Research papers

f-MOPSO: An alternative multi-objective PSO algorithm for conjunctive water use management

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A B S T R A C T

In recent years, evolutionary techniques have been widely used to search for the global optimum of combinatorial non-linear non-convex problems. In this paper, we present a new algorithm, named fuzzy Multi-Objective Particle Swarm Optimization (f-MOPSO) to improve conjunctive surface water and groundwater management. The f-MOPSO algorithm is simple in concept, easy to implement, and computationally efficient. It is based on the role of weighting method to define partial performance of each point (solution) in the objective space. The proposed algorithm employs a fuzzy inference system to consider all the partial performances for each point when optimizing the objective function values. The f-MOPSO algorithm was compared with two other well-known MOPSOs through a case study of conjunctive use of surface and groundwater in Najafabad Plain in Iran considering two management models, including a typical 12-month operation period and a 10-year planning horizon. Overall, the f-MOPSO outperformed the other MOPSO algorithms with reference to performance criteria and Pareto-front analysis while nearly fully satisfying water demands with least monthly and cumulative groundwater level (GWL) variation. The proposed algorithm is capable of finding the unique optimal solution on the Pareto-front to facilitate decisions to address large-scale optimization problems.

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1. Introduction

Conjunctive use of surface water and groundwater resources is commonly practiced in arid and semi-arid regions of the world to meet the growing water demand of urban, agricultural, and industrial users, while reducing climate change related water scarcity (Peralta et al., 1995; Marino, 2001; Schoups et al., 2006; Medellin-Azuara et al., 2008; Safavi et al., 2010; Connell-Buck et al., 2011; Mirchi et al., 2013). While surface water often has lower extraction cost as compared with groundwater withdrawal, it has higher probability of supply failure due to hydrologic variability, justifying the extensive use of more costly but reliable groundwater resources (Burt, 1964; O'Mara, 1988; Fisher et al., 1995; Yang et al., 2009), especially in arid areas of the world. Using both resources conjunctively can increase system reliability by decreasing water supply fluctuations that may disrupt day-to-day activities of users and cause economic loss (Montazar et al., 2010).

Different approaches and techniques have been applied to optimize the conjunctive use of surface water and groundwater (Vedula et al., 2005), including linear programming, dynamic programming, hierarchical optimization, non-linear programming and evolutionary algorithms. Classical optimization methods are typically based on gradient search techniques. The numerical estimation of the gradients is computationally intensive and can be applied only when the objective functions are differentiable and continuous in domain. Furthermore, these conventional methods are not applicable when searching for the global optimum of combinatorial non-linear non-convex problems. To address these drawbacks, population-based evolutionary techniques have been employed along with simulation models in the last four decades to develop efficient conjunctive management models (Maddock, 1974; Peralta et al., 1988; Willis et al., 1989; Ibanez-Castillo et al., 1997; Karamouz et al., 2004; Safavi et al., 2010; Singh and Panda 2013; Safavi and Esmikhani, 2013).

Bazargan-Lari et al. (2009) developed a conflict resolution methodology for conjunctive use of water resources by first generating trade-off curves using a multi-objective genetic algorithm, and then selecting the best non-dominated solution using the

Young conflict resolution theory (Young, 1993). Marques et al. (2010) applied a two-stage quadratic programming model to maximize economic benefits of conjunctive use from crops, irrigation technology, the areas under permanent and annual crops, and surface water supply. They assumed groundwater withdrawal is constrained by artificial recharge of the aquifer, while also limiting the surface water supply in each year to a "sustainable" annual amount. A set of hydrologic stochastic events with respective probability of occurrence were also considered to address uncertain climate change conditions. Rezapour Tabari and Soltani (2013) developed a multi-objective model for maximizing the reliability of an irrigation system's water supply, while minimizing the cost, using non-dominated sorting genetic algorithm (NSGA-II) to provide optimal compromising objectives. Peralta et al. (2014) used a simulation-optimization conjunctive use model. They applied an artificial neural network model to simulate various flow interactions, as well as an NSGA model to optimize water allocations by maximizing water supply, and hydropower production, while minimizing the operation costs of surface water transfer and groundwater extraction.

Due to multi-objective nature of most real-world water management problems with conflicting and/or incommensurable objectives (Madani and Lund, 2011), developing efficient and robust multi-objective water resources system optimization techniques remains an active research area. Traditional multi-objective optimization approaches such as weighting and ε-constraint methods can produce non-dominated solutions by transforming the multi-objective problems to single-objective ones based on bottom-up information flow. By contrast, in an evolutionary optimization model, the top-down information flow through implementation of preference methods is also needed to detect a unique optimum solution (Abido, 2010; Fallah-Mehdipour et al., 2011).

Particle Swarm Optimization (PSO) algorithm (Kennedy and Eberhart, 1995) is the most commonly used stochastic population-based evolutionary computation technique inspired by the evolution of nature (Kennedy and Eberhart, 1995). Compared to other meta-heuristic techniques (e.g., genetic algorithm), PSO has a more flexible and well-balanced mechanism to enhance and adapt the global and local exploration, needing fewer particles (solutions) to provide the required diversity and faster convergence rate (Abido, 2010). A Vector Evaluated PSO (VEPSO) was developed by Parsopoulos and Vrahatis (2002) based on the concept of Vector Evaluated Genetic Algorithm (VEGA) to perform multi-objective optimization. VEPSO uses one swarm for each objective and the best particle of each swarm is used as the global best particle to determine particle velocities and positions. Hu and Eberhart (2002) presented a multi-objective PSO (MOPSO) with a dynamic neighborhood strategy to obtain the global best for each particle in bi-objective problems. In this method, the global best particle in each stage is the local optimum among all neighbors selected in the previous stage with respect to the other objective value. However, this process poses limits to algorithm performance due to multi-objectivity of the problem, increasing the convergence rate without finding the global best particle (Abido, 2010).

A suite of MOPSO methods have been introduced in the past two decades. Coello and Lechuga (2002) proposed a MOPSO method based on investigation of externally archived non-dominated solutions. In this MOPSO, the best solution in the archive with the smallest density value is assigned the maximum probability to be found as the global best by imposing a selection operator similar to the roulette-wheel selection operator. To find the personal best particle in this MOPSO, the new position is selected only if it dominates the old position and in case of non-dominance of either position, one of them is randomly selected as the personal best position. Performance-wise, the main draw-back of these MOPSOs results from neglecting the fitness among the non-dominated solutions, the dominance criteria, and the way to consider density of solutions. Mostaghim and Teich (2003a) proposed a sigma method in which the sigma vector for each particle is the gradient of a line drawn between that particle and the origin. The algorithm selects the guide (global best) particle by finding the nearest non-dominated member in terms of Euclidian distance between that member's sigma value and that of the swarm member, assigning each particle a particular global best. This process may cause premature convergence in some cases such as multi-frontal problems (Abido, 2010). Furthermore, Mostaghim and Teich (2003b) proposed using ε-dominance in MOPSO. This method limits the number of non-dominated solutions in the archive which is very influential in the algorithm running time, rate of convergence and diversity (Abido, 2010). They also introduced a new method which uses the property of moving particles in MOPSO to divide the population into sub-swarms (Mostaghim and Teich, 2004), trying to cover the gaps between the non-dominated solutions found in the initial run.

Wei and Wang (2006) proposed a novel MOPSO algorithm in which a three-parent crossover operator was suggested in order to move the solutions toward the feasible region, and a dynamically changing inertia weight was designed to keep the diversity of the swarm and escape from local optima. Ireland et al. (2006) introduced a centroid method to construct the guide particle based upon a distance-weighted average of the archive members. They concluded that the centroid method generates more diversity in the Pareto-front with slow convergence as compared with the sigma method which has a tendency to converge too rapidly with very little diversity. Thus, they developed a hybrid centroid/sigma algorithm as a more efficient and robust MOPSO algorithm. Reddy and Kumar (2007a) proposed an efficient multi-objective PSO algorithm, in which a variable size external repository is employed to store non-dominated solutions. They also applied a crowding distance operator to measure the amount of diversity of the stored solutions whenever the size of the repository exceeds desired size while doing mutation on the solutions using a strategy called elitist-mutation whenever needed. Reddy and Kumar (2007b) employed their proposed EM-MOPSO algorithm to solve a multi-objective reservoir operation problem. Thereafter, they reduced the obtained non-dominated solutions to a few representative ones, applying a clustering technique to ease handling the solutions. Finally for facilitating the decision-making, a pseudo-weight vector was calculated for each objective over Pareto-front points and the desired weight combination was extracted. Cabrera and Coello (2010) proposed Micro-MOPSO to handle very small population sizes using an auxiliary archive for storing non-dominated solutions found throughout the search, and a final archive for storing final non-dominated solutions. In this algorithm, the global best particle (called the leader) is selected from a sub-set of the final archive members with the best crowding distances. The neighborhood for creating the swarm is then selected based on the smallest Euclidian distance to the leader particle, while implementing a reinitialization process and a mutation operator to avoid stagnation.

Abido (2010) introduced an approach using two sets of non-dominated solutions, i.e., a non-dominated local set to store the non-dominated solutions obtained by the jth particle to the current time (i.e., $S_j^*(t)$) and a non-dominated global set to store the non-dominated solutions obtained by all particles up to the current time (i.e., $S^{**}(t)$). Then the individual distances between members in $S_j^*(t)$ and members in $S^{**}(t)$ are measured in the objective space. If $X_j^*(t)$ and $X_j^{**}(t)$ are, respectively, members of $S_j^*(t)$ and $S^{**}(t)$ that give the minimum distance, they are selected as the personal best and the global best of the jth particle. Liu and Zhao (2011) pro-

posed εDMOPSO algorithm which was the basis for an improved multi-objective PSO with orthogonal design and crossover (Liu et al., 2012). In this method, the orthogonal design was used to generate the initial swarm, while a new crossover operator was designed to keep solutions in the feasible region.

There are few applications of PSO or MOPSO algorithm in water resources management, chiefly in reservoir operation problems (Baltar and Fontane, 2006; Kumar and Reddy, 2007; Afshar, 2012; Lu et al., 2013). In this paper, MOPSO has been applied for conjunctive surface water and groundwater management. A new algorithm structure is proposed that can perform better than other evolutionary algorithms in solving complex conjunctive use management problems. Section 2 provides background information on single-objective and multi-objective PSO, presenting a novel fuzzy MOPSO named f-MOPSO, discussing its theoretical underpinnings, as well as its unique capabilities as compared with other MOPSOs based on the introduced performance criteria. The case study and optimization model formulation are discussed in Section 3. Results are presented and discussed in Section 4. Section 5 concludes the paper.

2. Methodology

2.1. Single-Objective Particle Swarm Optimization

As the name suggests, single-objective PSO (SOPSO) is applied to optimization problems with one objective. Suppose for a d-dimensional optimization problem, $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ and $V_i = (v_{i1}, v_{i2}, \ldots, v_{id})$ are the ith particle's position vector and velocity vector, respectively. If $P_i = (p_{i1}, p_{i2}, \ldots, p_{id})$ is the best previously visited position or the personal best position of the ith particle and $P_g = (p_{g1}, p_{g2}, \ldots, p_{gd})$ represents the global best position of the swarm, the velocity and position of each particle are updated using Eqs. (1) and (2) (Norouzzadeh et al., 2012):

$$V_i^{t+1} = wV_i^t + c_1 r_1 \left(P_i^t - X_i^t \right) + c_2 r_2 \left(P_g^t - X_i^t \right) \tag{1}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{2}$$

where $d \in \{1, 2, \ldots, D\}$, $i \in \{1, 2, \ldots, N\}$, D is the number of dimensions and N is the swarm size; superscript t is the iteration number; w is the inertia weight that hinders the velocity vector to be unlimitedly large which may cause algorithm to diverge near the optimum positions; r_1 and r_2 are two random vectors and c_1 and c_2 are cognitive and social scaling parameters.

An efficient form of Eq. (1) is the constriction coefficient model shown below (Norouzzadeh et al., 2012):

$$V_i^{t+1} = \chi \left[V_i^t + \varphi_1 \left(P_i^t - X_i^t \right) + \varphi_2 \left(P_g^t - X_i^t \right) \right] \tag{3}$$

$$\chi = \frac{2k}{\left| 2 - \varphi - \sqrt{\varphi(\varphi - 4)} \right|}; \quad \varphi = \varphi_1 + \varphi_2; \quad \varphi_1 = c_1 r_1; \quad \varphi_2 = c_2 r_2 \tag{4}$$

where χ is constriction factor.

The parameter $k \in [0, 1]$ in Eq. (4) controls the exploration and exploitation abilities of the swarm, which can be calculated as follows (Shi and Eberhart, 1998a, 1998b; Veldhuizen, 1999):

$$k = k_{max} - \frac{k_{max} - k_{min}}{iter_{max}} \times n \tag{5}$$

where k_{max} and k_{min} are constants that must be set properly; n is the number of iterations; and $iter_{max}$ is the maximum number of iterations.

In this paper, the lower and upper bounds of velocity vector are limited to pre-defined values of V_{min} and V_{max} (Eq. (6)) to restrict the particles' velocity vector variations to preserve them in the solution space:

$$V_{min} < V_i^{t+1} < V_{max}; \quad V_{min} = -V_{max} \tag{6}$$

where V_{min} and V_{max} are the velocity vector bounds. When the particle's position exceeds the limits considered for that position, it is restored and fixed to the limits. To hinder the particle from exiting the feasible space in the next iterations V_i^{t+1} is replaced with $-V_i^{t+1}$ in the particle's dimension position.

2.2. Multi-objective PSO (MOPSO)

First method: The structure of the first method is similar to the VEPSO algorithm (Parsopoulos and Vrahatis, 2002), in which multiple swarms are employed rather than a single one to find an optimal Pareto-front. In VEPSO algorithm, the number of swarms is the same as the number of objectives. A particle's velocity when the number of particles is N is updated by:

$$V_{i,sn}^{t+1} = \chi \left[V_{i,sn}^t + \varphi_1 \left(P_{i,sn}^t - X_{i,sn}^t \right) + \varphi_2 \left(P_{g,sn^*}^t - X_{i,sn}^t \right) \right] \tag{7}$$

where $i \in \{1, 2, \ldots, N\}$; sn is swarm number; and sn^* is the swarm number from which the global best particle comes, which is calculated as follows:

$$sn^* = \begin{cases} m & \text{for} \quad sn = 1 \\ sn - 1 & \text{for} \quad sn = 2, \ldots, m \end{cases} \tag{8}$$

where m is the maximum number of swarms (Fallah-Mehdipour et al., 2011).

Second method: In this method, all objectives are used to find the personal best solutions, as well as the global best particle of the swarm. The velocity vector is updated with respect to all the objectives. Thus, Eq. (3) takes the following form (Eq. (9)):

$$V_i^{t+1} = \chi \left[V_i^t + \frac{\varphi_1}{m} \sum_{j=1}^m \left(P_{i,j}^t - X_i^t \right) + \frac{\varphi_2}{m} \sum_{j=1}^m \left(P_{g,j}^t - X_i^t \right) \right] \tag{9}$$

where m is the number of objectives, $P_{i,j}$ is the best position of ith particle for jth objective and $P_{g,j}$ is the best position of the swarm for jth objective. Other characteristics of the algorithm in this method are similar to the SOPSO (Fallah-Mehdipour et al., 2011).

2.3. Proposed method: fuzzy Multi-Objective Particle Swarm Optimization (f-MOPSO)

An important limitation of many MOPSO algorithms in solving multi-objective problems lies in the selection mechanisms. There are some recommended selection mechanisms such as: random selections or allocating all non-dominated solutions the same degree of importance in terms of fitness and discriminating them by crowding distance operator to select the best particle. For overcoming this problem, the need to select the best particle occasionally turns into having to select more than one best particle to generate the next population. The latter solution may cause the algorithm to prematurely converge to the optimum point. Thus, in this paper the former solutions are considered when identifying the global best solution. For this purpose, both the generating methods and preference methods common in Multi-Criteria Decision Making (MCDM) are required to simultaneously compare the obtained solutions. The suggested method utilizes the context of the weighting method to comprehensively generate and compare the solutions and give the personal and global bests. The weighting method determines the non-dominated points among all the points in the feasible solutions, forming the Pareto-optimal front. The Pareto-front consists of a number of points in which every point corresponds to a set of weights denoting the

partial derivatives of the pairwise objectives. The general weighting method equation is given below:

$$Z = W_1 Z_1 + W_2 Z_2 + \cdots + W_n Z_n \tag{10}$$

where W_i is the weight assigned to ith objective function and Z_i is ith objective function while $i = 1, 2, \ldots, n$. In a two-dimensional objective space of Z_1 and Z_2, the equation is:

$$\frac{W_2}{W_1} = -\frac{\partial Z_1}{\partial Z_2} \tag{11}$$

and in a three-dimensional objective space there are three equations as follows:

$$\frac{W_1}{W_2} = -\frac{\partial Z_2}{\partial Z_1} \tag{12}$$

$$\frac{W_1}{W_3} = -\frac{\partial Z_3}{\partial Z_1} \tag{13}$$

$$\frac{W_2}{W_3} = -\frac{\partial Z_3}{\partial Z_2} \tag{14}$$

By definition, each point on the Pareto-front is a non-dominated solution, which produces the best objective function values with respect to its own location. However, if other sets of weights or slopes belonging to other locations in the Pareto-front are imposed on these points, they will have a Z value in other locations (Eq. (10)). Thus, each point has a performance related to each set of weights and all these partial performances contribute to the overall performance of a point, indicating the solution's optimality. Hence, the weighting method could also work as a preference method to give the best point in the Pareto-front and discriminate the optimal and near-optimal solutions of the optimization process, simultaneously. This approach motivates employing the fuzzy logic (Zadeh, 1965), in MOPSO, and hence is named f-MOPSO. Each partial performance of a point could be stressed with a membership degree (MD) dedicating to that partial performance. The comparison process to distinguish the solutions could be done based on a Sugeno Fuzzy Inference System (SFIS) (Takagi and Sugeno, 1985), in which the objectives are the premises and the partial performances (Z values) are the consequences of SFIS rules. The SFIS formulation is as follows:

$$\text{If } Z_1' \text{ is } A_1^1 \text{ and } Z_2' \text{ is } A_2^1 \quad \text{Then } Z^1 = W_1^1 Z_1' + W_2^1 Z_2' \tag{15}$$

$$\text{If } Z_1' \text{ is } A_1^2 \text{ and } Z_2' \text{ is } A_2^2 \quad \text{Then } Z^2 = W_1^2 Z_1' + W_2^2 Z_2' \tag{16}$$

$$\vdots \qquad\qquad \vdots \qquad\qquad \vdots$$

$$\text{If } Z_1' \text{ is } A_1^n \text{ and } Z_2' \text{ is } A_2^n \quad \text{Then } Z^n = W_1^n Z_1' + W_2^n Z_2' Z_2' \tag{17}$$

In the bi-objective version of f-MOPSO (discussed in this paper), which can be developed to cope with any multi-objective problem, first, different sets of weights or slopes of the Pareto-front are considered, allowing each weight to change between 0 and 1 such that the sum of the two weights is equal to 1, i.e., increasing one weight results in decreasing the other weight. This weighting method covers all weight combinations, i.e., all slopes of the Pareto-front. The smaller the decreasing or increasing weight step, the more accurate the performance of the SFIS will be. Then, the objectives are normalized in order to become commensurable and different cases are considered to form the SFIS rules through the equations below:

$$Z_1' = \frac{Z_1 - Z_{1,min}}{Z_{1,max} - Z_{1,min}} \tag{18}$$

$$Z_2' = \frac{Z_2 - Z_{2,min}}{Z_{2,max} - Z_{2,min}} \tag{19}$$

For minimization purposes, if $W_1 < W_2$, considering the higher values of Z_1' along with the lower values of Z_2' results in a smaller value of Z, indicating the best performance of those objectives under these weights. The approach works when $W_1 > W_2$, too. In this case, the lower values of Z_1' as well as the higher values are considered. In practical applications, a pre-optimization process will be implemented whereby a number of uniformly distributed random solutions are generated, and the corresponding objective function values are calculated. The fitness of the number of generated objective functions depends on the ability of covering all functions being generated as the algorithm progresses. The obtained objective function values are then divided into three classes named High, Middle and Low based on the values of each objective. For each class a membership function (MF) is defined. In this paper, the descending Sigmoidal MF is chosen for this purpose. The MF's equation is as follows:

$$Sig(x, a, c) = f = \frac{1}{1 + e^{a(x-c)}} \tag{20}$$

where $a > 0$ denotes and controls the slope in crossover point and c represents the crossover point. For simplification, this MF is compared with a well-known Gaussian MF (Fig. 1):

$$Gaussian(x, \mu, \sigma) = f = e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{21}$$
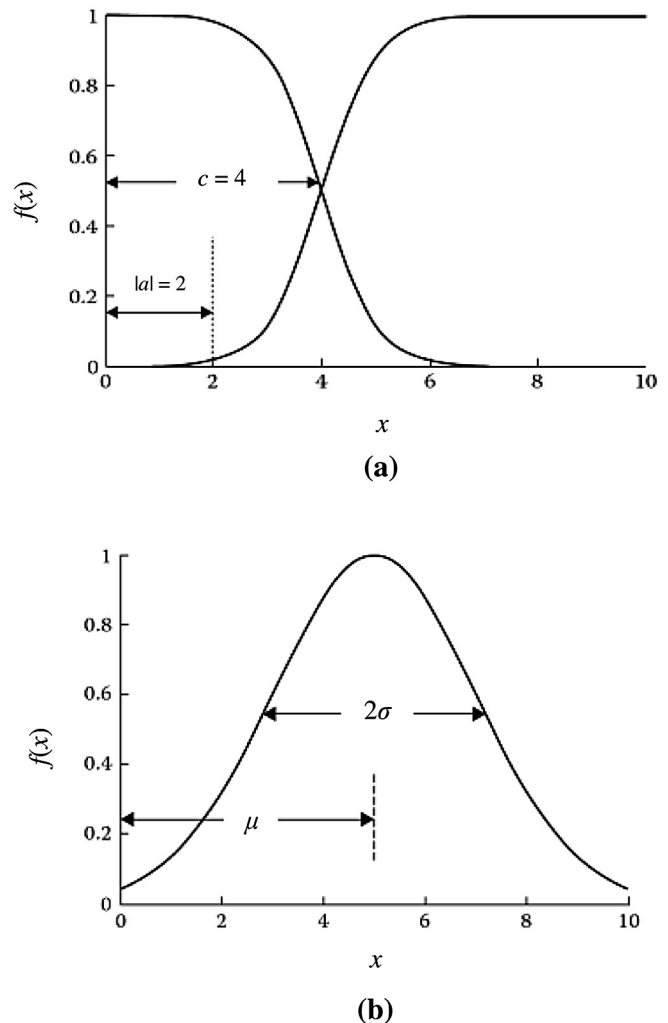

(a)

(b)

Fig. 1. (a) Sigmoidal and (b) Gaussian membership function.

in which μ is the mean of the variable (e.g., objective function value) fuzzified through this equation, and σ is the standard deviation of those values.

To avoid the trial and error procedure to determine MFs of the SFIS rules, the parameters a and c in Eq. (20) depend on the statistical parameters, e.g. μ and σ, in Eq. (21). The intersection point of the ascending and descending Sigmoidal MFs (Eq. (20)) with $a < 0$ and $a > 0$, respectively, is $x = c$. Since these two types of Sigmoidal MFs belong to two conflicting concepts, and are complementary, the x value of the intersection point will be the mean, thus $c = \mu$. This result comes from the corollary that the mean value of a fuzzy variable in complementary MFs is not biased to any direction and gives the same value of f in those MFs, which is 0.5 in this case.

Another approximation is related to the slope of the MFs in the crossover point as calculated below for the descending Sigmoidal functions in which $a > 0$:

$$Sig(x, a, c) = f = \frac{1}{1 + e^{a(x-c)}} \tag{22}$$

$$\frac{df}{dx} = f' = \frac{-a \cdot e^{a(x-c)}}{[1 + e^{a(x-c)}]^2} \tag{23}$$

$$f'(x = c) = -\frac{a}{4} \tag{24}$$

The crossover point of the Gaussian MF is calculated below:

$$Gaussian(x, \mu, \sigma) = f = e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{25}$$

$$\frac{df}{dx} = f' = -\frac{1}{\sigma^2}(x - \mu)e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{26}$$

$$\frac{d^2f}{dx^2} = f'' = e^{-\frac{(x-\mu)^2}{2\sigma^2}}\left(\frac{-1}{\sigma^2} + \frac{(x-\mu)^2}{\sigma^4}\right) \tag{27}$$

At crossover point, $(f'' = 0)$, so:

$$-\sigma^2 + (x - \mu)^2 = 0 \tag{28}$$

$$x_{crossover} = \mu + \sigma \tag{29}$$

And the slope in the crossover point of the Gaussian MF is calculated as follows:

$$Gaussian(x, \mu, \sigma) = f = e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{30}$$

$$\frac{df}{dx} = f' = -\frac{1}{\sigma^2}(x - \mu)e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{31}$$

$$f'(x_{crossover} = \mu + \sigma) = -\frac{1}{\sigma\sqrt{e}} \tag{32}$$

By equating the two slopes of Sigmoidal and Gaussian MFs in the crossover point in Eqs. (24) and (32), the parameter a is derived in terms of σ:

$$-\frac{a}{4} = -\frac{1}{\sigma\sqrt{e}} \tag{33}$$

$$a = \frac{4}{\sigma\sqrt{e}} \tag{34}$$

Consequently, the parameters a and c can be derived in terms of statistical parameters μ and σ.

In this method, the best overall performance of each point is compared to other points. This logic is underpinned by the SFIS rules. In a SFIS rule where $W_1 < W_2$ and the MF of Z'_1 is High and that of Z'_2 is Low, the equal absolute amount of Increase in Z'_1 and decrease in Z'_2 causes a decrease in the corresponding Z. Therefore, a larger MD must be assigned to that Z in order to impart importance to low values of Z to support the logic of this method. But in this case, based on the shape of descending Sigmoidal MFs, it can be seen that the larger the Z'_1, the smaller the MD, and the smaller the Z'_2, the larger its MD will be. Using the Mamdani implication function (Mamdani, 1974), the minimum of two MDs is considered as the resulting MD. This minimum may decrease, although it is expected to increase to make the lessened value of Z significant. To solve this problem the algebraic product-based Larsen implication is used instead, giving $(\mu^j = \mu^j_{Z_1} \times \mu^j_{Z_2})$ where j is the number of rule and μ^j is the MD of the consequence of the rule j resulting from implication. With a similar inference, the Larsen implication seems to be more appropriate for use in all the SFIS rules in the f-MOPSO algorithm. If the product of MDs is considered, even if the μ^j remains constant, then the value of Z of rule j has decreased and has its impact on the final defuzzified result. Furthermore, this impact will be less than the impact of a case in which Z'_1 and Z'_2 both decrease, increasing their MDs and the product of the MDs, which is logical and plausible.

Finally, the weighted average is utilized as a defuzzification method, and a comprehensive Dominance Index (DI) is obtained using the equation below:

$$DI = \frac{\sum_{j=1}^n \mu^j Z^j}{\sum_{j=1}^n \mu^j} \tag{35}$$

This equation gives the defuzzified value of Z over all rules of SFIS. The less the DI, the better that solution with the normalized objectives Z'_1 and Z'_2. Table 1 summarizes how the SFIS rules were applied in the current f-MOPSO application.

In any iteration of f-MOPSO, the minimum value of DI between current and new particle represents the personal best particle, and the minimum DI obtained from all personal bests of the swarm denotes the global best particle in that iteration. Other calculations

Table 1
Types of MFs contributing to form SFIS rules assuming weight step = 0.1.

W_1	W_2	Z'_1/Z'_2			
0	1	High/Mid	High/Low	Mid/Low	Low/Low
0.1	0.9	High/Mid	High/Low	Mid/Low	Low/Low
0.2	0.8	High/Mid	High/Low	Mid/Low	Low/Low
0.3	0.7	High/Mid	High/Low	Mid/Low	Low/Low
0.4	0.6	High/Mid	High/Low	Mid/Low	Low/Low
0.5	0.5	Low/Low	–	–	–
0.6	0.4	Low/Mid	Low/High	Mid/High	Low/Low
0.7	0.3	Low/Mid	Low/High	Mid/High	Low/Low
0.8	0.2	Low/Mid	Low/High	Mid/High	Low/Low
0.9	0.1	Low/Mid	Low/High	Mid/High	Low/Low
1	0	Low/Mid	Low/High	Mid/High	Low/Low

are the same as in a Single-Objective PSO (SOPSO). Moreover, the non-dominated solutions from each iteration round are stored in an external archive, while storing the best solution of that iteration round, found based on the minimum DI in another external archive. The final results stored in the archives include all the non-dominated solutions that form a Pareto-front, and the best of global best particles over all iterations of the algorithm as the best unique solution.

2.4. Performance criteria

To determine the best performing multi-objective method, the performance of each method is evaluated under different criteria. Results of the presented stochastic MOPSO methods depend on randomly generated starting populations. Therefore, a number of runs were performed for each method and evaluated along with the results of the other two methods based on three performance criteria, namely Generational Distance (GD), Spacing (S), and Number of Solutions (NS). Due to the evolutionary nature of the applied MOPSO methods, it is not unexpected to observe that performance would change under different runs of the same model. However, when the results obtained from multiple runs of each MOPSO method are synthesized, they represent the goodness of the overall performance of each MOPSO algorithm compared with other MOPSO algorithms. Thus, these performance criteria provide a reasonable and consistent basis for evaluating the MOPSOs, especially when they are applied in the context of a real-world conjunctive surface water and groundwater management optimization problem. The performance criteria are as follows.

2.4.1. Generational distance (GD)

This performance metric was suggested by Veldhuizen (1999) to find the average distance between the non-dominated solutions and the optimal Pareto-front to minimize the distance of the Pareto-front produced by MOPSOs with respect to the true Pareto-front:

$$GD = \frac{1}{NS}\sqrt{\sum_{i=1}^{NS} d_i^2} \qquad (36)$$

where GD = generational distance; NS = number of solutions found and d_i = Euclidean distance (in the objective space) between each non-dominated solution and the nearest member of the optimal Pareto-front.

In practical applications such as the example case in this study, because there is no user-specified Pareto-front, the ideal point including the best values of all objective functions has been considered as the reference-point and the basis of the Euclidean distance calculation. Thus, the GD value is calculated with reference to the comparative point called the ideal point.

2.4.2. Spacing (S)

This metric was proposed by Schott (1995) to maximize the distribution of solutions given by MOPSOs:

$$S = \sqrt{\frac{1}{NS-1}\sum_{i=1}^{n}(\bar{d} - d_i)^2} \qquad (37)$$

where S = spacing criteria and $\bar{d}$ = mean of all d_i.

d_i is calculated using Eq. (38):

$$d_i = Min\left(\sum_{k=1}^{m}\left|f_k^i(x) - f_k^j(x)\right|\right) \qquad (38)$$

where $i = 1, 2, \ldots, NS$, $j = 1, 2, \ldots, NS - 1$; m = number of objectives and $f_k^j(x)$ = kth objective for the jth solution. Thus, the minimum value of S is zero which means that the identified solutions are equidistantly distributed in the objective space.
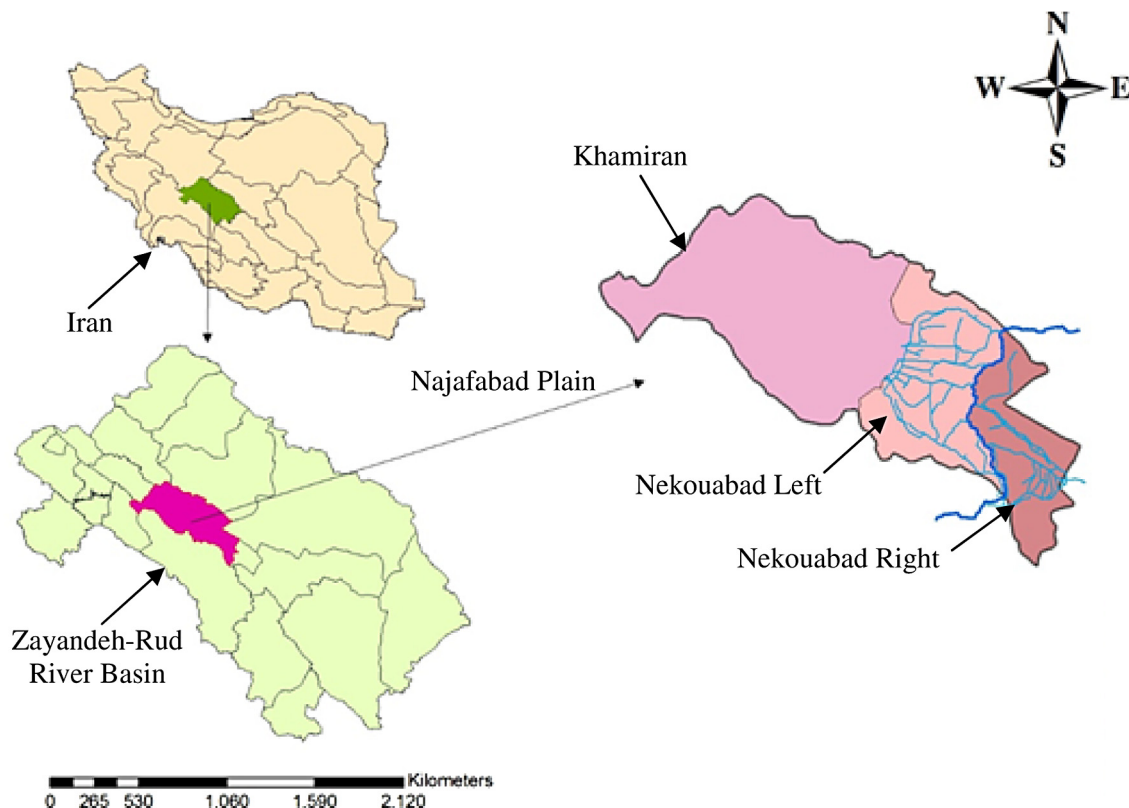

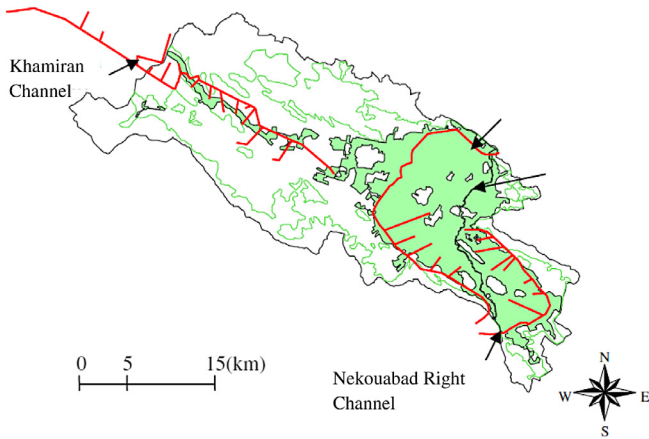**Fig. 2.** Najafabad Plain in the Zayandeh-Rud River Basin, Iran.

Fig. 3. Nekouabad irrigation channels.

2.4.3. Number of solutions (NS)

This performance metric was considered in order to attain the goal of maximizing the number of elements of the Pareto-optimal set. There is no upper bound for NS which means the greater the number of solutions, the better the set of non-dominated solutions. It is suggested to meticulously evaluate the values of the best objective functions, taking these metrics into account, too, as two more performance metrics.

3. Case study of conjunctive surface and groundwater use management

The study area is Najafabad Plain, a part of the Zayandeh-Rud River Basin (read more about this basin in Safavi et al. (2010), Safavi and Esmikhani (2013) and Gohari et al. (2013, 2014)) located in west-central Iran (Fig. 2). In recent years, water has become increasingly scarce in the region and the Zayandeh-Rud River Basin
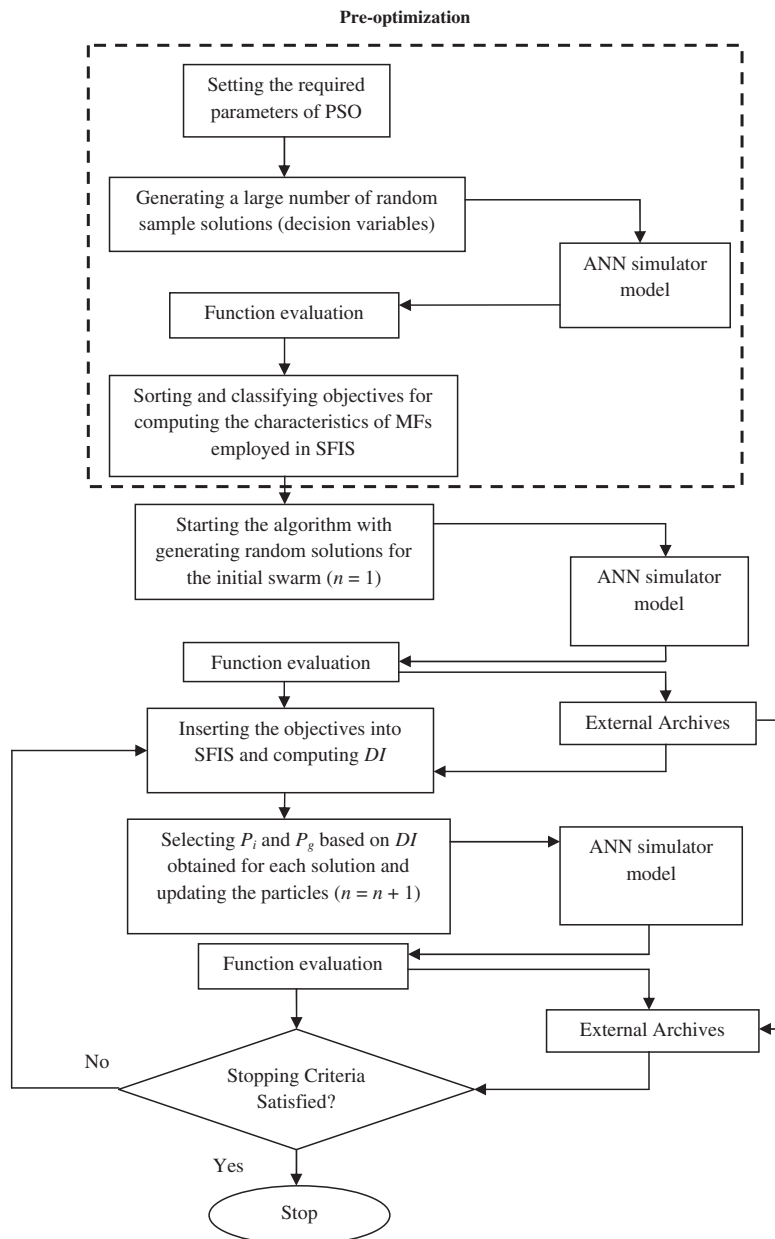

Fig. 4. Flowchart of the proposed simulation-optimization model.

Table 2
Correlation coefficients resulting from ANN model in all MOPSOs.

	Training (R)	Test (R)	Validation (R)	Total (R)
N-Right	0.60	0.38	0.51	0.55
N-Left	0.62	0.46	0.31	0.52

has shown signs of salinization of agricultural land and increased pollution in the lower reaches of the river. The Najafabad Plain occupies an area of approximately $1720\,km^2$ underlain by the Najafabad Aquifer with an area of about $1142\,km^2$, with geographical coordinates between $50°\ 57'$–$51°\ 44'$ North longitudes and $32°\ 20'$–$32°\ 49'$ East latitudes. The Najafabad Aquifer is recharged by irrigation infiltration, canal and river seepages, as well as direct precipitation on the plain. There are about 10,160 pumping wells in the area with depths ranging between 17 m and 120 m, and discharge rates ranging from 2 to 110 L/s (Safavi and Rezaei, 2015).

The Najafabad Plain is predominantly semi-arid with an average annual rainfall of only 150 mm most of which falls in winter months (i.e., December to April). Annual potential evapotranspiration is about 1950 mm. Modern surface irrigation started about 40 years ago after Nekouabad diversion weir was built. The weir controls two main channels on its left and right banks (two irrigation zones) as shown in Fig. 3. Over the past decade, historical low precipitation occurred at the head of the Zayandeh-Rud Basin, increasing water scarcity in the region. The water scarcity problem was further aggravated by growing demand for water. To cope with the drought condition, farmers have had to implement field scale response strategies, including increased groundwater use, adapted farming and production strategies, or adopting other activities for their livelihood (Safavi et al., 2010).

If groundwater extraction continues at present rate, there will be a drastic decline in groundwater storage. Thus, both sources of water must be used in order to minimize water supply related risks in drought conditions and minimize pressure on groundwater sources in non-drought conditions. A conjunctive water use model utilizing three MOPSO algorithms (including the aforementioned first and second MOPSOs and also the proposed f-MOPSO algorithm) is introduced so as to minimize water shortages as well as groundwater withdrawals in the Najafabad Plain subject to constraints related to allowable groundwater storage decline and maximum available surface water supply or irrigation channels' capacities.

In a conjunctive surface and ground water use system, surface water deficit is compensated for by increasing groundwater extraction in drought situations and/or groundwater is replenished by surface water when surface water is abundant. Optimal management of the surface water and groundwater resources is critical for effective and efficient conjunctive management schemes (Safavi et al., 2010). The MOPSO algorithms were applied to find the optimal surface water and groundwater allocation schemes in the water-scarce Najafabad Plain, examining the algorithms' capability to support decision making in a real-world context.

Table 4
Relative closeness index of the MOPSOs applied to a 12-month operation period (Boldfaced numbers indicate the best performing algorithm with reference to a certain zone).

	1st method	2nd method	f-MOPSO
Nekouabad Right zone	0	0.51	**0.91**
Nekouabad Left zone	0.36	0.41	**0.83**

The objectives of the optimization model were minimizing deficits in meeting irrigation demands in each of two main zones in the Najafabad Plain, and minimizing groundwater level (GWL) variation to prevent negative groundwater balance due to drawdown, and crop damage due to waterlogging. The model prescribes optimal groundwater extraction subject to such constraints as maximum and minimum allowable cumulative variation in GWL and the maximum surface irrigation systems supply. The optimization model formulation is given below (Eqs. (39)–(51)):

$$\text{Minimize} \quad Z_1 = \sum_{i=1}^{12}\left((D_{i,z} - Sup_{i,z,net})/D_{i,z}\right)^2 + Z_{pen} \quad \text{for } z$$
$$= 1, 2 \tag{39}$$

$$\text{Minimize} \quad Z_2 = \sum_{i=1}^{12}\left((\Delta H_{i,z} - \Delta H_{opt})/\Delta H_{opt}\right)^2 \quad \text{for } z = 1, 2 \tag{40}$$

Subject to:

$$Z_{pen} = R \cdot \left\{ 1 + sgn\left[\left(\sum_{i=1}^{12}\Delta H_{i,z} - \Delta H_{min} \right)\left(\sum_{i=1}^{12}\Delta H_{i,z} - \Delta H_{max} \right) \right] \right\} \tag{41}$$

$$D_{i,z} = \sum_{m=1}^{M} crop_{i,m}A_{i,m}; \quad \text{for } i = 1, 2, \ldots, 12 \tag{42}$$

$$A_{i,z} = \sum_{m=1}^{M} A_{i,m}; \quad \text{for } i = 1, 2, \ldots, 12 \text{ and } z = 1, 2 \tag{43}$$

$$Sup_{i,z,net} = GW_{i,z,net} + SW_{i,z,net} \tag{44}$$

$$GW_{i,z,net} = a_z GW_{i,z} \tag{45}$$

$$SW_{i,z,net} = a_z b_z c_z SW_{i,z} \tag{46}$$

$$SW_{i,z} = D_{i,z}/a_z b_z c_z \quad \text{and} \quad GW_{i,z} = 0; \quad \text{If } SW_{i,z,net} \geqslant D_{i,z} \tag{47}$$

$$GW_{i,z} = (D_{i,z} - SW_{i,z,net})/a_z; \quad \text{If } (SW_{i,z,net} < D_{i,z}) \text{ and } (GW_{i,z,net} \geqslant D_{i,z} - SW_{i,z,net}) \tag{48}$$

$$\Delta H_{min} \leqslant \sum_{i=1}^{12}\Delta H_{i,z} \leqslant \Delta H_{max}; \quad \text{for } z = 1, 2 \tag{49}$$

Table 3
Comparison of the MOPSOs' performance over a 12-month operation period (Boldfaced numbers represent the best performing algorithm with reference to a certain criterion).

Criterion	Nekouabad Right zone			Nekouabad Left zone		
	1st method	2nd method	f-MOPSO	1st method	2nd method	f-MOPSO
GD	0.77	0.3	**0.02**	12.97	3.62	**0.97**
S	0.40	0.09	**0.003**	0.81	3.55	**0.67**
NS	15	23	**744**	23	32	**141**
$Z_{1,min}$	0.70	**0.12**	0.47	**0.49**	0.73	0.92
$Z_{2,min}$	39.66	38.92	**17.15**	53.87	29.12	**7.59**
$Z_{1,optimum}$	–	–	0.97	–	–	4.76
$Z_{2,optimum}$	–	–	17.15	–	–	7.59

$$SW_{i,z} \leqslant SW_{i,z}^{avail}; \quad \text{for } i = 1, 2, \ldots, 12 \text{ and } z = 1, 2 \tag{50}$$

$$GW_{i,z} \leqslant D_{i,z}/a_z \tag{51}$$

where $D_{i,z}$ = volume of water demand in zone z in month i (MCM); $Sup_{i,z}$ = volume of water supply in zone z in month i (MCM); $\Delta H_{i,z}$ = GWL variation in zone z in month i (m); ΔH_{opt} = the optimum GWL variation, assumed to be a trivial value; Z_{pen} = penalty for satisfying cumulative GWL variation constraint mentioned in Eq. (49); R = penalty coefficient; $crop_{i,m}$ = volume of water needed per unit cultivated area for crop m in month i (MCM/m²); $A_{i,m}$ = cultivated

area of crop m in month i; $A_{i,z}$ = arable area of zone z in month i (ha); a_z = farm water use efficiency in zone z (set to be 0.56 here); b_z = efficiency of water use in the main channels in zone z (set to be 0.85 here); c_z = water use efficiency in the secondary channels in zone z (set to be 0.90 here); $GW_{i,z,net}$ = net volume of groundwater extracted in zone z in month i (MCM); $GW_{i,z}$ = gross volume of groundwater extracted in zone z in month i (MCM); $SW_{i,z,net}$ = net volume of surface water withdrawal delivered to zone z in month i (MCM); $SW_{i,z}$ = gross volume of surface water withdrawal delivered to zone z in month i (MCM); ΔH_{min} = minimum allowable cumulative GWL variation in a year; ΔH_{max} = maximum allowable
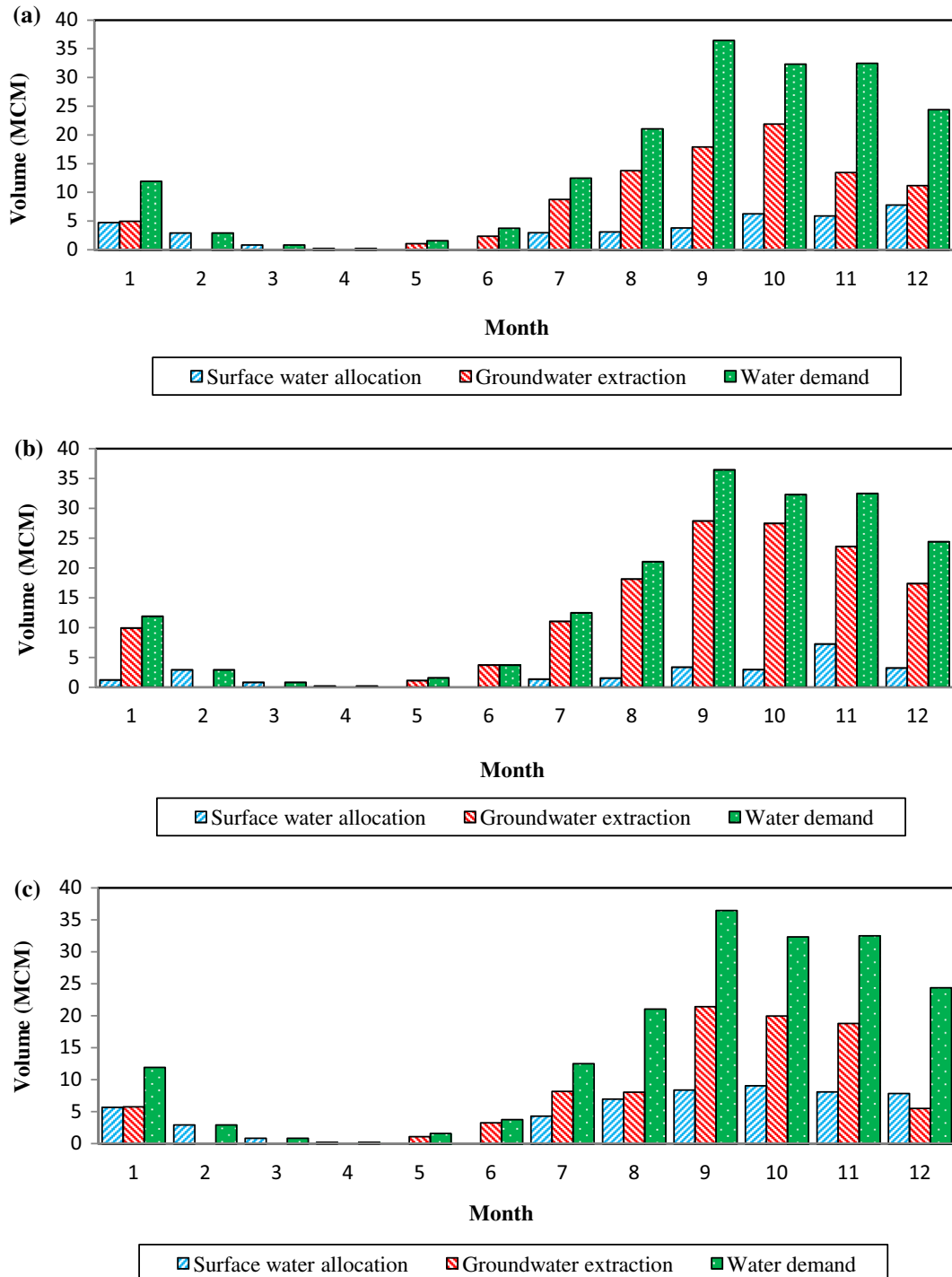

Fig. 5. Water demand and monthly surface water and groundwater allocated to Nekouabad Right zone based on the minimum Z_1 value of (a) first method, (b) second method and (c) the proposed f-MOPSO method.
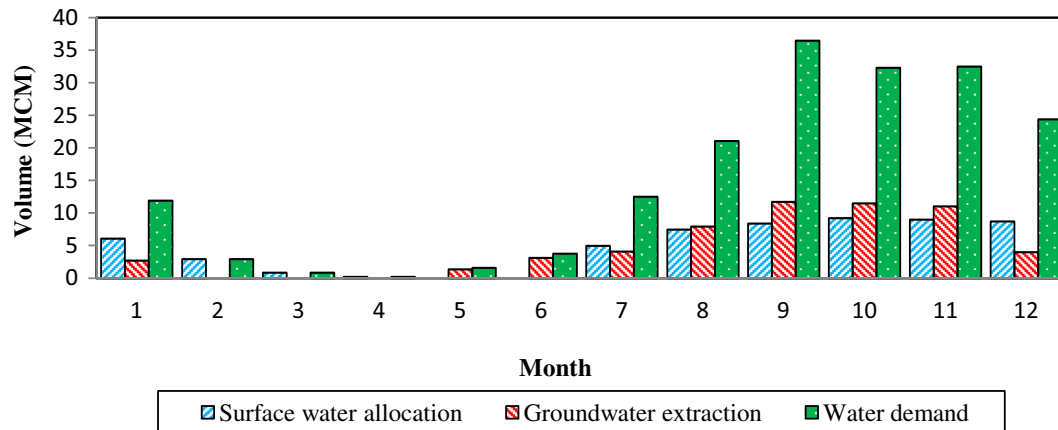
Fig. 6. Water demand and monthly surface water and groundwater allocated to Nekouabad Right zone based on the unique optimal solution of the proposed f-MOPSO algorithm.

cumulative GWL variation in a year; CC_z = zone z's maximum surface water delivery capacity in month i (MCM); α_z = zone z's surface water network efficiency; $SW_{i,z}^{avail}$ = maximum volume of surface water available to zone z in month i (MCM); i = number of months; z = number of zones; m = number of crops.

The surface water upper bound, imposed as a constraint in the optimization model, is the volume of available surface water in each period in each irrigation system. The upper bound of groundwater in each period was set equal to the demands in that period for each zone (Eq. (51)). The planning horizon is October 2005 through September 2006, spanning a normal water year. Thus, there are 24 decision variables including 12 monthly surface water allocations, and 12 monthly groundwater extractions. To calculate the GWL variation, and control this parameter in cumulative and relative forms, a simulation model was used. The flowchart of the coupled simulation-optimization framework employed to solve the optimization problem is shown in Fig. 4.

This simulation model is a single hidden layer back-propagation feed-forward Artificial Neural Network (ANN). The input layer of this network included five parameters: (1) groundwater extraction; (2) precipitation; (3) evaporation; (4) surface water allocation; and (5) Initial GWL. All the data are reported as monthly records and the output is, therefore, generated as monthly GWL variations. In the ANN model, the precipitation, evaporation and GWL parameters were considered as a monthly period-of-record mean based on a 20-year record (1991–2010). The ANN is a 5-30-1 network considering 30 neurons in the hidden layer. The number of hidden layer neurons was determined after a number of trial and errors in running the network until the maximum correlation coefficient and/or the minimum sum of squared errors was reached. For each two zones, the ANN model was independently designed and run. All the data sets were divided into three parts (i.e., 65% for training, 25% for testing, and 10% for validation) and the ANN performance was evaluated based on criterion R as the correlation coefficient. The calculated coefficients are shown in Table 2, indicating a plausible precision in ANN's learning without overtraining the model. In this table and in Tables 3 and 4, the expressions N-Right and N-Left stand for Nekouabad Right and Nekouabad Left zones, respectively.

4. Results and discussion

The three MOPSO algorithms were independently applied to find the best conjunctive use management policy for the Nekouabad Right and Nekouabad Left banks. The number of particles

was set to 20 in each swarm and the maximum number of iterations for the second and third (proposed) MOPSOs was set to 200 and for the first method 100 to consider the same number of function evaluations for all methods. Also a stall iteration number of 50 was considered for the second and third methods and 25 for the first method. It was assumed that the algorithm would stop when the maximum number of iterations is reached or the difference in both objective functions corresponding to the global best particles of each iteration over the number of stall iterations is less than 10^{-6}. Thus, iterations without any improvement in the objective function values were impeded, reducing the model's run time. The number of weight combinations employed in SFIS rules should be large enough to cover all examined points on the Pareto-front, allowing all these points to show their best performance. Furthermore, the combinations should render slopes of the Pareto-front to be equidistantly distributed in the objective space to represent all points of the Pareto-front unbiasedly to yield actual partial performances for the solutions. Thus, the growing step of the weights in the SFIS was set to 0.05. A set of 500 particles was adopted for the pre-optimization stage to find the characteristics of the MFs as well as the consequences' singleton MFs of the SFIS in the third method. Of the PSO parameters, $c_1 = c_2 = 2.05$ and the maximum level of velocity was set to be 0.1 times the difference between the maximum and minimum values of the positions of each particle (decision variables) in each dimension. The results are presented in Figs. 5–7.

A summary of the optimization results including the performance criteria along with minimum objective values for the first and second methods as well as the optimal objective values for the f-MOPSO method are presented in Table 3.

In the Nekouabad Right zone, the minimum GD, S and the maximum NS were obtained from the proposed f-MOPSO algorithm. The minimum Z_1 was obtained from the second method and the minimum Z_2 of the f-MOPSO. As shown in Fig. 5a–c, the maximum proportion of demand met using the first and second methods occurred in months 2–4 which have the least demands over the planning horizon. But the f-MOPSO nearly met full demand in autumn and winter seasons of the planning horizon while facing only a few shortages. The developed f-MOPSO algorithm outperformed the other MOPSO methods by finding optimal water allocations that meet the water demand in the noted high-demand months. In regard to the minimum Z_1, the water allocation on average met 81%, 93% and 86% of the water year demands in the first, the second, and the proposed algorithms, respectively, indicating marginal superior performance of the second method in minimizing shortages. These percentages were obtained from minimizing

water supply shortages corresponding to the worst values for the GWL variations.

A positive GWL variation indicates a rise in the groundwater table due to recharge whereas a negative variation means groundwater table drawdown due to withdrawal. The maximum groundwater table drawdowns in all three methods were seen in the last four months corresponding to a large volume of groundwater withdrawal as dictated by the large volume of water demand imposed on the model as the upper bound.

The maximum positive variation in GWL predominantly occurred in the months 4–6 with the highest volume of recharge due to winter precipitation. The cumulative GWL variation after conjunctive use of water over 12 months was 1.76, 1.54 and 1.16 m in the first, second and the proposed MOPSOs, indicating the proposed f-MOPSO method prescribes a better groundwater withdrawal scheme.

The f-MOPSO algorithm is capable of finding the unique optimal solution among a large number of non-dominated solutions. The results obtained from non-dominated solution analysis given by f-MOPSO are shown in Fig. 6. Briefly, the mean demand percentage met by the optimal solution was 77% corresponding to the cumulative GWL variation of 1.17 m. These values are consistent and
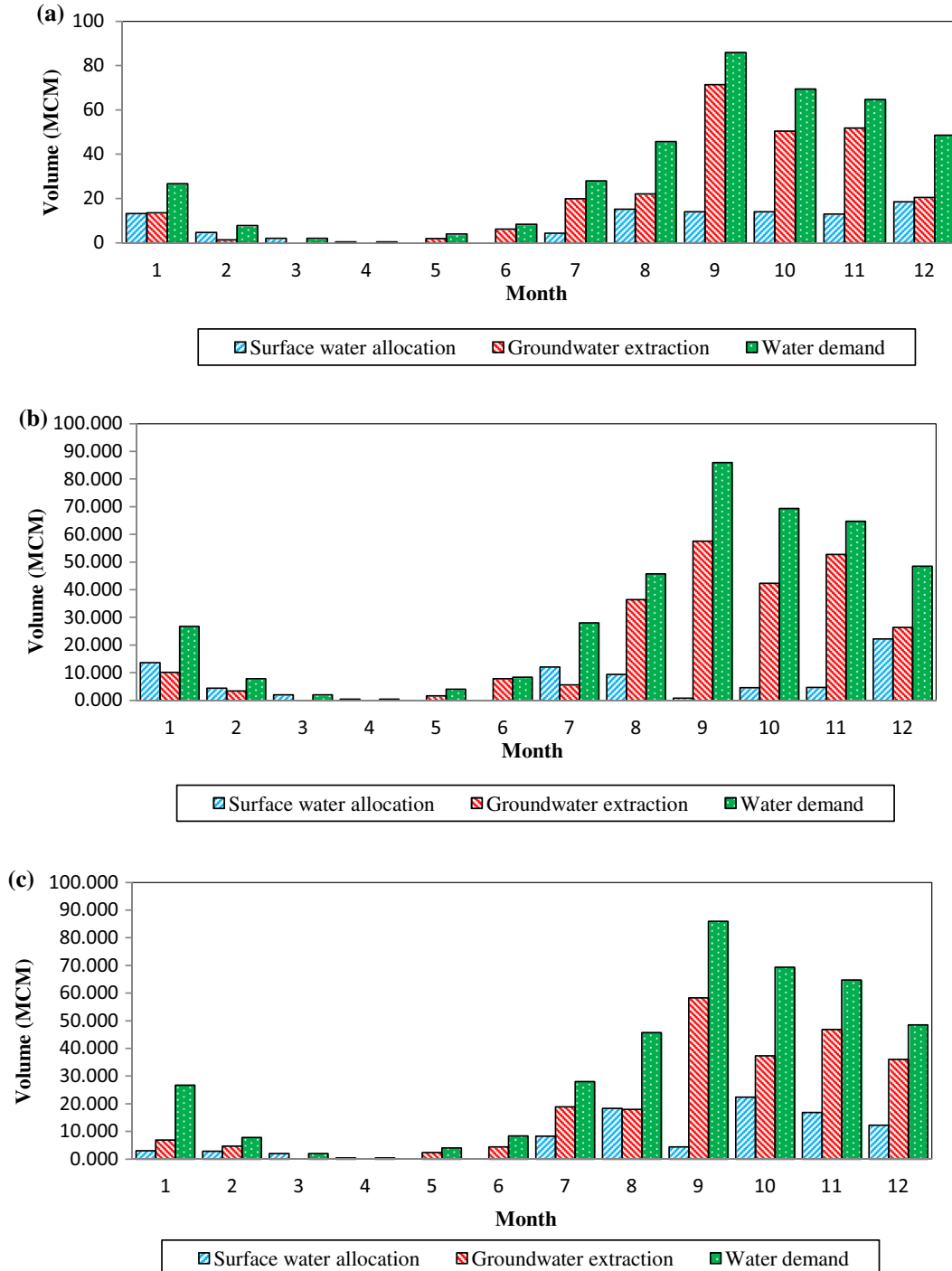

Fig. 7. Water demand and monthly surface water and groundwater allocated to Nekouabad Left zone based on the minimum Z_1 value of first method (a), second method (b) and (c) the proposed f-MOPSO method.
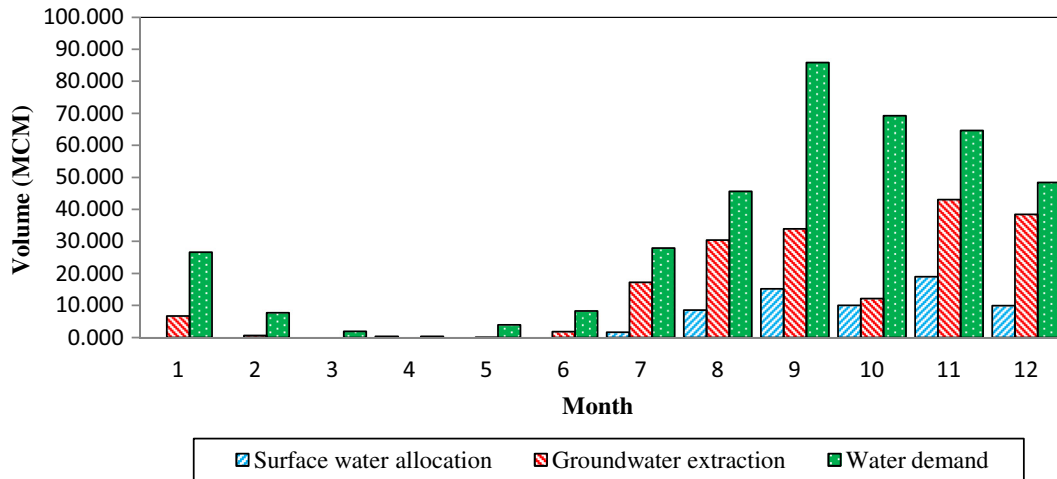
Fig. 8. Water demand and monthly surface water and groundwater allocated to Nekouabad Left zone based on the unique optimal solution of the proposed f-MOPSO algorithm.

Table 5
Comparison of the MOPSOs' performance in a 10-year planning horizon (Boldfaced numbers represent the best performing algorithm with reference to a certain criterion).

Criterion	Nekouabad Right zone			Nekouabad Left zone		
	1st method	2nd method	f-MOPSO	1st method	2nd method	f-MOPSO
GD	6.73	**3.51**	18.777	19.30	6.61	**0.036**
S	**1.46**	1.59	3.49	13.03	7.07	**0.028**
NS	25	14	**54**	15	14	**34**
$Z_{1,min}$	10.59	12.41	**0.32**	8.7	10.31	**1.85**
$Z_{2,min}$	**298.52**	329.62	346.47	**632.71**	648.31	643.51
$Z_{1,optimum}$	–	–	0.32	–	–	1.85
$Z_{2,optimum}$	–	–	508.49	–	–	643.54

demonstrate a relatively small GWL variation for water allocations in the 12-month operation period.

In the Nekouabad Left zone, the minimum GD and S and the maximum NS were given by the proposed f-MOPSO (Table 3). Minimum Z_1 was achieved by the first method, while the minimum Z_2 was found by f-MOPSO. As shown in Fig. 7a–c, for all methods, the trend of proportion of demand met in Nekouabad Left is similar to Nekouabad Right. The demands are almost completely met in the first four low demand months, mostly by surface water and partially met in other months, mainly by groundwater. The mean proportion of demand met is 87%, 84% and 82% for the first method, second method and the f-MOPSO, respectively.

The cumulative GWL variations over the 12-month planning horizon were 3.26, −1.47 and −3.35 m for the first and second methods and the f-MOPSO algorithm, respectively. These GWL variations illustrate high monthly fluctuations in GWL for the first method, while the surface and groundwater were exploited as much as possible over all months. However, negative variations in dry months were compensated by positive variations in wet months over total period, causing GWL to rise and meeting a large portion of demands. While, the f-MOPSO, and to some extent the second method attempted to allocate water resources in balance in order to maintain GWL on a monthly basis, rather than over the 12-month period. Thus, the less mean demand percentage met was provided by these methods compared to the first method and despite achieving the little values of monthly GWL variations, a large drawdown was obtained at the end of the period, mainly due to cumulating the small monthly drawdowns over total period.

Mean demand percentage met and cumulative GWL variation given by the f-MOPSO algorithm's unique optimal solution are 50% and −3.29 m, respectively, (Fig. 8). These alarming values are

not surprising because of high water demands and low surface water availability for irrigation in the Nekouabad Left zone. Increasing the reliability of meeting demand in the Nekouabad Left zone entails much more groundwater extraction, causing more cumulative drawdown at the end of the operation period, which underscores the challenges of short-term conjunctive water use management in this water-scarce region. However in long-term management, there may be all normal, wet and dry water years over total period which contribute to maintain the total cumulative GWL variations in balance, along with enhancing the water demand portion met. This advantage is more illustrated in this paper in the second scenario following at the end of this section.

To systematically evaluate the performance of the three algorithms in the presented case study, the technique for order preference by similarity to ideal solution (TOPSIS; Yoon and Hwang, 1995) was applied. TOPSIS is a multi-criteria decision making-based selection method that ranks the algorithms based on all the performance criteria. This is done by finding the alternative having the shortest distance from the ideal solution and the farthest distance from the least favorable solution (anti-ideal solution). Here, the multi-objective PSO algorithms are the alternatives, while the performance criteria (i.e., GD, S, and NS) and minimum obtained Z_1 and Z_2 are considered as the TOPSIS criteria. A decision matrix is constructed and normalized to make the criteria commensurable. Then, the ideal and anti-ideal solutions are determined and the Euclidean distance of each solution from the ideal and anti-ideal solutions is calculated. Finally, the relative closeness of each solution is calculated for all solutions as follows:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^+}; \quad 0 \leqslant C_i^* \leqslant 1 \text{ and } i = 1, 2, \ldots, p \tag{52}$$
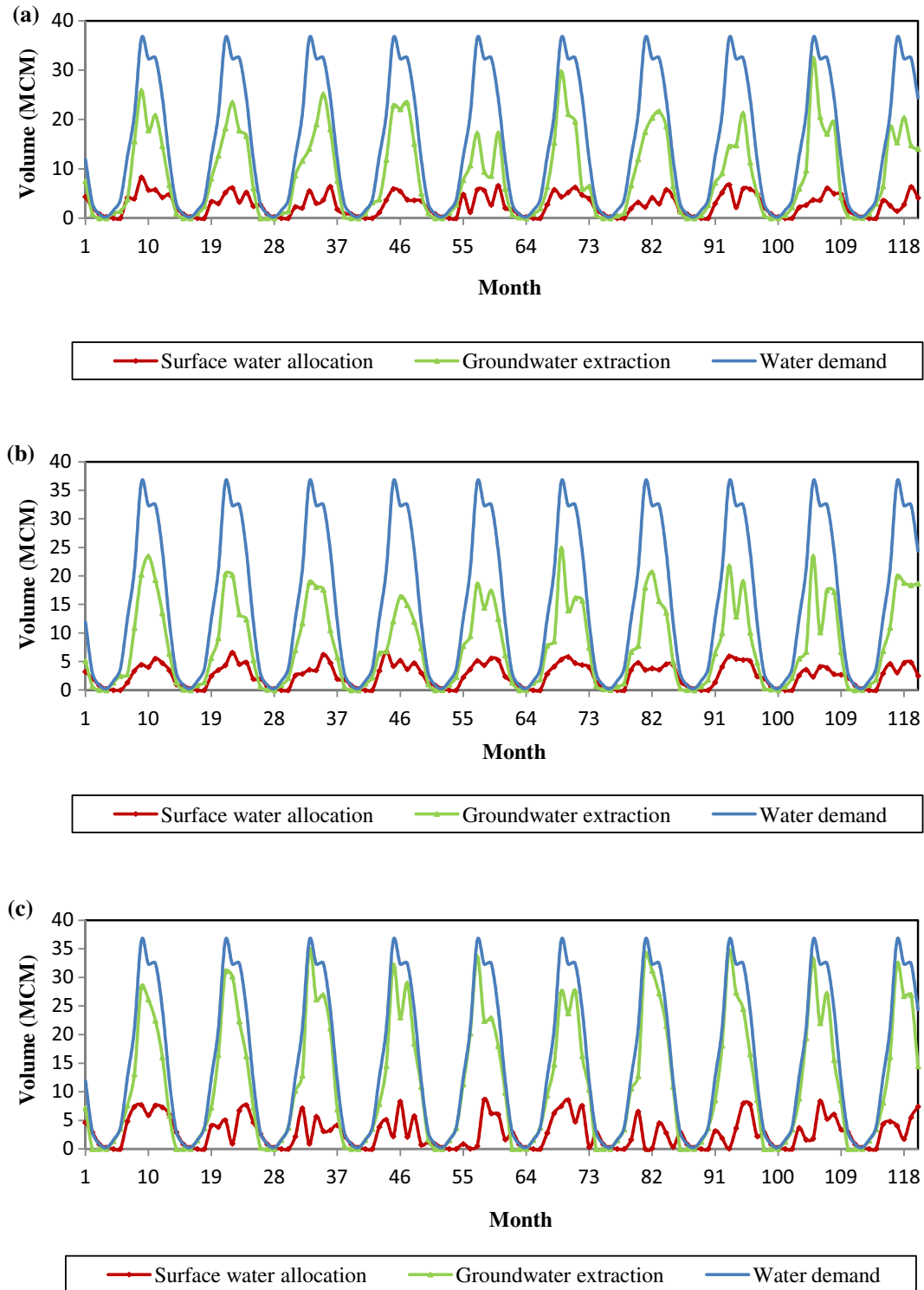
Fig. 9. Water demand and monthly surface water and groundwater allocated to Nekouabad Right zone based on the minimum Z_1 value of first method (a), second method (b) and (c) the proposed f-MOPSO method.

where C_i^* = relative closeness; S_i^- = Euclidean distance from the anti-ideal solution; S_i^+ = Euclidean distance from the ideal solution; and p = number of solutions. The solution with the maximum value of C_i^* is ranked first and marked as the best performing solution. Results of TOPSIS analysis of the solutions are shown in Table 4. All the criteria were given the same weight (0.2), meaning that they are equally important.

In a wide range of papers on multi-objective optimization, only the first three criteria (NS, S and GD) are addressed (Cabrera and Coello, 2010; Fallah-Mehdipour et al., 2011). But in this paper, the last two criteria (minimum Z_1 and Z_2) were also considered in the TOPSIS analysis to facilitate a robust performance evaluation. Despite having relatively good values of NS, S and GD, the Pareto-front generated by one algorithm may partially or entirely domi-
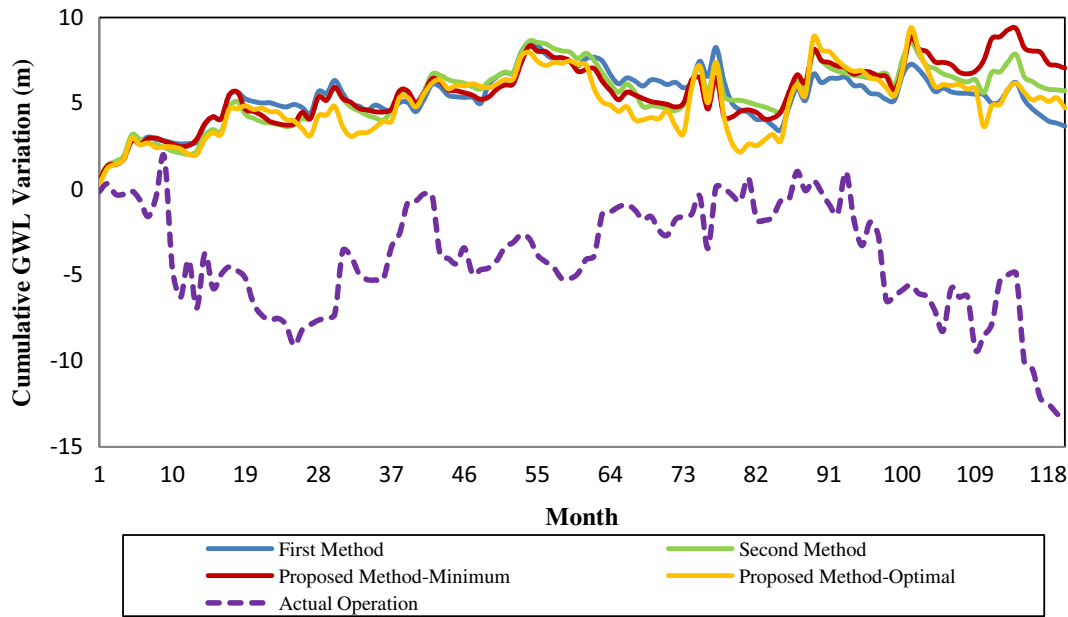
Fig. 10. Cumulative GWL variation in Nekouabad Right zone resulting from the best Z_2 values.
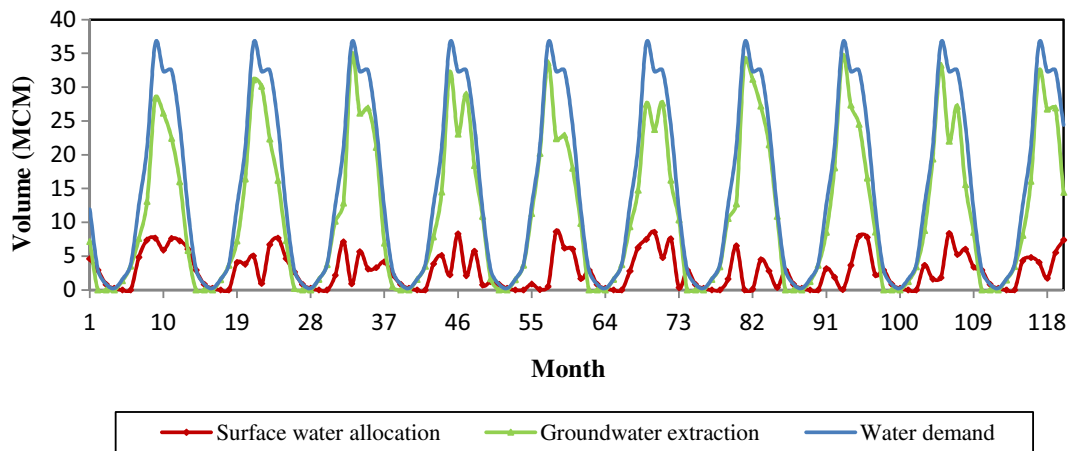

Fig. 11. Water demand and monthly surface water and groundwater allocated to Nekouabad Right zone based on the unique optimal solution of the proposed f-MOPSO method.

nate the Pareto-front given by another algorithm. The objective function values of the reference point of a Pareto-front may give a non-dominated point compared to those of a different Pareto-front. It is noteworthy that reference points should be included in TOPSIS analysis only when one of them dominates the other, which was the case in this paper. This is because two non-dominated reference points of two different Pareto-fronts will indicate no meaningful differentiation in performance, meaning that using the first three criteria for multi-criteria analysis will suffice.

The results attribute the first rank to the proposed f-MOPSO algorithm in both Nekouabad Right and Nekouabad Left zones compared to other algorithms tested in the 12-month operation period optimization. The second and third ranks are assigned to the second method and first method in both zones, respectively. f-MOPSO's performance was better than the other two MOPSO algorithms in four out of the five TOPSIS criteria in both zones.

Assuming that the conjunctive use operating policy recommended by MOPSO management models will be extended from 1-year operation period to a longer term planning period, the mod-

els were executed for a 10-year planning period (2004–2014) using observed values of precipitation and evapotranspiration and the upper bounds for groundwater extraction and surface water allocation volumes. The detailed results obtained from executing three MOPSOs are summarized in Table 5.

In both zones, the first and second methods met slightly smaller demand percentages over the 10-year period, as compared to the 12-month period. The f-MOPSO algorithm provides considerably larger demand satisfaction resulting from both minimum and optimal values of Z_1. The detailed results for Nekouabad Right and Nekouabad Left zones are shown in Figs. 9–11 and Figs. 12–14, respectively. TOPSIS analysis of the algorithms' performance over the 10-year planning horizon shows that, in the Nekouabad Left zone, by far the largest relative closeness value was assigned to the f-MOPSO algorithm, followed by the second method, and first method (Table 6). However, in the Nekouabad Right zone, the performances of f-MOPSO and the first algorithm are identical, with equal relative closeness values that are only marginally better than the second method's.
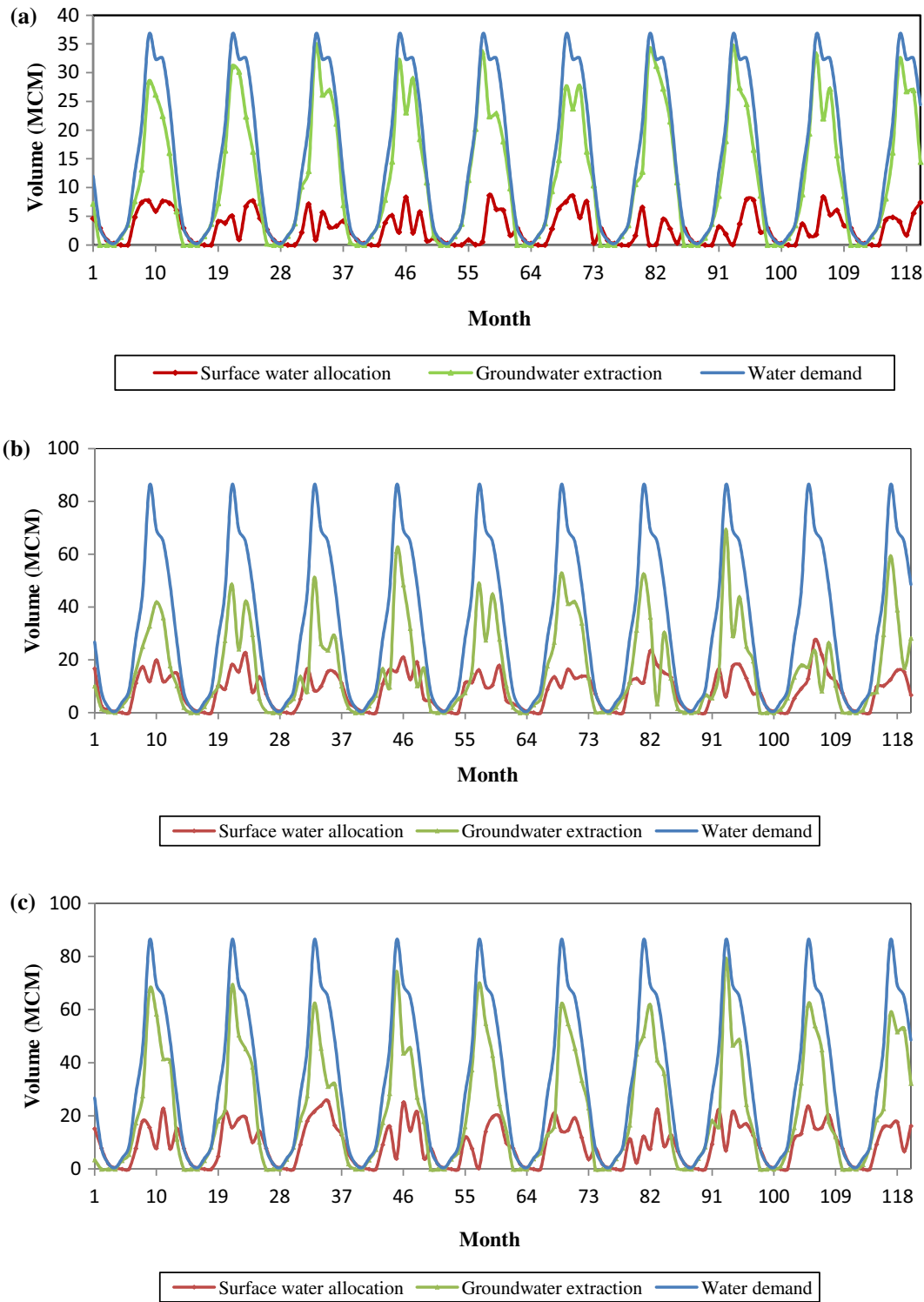
Fig. 12. Water demand and monthly surface water and groundwater allocated to Nekouabad Left zone based on the minimum Z_1 value of first method (a), second method (b) and (c) the proposed f-MOPSO method.

Finally, a comparative analysis was carried out on the potential positive impacts of implementing the operating policy obtained based on the f-MOPSO management model as compared to the actual operations. The results suggest room for significant improvements in conjunctive water resources management in the Najafabad Plain. Nearly all annual demands could be met while maintaining reasonable GWL variations (Table 7).

5. Conclusions

This paper proposed a new approach to deal with multi-objectivity in MOPSO algorithms based on the role of weighting method in Multi-Criteria Decision Making (MCDM). Each solution is considered to have a partial performance in minimizing/maximizing the objectives corresponding to different combinations of
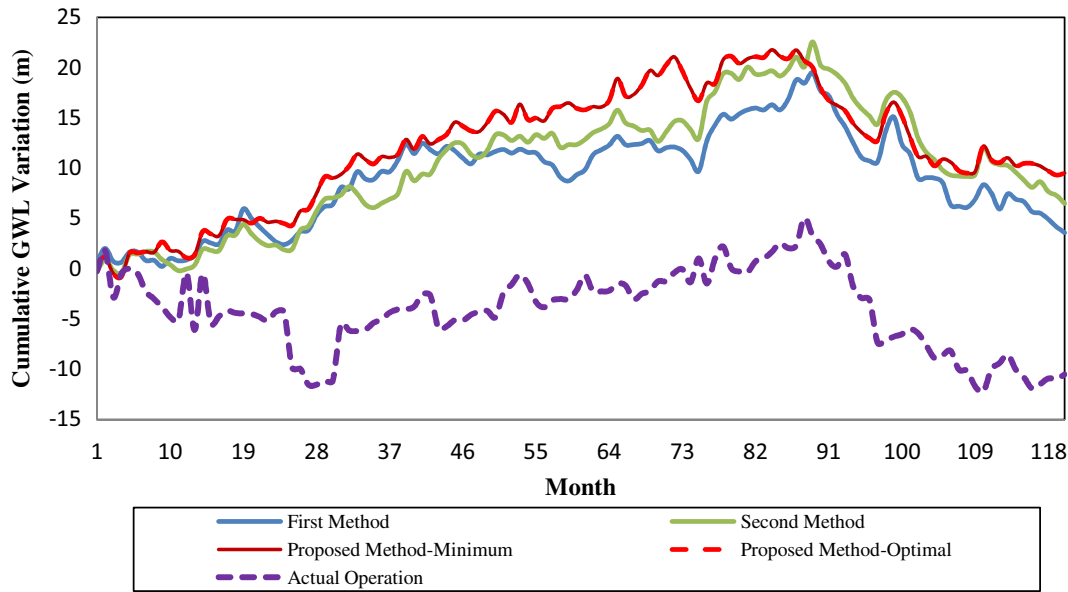
Fig. 13. Cumulative GWL variation in Nekouabad Left zone resulting from the best Z_2 values.
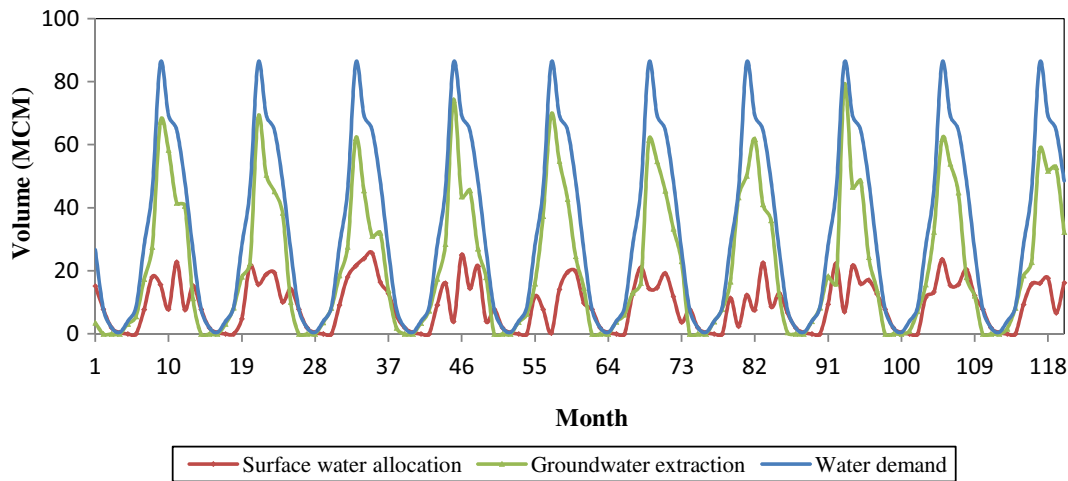

Fig. 14. Water demand and monthly surface water and groundwater allocated to Nekouabad Left zone based on the unique optimal solution of the proposed f-MOPSO method.

Table 6
Relative closeness to the ideal point for solutions of the MOPSOs applied to a 10-year planning horizon (Boldfaced numbers indicate the best performing algorithm with reference to a certain zone).

	1st method	2nd method	f-MOPSO
Nekouabad Right zone	**0.52**	0.47	**0.52**
Nekouabad Left zone	0.07	0.36	**0.99**

weights denoting a particular point in the objective space. To take all these partial performances into account, a Sugeno fuzzy inference system was designed. A comparison between Sigmoidal and Gaussian membership functions was carried out to avoid trial and error in determining membership function's parameters. The Sigmoidal function's parameters were tuned based on the statistical parameters derived from a large domain of objective function values in the pre-optimization stage. The proposed f-MOPSO method discriminates both near-optimal and optimal solutions in a MOPSO and selects the best unique solution when personal bests

or global best are needed in the iterations of the algorithm. The method was compared with two other MOPSOs within a coupled simulation-optimization model to solve the bi-objective conjunctive water use problem of the Najafabad Plain, Iran. The models' performance was investigated through two different management scenarios, i.e., a normal 12-month period and a 10-year horizon representing long-term operation and planning of the plain's two irrigation zones, i.e., Nekouabad Right and Nekouabad Left. In general, superior solutions were obtained from the f-MOPSO as compared with the other two MOPSO methods under both scenarios, The f-MOPSO's performance in the Nekouabad Right zone for a 10-year planning horizon was just similar to one of the other MOPSO algorithms examined and better than all MOPSOs in the Nekouabad Left zone. According to the management results, the f-MOPSO solutions almost fully satisfied water demands in the two irrigation zones throughout the 10-year planning horizon, while maintaining monthly and cumulative groundwater level (GWL) variations. Furthermore, the computational burden and runtime of the proposed algorithm in the simulation-

Table 7
Comparison of water demand percentages met in actual operation conditions and as prescribed by the f-MOPSO management model.

Planning period (year)	Actual operation		f-MOPSO-based operating policy	
	N-Right	N-Left	N-Right	N-Left
2004–2005	64.61	37.74	96.79	91.44
2005–2006	100.00	65.89	96.89	96.26
2006–2007	100.00	72.88	98.45	97.15
2007–2008	100.00	85.79	96.06	95.51
2008–2009	100.00	90.36	96.93	93.22
2009–2010	100.00	100.00	98.78	93.00
2010–2011	100.00	99.75	96.28	96.23
2011–2012	100.00	77.10	95.84	96.16
2012–2013	100.00	74.40	94.97	90.07
2013–2014	100.00	82.76	96.85	94.43

optimization model were similar to the other two examined MOPSO algorithms. The f-MOPSO offers a novel robust multi-objective optimization algorithm to find a unique optimal solution from among a large number of non-dominated solutions on the Pareto-front.

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