z = \sum_{c=1}^{2} w_1.f_1(x) + w_2 f_2(x), \quad \text{where } w_1 + w_2 = 1 \tag{11}$$

where Z = total objective function including two objectives; and w_1 and w_2 = weighing coefficients for the first and second objective functions, respectively. These coefficients are used to reflect the importance of each objective on the value of Z. If either one of them is set equal to 1 (which means that the other coefficient must equal 0), the multiobjective problem transforms into a single-objective problem. If the weighing coefficients are set between 0 and 1, a nondominated solution is achieved (Deb 2001).

The next sections describe the application of the HBMO to the optimization of WDN with intermittent water supply. The parameters of the HBMO algorithm used in this study are listed in Table 2.

Optimization of a Two-Loop WDN

The two-loop WDN is a benchmark network used as the first case study in this paper. Alperovits and Shamir (1977) presented this simple network with eight pipes and six consumption nodes but with no pump or storage tank. Fig. 2 shows the schematic of this network. The characteristics of the consumption nodes and pipes are available in Alperovits and Shamir (1977). The length of each pipe is 1,000 m, and the Hazen-Williams coefficient is assumed to be 130 for all pipes. The allowable range of pressure head in all nodes is between 30 to 60 m.

Water shortage may occur for two reasons, herein called States 1 and 2 as follows: (1) insufficiency of available water resources; and

Table 1. Coefficients of Hourly Water Use in Five Intraday Periods

Simulation period	Starting and stopping times	Coefficient of hourly water use
1	3:15 a.m.–08:05 a.m.	0.5600378
2	8:05 a.m.–12:55 p.m.	0.6634486
3	12:55 p.m.–5:45 p.m.	0.6697428
4	5:45 p.m.–10:35 p.m.	0.9257923
5	10:35 p.m.–3:15 a.m.	0.3948674

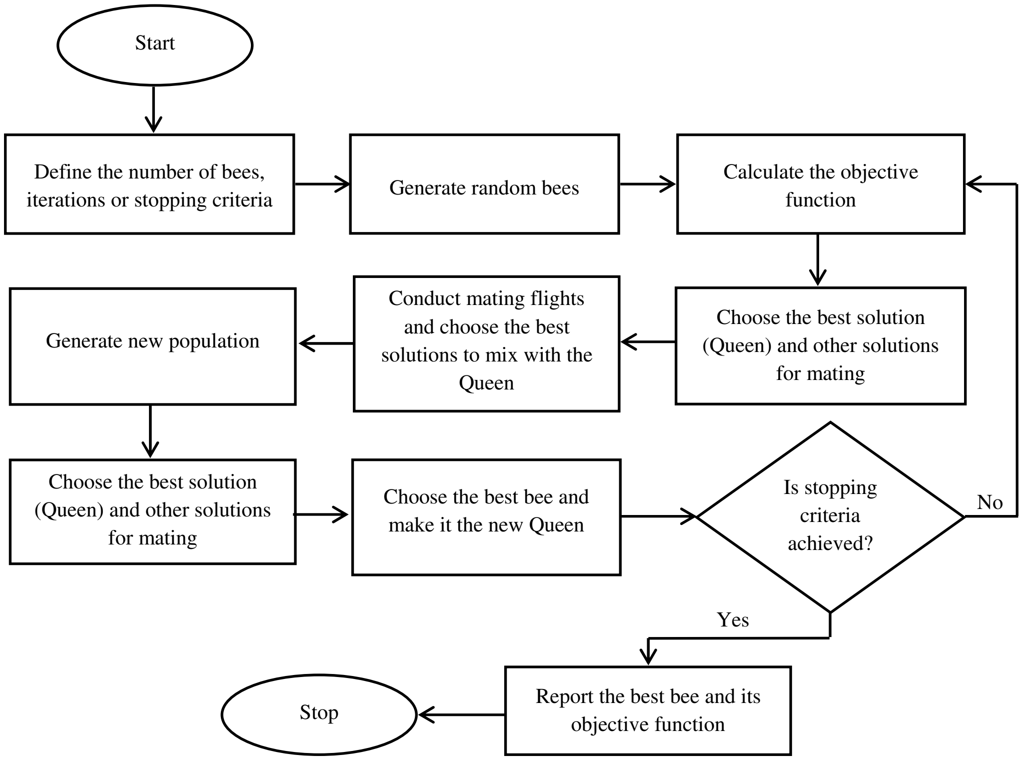


Fig. 1. Flowchart of the HBMO algorithm

Table 2. HBMO Algorithm Parameters

	Case study	
Parameter	First	Second
Number of runs	10	3
Number of iterations in each run (number of mating flights)	2,000	10,000
Number of solutions in each iteration (number of bees)	220	220

Table 3. Values of Input Parameters of Defined Scenarios for the First Case Study

Scenario	$\frac{Q'_{\text{in}}}{Q_{\text{in}}}$	$\frac{R'_{De}}{R_{De}}$	Input water (m^3/day)	Network's demand (m^3/day)	Initial reservoir storage (m^3/day)
1	0.50	1.00	8,640	17,280	18,666
2	0.75	1.00	12,960	17,280	16,938
3	1.00	1.00	17,280	17,280	15,210
4	1.00	1.25	17,280	21,600	15,741
5	1.00	2.00	17,280	34,560	17,333

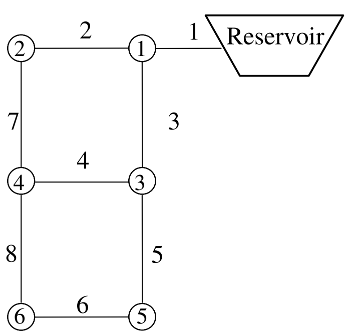


Fig. 2. Schematic of the two-loop network

(2) increase in water use. In the first state, the values of precipitation and water storage are less than water use. In the second state, the balance between water storage and water demand is lost because of heightened water use. Optimization Scenarios 1 and 2 correspond to the first state of water shortage, Scenario 3 is related to ideal conditions (without water shortage), and Scenarios 4 and 5 correspond to the second state of shortage. Defined scenarios and input parameters to the model in the first case study are listed in Tables 3. The capacity of the reservoir equals 20,000 m^3.

In Table 3, Q_{in} and R_{De} refer to the design input water and water demand in the network, respectively. Q'_{in} and R'_{De} refer to real input water and water demand in the network, respectively. In Scenario 1, the value of input flow to the network is 50% of the demanded flow at consumption nodes. Scenario 2 is similar to Scenario 1 but the value of input flow to the network is 25% less than the demanded flow. Scenarios 1 and 2 represent shortage of water scenarios. In Scenario 3, the value of input flow to the network is equal to the demanded flow at network nodes. Scenario 3 does not imply a water shortage. In Scenario 4, the value of input flow to the network is the same as that of the basic Scenario 3, but the value of water demand is 1.25 times that of Scenario 3. In Scenario 5, the value of input flow to the network is the same as that of Scenario 3 but the value of demanded flow is double the input flow. Scenarios 4 and 5 describe increases in water demand.

Single-objective optimization was performed for each scenario and the best solutions are presented in Table 4.

Table 4. Optimized Objectives and Simulated Objectives for the First Case Study

	Mechanical reliability		Supply resiliency	
Scenario	Supply resiliency (simulated)	Mechanical reliability (optimized)	Mechanical reliability (simulated)	Supply resiliency (optimized)
1	6.4×10^{-4}	0.1250	0.0185	1
2	0.01667	0.3333	0.0384	1
3	1.0000	1.0000	1.0000	1
4	0.0833	0.5000	0.0476	1
5	6.4×10^{-5}	0.1250	0.0185	1

It is seen in Table 4 that if the supply resiliency is selected as the objective, the objective function value (supply resiliency) is equal to the best possible value for all scenarios (fifth column). On the contrary, if the mechanical reliability is selected as the objective, the objective function value (mechanical reliability) reaches the best value only when there is no water shortage (Scenario 3). In the other scenarios, depending on the water shortages, the objective function (mechanical reliability) value is reduced (third column). In other words, the mechanical reliability of the network is reduced with increasing water shortage. The mechanical reliability measures the system value and the water supply resiliency in the system measures the water consumers' welfare. The optimized resilience

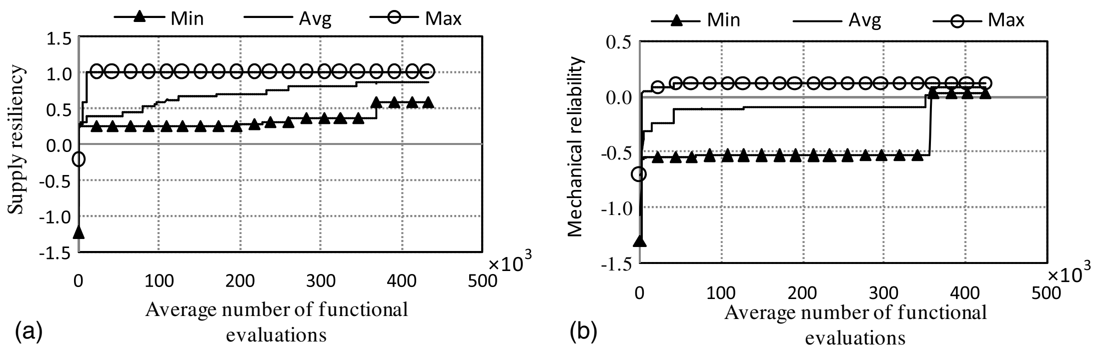


Fig. 3. Algorithm convergence in Scenario 1, first case study

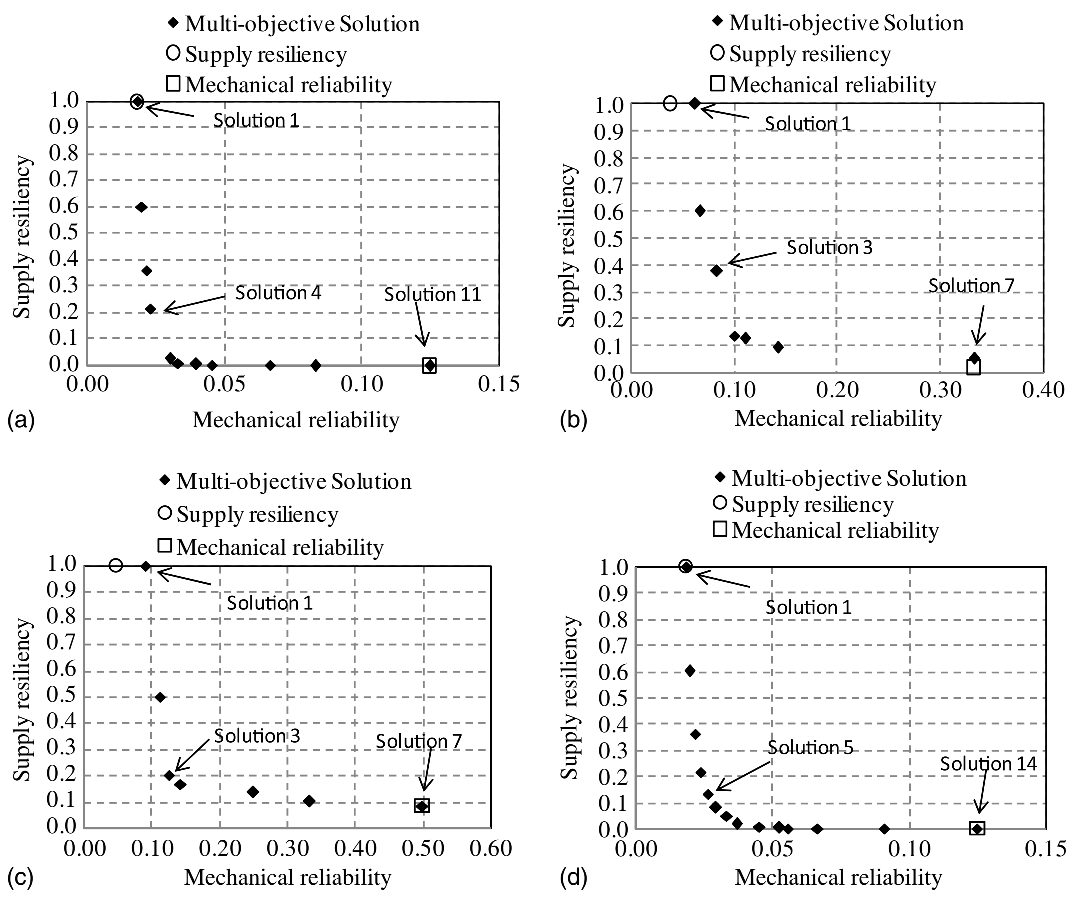


Fig. 4. Optimal Pareto boundaries in multiobjective optimization model, first case study

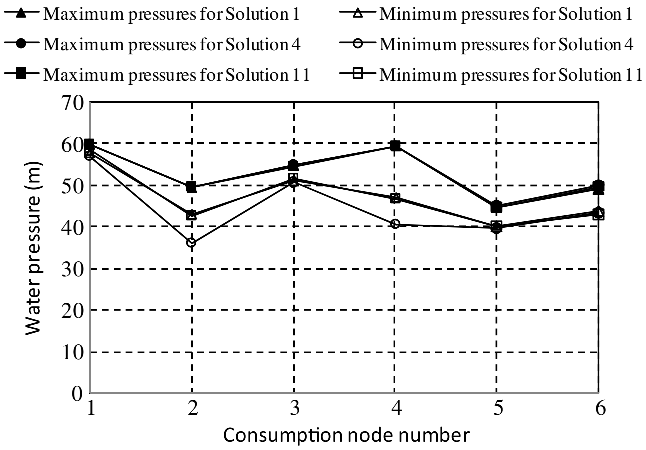


Fig. 5. Node pressures for Scenario 1 of first case study in multiobjective model

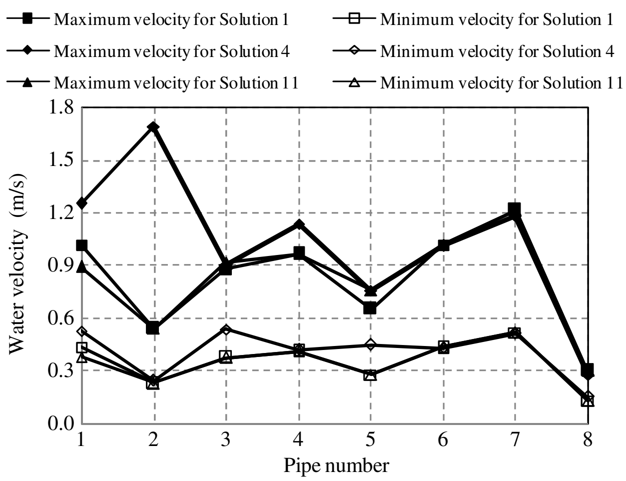


Fig. 6. External velocities for Scenario 1 of first case study in multiobjective model

equal 1 (that is, 100%) for all scenarios in Table 4, and that increasing water shortage increases the depreciation of the system. Moreover, the supply resiliency (optimized) values and the mechanical reliability (optimized) were calculated by using the *EPANET2* (Rossman 2000) hydraulic simulator as shown in the second and fourth columns in Table 4, which correspond to the mechanical reliability and the supply resiliency used as the optimization objectives in the model, respectively. According to the results, it can be seen that the simulated supply resiliency has a more significant decline than the optimized supply resiliency. In addition, the optimized and simulated reliability values show that when the supply resiliency is the objective of the optimization model, the mechanical reliability is almost 10 times worse. Thus, it can be concluded that the objectives of mechanical reliability and supply resiliency are in conflict with each other. The worst possible value for mechanical reliability was 0.0185 achieved for Scenarios 1 and 5 during the optimization of supply resiliency. Also, the worst possible value for supply resiliency was 6.4×10^{-5} achieved for Scenario 5 during the optimization of mechanical reliability.

Fig. 3 shows that the optimization model with two objectives converges rapidly to the maximum value. Therefore this model exhibits suitable performance and rapid convergence for the chosen objectives.

Fig. 4 shows Pareto boundaries obtained from multiobjective optimization for each of the five scenarios, except Scenario 3, which has only one solution. It is seen in Fig. 4 that no solution is superior to others, and choosing one solution over another depends on the operator's preferences.

For easier evaluation of results, maximal and minimal pressure heads and velocities in various simulation periods were calculated. Fig. 5 displays all extreme pressure head values are in the allowable range between 30 and 60 m.

Fig. 6 shows solutions for two corner points (each corresponding to one of the single-objective optimizations) and for a middle point on the Pareto Boundary (in which the two single objectives participate). The three solutions in Fig. 3 show that that water velocities in the pipes are mostly within the allowable range 0.3 to 2 m/s (Brix et al. 1963). Water velocities less than 0.3 m/s

Table 5. Supplied Water in m^3/h with Solutions 1, 4, and 11 of Scenario 1 of the First Case Study

	Simulation period									
Node	1	2	3	4	5	6	7	8	9	10
Solution 1										
1	0.00	66.34	0.00	92.58	0.00	56.00	0.00	66.97	0.00	39.49
2	0.00	66.34	0.00	92.58	0.00	56.00	0.00	66.97	0.00	39.49
3	0.00	79.61	0.00	111.10	0.00	67.20	0.00	80.37	0.00	47.38
4	151.21	0.00	180.83	0.00	106.61	0.00	179.13	0.00	249.96	0.00
5	0.00	218.94	0.00	305.51	0.00	184.81	0.00	221.02	0.00	130.31
6	112.01	0.00	133.95	0.00	78.97	0.00	132.69	0.00	185.16	0.00
Solution 4										
1	56.00	66.34	0.00	92.58	39.49	0.00	0.00	66.97	0.00	0.00
2	0.00	66.34	0.00	92.58	39.49	56.00	0.00	66.97	0.00	0.00
3	67.20	0.00	80.37	0.00	47.38	0.00	79.61	0.00	111.10	0.00
4	0.00	179.13	0.00	249.96	0.00	151.21	0.00	180.83	0.00	106.61
5	184.81	0.00	221.02	305.52	130.31	0.00	218.94	0.00	0.00	0.00
6	112.01	0.00	133.95	0.00	78.97	0.00	132.69	0.00	185.16	0.00
Solution 11										
1	0.00	0.00	0.00	0.00	0.00	56.00	66.34	66.97	92.58	39.49
2	56.00	66.34	66.97	92.58	39.49	0.00	0.00	0.00	0.00	0.00
3	67.20	79.61	80.37	111.10	47.38	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	151.21	179.13	180.83	249.96	106.61
5	0.00	0.00	221.02	305.51	130.31	184.81	218.94	0.00	0.00	0.00
6	112.01	132.69	133.95	0.00	0.00	0.00	0.00	0.00	185.16	78.97

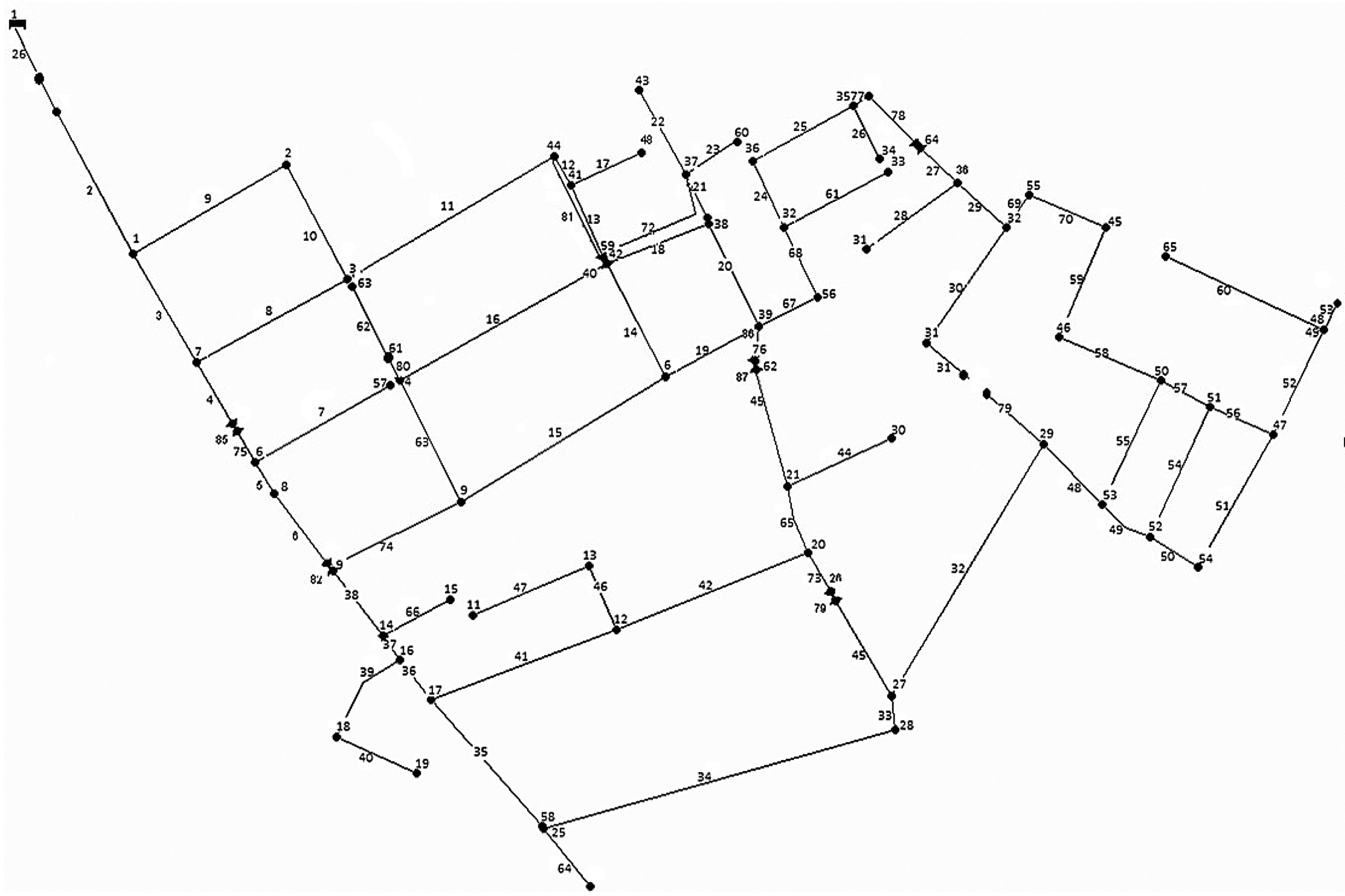


Fig. 7. Schematic of Tehran's reservoir number 30 WDN

can be ignored. Solutions for Scenarios 1 and 2 obtained with the network operation program, including the value of water supply, are shown in Table 5 for different simulation periods and various nodes.

Optimization of Tehran's WDN with Reservoir 30

The second case study is the WDN of Tehran reservoir number 30. This network has 65 nodes and 81 pipes. Fig. 7 shows a schematic of this network. The characteristics of consumption nodes and network pipes are available in Solgi et al. (2015). The Hazen-Williams coefficient is 85 in all pipes. The allowable range of pressure head for this network is between 14 and 50 m (Brix et al. 1963).

Defined scenarios and input parameters to the model in the second case study are listed in Table 6. In Scenario 1, the value of input flow to the network is 75% of demanded flow at consumption nodes. In Scenario 2, the value of demanded flow is 1.25 times input flow. Scenarios 1 and 2, respectively, are similar to Scenarios 2 and 4 of the first case study. The reservoir capacity in the second case study is equal to the network design demand, which is 5,000 m^3.

The single-objective optimization was solved for Scenarios 1 and 2 and the best solutions among various runs for each scenario are shown in Table 7.

It is seen in Table 7 that the supply resiliency objective in both scenarios takes the maximum value of 1. The worst possible value for mechanical reliability was 0.0027 obtained when optimizing the supply resiliency in Scenario 2. On the other hand, the worst possible value for supply resiliency was 5.78×10^{-16} obtained when optimizing mechanical reliability optimization in Scenario 2. Table 7 shows that there are considerable differences between optimization and simulation values related to each objective (compare Columns 2 and 5 for supply resiliency, and Column 3 and 4 for the mechanical reliability objective). These pronounced differences demonstrate the importance of multiobjective optimization in

Table 6. Values of Input Parameters of Defined Scenarios for the Second Case Study

Scenario	$\frac{Q'_{in}}{Q_{in}}$	$\frac{R'_{De}}{R_{De}}$	Input water (m^3/day)	Network's demand (m^3/day)	Initial reservoir storage (m^3/day)
1	0.75	1.00	3,600	4,800	4,149
2	1.00	1.25	4,800	6,000	3,816

Table 7. Optimized Objectives and Simulated Objectives for the Second Case Study

	Mechanical reliability		Supply resiliency	
Scenario	Supply resiliency (simulated)	Mechanical reliability (optimized)	Mechanical reliability (simulated)	Supply resiliency (optimized)
1	1.05×10^{-9}	0.0233	0.0028	1
2	5.78×10^{-16}	0.0287	0.0027	1

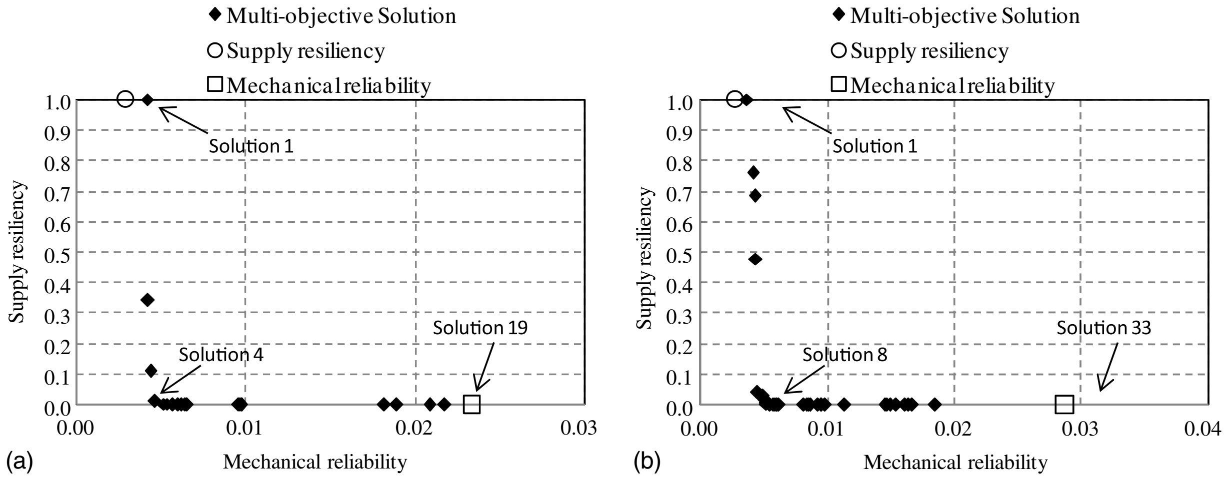


Fig. 8. Optimal Pareto in multiobjective optimization model, second case study

achieving best results. Multiobjective optimization for the second case study was carried out and the Pareto boundaries for each scenario are presented in Fig. 8.

Fig. 8 shows very different Pareto boundaries for each of the two scenarios. Such difference shows that the optimization algorithm (HBMO) performed very well in finding widely contrasting solutions. Also, it is obvious in each scenario that there is little difference between the optimal the single-objective solutions and the multiobjective solutions; 19 and 33 solutions calculated for Scenarios 1 and 2 are on the optimal Pareto boundary, respectively. Solutions 1, 4, and 19 of Scenario 1, and Solutions 1, 8, and 33 of Scenario 2 are shown in Fig. 9 to compare pressure heads, water velocities, and values of water supply.

It is seen in Fig. 9 that all pressure heads are in the allowable range between 14 and 50 m. According to Fig. 10, almost all the values of water velocities are in the allowable range less than

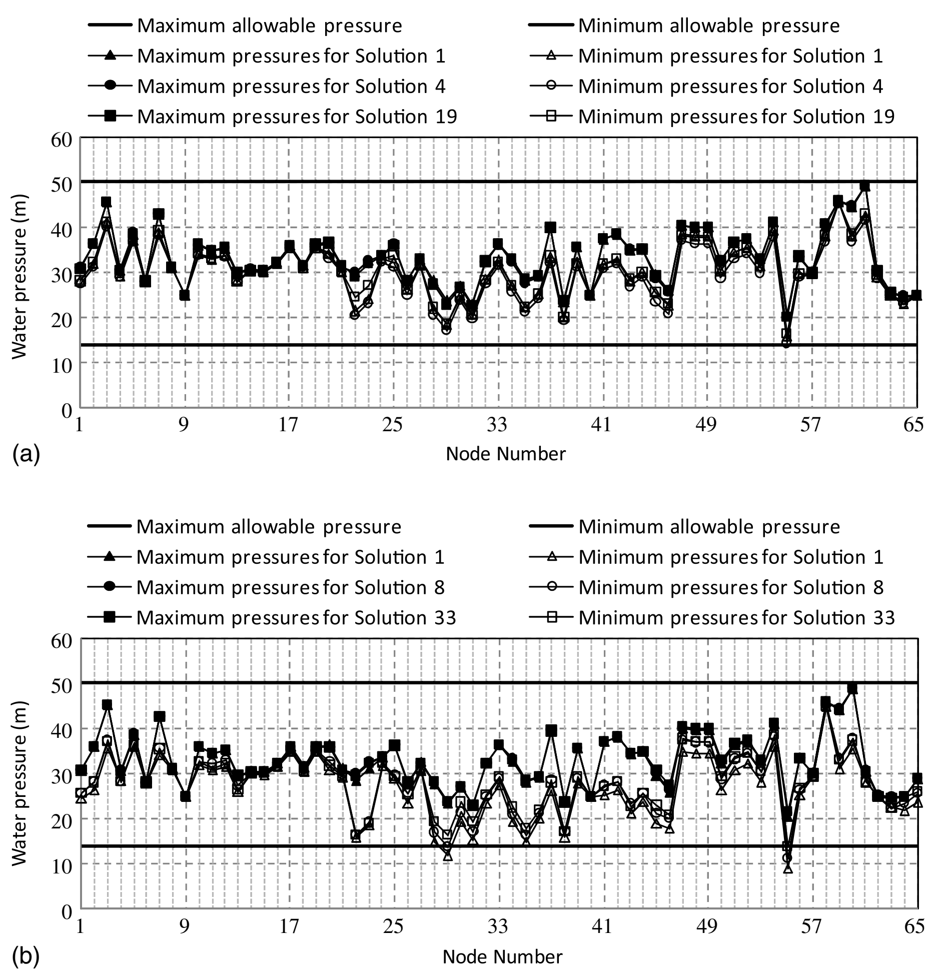
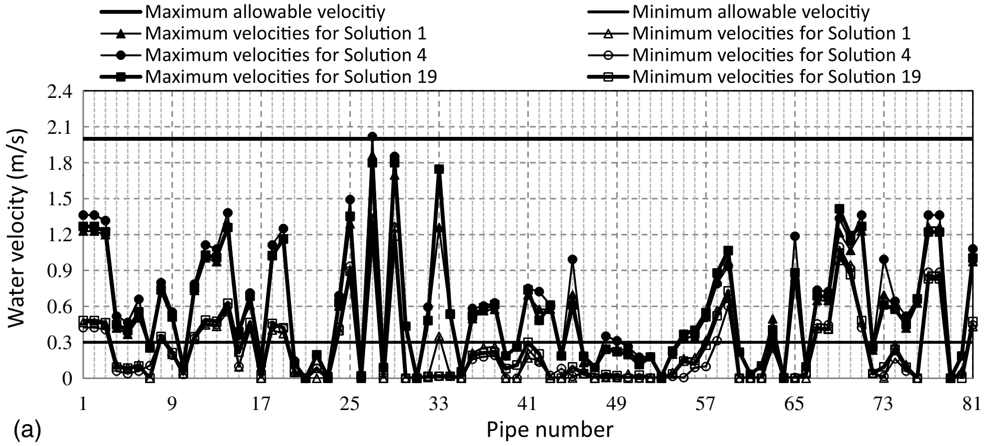


Fig. 9. Nodal pressure head for scenarios of second case study in multiobjective model



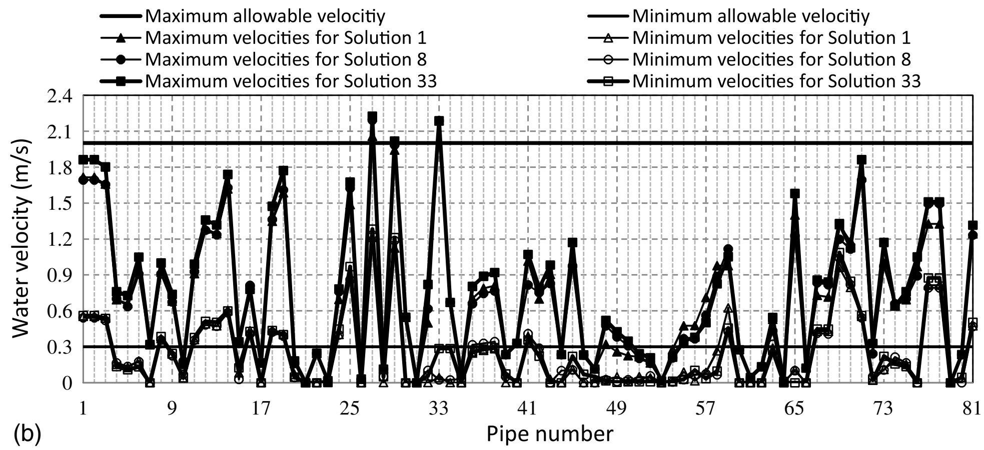


Fig. 10. Water velocities for scenarios of second case study in multiobjective model

Table 8. Selection Criteria in Multi-Objective Optimization

	Scenario 1			Scenario 2		
	Solution					
Criterion	1	4	19	1	8	33
Average failure duration in the network nodes	1.00	3.36	3.54	1.00	2.60	3.34
Euclidean distance	1.00	0.01	0.02	1.00	0.01	0.03
Number of nodes with continuous demand supply	16	32	0	24	25	0

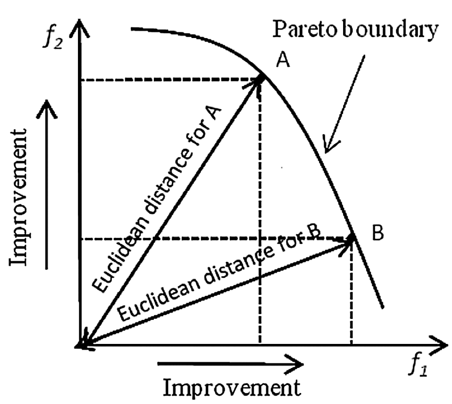


Fig. 11. Euclidean distance concept

2 m/s. A few of the pipe velocities fall below the allowable range because of low flow in some of the water shortage scenarios herein considered. Also, in the increased demand scenarios, some pipe velocities occasionally have values larger than the allowable range because of the high flow.

Since the numbers of nodes in the second case study are too many to evaluate, criteria were introduced to compare solutions. These criteria distinguish between various solutions and desired goals. The criterion to compare solutions from the viewpoint of desired goals is the average failure duration in the network nodes, and the criteria to choose solutions are (1) the Euclidean distance, (2) the number of nodes with continuous water supply. Each criterion used was evaluated independently, and choosing a solution depends on which criteria are used by the operator. Table 8 indicates the criteria between solutions.

The results of Table 8 show that in Scenario 1, Solution 1 produces of the shortest failure duration that is equal to 1, and the failure duration of Solution 19 is longer than that of Solution 1. Solution 4 is halfway between these two solutions. Solution 1 is in a corner of the Pareto boundary, and Solution 19 is in the other corner of the Pareto boundary. Solution 4 is between these two solutions. There is an increase in failure duration from Solution 1 to Solution 19. This is true for Scenario 2, also.

The Euclidean distance denotes separation from center of gravity (center of the optimal Pareto coordinate axis). This distance is indicated in Fig. 11, and it shows how superior one objective is relative to another objective.

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It is seen in Table 8 that Solution 1 has the longest Euclidean distance in Scenarios 1 and 2. This means that the supply resiliency objective has considerable value in Solution 1, whereas the mechanical reliability objective is negligible. Another criterion used for discriminating among solutions is the number of nodes with continuous demand supply. If this criterion is important for the operator, then it can be used to select a solution with the largest number of continuous supply nodes.

From the results in Table 8, the nodes in Solution 4 of the first scenario and the nodes in Solution 8 of the second scenario achieve continuous supply (without intermittent supply) and are selected as the preferred solutions in this instance. Solutions 19 and 33 indicate that increasing the number of nodes in which water supply is maintained continuously would not lead to increased mechanical reliability. In contrast, this increase may reduce the mechanical reliability. In other words, although the valves never open or close in the nodes that provide the continuous supply, increasing the number of such nodes would reduce the mechanical reliability of the network (increased depreciation of system) in water shortage situations.

Concluding Remarks

Implementation of intermittent water supply compels consumers to withstand periods of interrupted water supply. On the other hand, intermittent operation increases operator costs for intermittent control and maintenance costs attributable to damage of pipes and valves caused by water pressure fluctuations. Accordingly, in the present study, the consumers' welfare and the system depreciation was considered simultaneously for the water distribution network in the optimization model that finds the optimal scheduling of intermittent supply. First, a single-objective problem was solved. When the supply resiliency was the objective, the results showed that regardless of the severity of the water shortage in all scenarios, the optimization model is able to provide the best possible value for the supply resiliency equal to 1 (or 100%). When the mechanical reliability was the objective of single-optimization model, the mechanical reliability decreased with increasing severity of water shortage. In addition, the results showed that the two cited objectives may be in conflict with each other. It was found that reaching the best possible state in one objective leads to the worst possible state in the other objective, thus implying a tradeoff between optimization of the two objectives: as one improves, the other worsens.

References

Alperovits, E., and Shamir, U. (1977). "Design of optimal water distribution systems." *Water Resour. Res.*, 13(6), 885–900.

Ameyaw, E. E., Memon, F. A., and Bicik, J. (2013). "Improving equity in intermittent water supply systems." *J. Water Supply Res. Technol.*, 62(8), 552–562.

Andey, S., and Kelkar, P. (2009). "Influence of intermittent and continuous modes of water supply on domestic water consumption." *Water Resour. Manage.*, 23(12), 2555–2566.

Babu, K., and Vijayalakshmi, D. (2013). "Self-adaptive PSO-GA hybrid model for combinatorial water distribution network design." *J. Pipeline Syst. Eng. Pract.*, 10.1061/(ASCE)PS.1949-1204.0000113, 57–67.

Batish, R. (2003). "A new approach to the design of intermittent water supply networks." *World Water and Environmental Resources Congress*, ASCE, Philadelphia.

Bozorg Haddad, O., Adams, B. J., and Mariño, M. A. (2008). "Optimum rehabilitation strategy of water distribution systems using the HBMO algorithm." *J. Water Supply Res. Technol.*, 57(5), 337–350.

Bozorg Haddad, O., Afshar, A., and Marino, M. A. (2006). "Honey-bees mating optimization (HBMO) algorithm: A new heuristic approach for water resources optimization." *Water Resour. Manage.*, 20(5), 661–680.

Bozorg Haddad, O., Afshar, A., and Mariño, M. A. (2011). "Multireservoir optimisation in discrete and continuous domains." *Proc. Inst. Civ. Eng. Water Manage.*, 164(2), 57–72.

Brix, J., Heyd, H., and Gerlach, E. (1963). *Die Wasserversorgung*, 6. Auflage, Oldenbourg, Berlin (in German).

Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms*, Indian Institute of Technology, Kanpur, India.

Ezzeldin, R., Djebedjian, B., and Saafan, T. (2014). "Integer discrete particle swarm optimization of water distribution networks." *J. Pipeline Syst. Eng. Pract.*, 10.1061/(ASCE)PS.1949-1204.0000154, 04013013.

Fallah-Mehdipour, E., Bozorg Haddad, O., Beygi, S., and Mariño, M. A. (2011). "Effect of utility function curvature of Young's bargaining method on the design of WDNs." *Water Resour. Manage.*, 25(9), 2197–2218.

Gass, S. I., and Saaty, T. L. (1955). "The computational algorithm for the parametric objective function." *Nav. Res. Logist. Q.*, 2(1–2), 39–45.

Hashimoto, T., Stedinger, J. R., and Loucks, D. P. (1982). "Reliability resiliency and vulnerability criteria for water resources system performance evaluation." *Water Resour. Res.*, 18(1), 14–20.

Jahanshahi, G., and Bozorg Haddad, O. (2008). "Honey-bee mating optimization (HBMO) algorithm for optimal design of water distribution systems." *World Environmental and Water Resources Congress*, Honolulu.

Karimi, S., Mostoufi, N., and Soutodeh Gharebagh, R. (2013). "Evaluating performance of honey bee mating optimization." *J. Optim. Theory Appl.*, 160(3), 1020-1026.

Rossman, L. A. (2000). *EPANet 2 users manual*, U.S. Environmental Protection Agency, Cincinnati.

Sabbaghpour, S., Naghashzadehgan, M., Javaherdeh, K., and Bozorg Haddad, O. (2012). "HBMO algorithm for calibrating water distribution network of Langarud city." *Water Sci. Technol.*, 65(9), 1564–1569.

Sashikumar, N., Mohankumar, M. S., and Sridharan, K. (2003). "Modeling an intermittent water supply." *Proc., World Water and Environmental Resources Congress*, Paul Bizier and Paul DeBarry, eds., Philadelphia.

Seifollahi-Aghmiuni, S., Bozorg Haddad, O., Omid, M. H., and Mariño, M. A. (2011). "Long-term efficiency of water networks with demand uncertainty." *Proc. Inst. Civ. Eng. Water Manage.*, 164(3), 147–159.

Seifollahi-Aghmiuni, S., Bozorg Haddad, O., Omid, M. H., and Mariño, M. A. (2013). "Effects of pipe roughness uncertainty on water distribution network performance during its operational period." *Water Resour. Manage.*, 27(5), 1581–1599.

Solgi, M., Bozorg Haddad, O., Seifollahi-Aghmiuni, S., and Loaiciga, H. A. (2015). "Intermittent operation of water distribution networks considering equanimity and justice principles." *J. Pipeline Syst. Eng. Pract.*, 10.1061/(ASCE)PS.1949-1204.0000198, 04015004.

Soltanjalili, M. J., Bozorg Haddad, O., and Mariño, M. A. (2013). "Operating water distribution networks during water shortage conditions using hedging and intermittent water supply concepts." *J. Water Resour. Plann. Manage.*, 10.1061/(ASCE)WR.1943-5452.0000315, 644–659.

Suribabu, C. (2012). "Heuristic-based pipe dimensioning model for water distribution networks." *J. Pipeline Syst. Eng. Pract.*, 10.1061/(ASCE)PS.1949-1204.0000104, 115–124.

Totsuka, N., Trifunovic, N., and Vairavamoorthy, K. (2004). "Intermittent urban water supply under water starving situations." *People-Centred Approaches to Water and Environmental Sanitation, 30th WEDC Int. Conf.*, WEDC, Vientiane, Lao PDR.