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An ecohydraulic-based expert system for optimal management of environmental flow at the downstream of reservoirs

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ABSTRACT

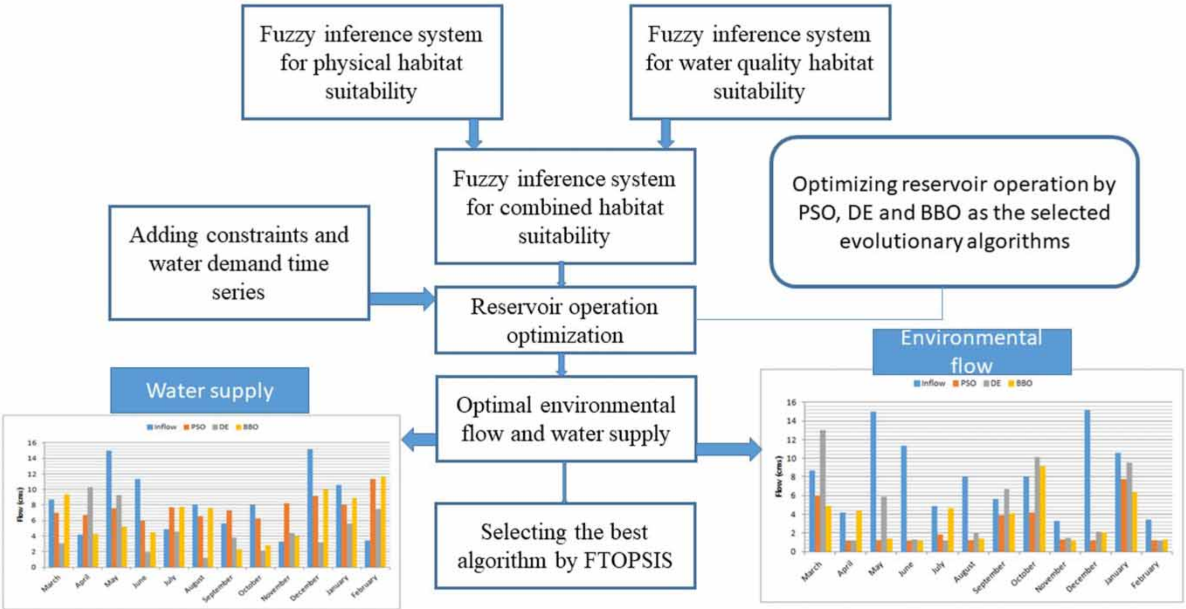
Linking ecohydraulic modeling and reservoir operation optimization is a requirement for robust management of the environmental degradations at the downstream of the reservoirs. The present study proposes and evaluates an ecohydraulic-based expert system to optimize environmental flow at the downstream of the reservoirs. Three fuzzy inference systems including physical habitat assessment, water quality assessment and combined suitability assessment were developed based on the expert panel method. Moreover, water temperature and dissolved oxygen were simulated by the coupled particle swarm optimization (PSO)–adaptive neuro-fuzzy inference system. Three evolutionary algorithms including PSO, differential evolution algorithm (DE) and biogeography-based optimization were applied to optimize the environmental flow regime. A fuzzy technique for order of preference by similarity to ideal solution was applied to select the best evolutionary algorithm to assess environmental flow. Based on the results in the case study, the proposed method provides a robust framework for simultaneous management of environmental flow and water supply. DE was selected as the best algorithm to optimize environmental flow. The optimization system was able to balance habitat losses, storage loss and water supply loss that might reduce negotiations between the stakeholders and environmental managers in the reservoir management.

Key words: environmental flow, habitat suitability, knowledge-based system, metaheuristic optimization, reservoir operation

HIGHLIGHTS

- Environmental flow at downstream of dams is critical to protect river habitats.
- The present study proposes an ecohydraulic expert system for the reservoir operation.
- Optimal environmental flow and water supply are the outputs of the model.
- The developed system can minimize physical and water quality habitat losses.
- Differential evolution was the best optimization algorithm in the case study.

GRAPHICAL ABSTRACT



1. INTRODUCTION

The importance of dams has been highlighted in the literature due to their significant role in the development of the communities (Altinbilek 2002). However, the environmental impacts at the upstream and downstream are undeniable (Wang *et al.* 2012). Increasing population might exacerbate the destruction of the river ecosystems due to raising offstream flow in the rivers (Postel 1998). Due to the importance of protecting river ecosystems, different methods have been proposed to mitigate environmental impacts of hydraulic structures such as dams. Allocating an environmental flow regime is an effective solution to protect river ecosystems or aquatic river habitats that might be destroyed due to lack of adequate instream flow in the rivers. Many methods have been suggested to assess environmental flow in the rivers (Tharme 2003). For example, hydrological desktop methods and hydraulic rating methods are the simplest methods to assess environmental flow (Jowett 1997). However, they are not efficient due to lack of focus on the regional ecological values in the study area (Sedighkia *et al.* 2017).

Advanced methods such as instream flow incremental methodology (IFIM) have an integrated simulation methodology in which physical and water quality factors are simultaneously considered (Maddock 2018). It should be noted that IFIM is a basic framework or process to manage environmental impacts in the river ecosystem. In fact, IFIM provides general methods that should be used to assess the environmental flow regime by proposing some phases and mathematical models. Developers encouraged users to consider innovation and creativity in the applications (Stalnaker 1994). The initially proposed methods by IFIM are too old, which means that they might not be efficient to solve the complex environmental problems in the river basins. For example, one of the components of IFIM is physical habitat simulation. The univariate method has originally been proposed by IFIM to simulate physical habitats (Ahmadi-Nedushan *et al.* 2006). However, this method has been criticized in the literature due to lack of accuracy to simulate interactions among physical parameters including depth, velocity and substrate (Noack *et al.* 2013; Railsback 2016). In fact, this method computes the suitability of each parameter and then uses a mathematical index such as geometric mean to compute combined habitat suitability. Using other approaches such as multivariate methods has been highlighted in the literature. One of the applicable and efficient novel methods that might be robust to simulate physical habitats is fuzzy physical habitat simulation. The main advantage of this method is the possibility of using the expert opinions in the development of the fuzzy physical habitat rules. It seems that the response of the fuzzy physical habitat simulation is close to the actual response of the aquatics in the river habitat (Noack *et al.* 2013). It should be noted that using knowledge-based models might be greatly applicable due to the complexities of the physical habitat simulation. Some recent studies used this method in the conventional form to assess environmental flow (e.g. Sedighkia *et al.* 2021). Water quality simulation is another challenge in the assessment of the environmental flow regime. Hydrodynamic models have been developed to simulate water quality factors such as dissolved oxygen (DO) or water temperature (e.g. Fang *et al.* 2008; Sedighkia *et al.* 2019). However, these models might not be flexible for applying in the complex water resource management systems. Thus, artificial intelligence (AI) methods such as artificial neural networks (ANNs) have been utilized in previous studies (Singh *et al.* 2009). Due to drawbacks of the ANN such as working as black box, other advanced methods such as adaptive neuro-fuzzy inference systems (ANFIS) have been used as well (Tiwari *et al.* 2018). The ANFIS puts a fuzzy inference system in the structure of the neural network that might increase the interpretability of the prediction system (Jang 1993).

Reservoirs are one of the complex water resource systems that should be operated optimally due to the high cost of the construction of dams. In fact, optimal operation of the reservoirs is critical for maximizing benefits from the reservoir. Linear programming (LP) is a simple method that was used to optimize reservoir operation in previous studies (Reis *et al.* 2006). However, it was not able to provide an optimal solution for the reservoir operations due to the non-linear nature of the problem (Ahmad *et al.* 2014). Thus, using non-linear programming (NLP) and dynamic programming was the next step to improve the optimization methods of the reservoir operation (e.g. Arunkumar & Jothiprakash 2012). Reservoir operation might have a complex objective function. Thus, using advanced computational methods was essential that have been utilized in the literature. Different classic and new generation algorithms have been applied to optimize reservoir operation in recent years (e.g. Afshar *et al.* 2007, 2011; Haddad *et al.* 2015, 2016; Ehteram *et al.* 2018a, 2018b). The definition of the objective function is another aspect in the reservoir operation problems. Hashimoto *et al.* (1982) defined a basic form of the loss function that minimizes the difference between the target and the release. Target might be defined as the water demand in the reservoir operation system. Datta & Burges (1984) highlighted adding storage loss in the reservoir operation system. In fact, deviation from the optimal storage might increase storage loss in the system. This form of loss function has been used in many studies, even in the recent reservoir operation studies (e.g. Ehteram *et al.* 2018a, 2018b). However, it seems that this form of loss function is not responsive to overcome environmental challenges at the downstream of the reservoir. In fact, developing the novel form of the optimization system is required that should be able to consider reservoir benefits and complex environmental issues simultaneously. Reviewing recent studies regarding the optimization of the reservoir operation is required. Predicting the inflow of the reservoir is one of the requirements for the management of the reservoirs. Recent studies indicated the applicability of deep learning methods and improved AI methods in this regard (Taormina & Chau 2015; Fu *et al.* 2020; Shamshirband *et al.* 2020). The prediction of flood is another important improvement in the reservoir managements (Fotovatikhah *et al.* 2018; Kaya *et al.* 2019). Furthermore, reservoir operation has been optimized considering climate change and related uncertainties (Ehteram *et al.* 2018a, 2018b).

Simultaneous management of water supply and environmental flow is a complex process. Conventional optimization systems of the reservoir operation are not able to consider the environmental issues in the management of the reservoirs. Hence, the improvement of the reservoir operation models considering environmental impacts is essential. Due to the complexities of the environmental modeling in the river ecosystems, using the expert opinions and optimization system is necessary for improving the environmental management of the reservoirs. The main motivation of the present study is lack of robust expert systems in the environmental management of the reservoirs. In fact, the present study proposes an integrated expert system to optimize the environmental flow regime at the downstream of the reservoir that might help the water resource managers to overcome the environmental complexities in the reservoir management. The developed model simultaneously mitigates the water supply loss and environmental impacts considering expert opinions. In recent years, ecohydraulic engineering was developed to manage environmental requirements of the river ecosystem in which interactions between abiotic factors such as water quality and quantity with habitat suitability could be utilized for simulating habitats. However, interactions are quite complex that means using AI methods could be highly beneficial. In fact, the development of AI methods for modeling environmental challenges is one of the smart solutions that is the main motivation for the present study. Water quality and quantity are separately effective for the suitability of habitats, which means that their integration is necessary for managing environmental degradations to reservoirs. Based on the presented necessities, the present study develops two fuzzy inference systems for assessing water quality suitability and water quantity suitability. Then, these two fuzzy inference systems are integrated into one combined fuzzy inference system to assess combined ecohydraulic suitability. In fact, a knowledge-based system is developed in which fuzzy inference systems are utilized to assess aquatic habitat suitability based on the expert opinions. Then, a developed knowledge-based system was applied in the structure of metaheuristic optimization to optimize environmental flow at the downstream of the reservoir. In fact, the proposed coupled knowledge-based optimization system can simultaneously consider environmental issues and reservoir losses. The present study might open new windows to apply the knowledge-based system in the environmental management in the structure of the water resource operation systems. In fact, each water resource engineering system needs to be managed considering environmental issues. The proposed framework provides an upgradable environment that could demonstrate the high efficiency of the knowledge-based system to solve environmental challenges of the water resource systems.

2. APPLICATION AND METHODOLOGY

The proposed method contains three Mamdani fuzzy inference systems including physical habitat suitability assessment system, water quality suitability assessment system and combined suitability assessment system. Moreover, the coupled particle swarm optimization–adaptive neuro-fuzzy inference system (PSO–ANFIS) data-driven model was utilized to simulate water temperature and DO at the downstream of the reservoir. Furthermore, different evolutionary algorithms were used to optimize environmental flow. Considering the fuzzy inference system of combined suitability assessment, in which two fuzzy inference systems including physical habitat assessment and water quality assessment are used, is advantageous in terms of integrated assessment of the river ecosystem. Other feasible alternatives might be to apply the fuzzy inference system of physical habitat assessment or fuzzy inference system of water quality separately that might not be able to assess integrated environmental suitability. For example, some previous studies only applied a fuzzy inference system of physical habitat suitability that is not an efficient method for integrated assessment. Due to complexities of each part of the developed system, a full description of different parts of the simulation–optimization system is presented in the following sections. Finally, a case study is described.

2.1. Mamdani fuzzy inference system for physical habitat assessment

Two main effective physical parameters were considered in the physical habitat assessment including depth and velocity. A river reach with a length of 10,000 m was considered at the downstream of the reservoir. Different cross-sections were surveyed at an average distance of 100 m. Then, the relationships between depth and discharge as well as velocity and discharge were developed. These developed relationships were utilized in the optimization system to assess depth and velocity in each cross-section in each time step. An expert panel was established including an experienced ecologist who was familiar with the regional ecological status of the case study, a water resource engineer and one of the managers of the regional department of environment. A specific method was used to develop fuzzy rules of physical habitats. Figure 1 shows the workflow of developing fuzzy rules of physical habitats. For example, one of the verbal fuzzy physical rules is displayed as follows. Table 1 shows the main characteristics of the physical habitat fuzzy inference system. Figure 2 shows depth and velocity suitability curves used in the case study.

‘If depth suitability is medium and velocity suitability is very high, then physical habitat suitability is high.’

It is essential to present more details regarding the expert panel in the proposed framework. The expert panel includes three members who are familiar with the study area in terms of regional ecological values, management of water resources and regional challenges for environmental management. In fact, the experienced ecologist has extensive information regarding the aquatics needs in the river ecosystem. Moreover, a water resources engineer is familiar with the reservoir operation difficulties and needs. Finally, a regional environmental manager can address environmental challenges such as negotiations between stakeholders and environmentalists in the panel. At the first glance, it seems that the number of experts involved in the panel is not sufficient for making a robust decision. However, each member of the panel might have an independent research team or a group of colleagues who might be effective on the opinions. In fact, each member can reflect the opinions by a group of experts that sounds enough and logical for a robust expert panel. Another important issue is how conflicting feedback can be handled in the expert panel. As presented in Figure 1, two external reviewers who are not the member of the panel would be used to resolve conflicts between the members of the panel. The reviewers’ comments will be considered by the chief of the panel (experienced ecologist) to finalize the rules. The proposed panel can develop robust rules that are significantly effective on the outputs of the optimization system. In fact, this form of the expert panel provides a reliable environment to address scientific and technical issues and regional considerations for developing fuzzy rules.

According to the literature, three main physical factors are effective in the physical habitat suitability including depth, velocity and substrate or bed particle size. However, we only considered two parameters including depth and velocity in the present study due to some reasons. First, the effect of depth and velocity is considerably more important on physical

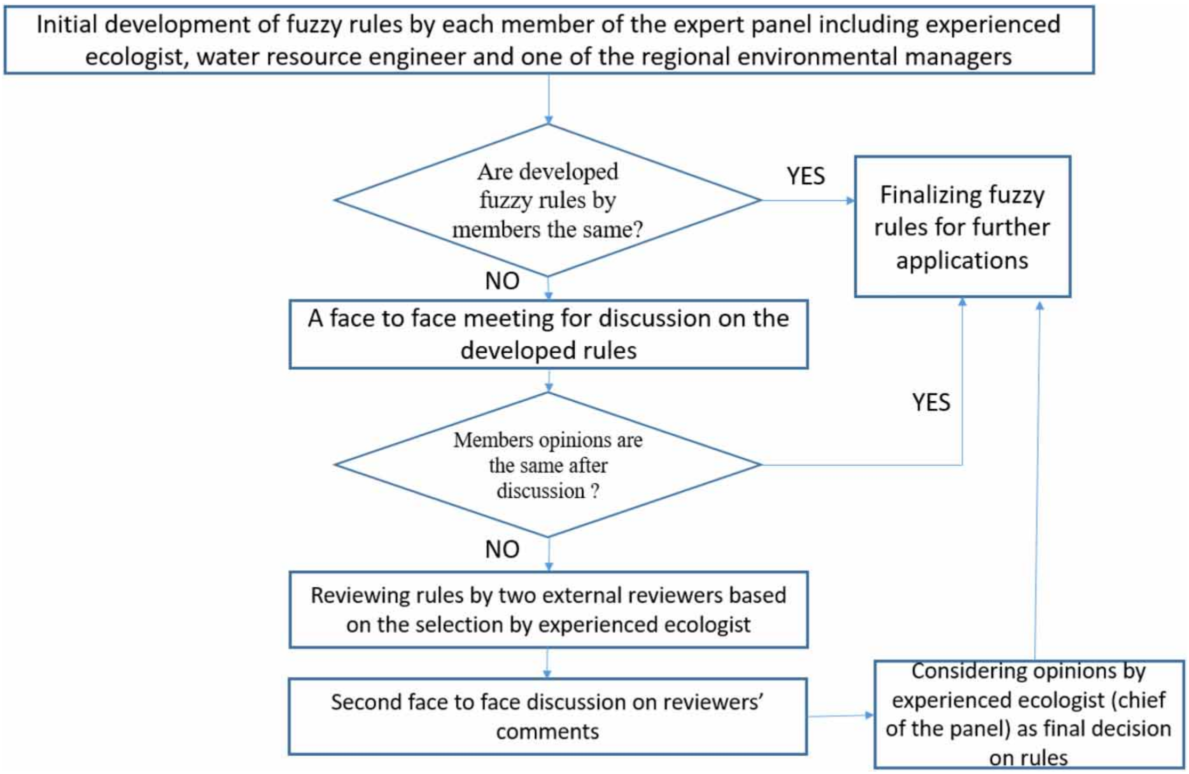


Figure 1 | Workflow of the expert panel.

Table 1 | Main characteristics of the knowledge-based physical habitat model (fuzzy inference system)

Inputs	**Number of MFs (inputs)**	**Type of MFs (inputs)**	**Outputs**	**Number of MFs (output)**	**Type of MFs (output)**
Depth suitability (between zero and one)	5	Triangular	Physical habitat suitability (between zero and one)	5	Triangular
Velocity suitability (between zero and one)	5	Triangular			

suitability. For example, depth and velocity are effective on the energy consumption by the fish. However, the substrate has less effect on the suitability. Moreover, the particle size distribution in the representative reach of the case study was approximately uniform, which means that the substrate could be excluded in the fuzzy inference system. Generally, three membership functions (MFs) could be utilized in the fuzzy inference systems including triangular, Gaussian and trapezoidal. The previous studies regarding the application of fuzzy inference systems for river habitat suitability corroborate that triangular MFs might provide the proper response. Hence, the triangular MF was applied in the present study. Using this form of MF makes it possible to compare the developed fuzzy inference system in the present study with previous studies that might be advantageous for future studies.

2.2. Mamdani fuzzy inference system for water quality suitability assessment

A fuzzy inference system was developed for the water quality suitability assessment as well. We considered two main water quality factors including water temperature and DO that might be highly effective on the biological activities of the aquatics such as reproduction and searching for food. Other parameters might be important. However, the initial assessment in the case study indicated that water temperature and DO could be selected as the key water quality factors. Hence, a fuzzy inference system was developed based on these parameters. An expert panel was established to develop fuzzy rules like physical

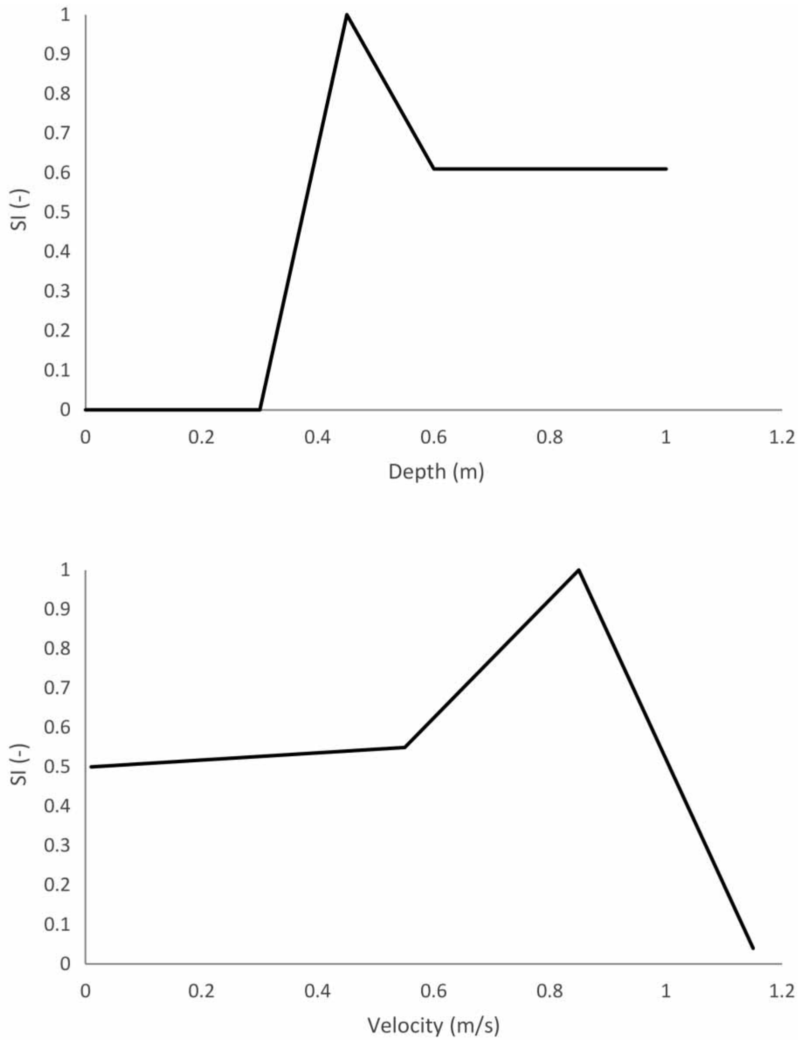


Figure 2 | Depth and velocity suitability curves.

parameters. The following sentence shows one of the examples of the water quality suitability fuzzy rules in the present study. Table 2 shows the main characteristics of the water quality assessment fuzzy inference system. Figure 3 shows used biological water temperature and DO models to calculate tension or suitability in the case study.

'If DO suitability is high and water temperature suitability is low, then water quality suitability is medium.'

Many water quality parameters can be considered in the habitat suitability assessment such as DO and total dissolved solids. However, two main water quality parameters that might be highly effective on the suitability are water temperature

Table 2 | Main characteristics of the knowledge-based water quality suitability model (fuzzy inference system)

Inputs	Number of MFs (inputs)	Type of MFs (inputs)	Outputs	Number of MFs (output)	Type of MFs (output)
DO suitability (between zero and one)	5	Triangular	Water quality suitability (between zero and one)	5	Triangular
Water temperature suitability (between zero and one)	5	Triangular			

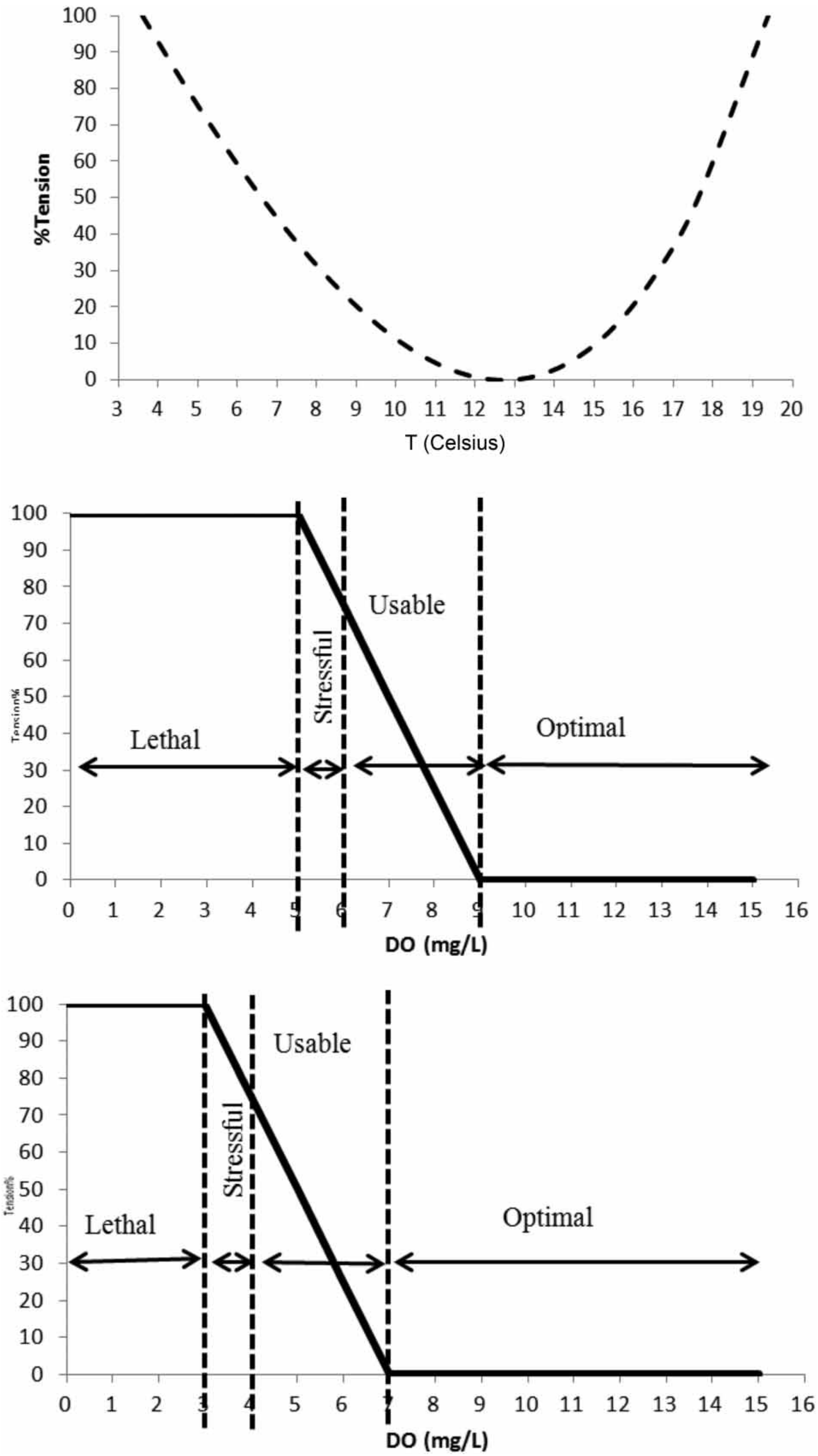


Figure 3 | Water temperature and DO biological models (developed by Sedighkia *et al.* (2019)).

and DO. Hence, these two parameters were taken into account in the development of a fuzzy inference system. The concentration of other constituents might change the water temperature and DO concentration in the water. Thus, these two parameters are proper indices for using in the structure of the fuzzy inference system.

2.3. Simulation of water temperature and DO

The simulation of the water temperature and DO might be a complex process. We need a flexible model that could be used in the structure of the optimization model. Thus, the ANFIS-based data-driven model was utilized in this regard due to several advantages. Using evolutionary algorithms might improve the training process of the ANFIS-based models. Hence, we applied a coupled PSO–ANFIS model to simulate water quality factors in the present study. Figure 4 shows the workflow of the ANFIS-based model in which PSO trains the data-driven model. Tables 3 and 4 shows the main characteristic of the water temperature and DO data-driven models, respectively. The models were used to simulate these water quality factors in different cross-sections of the representative reach that were described in the previous section. Two indices were utilized to measure predictive skills of the data-driven model including the Nash–Sutcliffe model efficiency coefficient (NSE) and root-mean-square error (RMSE) as displayed in the following equations:

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T} (\mathrm{OBS}_t - \mathrm{SIM}_t)^2}{\sum_{t=1}^{T} (\mathrm{OBS}_t - \mathrm{OBS}_m)^2} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{T} (\mathrm{SIM}_t - \mathrm{OBS}_t)^2}{T}} \tag{2}$$

where OBS_t is the observed or recorded data in the time step t, SIM_t is the simulated data by the model and T is the total number of time steps.

Many types of data-driven models such as neural networks and support vector machines could be applied to simulate water quality in the water bodies. However, the previous studies corroborated the robustness of the ANFIS for simulating water quality. Thus, the ANFIS-based model was selected in the present study. Different methods could be utilized for training

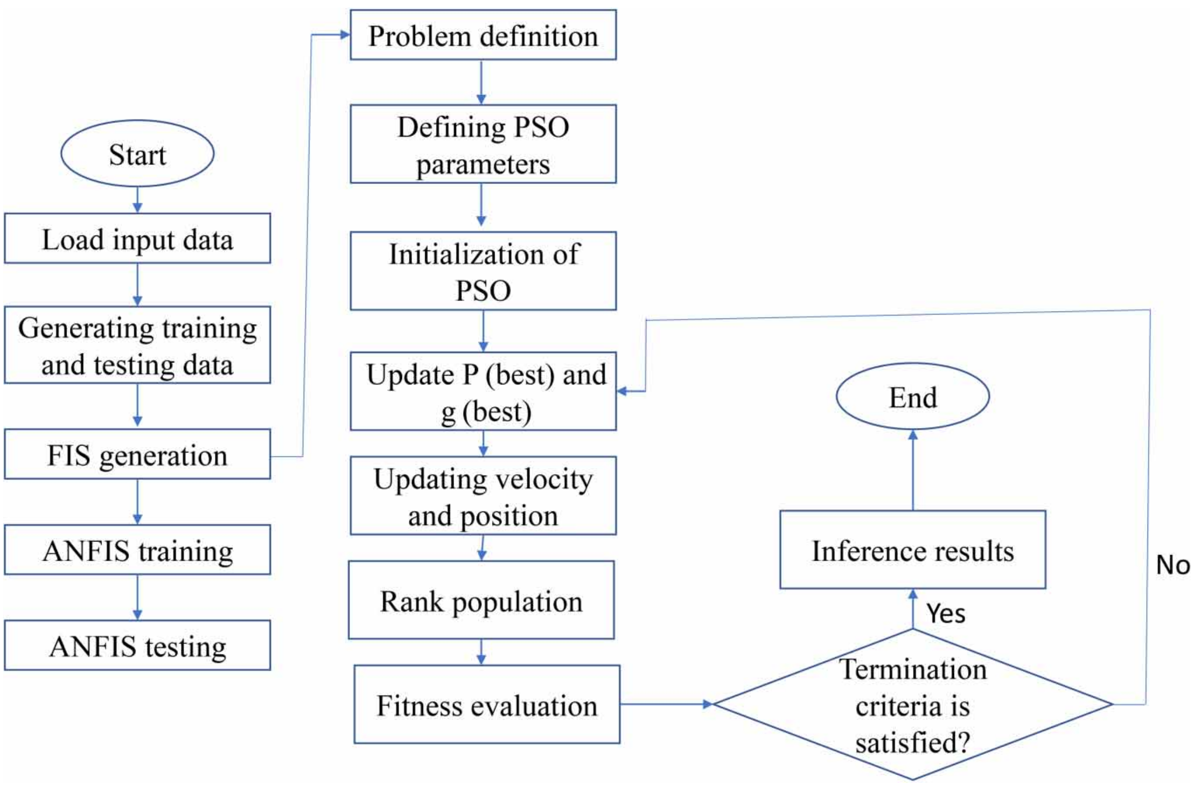


Figure 4 | PSO–ANFIS flowchart.

Table 3 | Main characteristics of the ANFIS-based temperature model

Inputs	Number of MFs (inputs)	Type of MFs (inputs)	Outputs	Number of MFs (output)	Type of MFs (output)	Clustering method
Flow rate (m^3/s)	10	Gaussian	Water temperature at each cross-section	10	Linear	Subtractive clustering
Wetted perimeter (m)	10	Gaussian				
Distance from the reservoir	10	Gaussian				
Elevation level from the sea	10	Gaussian				
Water temperature at distance = 0 m (°C)	10	Gaussian				
Air temperature (°C)	10	Gaussian				

Table 4 | Main characteristics of the ANFIS-based DO model

Inputs	Number of MFs (inputs)	Type of MFs (inputs)	Outputs	Number of MFs (output)	Type of MFs (output)	Clustering method
Month (Jan to Dec)	10	Gaussian	DO concentration at each cross-section	10	Linear	Subtractive clustering
Rate of flow (m^3/s)	10	Gaussian				
Distance from the reservoir	10	Gaussian				
Water temperature at each cross-section (°C)	10	Gaussian				

ANFIS-based models such as backpropagation, hybrid and evolutionary algorithms. Recent studies corroborated that using evolutionary algorithms might be a more robust option to train the ANFIS-based models. PSO was selected as the best option to train the data-driven model. Hence, the coupled PSO–ANFIS model was applied to generate the data-driven models in the present study. Moreover, the previous studies highlighted the effect of several factors on the changing water temperature in the rivers. However, some factors are significantly more effective including considered parameters in Table 3. Using these parameters makes the data-driven model simple and robust to simulate water temperature. In fact, selecting these parameters can generate reliable results, when required field measurements are minimized. Similarly, effective parameters were selected for simulating DO concentration in the case study. Furthermore, an explanation is needed regarding the MFs. Different types of MFs were tested for developing the ANIFS-based model before the main simulation of water temperature and DO concentration for the case study. The initial simulations indicated that the Gaussian function is the most robust MF for simulating water temperature and DO. Hence, this type of MF was selected for the inputs in the ANFIS-based models of water temperature and DO.

2.4. Mamdani fuzzy inference system for combined habitat suitability

This fuzzy inference system was developed to assess combined habitat suitability in which physical habitat suitability and water quality habitat suitability were considered as the inputs of the system and combined habitat suitability is the output of the system. The expert panel-based method was utilized to develop fuzzy rules like previous fuzzy inference systems. Table 5 shows the main characteristic of the developed expert system.

2.5. Optimization system

The development of a correct objective function is the main requirement of each optimization system in engineering. Equation (3) displays the initial form of the developed objective function in the present study. This equation contains two terms including water demand loss and environmental suitability loss. In fact, the supply of water demand is the main purpose for the construction of many reservoirs. Thus, it should be in the objective function. This term minimizes the difference between target water demand and release for the demand. Moreover, the second term minimizes the difference between combined habitat suitability in the natural flow and the optimal release for environment by the reservoir. It should be noted that

Table 5 | Main characteristics of the knowledge-based combined habitat suitability model (fuzzy inference system)

Inputs	Number of MFs (inputs)	Type of MFs (inputs)	Outputs	Number of MFs (output)	Type of MFs (output)
Physical habitat suitability (between zero and one)	5	Triangular	Combined suitability (between zero and one)	5	Triangular
Water quality suitability (between zero and one)	5	Triangular			

considering habitat suitability in the natural flow is essential to environmental assessment. In fact, the objective function tries to minimize habitat loss that might be possible due to the construction of dam and changing the flow regime in the river. D_t is the target water demand, R_t is the release for demand, NCS_t is the combined suitability in the natural flow and OCS_t is the combined suitability in the optimal environmental flow.

$$\text{Minimize (OF)} = \sum_{t=1}^{T} \left(\frac{D_t - R_t}{D_t}\right)^2 + \left(\frac{\mathrm{NCS}_t - \mathrm{OCS}_t}{\mathrm{NCS}_t}\right)^2 \tag{3}$$

Each optimization model might need some constraints. In the proposed model, three constraints are required including minimum operational storage in the reservoir, maximum storage in the reservoir and maximum requested water demand from the reservoir. We focused on using metaheuristic optimization in the present study. Thus, it was required to utilize a solution to put the constraints in the structure of the optimization algorithm. The penalty function method is a known method in this regard that has been used in many previous studies (developed by Agarwal & Gupta (2005)). In fact, defined penalty functions increase the penalty of the system when constraints are violated. Three penalty functions were developed as displayed in the following equations. $c1$–$c3$ are the constant coefficients that were determined based on the initial sensitivity analysis.

$$\text{if } S_i > S_{\max} \rightarrow P1 = c1\left(\frac{S_t - S_{\max}}{S_{\max}}\right)^2 \tag{4}$$

$$\text{if } S_i < S_{\min} \rightarrow P2 = c2\left(\frac{S_{\min} - S_t}{S_{\min}}\right)^2 \tag{5}$$

$$\text{if } R_t > D_t \rightarrow P3 = c3\left(\frac{R_t - D_t}{D_t}\right)^2 \tag{6}$$

Storage in the reservoir should be updated in each time step which is possible by Equation (7). Furthermore, overflow could be calculated by Equation (8). E_t is the evaporation from the reservoir, A_t is the area of the reservoir, I_t is the inflow of the reservoir, ENV_t is the environmental flow and T is the time horizon.

$$S_{t+1} = S_t + I_t - R_t - \mathrm{ENV}_t - \left(\frac{E_t \times A_t}{1,000}\right), t = 1, 2, \ldots, T \tag{7}$$

$$\begin{cases} \text{if } \left(S_t + I_t - \left(\frac{E_t \times A_t}{1{,}000}\right)\right) \geq S_{\max} \rightarrow F_t = S_t + I_t - \left(\frac{E_t \times A_t}{1{,}000}\right) - S_{\max} \\ \text{if } \left(S_t + I_t - \left(\frac{E_t \times A_t}{1{,}000}\right)\right) < S_{\max} \rightarrow F_t = 0 \end{cases} \tag{8}$$

2.6. Optimization algorithms

Different evolutionary algorithms might have different efficiencies in the optimization problems. Thus, using different algorithms might be necessary. Three evolutionary algorithms were utilized in the present study including PSO, differential evolution algorithm (DE) and biogeography-based optimization (BBO). Selecting these algorithms was useful to compare the performance of algorithms with different origins. PSO is a classic algorithm that has been used in many previous optimization problems successfully (Eberhart & Kennedy 1995). This algorithm imitates the social behavior of the organism such as the movement of organisms in a bird flock or fish school. DE is a nonanimal-inspired algorithm that is able to indicate the performance of a nonanimal-inspired algorithm (Qin *et al.* 2008). BBO is a new generation algorithm that describes speciation (the evolution of new species), the migration of species (animals, fish, birds or insects) between islands and the extinction of species in its mathematical model (Simon 2008). More details regarding used algorithms have been addressed in the cited documents. Hence, more details have not been presented.

Many evolutionary algorithms have been developed in the literature that might be useable for the optimization problems. However, we selected three algorithms including PSO, DE and BBO based on their originality. PSO is a classic and an animal-inspired algorithm that has been utilized in many previous studies. Selecting this algorithm is helpful to investigate the performance of classic algorithms for novel optimization models. Moreover, DE is a known nonanimal-inspired algorithm that could indicate the performance of the nonanimal-inspired algorithms compared with animal-inspired algorithms. Furthermore, BBO is a new generation and animal-inspired algorithm that was selected to compare outputs of the classic and new generation algorithm in the developed optimization model. Thus, selecting these algorithms among many available evolutionary algorithms is beneficial for comparing outputs of the algorithms in terms of the optimization of environmental flow.

2.7. Measurement indices and decision-making system

The performance of each optimization system should be measured to judge the outputs. Defining measurement indices should be based on the requirements and the purposes of the developed system. In the present study, three aspects must be considered in the performance measurement including water demand loss, combined suitability loss and storage loss. In fact, loss of water demand and storage are measured to analyze the performance of the reservoir in terms of pre-defined purposes of dam construction. Moreover, suitability loss should be measured to assess the performance of the system in terms of the design of a proper environmental flow regime. The reliability index was utilized to measure the robustness of the system in terms of water demand supply as displayed in the following equation:

$$\mathrm{RI}_{\text{water demand}} = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t} \tag{9}$$

Two indices were used to measure the performance of the system in terms of storage loss including vulnerability index and RMSE as displayed in the flowing equations:

$$\mathrm{VI}_{\text{storage}} = \operatorname*{Max}_{t=1}^{T}\left(\frac{S_{\text{optimum}} - S_t}{S_{\text{optimum}}}\right) \tag{10}$$

$$\mathrm{RMSE}_{\text{Storage}} = \sqrt{\frac{\sum_{t=1}^{T} (S_t - S_{\text{Optimum}})^2}{T}} \tag{11}$$

Moreover, three indices were applied to measure the performance of the system in terms of combined habitat suitability or appropriateness of the designed environmental flow regime. The following equations display used indices. Similarly, these indices were used for measuring physical habitat suitability in the final analysis of the outputs:

$$\mathrm{RMSE}_{\text{habitat loss}} = \sqrt{\frac{\sum_{t=1}^{T} (\mathrm{OCS}_t - \mathrm{NCS}_t)^2}{T}} \tag{12}$$

$$\mathrm{VI}_{\text{habitat loss}} = \operatorname*{Max}_{t=1}^{T}\left(\frac{\mathrm{NCS}_t - \mathrm{OCS}_t}{\mathrm{NCS}_t}\right) \tag{13}$$

$$\mathrm{NSE}_{\text{habitat loss}} = 1 - \frac{\sum_{t=1}^{T} (\mathrm{NCS}_t - \mathrm{OCS}_t)^2}{\sum_{t=1}^{T} (\mathrm{NCS}_t - \mathrm{NCS}_o)^2} \tag{14}$$

Why these indices were selected in the present study to evaluate the simulation–optimization system should be explained. The reliability index is one of the basic indices that should be used in the reservoir operation models. More details regarding the importance and role of this index in the reservoir operation optimization have been addressed in the literature. Similarly, the vulnerability index is another basic index for measuring the performance of the optimization models of the reservoir operation. More details are available in the cited documents for the reliability index. Moreover, NSE is a robust index for measuring the performance of hydrological models. This index was selected due to its ability for demonstrating how the model can generate the ideal solution for the problem. In fact, NSE provides a transparent picture from the performance of the model compared with the ideal solution. Furthermore, RMSE is a robust statistical index to compare the ideal solution and optimal or simulated solution that has been applied in many previous studies. Selecting these familiar and known indices in the literature makes the output of the case study comparable with other case studies that might be helpful to develop a robust optimization system in practice.

Owing to using different evolutionary algorithms in the proposed framework, it is necessary to apply a decision-making system to select the best algorithm for the developed optimization system. The technique for order of preference by similarity to ideal solution (TOPSIS) is the most known decision-making system that has been used in many water resource management models. Thus, using this decision-making system seems logical to select the best algorithms. However, we applied the fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS) in the present study due to some advantages. First, it is possible to consider the expert opinions in the structure of the decision-making system. Moreover, FTOPSIS used the weight of importance for each criterion that means regional challenges of the environmental management could be considered in the decision-making system. Hence, FTOPSIS is a robust decision-making system that has been addressed in the literature (Chen 2000). Figure 5 shows the flowchart of this algorithm to select the best candidate among available

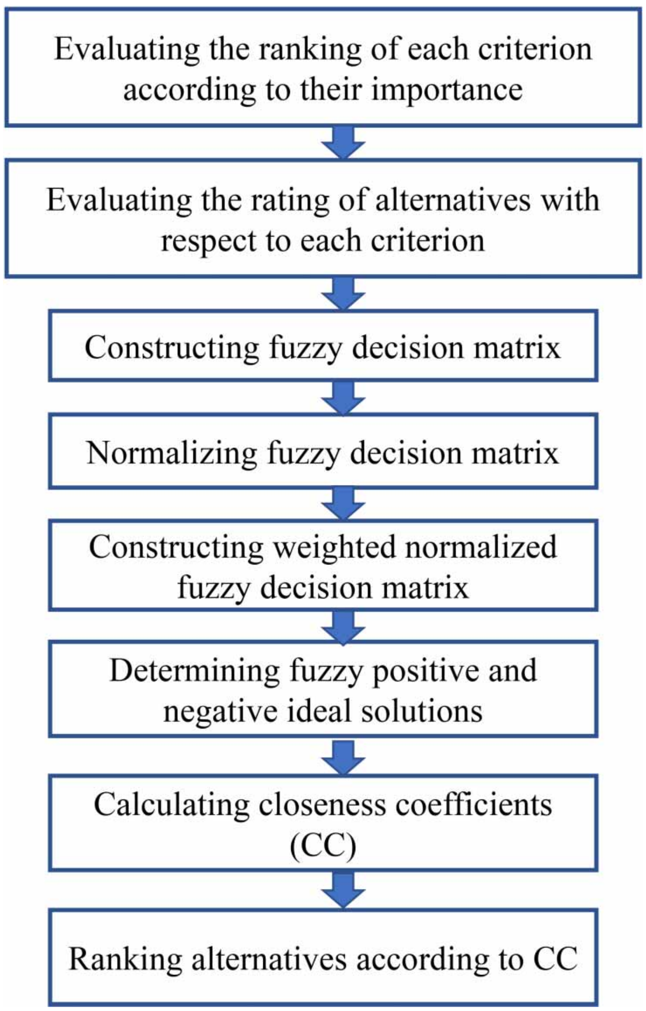


Figure 5 | Flowchart of FTOPSIS (Chen 2000).

candidates or alternatives. Three levels were defined in the developed hierarchical system including goal of the system, criteria and candidates. The goal of the system is to select the best algorithm. Criteria include computed measurement indices for the optimization system, and candidates are the evolutionary algorithms.

2.8. Case study

The Jajrood river is one of the important rivers in the Ghom lake basin in Iran where there is a habitat for several native fish species. Moreover, this river is responsible for the supply of part drinking water demand of the capital territory in Iran. The Latian dam has been constructed at the midstream of this river to regulate water supply. The department of environment is concerned regarding the protection of aquatic habitats at downstream of this reservoir due to lack of sufficient release to downstream. On the other hand, the regional water authority is concerned regarding loss of the water supply and storage due to considerable release for environment. Owing to the importance of protecting the river habitats and minimizing loss of the reservoir, using a simulation–optimization system that is able to optimize the operation of the reservoir in terms of water supply and environmental considerations is necessary. In fact, the simulation–optimization system should be able to minimize habitat loss and reservoir losses simultaneously. Utilizing a knowledge-based system might be the best option due to complexities of habitat selection in the river habitats. The Brown trout was selected as the target species based on the opinion of the experienced ecologist who was familiar with ecological zones in the river basin. Figure 6 shows the river network and elevations at the upstream catchment of the Latian dam and the location of the reservoir. A 12-month

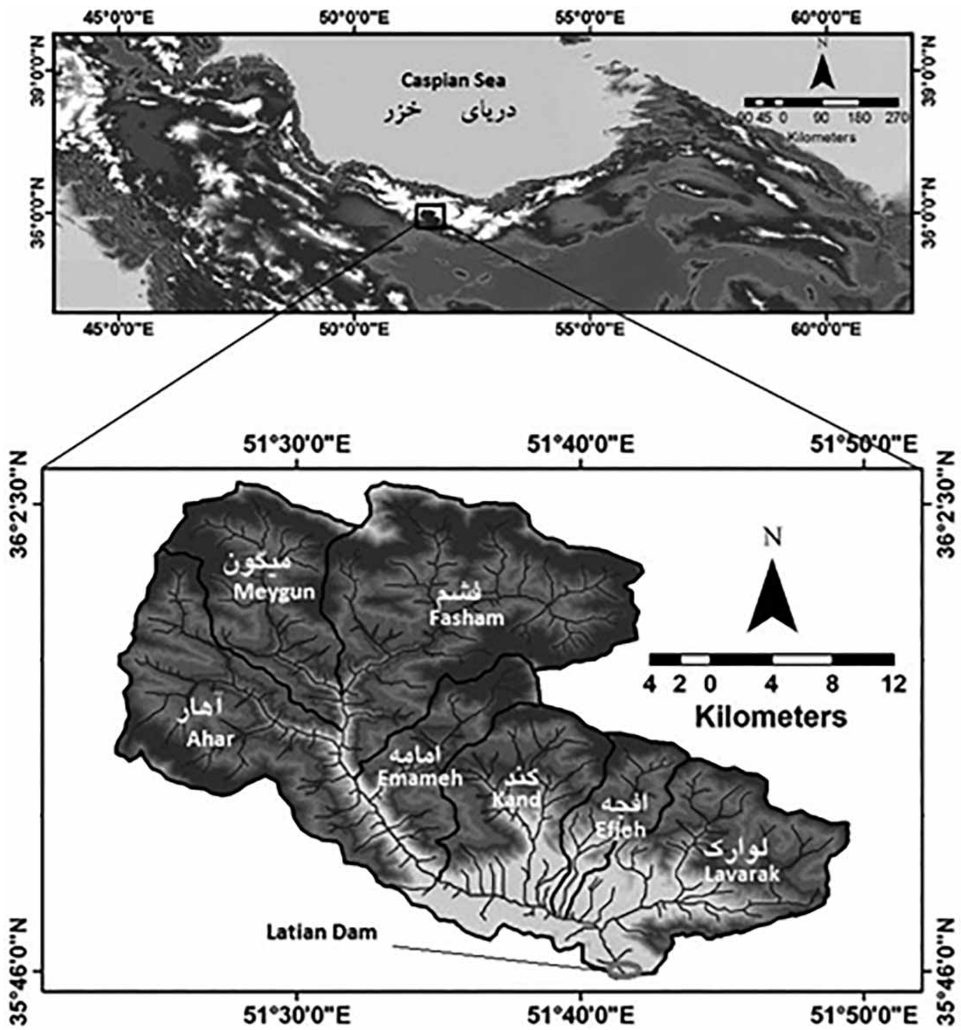


Figure 6 | Location of the study area at upstream of the Jajrood river basin.

period was selected as the simulation period. From the technical view, the Jarood river was a good option as the case study. In fact, we selected the Jajrood river as the case study due to the following reasons:

1. The extensive ecological field studies had been carried out in this river that means adequate ecological information for the development of the habitat suitability fuzzy inference systems were available. It should be noted that the availability of the previous ecological studies in the river ecosystem is a prerequisite for using the proposed method in each case study.
2. Environmental management is a challenging issue in this river due to considerable water demand and valuable habitats. Hence, using the proposed method in the Jajrood river can demonstrate the abilities of the proposed method for managing environmental challenges of the reservoirs.

3. RESULTS AND DISCUSSION

In the first step, the results of the ANFIS-based model of the water temperature and DO are presented and discussed. Figures 7 and 8 show results of the training and testing process of the water temperature and DO model, respectively. The computed NSE and RMSE are shown in the figures. NSE for the water temperature model is 0.81, which demonstrates that the model is quite robust to simulate the water temperature of the stream. According to the literature, if NSE is more than 0.5, then predictive skills of the model will be highly robust. Moreover, RMSE is 1.06, which demonstrates that the mean error of the model to simulate water temperature is negligible for application in environmental studies. NSE for the DO model is 0.77. Thus, the DO model is reliable and robust as well. The low mean error of the DO model corroborates the reliability of the model to simulate DO in the further steps.

Tables 6–8 provides developed fuzzy inference systems or knowledge-based systems for the assessment of physical habitat suitability, water quality suitability and combined suitability. It seems that the role of velocity suitability is significant. In fact, reducing velocity suitability might decrease physical habitat suitability considerably. Depth suitability is important as well. However, velocity might be more important in the physical habitat suitability. The main reason for the significant role of velocity suitability is an alteration of energy consumption by fish due to changing flow velocity. In fact, fishes should swim to the upstream of the river for main biological activities such as reproduction. Thus, increasing flow velocity would rise needed energy for swimming to the upstream that might reduce physical suitability. Developed physical fuzzy rules were utilized in the optimization model directly.

Table 7 shows fuzzy rules for the water quality suitability in which DO suitability and water temperature suitability were considered as the inputs of the system. It seems that the importance of the DO suitability is considerable. It should be noted that the target species is such sensitive to DO suitability. Hence, the significant role of DO in the water quality suitability is clear based on the developed fuzzy rules. It sounds that water temperature suitability in a combination of the DO suitability might be highly effective to reduce suitability when DO suitability is medium to high. In fact, the role of water temperature and depth in the knowledge-based systems are similar. The developed rules indicate that the expert panel should be familiar with the role of parameters to assess the biological response of aquatics in the study area. It sounds that the selected

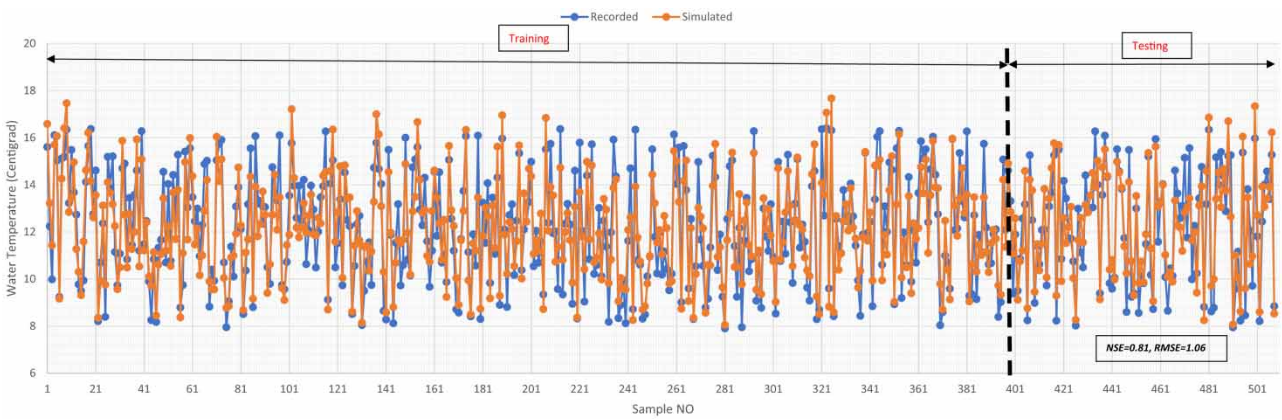


Figure 7 | Training and testing process of the stream temperature model.

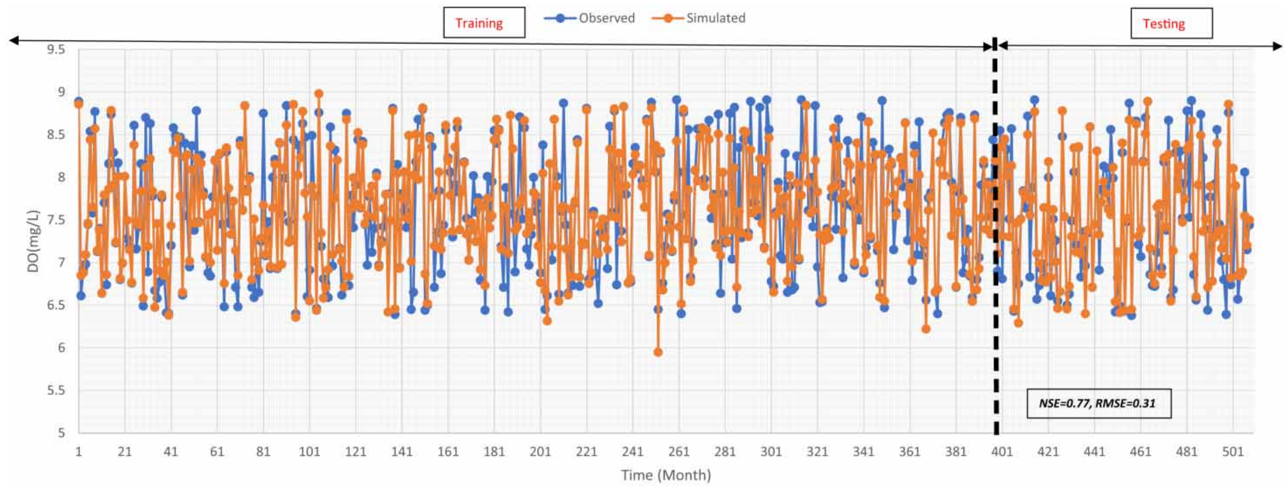


Figure 8 | Training and testing process of the DO model.

Table 6 | Parts of fuzzy rules for the knowledge-based physical habitat model

Rule code	Depth suitability	Velocity suitability	Physical habitat suitability
P1	*VL*	*VL*	*VL*
P2	*VL*	*L*	*VL*
P3	*VL*	*M*	*L*
P4	*VL*	*H*	*M*
P5	*VL*	*VH*	*M*

VL means very low, L means low, M means medium, H means high and VH means very high – the total number of rules is 25.

Table 7 | Parts of fuzzy rules for the knowledge-based water quality suitability model

Rule code	DO suitability	Water temperature suitability	Water quality suitability
Q1	*VL*	*VL*	*VL*
Q2	*VL*	*L*	*VL*
Q3	*VL*	*M*	*VL*
Q4	*VL*	*H*	*VL*
Q5	*VL*	*VH*	*VL*

VL means very low, L means low, M means medium, H means high and VH means very high – the total number of rules is 25.

procedure in the development of knowledge-based rules is correct. In fact, experienced ecologists should make final decision on the rules. However, opinions by other experts would be considered in the discussions when there are significant discrepancies. Table 8 shows combined suitability fuzzy rules that show a similar role of physical habitat suitability and water quality suitability in this knowledge-based system. The rule code was used in the meetings of the expert panel for being concise in the discussions. For example, if one of the members was not satisfied with one of the rules, then he/she only declares the rule code for shortening the discussions.

Table 8 | Parts of fuzzy rules for the knowledge-based combined suitability model

Rule code	Water quality suitability	Physical habitat suitability	Combined habitat suitability
C1	*VL*	*VL*	*VL*
C2	*VL*	*L*	*VL*
C3	*VL*	*M*	*VL*
C4	*VL*	*H*	*VL*
C5	*VL*	*VH*	*VL*

VL means very low, L means low, M means medium, H means high and VH means very high – the total number of rules is 25.

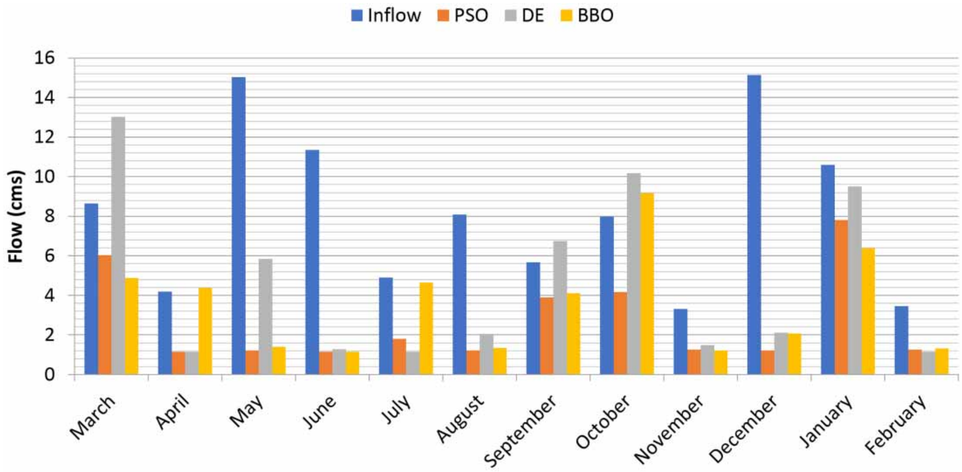


Figure 9 | Assessed environmental flow regime by different algorithms.

In the next step, the output of the optimization system as the main results of the proposed framework is presented and discussed. Figure 9 shows the proposed environmental flow by the optimization system in which results of three used algorithms are shown. The performance of different algorithms is not similar. In fact, assessed environmental flow regimes indicate the importance of using different algorithms in the optimization system. Utilizing one algorithm might generate unreliable results, whereas using different algorithms makes it possible to select the best outputs of the optimization system. It should be noted that applying more algorithms might be a better option. However, it is time-consuming. Hence, selecting algorithms should be based on technical considerations similar to the present study. Three to four algorithms with different origins might be a good option in practical projects.

Figure 10 shows supplied water demand by different algorithms. It should be noted that maximum water demand was considered 13 m^3/s in all time steps. It seems that either PSO or BBO releases more water for demand compared with DE. Thus, these algorithms might be robust in terms of water demand supply in the case study. However, better judgment needs using the reliability index. Figure 11 shows storage time series in the simulated period for three algorithms. The performance of penalty functions including maximum storage and minimum operational storage is robust. However, owing to simulating a challenging period, storage in the reservoir is not close to maximum storage. Thus, the performance of the minimum storage functions is a better criterion to judge the performance of the optimization model in terms of the storage penalty function. Minimum operation storage is 19 MCM. All algorithms optimized storage in the reservoir considering this minimum value. However, the performance of PSO is slightly weaker than others.

The performance of the optimization system is investigated in terms of designing environmental flow. Optimized physical habitat suitability, water quality suitability and combined habitat suitability should be compared with these values in the natural flow. Figure 12 shows physical habitat suitability by different algorithms in the optimal release for environment and the natural flow. Better performance of DE compared with other algorithms in terms of physical habitat suitability is clear

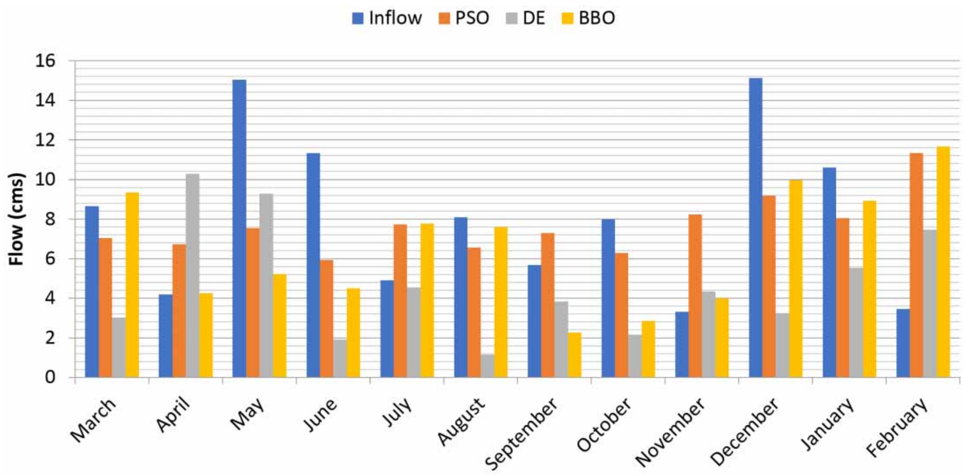


Figure 10 | Release for water demand by different algorithms.

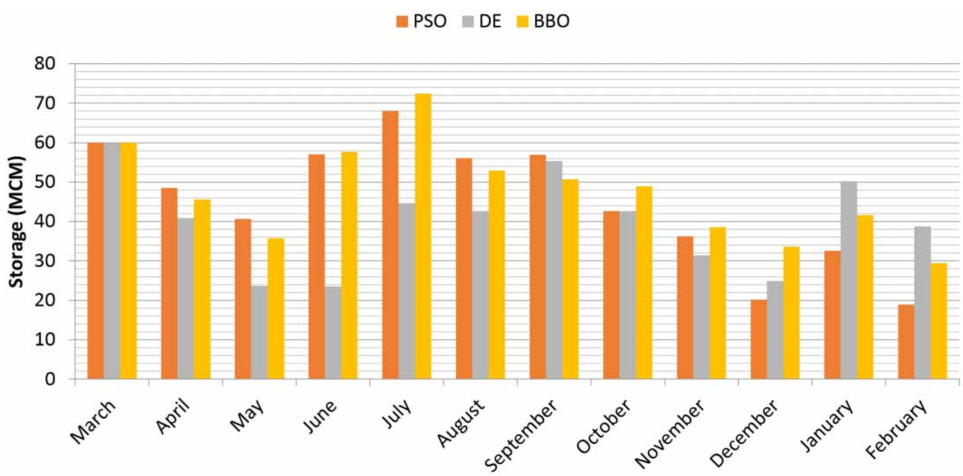


Figure 11 | Storage time series by different algorithms.

because it is able to minimize the difference between optimal physical habitat suitability and the physical habitat suitability for the natural flow. Moreover, the performance of BBO is better than PSO in terms of physical habitat loss.

Water quality suitability for different algorithms indicates that the optimization model is robust in this regard (Figure 13). The performance of the three used algorithms is quite good, which means that they are able to minimize the difference between suitability of optimal release for environment and natural flow. Thus, the optimization model is able to reduce environmental advocators' concerns regarding water quality. It should be noted that unsuitable concentrations of DO and water temperature might be a primary reason for perishing sensitive aquatics such as the Brown trout. In fact, DO and water temperature have a remarkable impact on the biological activities of the Brown trout. The previous biological studies in the tanks demonstrated that the unsuitable water temperature raises the biological tensions for the Brown trout quickly. In other words, all the biological activities such as searching for food and reproduction can be stopped in the unsuitable water temperature that means survival of the fish might be threatened. Furthermore, the previous studies corroborate that a high concentration of DO is a vital requirement for the Brown trout that means a low concentration of DO is considerably detrimental for the survival of the Brown trout.

Figure 14 shows combined habitat suitability which is the result of using a knowledge-based combined habitat suitability system in the structure of the reservoir operation optimization. In previous parts, some qualitative judgments on the results

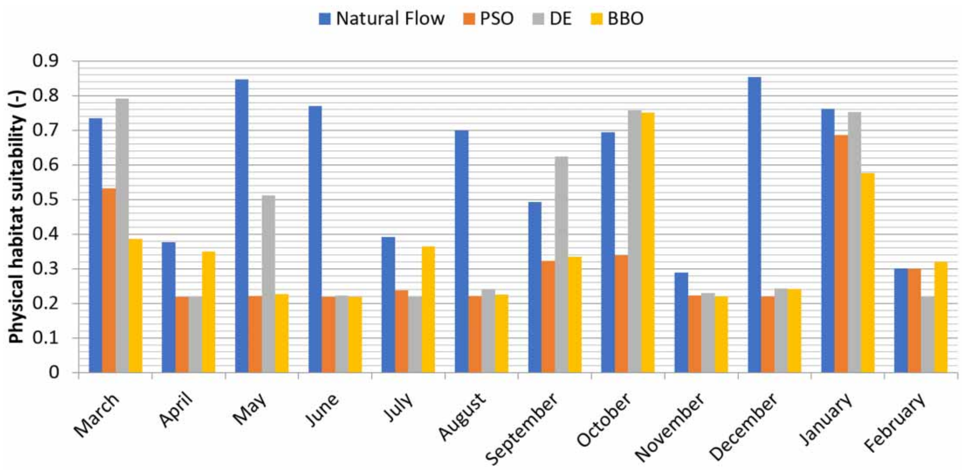


Figure 12 | Physical habitat suitability by different algorithms.

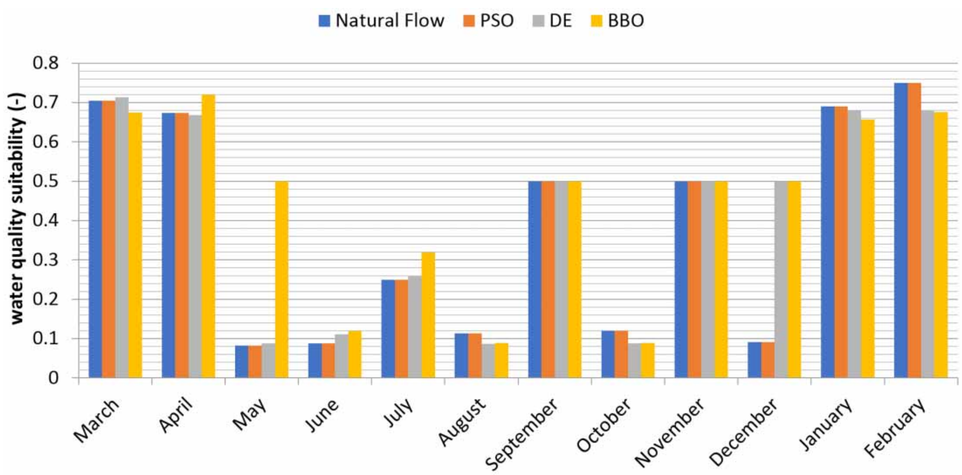


Figure 13 | Water quality suitability by different algorithms.

were possibly observed. However, judgment on the algorithms in terms of combined habitat suitability might not be possible observably. Generally, qualitative judgment on the environmental parameters might not be applicable to use in the robust decision-making system. Hence, using qualitative assessments for making final decisions is not recommendable in the practical project of the environmental flow assessment. Measurement indices are quite helpful in this regard to make a right decision for the final design of the environmental flow regime.

Figure 15 shows measurement indices for reservoir losses including reliability index for water supply, vulnerability index and RMSE for storage loss. Moreover, Figure 16 shows measurement indices for combined habitat loss. PSO is the best algorithm in terms of water supply. In fact, it is able to supply 60% of requested demand for the reservoir. DE has the lowest reliability for water demand based on outputs of the optimization system. The performance of the optimization system in terms of storage loss might be more complex. PSO has the highest vulnerability index. However, it does not have the highest RMSE. In other words, the performance of the PSO in one of the time steps is quite weak that might generate the highest vulnerability. Whereas the mean error of the DE is higher than PSO. The performance of the BBO is between these two algorithms.

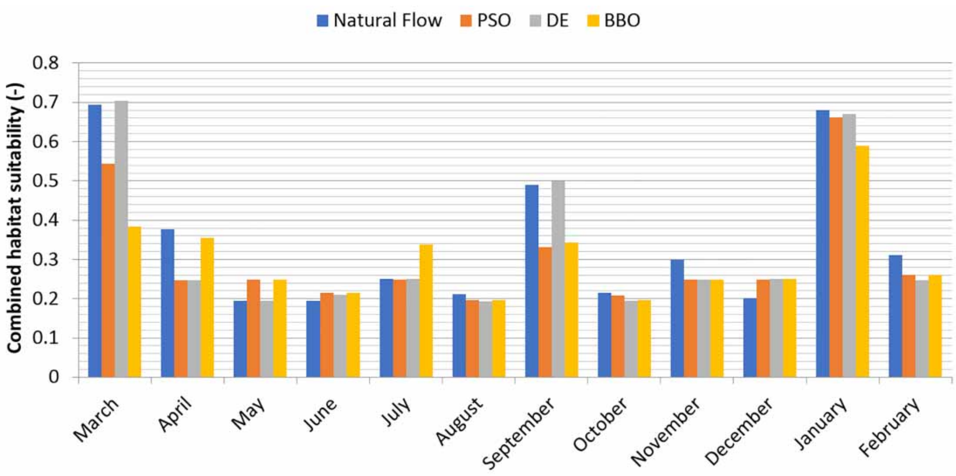


Figure 14 | Combined suitability by different algorithms.

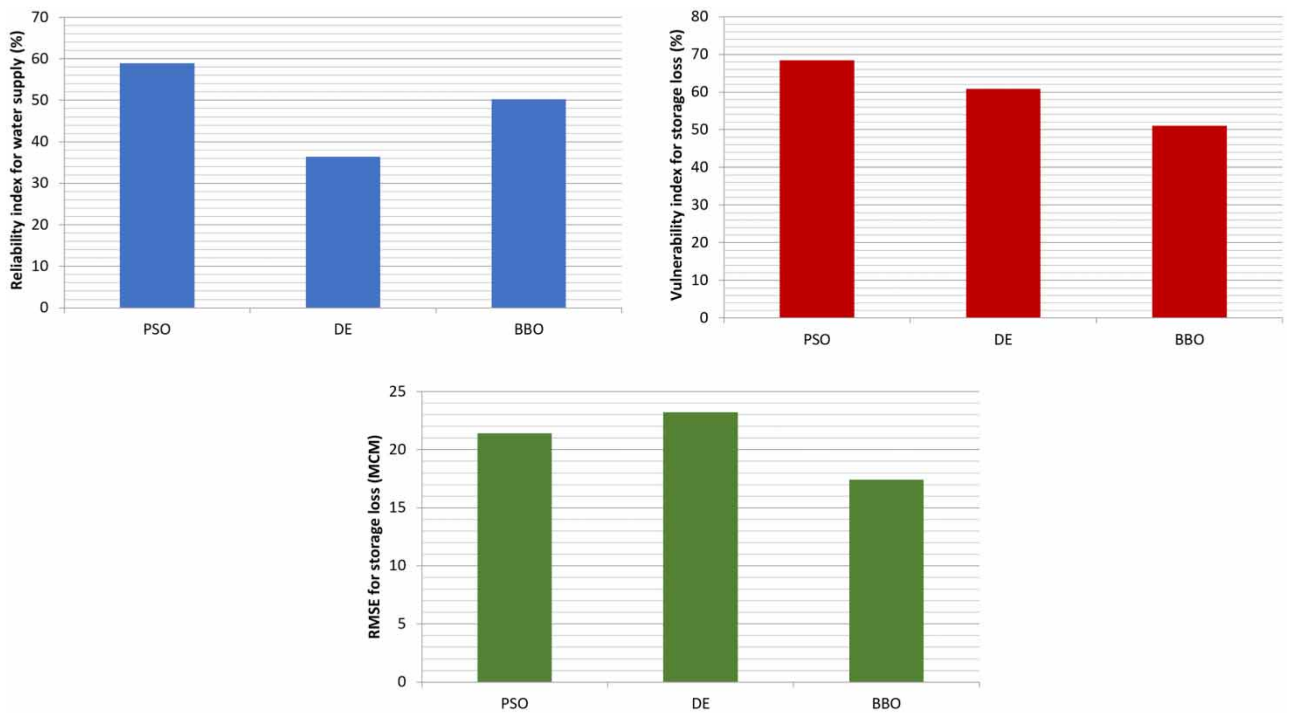


Figure 15 | Measurement indices for water demand loss and storage loss.

The main purpose of the proposed framework is to develop a robust knowledge-based system to optimize environmental flow at downstream of the reservoirs. Hence, evaluation of the performance of the optimization system in terms of environmental aspects including physical, water quality and combined suitability might be the most important part of the discussion on the results. Some points should be noted before discussion on the result of the measurement indices for environmental aspects. First, it might be logical to discuss on the results only by using measurement indices for combined habitat suitability because it shows the final output of the system. However, we computed measurement indices for physical habitat suitability as well to increase the reliability of the analysis. Secondly, it should be noted that the performance of the optimization system in

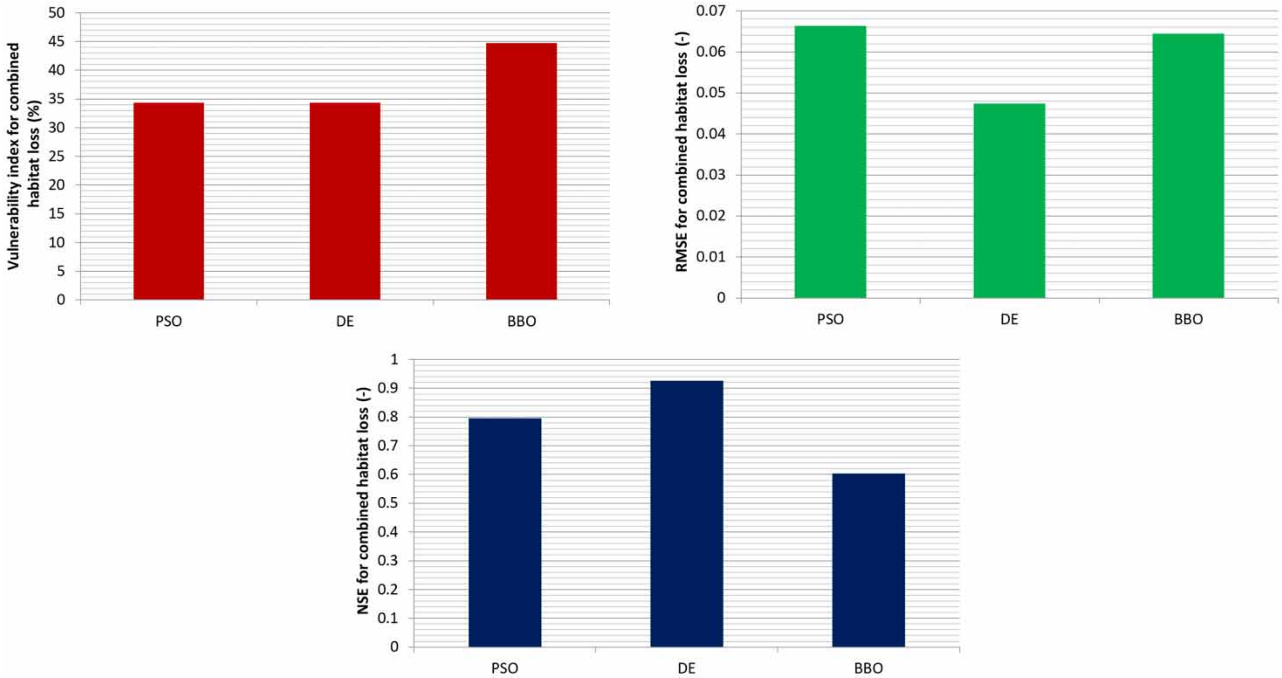


Figure 16 | Measurement indices for combined habitat loss.

terms of water quality suitability was highly robust that could be judged observably. Thus, we did not consider measurement indices for the water quality suitability in the discussion and decision-making system separately.

Figure 17 shows computed measurement indices for the physical habitat suitability in which vulnerability index, RMSE and NSE have been applied. Each index is helpful to measure one of the aspects in the analysis of the results. The vulnerability index indicates how the optimization system might harm the river habitats in the worst time step. Moreover, RMSE might show mean error in the simulated period compared with the natural flow. The best status of the river is the natural flow. Hence, using NSE could be helpful to demonstrate how the optimization model is able to simulate the suitability of natural flow in the optimal release for environment. The vulnerability index for all algorithms is close that indicates none of the algorithms is highly robust in this regard. It is because the vulnerability index is close to 70% that might be a serious concern. The vulnerability index indicates the maximum difference between natural suitability and optimal suitability in the simulated period. When the vulnerability index is 70%, the optimal suitability is considerably lower than natural suitability in some timesteps that might be a serious threat for providing a suitable environment for the aquatics in the river. However, it should be noted that simultaneous management of the environment and water demand might be challenging in the river ecosystem, and some threats are inevitable. Owing to the simulation of a challenging period of the reservoir operation, this output might not be surprising. The supply of water demands, storage requirements and environmental demands might not be possible perfectly. High RMSEs for all algorithms corroborate the weakness of the optimization system in terms of physical habitat suitability due to low inflow to the reservoir. However, the performance of DE is better than other algorithms. NSEs demonstrate that the optimization model is not able to provide physical suitability close to the natural flow because NSEs for three algorithms are less than zero that might show the weaknesses of the system in the case study. It should be noted that it is not the weakness of the developed knowledge-based method. In fact, it is a result of the low inflow to the reservoir. The results of the case study demonstrate that the assessment and management of the environmental flow might be highly complex in challenging periods. Thus, not only would using a robust knowledge-based system be a good suggestion, but it is also a requirement for the assessment and management of the environmental flow at downstream of the reservoirs in many cases.

The vulnerability index for the combined habitat suitability is much less than physical habitat suitability that demonstrates some key points. First, the optimization system used generated suitability by the water quality suitability system to reduce the combined unsuitability in the objective function that might be logical. In other words, we face a complex situation in the river

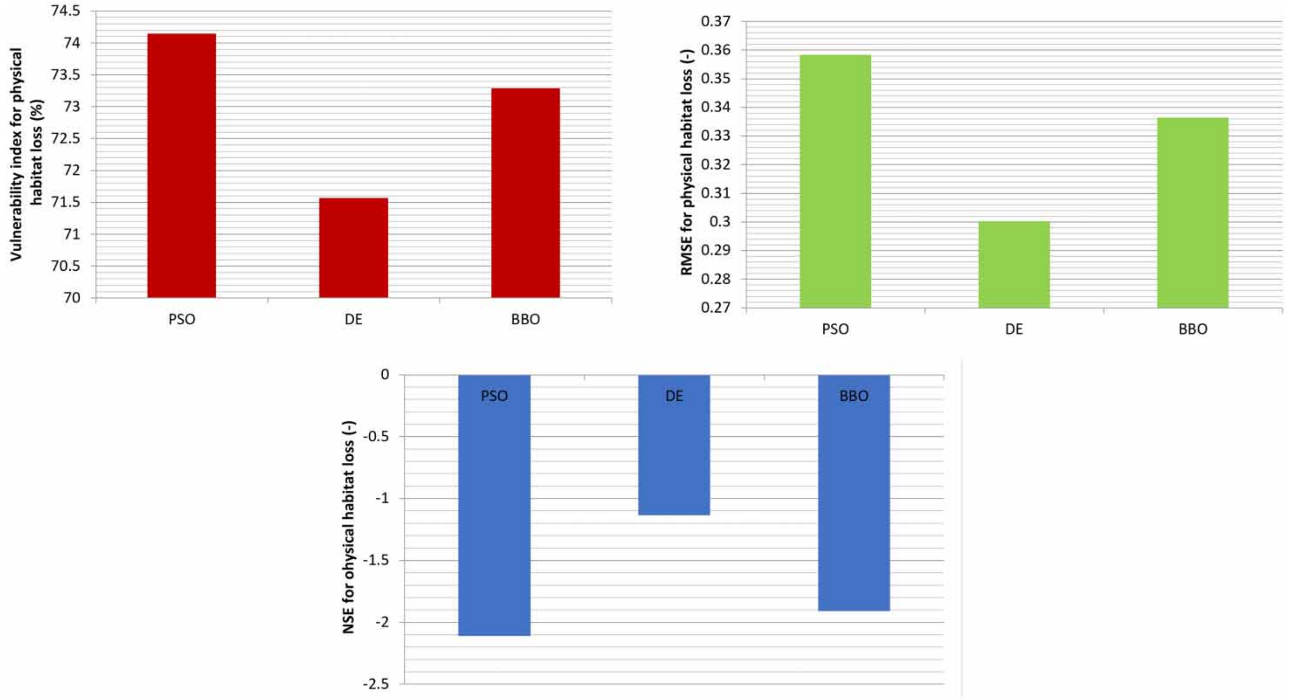


Figure 17 | Measurement indices for physical habitat loss.

ecosystems that might be analyzed from different views. RMSEs and NSEs indicate that the optimization model is able to provide sufficient combined suitability for downstream river ecosystems compared with the natural flow. To sum up, the performance of the optimization model is generally acceptable. It is able to increase combined suitability dramatically. However, its performance in terms of physical habitat suitability is not perfect. Table 9 shows the rating of alternatives for applying the FTOPSIS method. Figure 18 shows the final ranking of the methods by the FTOPSIS method. DE is the best candidate to optimize environmental flow in the proposed method.

One of the questions that should be answered is how the input parameters of the model were selected in the present study. It should be noted that the particular set of parameters for each model was selected based on the previous studies. For example, the previous studies corroborate that depth and velocity are the most important parameters that are effective on the physical habitat suitability of the river habitats that were the main reasons for selecting these parameters in the physical habitat model. Moreover, sensitivity analysis of effective parameters on the water temperature by the previous studies demonstrated that selected parameters are the most sensitive parameters for changing water temperature in the streams. To sum up, the parameters were selected based on many previous studies on the river habitats that determined sensitive parameters for simulating habitat suitability in the rivers.

More discussion on the technical aspects and details of the developed model is essential. The proposed method considered the physical habitat suitability and water quality suitability as the most important factors in the river habitats in an integrated

Table 9 | Sample of rating of alternatives for some selected indices (based on the method by Chen (2000))

	PSO	DE	BBO
RI (water supply)	*G*	*RG*	*RP*
VI (storage)	*VG*	*G*	*RG*
RMSE (storage)	*G*	*G*	*RG*
VI (combined suitability)	*G*	*G*	*VG*

RP, RG, G, VG mean relatively poor, relatively good, good and very good respectively.

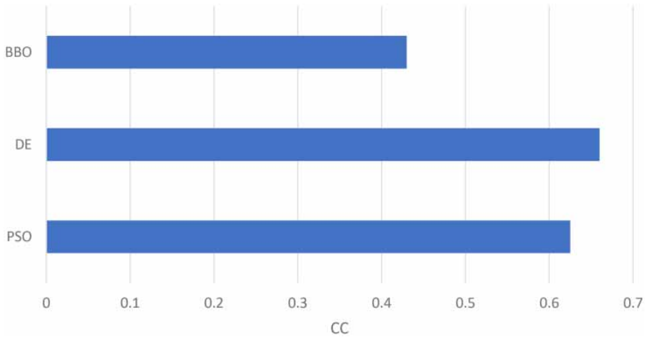


Figure 18 | Final ranking by the FTOPSIS method.

framework that is the main advantage of the proposed method. Flow velocity and depth are effective on the energy consumption by the fish that means considering these two parameters is necessary for each habitat suitability assessment of the aquatics. Depth might be important for sheltering the fishes in the habitats as well. It seems that suitable management of velocity and depth is able to provide the minimum requirements for protecting aquatic habitats in terms of physical factors. Moreover, the water temperature and the concentration of DO are key water quality factors that might be effective on the suitability of river habitats. Other parameters could be added to the system as well. However, these two water quality parameters are good indexes that are able to demonstrate the impact of all the water quality factors on the river habitats. It should be noted that changing the concentration of other constituents such as total dissolved solids or total suspended solids might change the water temperature and the concentration of DO in the water bodies. Hence, it is recommendable to apply the water temperature and the concentration of DO as the critical water quality parameters for modeling the suitability of river habitats. Furthermore, adding climate change models to the proposed expert system is recommendable for future studies. In fact, climate change might alter the streamflow or inflow of the reservoir that is significantly effective in the management of environmental flow in the reservoirs. It should be highlighted here that the abiotic parameters are considered in the present study. It is recommendable to add biotic factors such as predation in future research work.

Each method or system might have some advantages and disadvantages that should be noticed for practical projects. In fact, discussion on the strength and limitation of the proposed method is essential. Moreover, it should be discussed why the proposed mechanism was prosperous in the case study to assess the environmental flow regime. Using a knowledge-based system is useful in the assessment of environmental flow. We face a complex ecological status in the rivers that might not be measurable in many aspects. However, experts might have strong views on the complexities of the system that is based on many qualitative observations and studies on the ecological aspects of the case study. These experts' opinions might not be useable without the development of a robust knowledge-based system. Moreover, water resource systems such as reservoirs are complex. They should be able to supply different needs including humans' needs and environmental needs. Thus, using optimization models in the management of the water resource systems is necessary. The proposed method puts a knowledge-based environmental model in the structure of an optimization system that might be the most important point to propose an appropriate environmental flow regime. This system was able to provide requirements of the reservoir management simultaneously. Hence, we can claim that the proposed method is an integrated method to assess the environmental flow regime. Another advantage of the proposed model is upgradability. In other words, other effective factors could be added to the system in future studies. It should be noted that fishes are not the main species for all of the rivers. Hence, using other target species might be another option in the assessment of the environmental flow regime. The proposed method is upgradable in this regard. The main limitation of the proposed method is high computational complexities. This term can be defined as the required time and memory to the optimization model to find the best solution. Practical projects might need many simulations or covering a long-term period. The proposed method needs much time for running due to using several fuzzy inference systems in the structure of the evolutionary algorithm. Furthermore, simultaneous simulations might need considerable memory that might be a concern for the successful application of the proposed method in practical projects. We recommend focusing on the reduction of computational complexities in future studies that increases the applicability of this method.

Moreover, some key points should be discussed regarding the optimization model. First, why three different evolutionary algorithms have been applied in the present study. Second, why the single objective evolutionary algorithms have been utilized to optimize reservoir operation. Third, more details regarding the application of the evolutionary algorithms in the present study. The main drawback of the evolutionary algorithms is the inability to guarantee the global optimization that means using one evolutionary algorithm might not be reliable to find the best solution. Thus, utilizing different evolutionary algorithms and a robust decision-making system is a requirement for the complex optimization system such as the developed model in the present study. It should be noted that there is a serious concern for guaranteeing the global optimization by the evolutionary algorithms, particularly in the complex objective functions. Furthermore, it is observable that the proposed objective function contains different terms that might be useable in the structure of the multi-objective optimization algorithms. However, two points convinced the researchers of the present study to apply single objective algorithms instead of multi-objective algorithms. First, the proposed method in the single objective form has high computational complexities that are a limitation for the system. Multi-objective optimization algorithms such as multi-objective PSO inherently have higher computational complexities compared with single objective optimization algorithms. Hence, using the multi-objective algorithms might make the optimization model highly complex. In other words, required time and memory will be very high for implementing the model in the projects that might reduce the applicability of the model for the engineers. Secondly, the limited number of multi-objective algorithms have been developed in the literature that means applying these algorithms might not be reliable enough in terms of global optimization in the current condition. However, many single objective algorithms have been developed in the literature with different origins that might help the researchers to find the best solution using a robust decision-making system such as FTOPSIS. In the present study, a number of iterations were considered as the stop criterion for the evolutionary algorithms. In other words, a high number of iterations (i.e. 10,000) was considered for the optimization algorithms to find the best solution. This number of iterations was highly reliable as the stop criterion in the optimization model. In fact, the best solution was found by the algorithms when the number of iterations was 5,000 that means the selected criterion was highly reliable.

4. CONCLUSIONS

The present study proposed a coupled knowledge-based system–optimization model to assess environmental flow at the downstream of the reservoirs as one of the important water resource systems. Three Mamdani fuzzy inference systems were developed including physical habitat suitability, water quality suitability and combined habitat suitability. Depth and velocity suitability were assessed based on the developed suitability criteria. Moreover, water temperature and DO were simulated by the PSO–ANFIS model. Three different evolutionary algorithms including PSO, DE and BBO were utilized to optimize reservoir operation in which environmental knowledge-based systems were considered in the structure of the optimization model. Based on the results in the case study, the proposed method is able to optimize environmental flow properly. Moreover, it is able to minimize storage loss and water supply loss in the reservoir. FTOPSIS was used as a decision-making system to select the best algorithm that is DE. The main limitation for the application of the proposed method is high computational complexities that means considerable time and memory are needed for implementing the proposed optimization system. Moreover, it is recommendable to add the biotic factors of the river habitats such as predation to the proposed method. Furthermore, it might be useful to add the climate change models to the framework in future studies.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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