

Reducing the conflict of interest in the optimal operation of reservoirs by linking mesohabitat hydraulic modeling and metaheuristic optimization

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ABSTRACT

The present study proposes a novel framework to optimize the reservoir operation through linking mesohabitat hydraulic modeling and metaheuristic optimization to mitigate environmental impact downstream of the reservoir. Environmental impact function was developed by mesohabitat hydraulic simulation. Then, the developed function was utilized in the structure of the reservoir operation optimization. Different metaheuristic algorithms including practice swarm optimization, invasive weed optimization, differential evolution and biogeography-based algorithm were used to optimize reservoir operation. Root mean square error (RMSE) and reliability index were utilized to measure the performance of algorithms. Based on the results in the case study, the proposed method is robust for mitigating downstream environmental impacts and sustaining water supply by the reservoir. RMSE for mesohabitats is 8%, which indicates the robustness of proposed method to mitigate environmental impacts at downstream. It seems that providing environmental requirements might reduce the reliability of water supply considerably. Differential evolution algorithm is the best method to optimize reservoir operation in the case study.

Key words: downstream environmental impact, metaheuristic optimization, optimal reservoir operation, pool/riffle systems

HIGHLIGHTS

- A novel method for reservoir operation optimization.
- Linking river habitats field studies and two dimensional hydraulic modeling for developing environmental impact function.
- The results showed the ability of the method to optimize water supply.
- The proposed method mitigates environmental impacts at downstream properly

1. INTRODUCTION

The importance of reservoirs in development has been highlighted in the literature. In fact, reservoirs play a key role to supply water and electricity demand (Altinbilek 2002). Optimization of reservoir operation is the most critical task after construction of dams (Labadie 2004; Reis et al. 2006). It is required to apply a reliable method for optimizing the reservoir operation. Advanced computational methods are highly applicable for the reservoir operation optimization due to their abilities for handling complex objective functions. Thus, metaheuristic optimization has been highlighted as a powerful method to optimize reservoir operation in recent decades. A wide range of metaheuristic algorithms including classic and new generation algorithms have been used to optimize the reservoir operation (e.g Afshar et al. 2007, 2011; Jahandideh-Tehrani et al. 2015; Ehteram et al. 2018; Yaseen et al. 2019). It should be noted that the previous studies maximize benefits without simultaneous simulation of environmental impacts. An applicable form of the loss function has been utilized in many recent studies regarding the reservoir operation optimization (e.g Karami et al. 2019). This function minimizes difference between target or water demand and release from the reservoir. Moreover, it is highlighted that storage constraints should be added to the optimization model (Ehteram et al. 2017). The main drawback of this loss function is absence of environmental impact function in the reservoir operation.

Construction of dams might have profound impacts on the ecological suitability of the river ecosystem at downstream and upstream. These impacts are considerable at downstream aquatic habitats. Hence, protecting downstream river habitats is essential to mitigate environmental impacts downstream of hydraulic structures such as gravity dams and water diversion

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projects. The environmental flow concept has been defined to protect river habitats. In other words, this flow regime might guarantee sustainability of the ecological status in the rivers (Sedighkia *et al.* 2017). Different methods have been utilized to assess the environmental flow regime in rivers including hydrological methods, hydraulic rating methods, habitat simulation methods and holistic methods (Tharme 2003; Jowett 1997). Some previous studies optimized environmental flow downstream of reservoirs (Yin *et al.* 2012; Cai *et al.* 2013; Horne *et al.* 2017). However, they might not be robust enough due to an inability to highlight the regional ecological values and reservoir benefits simultaneously. Due to a lack of ecological simulation components, some methods such as hydrological methods and hydraulic rating methods are not applicable in all the cases (Sedighkia & Abdoli 2021). Using habitat simulation methods in the context of instream flow incremental methodology (IFIM) is a known method to assess habitat suitability and environmental flow (Sedighkia & Abdoli 2021). Evaluation of mesohabitats and microhabitats might come into the picture in an integrated habitat simulation. River ecosystems might provide suitable environments for all the aquatic organisms in natural status. Hence, if evaluation of environmental flow is based on average suitability of river habitats for all of the aquatic organisms, it may guarantee the suitability of habitats.

Evaluation of mesohabitats is an appropriate procedure to simulate the general suitability of the river habitats. Distinguished habitats are identifiable in streams that are composed of a series of pools, riffles and runs. Riffles are areas that have been classified by their shallow depth with fast, turbulent water and rocky bed (Jowett 1993). These characteristics provide some ecological advantages including protection from predators, food deposition and shelter. Pools have been recognized by slow flow and high depth. Pools are important for providing suitable ecological status in rivers. Still water is accessible in these habitat units that might be necessary for the aquatics. In other words, aquatics such as fishes need still waters to minimize energy consumption of swimming. Runs have moderate current, continuous surface and depth greater than riffles. Suitable river habitats should include three types of mesohabitats that means each mesohabitat unit has the significant role to support biological activities. Objectively identification of pools, riffles and runs has been reviewed in the literature. Some studies identified mesohabitats without hydraulic criteria (more details are reviewed by Mahdade *et al.* 2018). However, other studies provided quantified criteria to recognize mesohabitats. For example, previous studies developed five models to distinguish habitat units including Froude number model, slope model, velocity to depth ratio model, combined Froude number and slope model and combined velocity to depth ratio and slope model (Jowett 1993). Using mesohabitat units has been highlighted in recent studies to simulate habitats of the streams. For instance, utilizing hydraulic models for habitat modeling in pool/riffle sequences has been highlighted (Booker *et al.* 2001; Najafabadi & Afzalimehr 2019). Complex effects of pool/riffle morphological features on river flow characteristics such as river mixing indicate the importance of pool/riffle sequences to manage the river ecosystem (Fuentes-Aguilera *et al.* 2020). Importance and methods of mesohabitat modeling in the fish ecology have been reviewed in the literature (Wegscheider *et al.* 2020).

The present study proposes and evaluates a novel framework to mitigate environmental impact of the reservoirs at downstream river habitats by a linked mesohabitat modeling-optimization method. One of the most important impacts of the reservoir is reduction of river flow that might directly affect the pool/riffle sequences. Changing pool, run and riffle area might reduce habitat suitability at downstream river reach due to specific role of each mesohabitat unit for the biological activities of the aquatics such as fish. Hence, one of the effective methods for mitigating downstream environmental impact of reservoirs could be minimization of the difference between area of mesohabitat units in the natural status and the optimal status. However, the proposed reservoir operation model must be able to maximize benefits from the reservoir. The proposed method in the present study is applicable for cases in which downstream environmental impact of a reservoir is a serious concern and different species could be observed at the downstream river reach. In fact, existence of different species indicates that using target species-based ecological environmental methods such as physical habitat simulation might not be able to protect all the species. Use of the mesohabitat modeling method is generally able to maximize habitat suitability for all the species. Hence, it would be one of the proper methods to mitigate downstream environmental impacts of reservoirs.

2. APPLICATION AND METHODOLOGY

2.1. Study area and problem definition

The southern Caspian Sea basin consists of many rivers and streams that have been recognized as valuable habitats for many aquatic species. Tajan River is one of the most important rivers in this basin, which is a proper habitat for many aquatics. Moreover, this river is responsible for supply of irrigation demand for downstream farms. In other words, supply of water

for environment and irrigation demand is a challenge in this region. Rajaei dam has been constructed at the upstream of this river to supply water and electricity demands. On the one hand, the regional department of environment (DOE) highlights a lack of habitat suitability at the downstream river reach as a serious concern for river ecosystems. On the other hand, the regional water authority is concerned regarding benefits from the reservoir. Hence, design of an integrated optimization framework that is able to minimize all the losses might be essential for management of the reservoir in the future periods. Figure 1 displays the location of Tajan river basin, Rajaei dam and land use. Minimum operational storage, maximum possible storage and optimal storage in the reservoir are defined as 60, 160 and 140million cubic meters (MCM) in the present study respectively. Water demand time series at downstream of the reservoir is displayed in Figure 2. We considered that the reservoir should be able to supply this demand as much as possible. Moreover, Figure 3 displays evaporation from the surface of the reservoir. Evaporation is one of the required data for the optimization model.

2.2. Mesohabitat modeling

We carried out velocity and depth measurements and subjective field studies in different cross sections of the river reach to recognize pools, riffles and runs. Then, developed criteria was combined with the results of 2D hydraulic simulation to assess

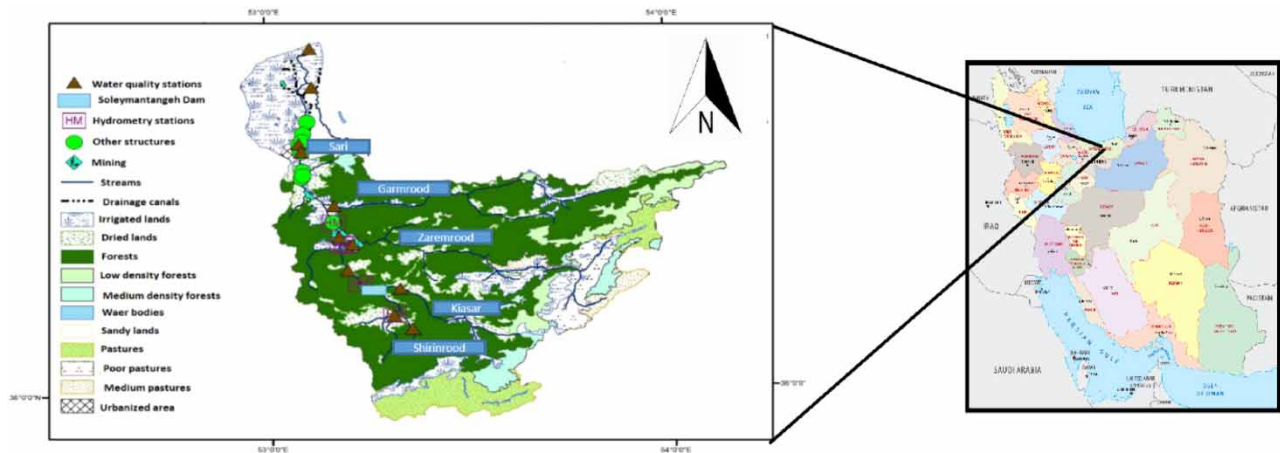


Figure 1 | Land use and river network map of Tajan basin.

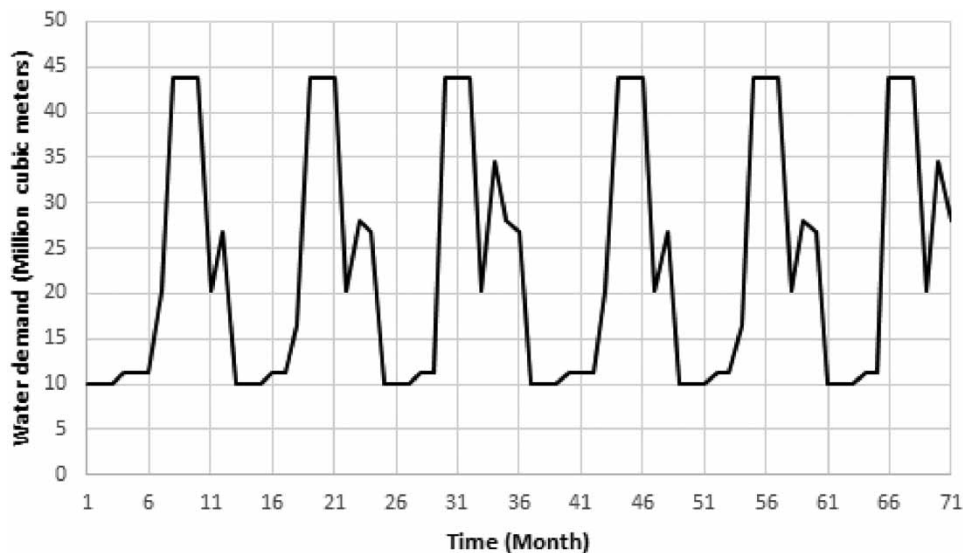


Figure 2 | Maximum water demand in the simulated period (6 years).

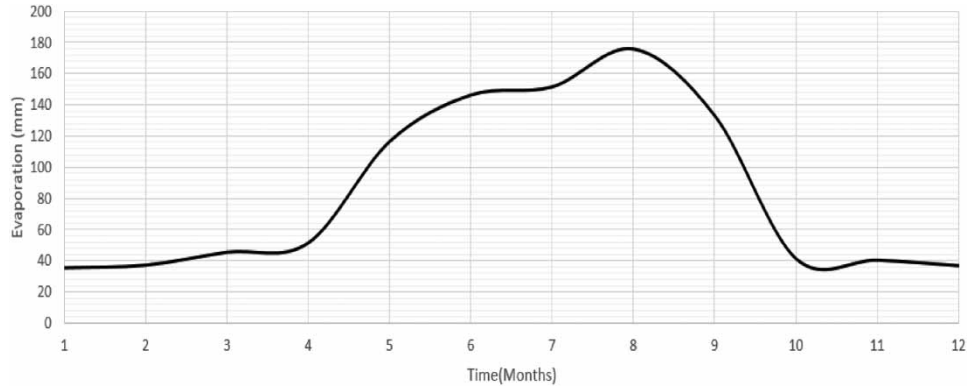


Figure 3 | Evaporation from surface of reservoir in different months (annually- Jan to Dec).

area of pools, riffles and runs in each rate of flow. More details on mesohabitat modeling are presented as displayed in Figure 4.

Figure 4 indicates that final output of mesohabitat modeling is a relationship between the area of mesohabitat units and flow rate. This relationship was utilized in the structure of optimization model to mitigate environmental impact of the reservoir downstream. Structure of the optimization model is presented in the next section.

2.3. Optimization model

Using an appropriate objective function is the basic need for developing a reservoir operation model. This objective function might be defined based on the requirements of reservoir management. Two main purposes were considered in the initial objective function including minimizing difference between water demand and release for demand and minimizing difference between ratio of riffle to pool in the natural flow and environmental flow downstream as displayed in Equation (1)

$$OF = \sum_{t=1}^T \left(\frac{D_t - R_t}{D_t} \right)^2 + \left(\frac{NPR_t - OPR_t}{NPR_t} \right)^2 \quad (1)$$

where D_t is target demand, R_t is release for demand, NPR_t and OPR_t are natural ration of riffle and run areas to pool area in the natural status and optimal operation of the reservoir. As a description regarding NPR and OPR, they define environmental suitability at the downstream simulated river. A proper ratio of riffle plus run area to the pool area could be considered as the suitability index for the river habitats. NPR is the suitability ratio in the natural flow and OPR is the suitability ratio in the optimal operation of the reservoir. Minimizing the difference between these two values was considered as

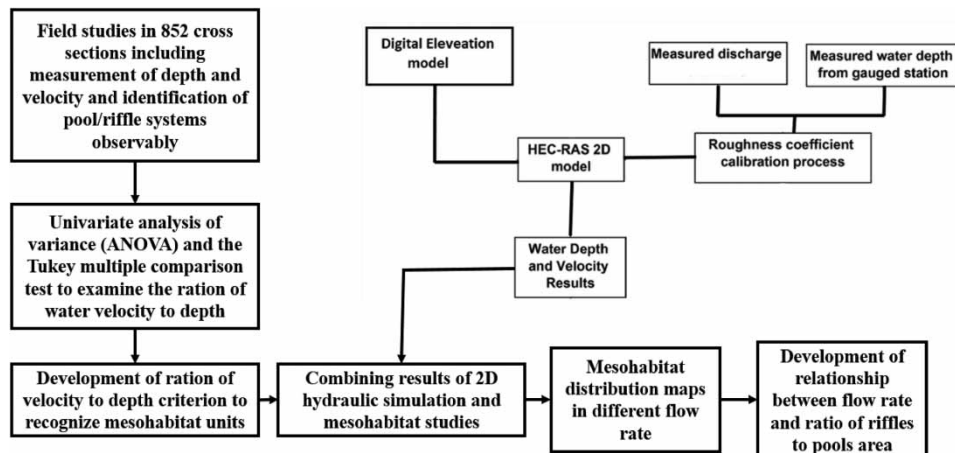


Figure 4 | Workflow of mesohabitat modeling in the present study.

one of the purposes of the optimization model. Moreover, it is essential to add some constraints for reservoir operation optimization. Three constraints should be considered including constraint on the maximum storage, minimum operational storage and maximum water demand. Using constraints in the metaheuristic algorithms might need a tricky method to insert the constraints in the structure of optimization model. Penalty function method is a smart solution that has widely been used in the previous reservoir operation studies. Hence, we applied this method in the present study. More details regarding the penalty function method have been addressed in the literature (Liang *et al.* 2019). Equation (2) displays added penalty functions

$$\begin{cases} \text{if } S_t > S_{max} \rightarrow P1 = c1 \left(\frac{S_t - S_{max}}{S_{max}} \right)^2 \\ \text{if } S_t < S_{min} \rightarrow P2 = c2 \left(\frac{S_t - S_{min}}{S_{min}} \right)^2 \\ \text{if } R_t > D_t \rightarrow P3 = c3 \left(\frac{R_t - D_t}{D_t} \right)^2 \end{cases} \quad (2)$$

where s_{max} is maximum possible storage, s_{min} is minimum operational storage, s_t is storage in time step t and D_t is demand in time step t . These penalty functions are added to the objective function for the optimization process. Equation (3) displays the final form of the objective function in the present study.

$$\text{minimize (OF)} = \sum_{t=1}^T \left(\frac{D_t - R_t}{D_t} \right)^2 + \left(\frac{NPR_t - OPR_t}{NPR_t} \right)^2 + P1_t + P2_t + P3_t \quad (3)$$

Furthermore, storage should be updated in each time step t , Equation (4) was utilized to update storage in each time step.

$$S_{t+1} = S_t + I_t - R_t - E_t - F_t - \left(\frac{EV_t \times A_t}{1000} \right), t = 1, 2, \dots, T \quad (4)$$

where S_t is storage at time period t , I_t is inflow to reservoir at time t , EV_t is evaporation from reservoir surface at time t , A is area of reservoir surface, R_t is release for demand and E_t is release for environment and F_t is overflow. T is the time horizon. Overflow is calculated based on the Equation (5).

$$\begin{cases} \text{if } \left(S_t + I_t - \left(\frac{EV_t \times A_t}{1000} \right) \right) \geq S_{max} \rightarrow F_t = S_t + I_t - \left(\frac{EV_t \times A_t}{1000} \right) - S_{max} \\ \text{if } \left(S_t + I_t - \left(\frac{EV_t \times A_t}{1000} \right) \right) < S_{max} \rightarrow F_t = 0 \end{cases} \quad (5)$$

It is required to explain how the overflow was defined in the operation of the reservoir in the present study. Overflow was considered as the release to the downstream of the reservoir. In fact, water supply is directly being pumped from the reservoir and overflow and environmental flow are released to the downstream. Hence, the treatment method in the present study is consistent with the water balance of the reservoir system.

Defining water demand and other factors in the optimization system should be explained as well. In the case study, agriculture was the main economic activity and the source of water consumption. In other words, reservoir has considerable role for supply of irrigation demand. The maximum water demand was defined based on the maximum irrigation demand at downstream agricultural lands proposed by the regional agricultural authority. Moreover, minimum operational storage was defined based on the recommendations by the regional water resources engineers who were responsible for management of the reservoir (Minimum operational storage was considered 60 MCM). The capacity of the reservoir (160 MCM) was defined based on the technical report of the dam as the maximum storage in the optimization model.

Another question is how the NPR and OPR were computed in the optimization system? NPR and OPR were calculated based on the R/P function (presented in the results and discussion) as the output of the mesohabitat modeling in which river flow is input and the R/P is the output of the function. R/P in the natural flow could be defined as the NPR and R/P in the optimal release could be considered as the OPR in each time step.

2.4. Metaheuristic algorithms

We utilized four metaheuristic algorithms including invasive weed optimization, particle swarm optimization (PSO), differential evolution algorithm (DE) and biogeography-based optimization (BBO) to optimize reservoir operation in the present study. It should be noted that general workflow of metaheuristic algorithm is the same. However, they utilize different strategies to improve candidates during iterations. Efficiency of the algorithms might be different based on complexity of the objective function and origin of the algorithm. Hence, using different metaheuristic algorithms might be helpful to find the best solution for the problem. The variables in the optimization algorithms were environmental flow and release for water demand. The number of iterations for all the algorithms were considered as the same. In fact, 10,000 iterations were considered in the optimization process for all the algorithms that was adequate for convergence of the optimization results. In other words, a high number of iterations was helpful for increasing the reliability of the solutions. Based on the experiments, when the number of iterations was more than 5,000, the convergence output of the optimization algorithms had limited changes that means the solutions with 10,000 iterations could be highly reliable. Generally, metaheuristic algorithms initialize the optimization process considering the initial population or candidates. Then, fitness function is used to compute the fitness of the candidates as the solutions. If the termination criterion is not satisfied, then the population will be updated. This process will be repeated until the termination criterion is satisfied. In the present study, the termination criterion was the number of iterations that could provide the excellent results as discussed. Figures 5–8 display a flowchart of each algorithm as follows. The PSO solves the optimization problem considering a population of candidates and moving these particles or candidates around in the search-space based on the particle's position and velocity. This algorithm is inspired by the social behavior of the animals or the movement of organisms in a bird flock or fish school. The DE is applied for multidimensional real-valued functions. However, it does not utilize the gradient of the problem, which means DE does not require the optimization problem to be differentiable. It should be noted that DE might not guarantee the finding of optimal solution for the problem. IWO, which is inspired by colonizing weeds, consists of some main steps including initialization, reproduction of the seeds, spatial distribution of the seeds, competitive exclusion for eliminating undesirable plants with poor fitness, and checking the termination criterion. The BBO is inspired by the biogeography mathematical models in which speciation (the

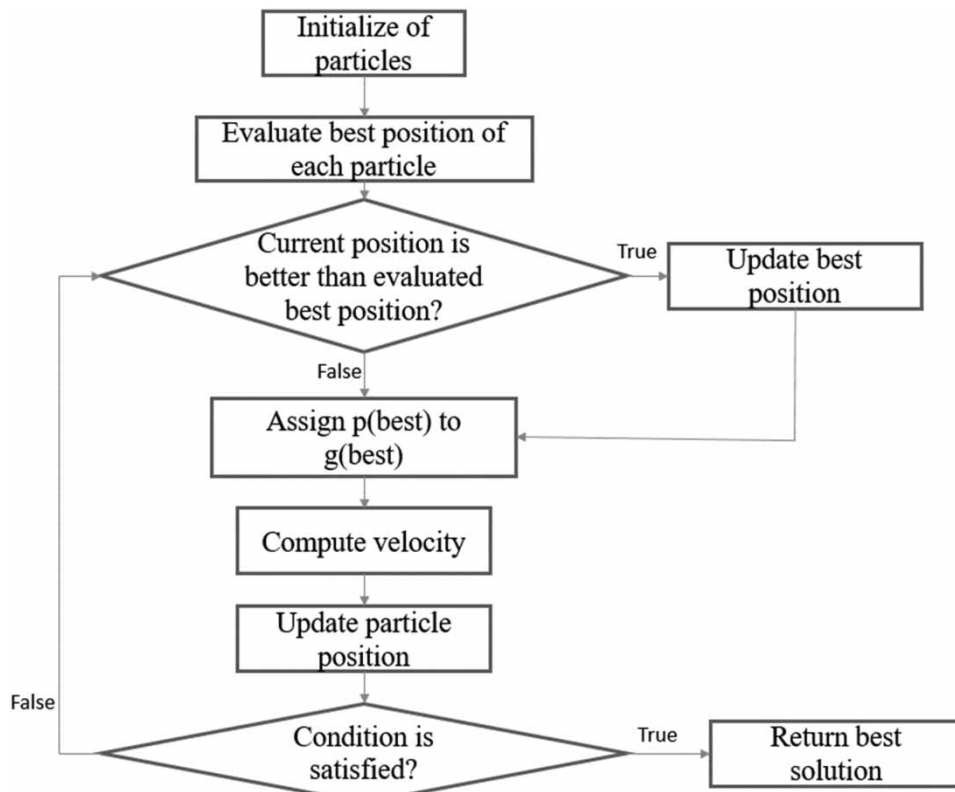


Figure 5 | Particle swarm optimization (PSO) flowchart (Kennedy & Eberhart 1995).

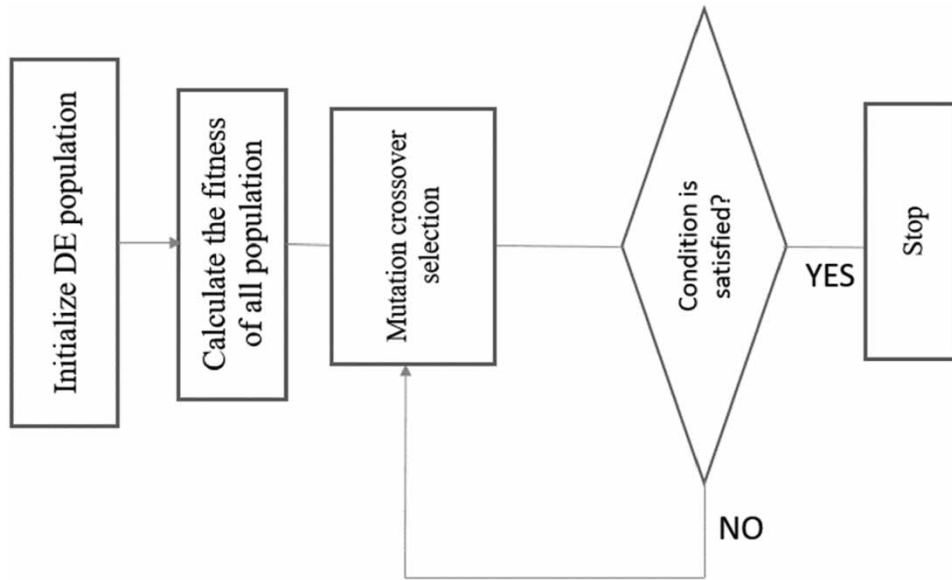


Figure 6 | Flowchart of DE (Qin et al., 2008).

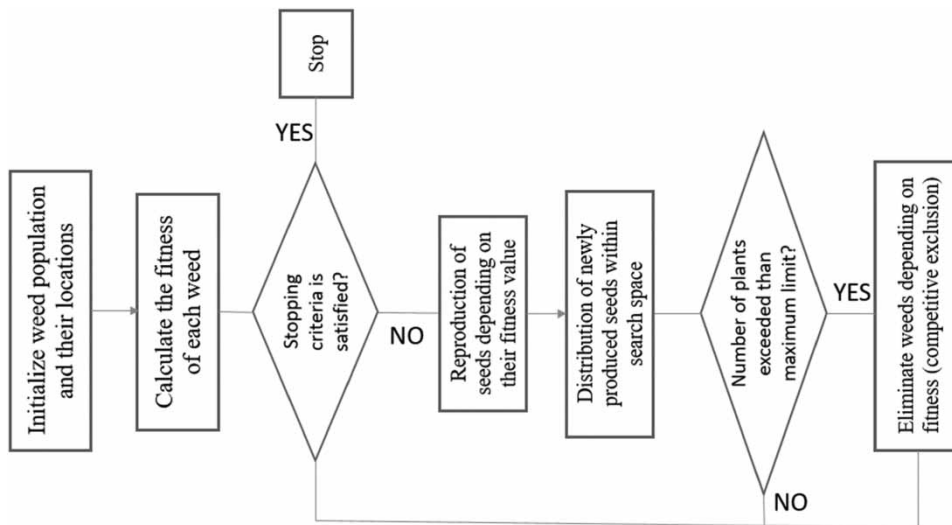


Figure 7 | Flowchart of IWO (Mehrabian and Lucas, 2006).

evolution of new species), the migration of species (animals, fish, birds, or insects) between islands, and the extinction of species could be described. Habitat suitability index (HSI) is the criterion for comparing islands for finding the best solution.

2.5. System performance measurement

Each optimization system needs some indices to measure the robustness of performance. Three issues, including supply of water demand, storage loss and mesohabitat loss, must be taken into account for measurement of the performance in the present study. We applied the reliability index to measure the robustness of the optimization model in terms of water supply due to the possibility of secondary storage in the farms. In other words, if an optimization solution is able to maximize reliability of water supply, it will be the best solution. Equation (6) displays the mathematical form of the reliability index for water supply.

$$Reliability\ index = \frac{\sum_{t=1}^T R_t}{\sum_{t=1}^T D_t} \tag{6}$$

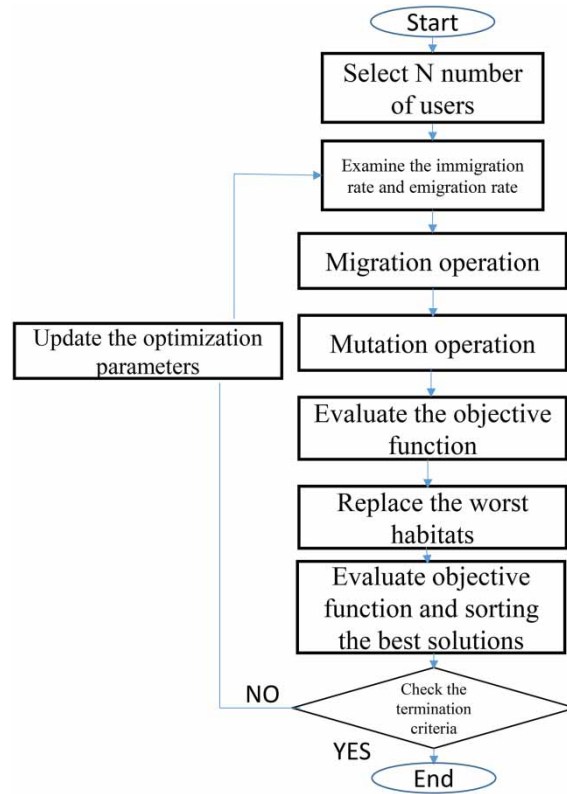


Figure 8 | Flowchart of BBO (Simon 2008).

Moreover, it is essential to measure the system performance in terms of storage loss. Root means square error is an applicable index to measure storage loss in the reservoir. It is able to calculate mean error for actual storage compared with optimal storage. Furthermore, we applied root mean square error to measure system performance in terms of mesohabitat areas. Moreover, RMSE was used to measure robustness of performance in terms of water supply as a secondary measurement index. The mathematical form of RMSE is displayed in Equation (7) for water demand. Equation (8) displays RMSE for storage as well as Equation (9) for mesohabitat units. Optimal storage used in the measurement index is a predefined storage level based on the recommendations by the water authority as the optimal value for the storage in the reservoir. In fact, deviation from the optimal storage might increase the storage loss in the reservoir.

$$RMSE_R = \sqrt{\frac{\sum_{t=1}^T (D_t - R_t)^2}{T}} \quad (7)$$

$$RMSE_R = \sqrt{\frac{\sum_{t=1}^T (\text{Optimal storage} - s_t)^2}{T}} \quad (8)$$

$$RMSE_R = \sqrt{\frac{\sum_{t=1}^T (NPR_t - OPR_t)^2}{T}} \quad (9)$$

3. RESULTS AND DISCUSSION

In the first section of the results and discussion, the results of mesohabitat modeling are presented including results of hydraulic simulation, mesohabitat criteria and combining results of hydraulic simulation and mesohabitat field studies. Figure 9 displays the verification results of the hydraulic model in terms of simulating depth and velocity in the simulated river

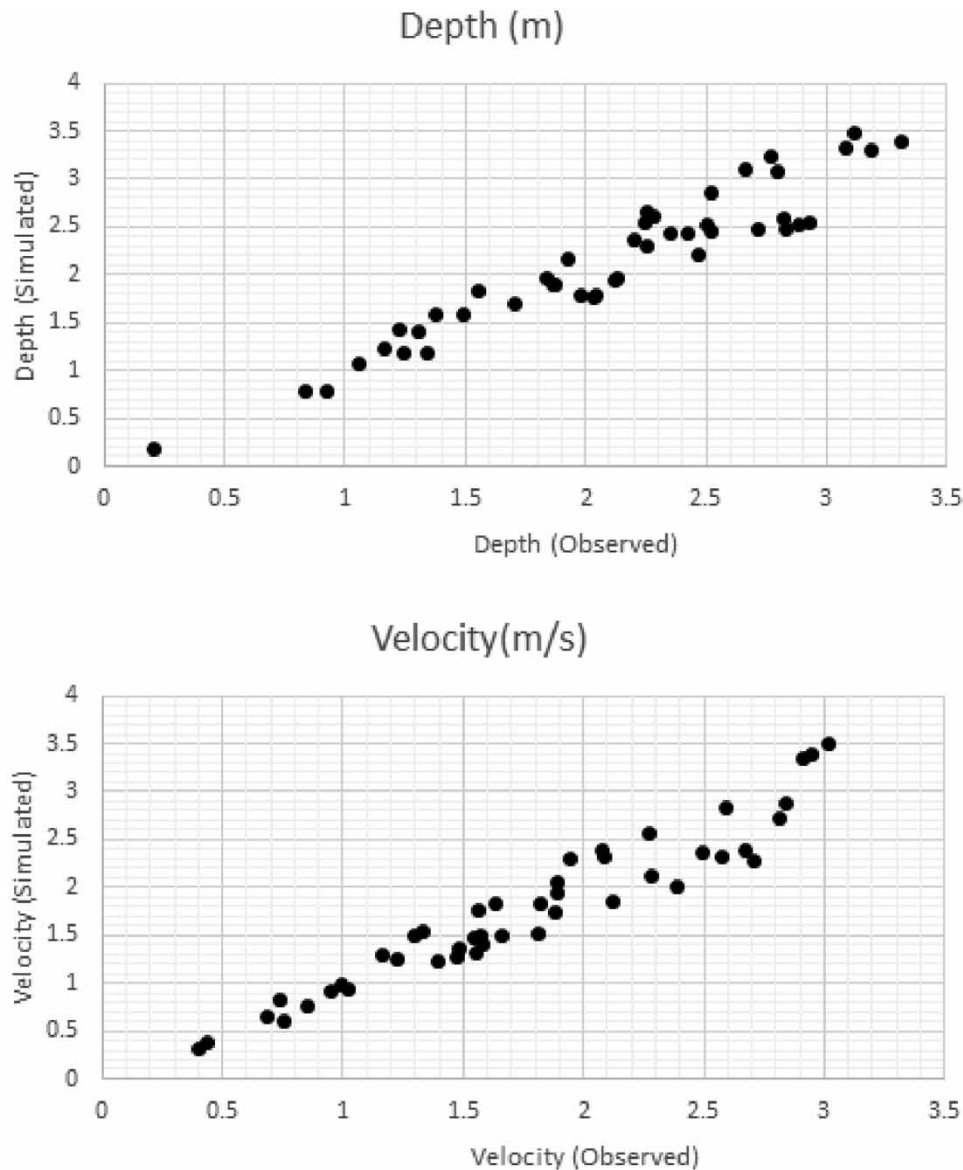


Figure 9 | Verification results of the hydraulic simulation at the downstream river reach.

reach. It seems that the model is robust to simulate hydraulic parameters due to the limited difference between the simulated parameter and observed parameter. Figures 10 and 11 display the velocity and depth distribution in the representative downstream reach simulated by HEC-RAS 2D at a flow rate of $30.05 \text{ m}^3/\text{sec}$. It should be noted that these figures are the final simulated depth and velocity after the verification process. Velocity changes indicate that flow velocity at upstream of reach is lower than downstream. In other words, velocity is increased toward the downstream. However, depth changes indicate that depth is reduced toward the downstream. Difference between hydraulic status at upstream and downstream demonstrates that the types of mesohabitats might be different. Table 1 shows result of development of criteria to identify mesohabitats based on the described methodology in Figure 4.

Figure 12 displays a microhabitat map based on combining the result of field studies and hydraulic simulation in the GIS environment. Initial habitat survey in the representative reach demonstrated that most of the habitats are pools due to bed particle size and slope of the river. We considered the role of run and riffle as the same in the present study. In other words, runs and riffles have the same biological role to protect suitability of river habitats. Protecting riffle or run habitats in the simulated reach is vital, which means a lack of sufficient runs or riffles might be effective to reduce the possibility of biological activities such as searching for food. For example, some fishes might use the macroinvertebrates and insects

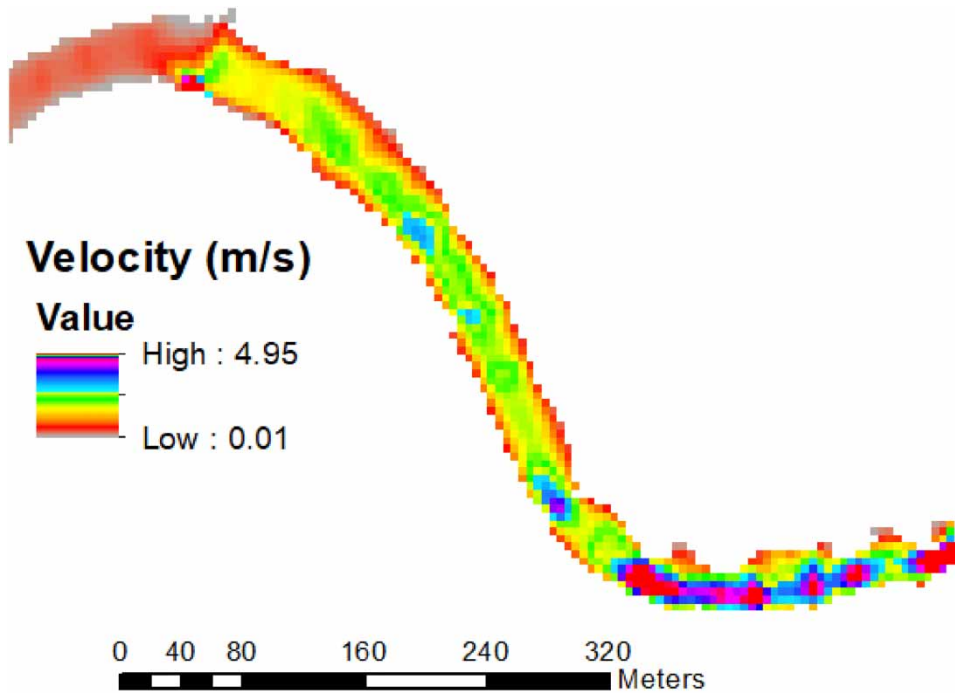


Figure 10 | Velocity changes resulted from hydraulic simulation at flow rate of 30.05 m³/sec as a sample of hydraulic simulation results in the simulated downstream reach.

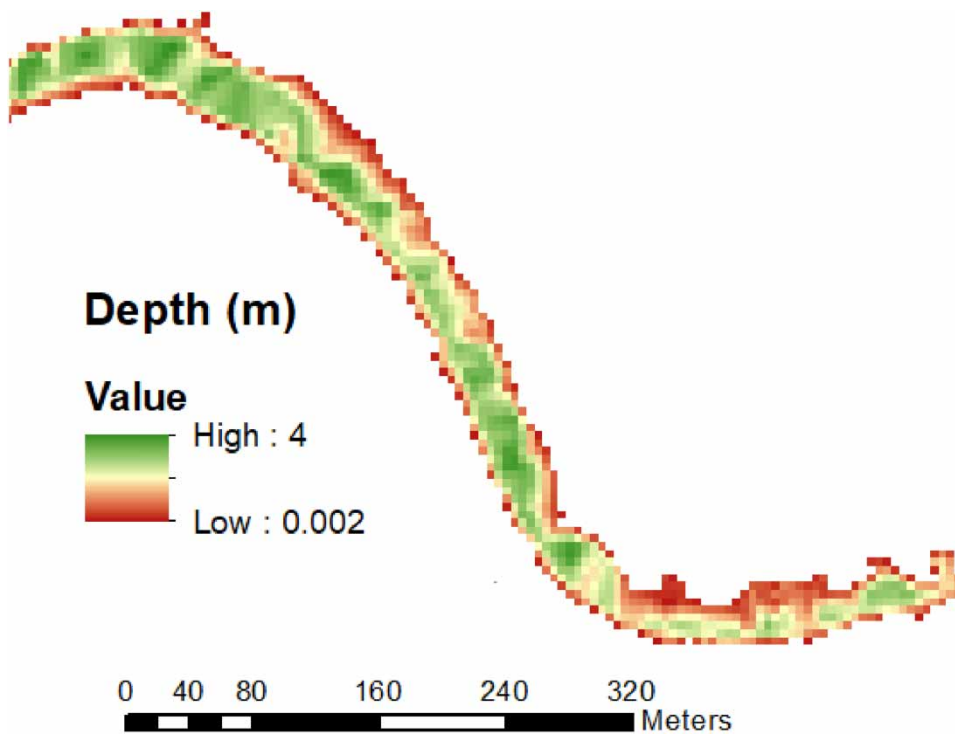


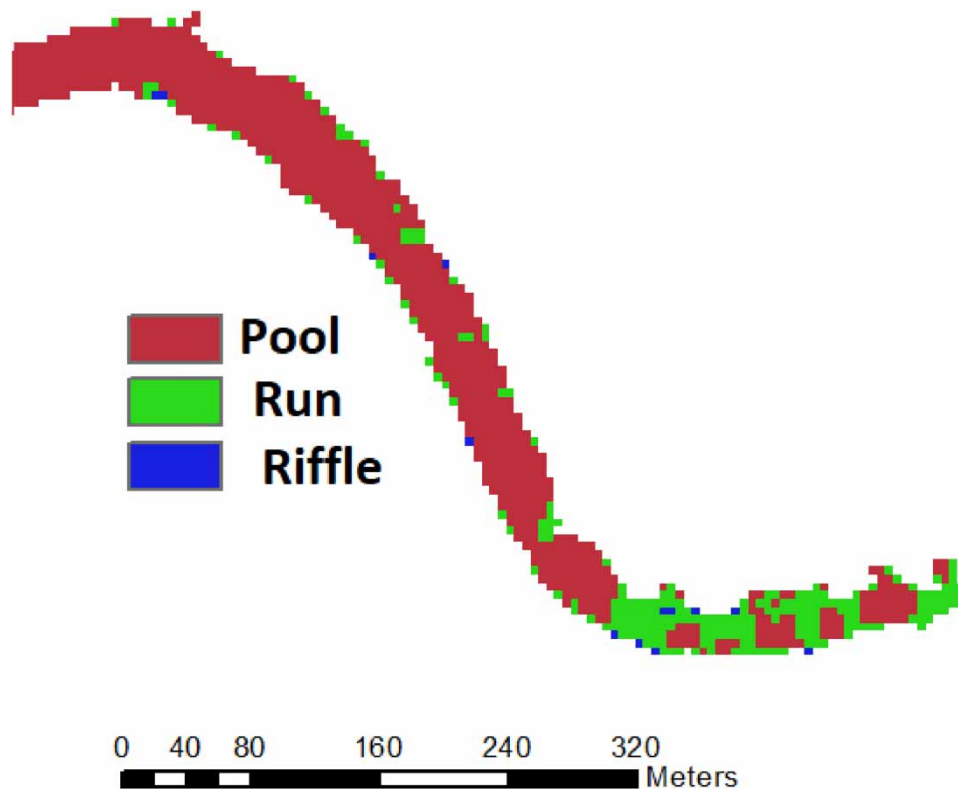
Figure 11 | Depth changes resulted from hydraulic simulation at flow rate of 30.05 m³/sec as a sample of hydraulic simulation results in the simulated downstream reach.

Table 1 | Developed criteria for identification of pools, runs and riffles

Mesohabitat type	Pool	Run	Riffle
Ratio velocity to depth	$V/D < 0.65$	0.65–4.64	$4.64 < V/D$

that are considerably available in the riffle or run habitats. In other words, lack of availability of riffles or runs might reduce the potential food for the fishes. In fact, the fishes have the movement between riffle and pools that is a requirement for a sustainable ecological status of the river ecosystem. Hence, the main objective of the simulation-optimization method is to minimize the difference between the ratio of run and riffle areas to pool areas (R/P) in the natural flow and optimal release from the reservoir. The relationship between flow and R/P is displayed in Figure 13. It seems that the general trend of the developed relationship demonstrates that the area of run and riffle will enhance by increasing rate of flow. This relationship was utilized in the optimization model directly.

In the second section, we discuss the optimization results as the main outputs of the present study. First, it is essential to present direct outputs of reservoir operation optimization. Figure 14 displays release for demand by different metaheuristic algorithms in the optimization model. As presented in the previous section, the reservoir will not be able to supply maximum demand for the agriculture in the downstream area, which means other water resources such as ground water might be useable. However, the target of optimal reservoir operation is to supply maximum demand by the reservoir as much as possible. Results of the optimization demonstrate that the performance of different algorithms might be different in terms of water supply. In other words, it seems that RMSE of water supply for some algorithms is considerable. Moreover, the reliability of water supply was considered in the system performance measurement. Based on the results, the optimization model is able to consider the constraints in the optimization process, which means the performance of the penalty function method is reliable. As can be observed, release is not more than the maximum requested water demand in all simulated months.

**Figure 12** | Mesohabitat map resulted from the described methodology in Figure 4 at flow rate of $30.05 \text{ m}^3/\text{sec}$ as a sample of hydraulic simulation results in the simulated downstream reach.

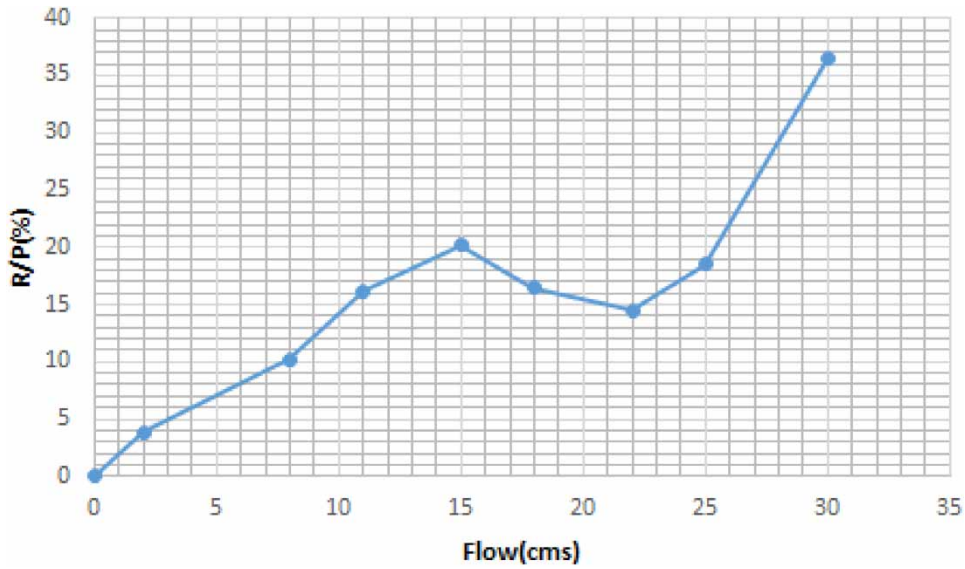


Figure 13 | Final relationship between flow rate and R/P applied in the reservoir operation optimization (flow in cubic meters per second).

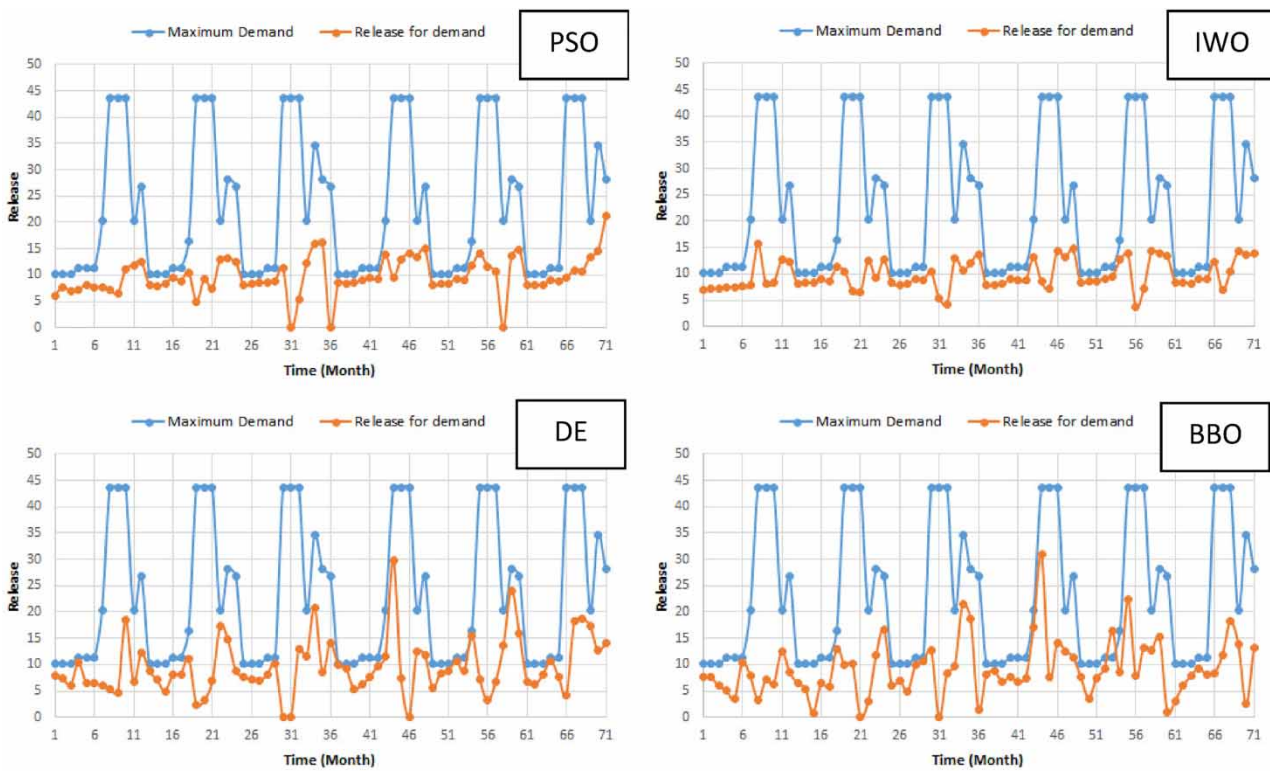


Figure 14 | Optimal release for water demand by different optimization algorithms (million cubic meters).

Figure 15 displays storage in the simulated period for different metaheuristic algorithms. Some points must be noted in this regard. First, some algorithms such as DE estimate more storage in many time steps compared with other algorithms such as PSO. It should be considered as a major point in the optimization model due to the importance of storage in the reservoir. Hence, it seems that performance of algorithms might directly affect benefits from the storage in the reservoir. In other words, results of storage optimization indicate that using different algorithms is necessary to evaluate the performance of reservoir

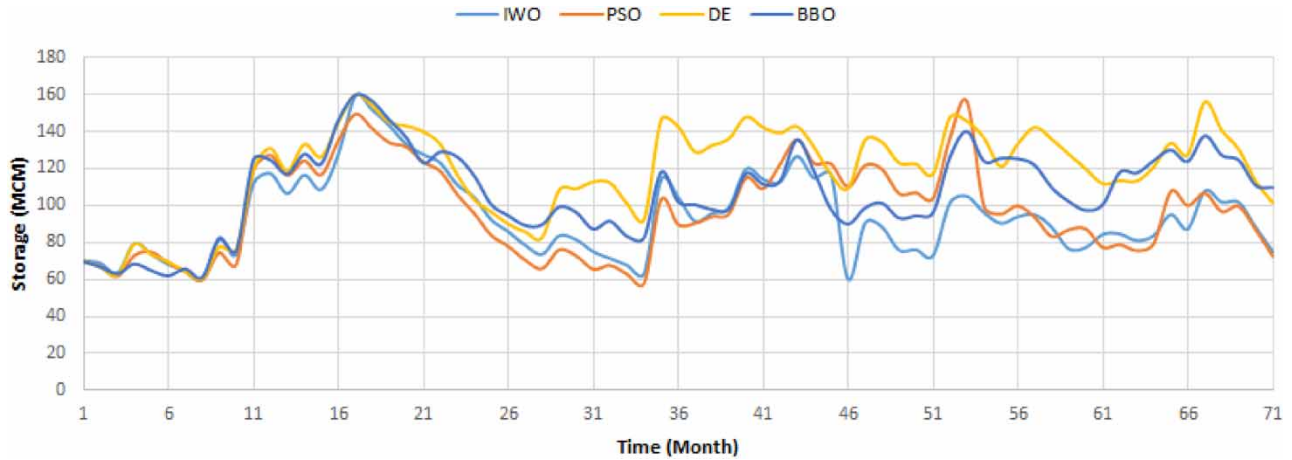


Figure 15 | Optimal storage for water demand by different optimization algorithms.

operation optimization. It is more essential in cases such as the developed optimization model, which is a complex operation model. In fact, the optimization of reservoir operation in terms of water supply, storage and environmental impacts should simultaneously be considered. Performance of the minimum operational storage penalty function should be discussed. Robust performance of the penalty function could be observed in the storage time series. Minimum storage in all the algorithms is very close to 60 MCM as the minimum operational storage defined by the water authority, which has been considered in the optimization model. Moreover, performance of the maximum storage penalty function is perfect. Because the maximum storage in the simulated period in all time steps is not more than the maximum possible storage in the reservoir.

Assessing mesohabitats should be carried out based on R/P (%) in the optimal operation compared with natural condition. Figures 16–19 display R/P (%) time series in the simulated period for different metaheuristic algorithms. It seems that the performance of algorithms is not similar in terms of mesohabitat units. However, more discussion on the results is not possible without computing measurement indices. It is required to explain how R/P (%) can be used for assessing the optimization model in terms of environmental suitability. In fact, if the optimization algorithm is able to minimize R/P in the natural flow and the optimal release, it might be more robust in terms of providing environmental suitability at the downstream river of the reservoir. In other words, the natural flow might provide a sustainable environmental condition in the river ecosystem in terms of ecological status of the mesohabitats. In the optimization model, the purpose is to provide the R/P like the natural flow. However, it might not be possible due to needs for supply of water demand in practice. Thus, minimizing difference between R/P in the natural flow and optimal release was considered as the purpose in the optimization system.

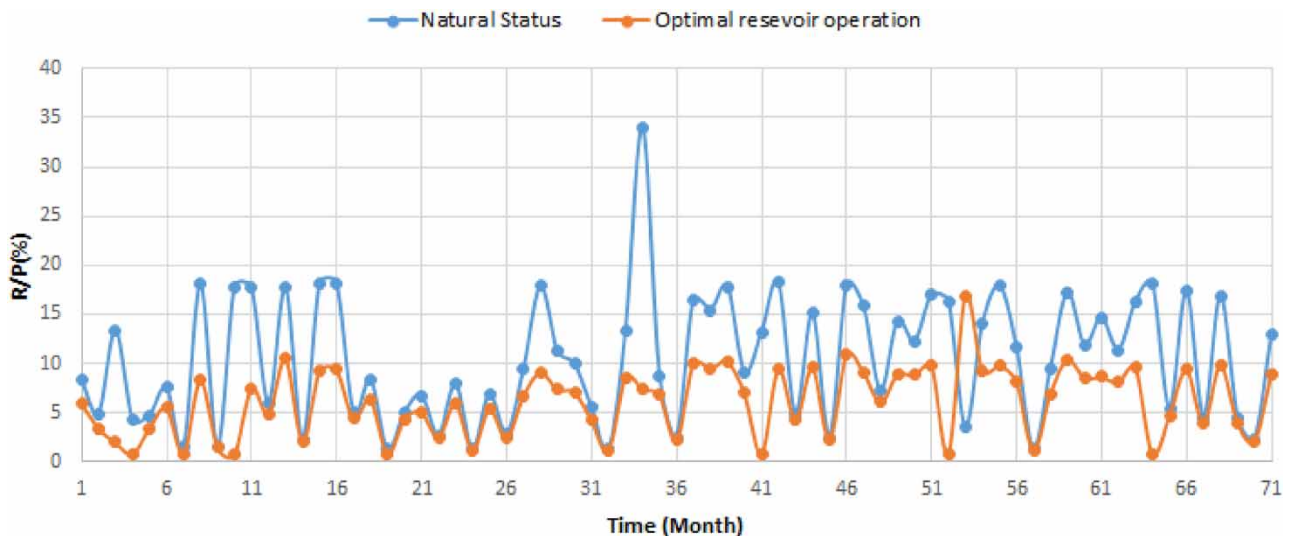


Figure 16 | R/P at optimal release and natural flow in the simulated period by PSO.

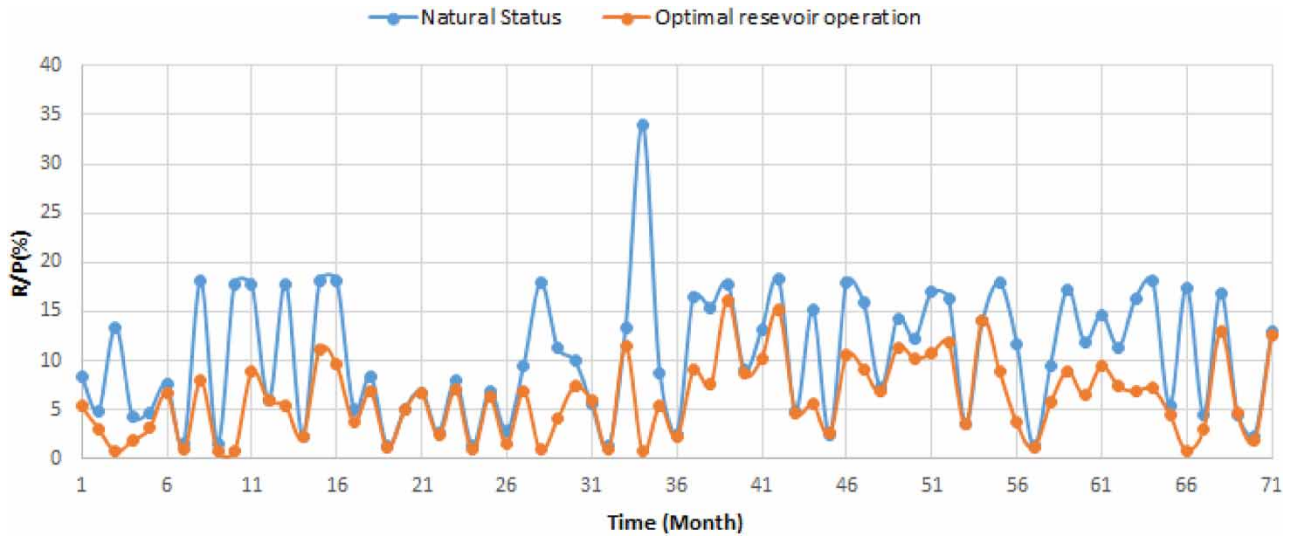


Figure 17 | R/P at optimal release and natural flow in the simulated period by DE.

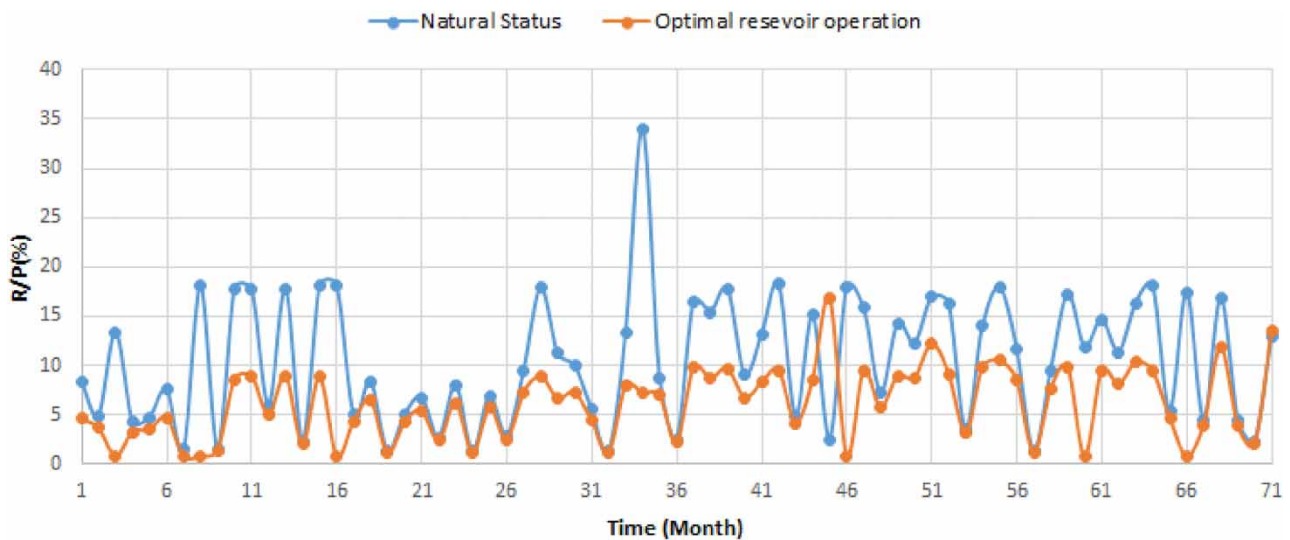


Figure 18 | R/P at optimal release and natural flow in the simulated period by IWO.

Figure 20 displays release for environment based on the simulated mesohabitat modeling. According to the results, each algorithm proposes different release for environment in the simulated period. However, there are some similarities between algorithms. More discussion on results needs to use measurement indices. Figure 21 displays the calculated RMSE for water demand, mesohabitats (pool/riffle systems) and storage. It should be noted that their units are not the same. In other words, the unit for RMSE is the same as the original parameter for calculation. The first point is robust performance of algorithms in terms of mesohabitat units as the main purpose of the present study. In fact, results demonstrate that RMSE for pool/riffle system is 8% approximately. Hence, the optimization process could reduce differences between natural flow and optimal release for environment in terms of mesohabitat suitability. In other words, environmental impact is mitigated in the case study. A balance between mesohabitat areas compared with natural flow helps the river ecosystem to protect biological activities of inhabitants. The proposed environmental flow is able to protect the diversity of mesohabitats. In fact, the proposed flow improves suitability of the river habitats compared with conventional reservoir operation optimization. For example, if runs or riffles have a significant role for nutrition, their areas must be close to natural status. The proposed optimal release

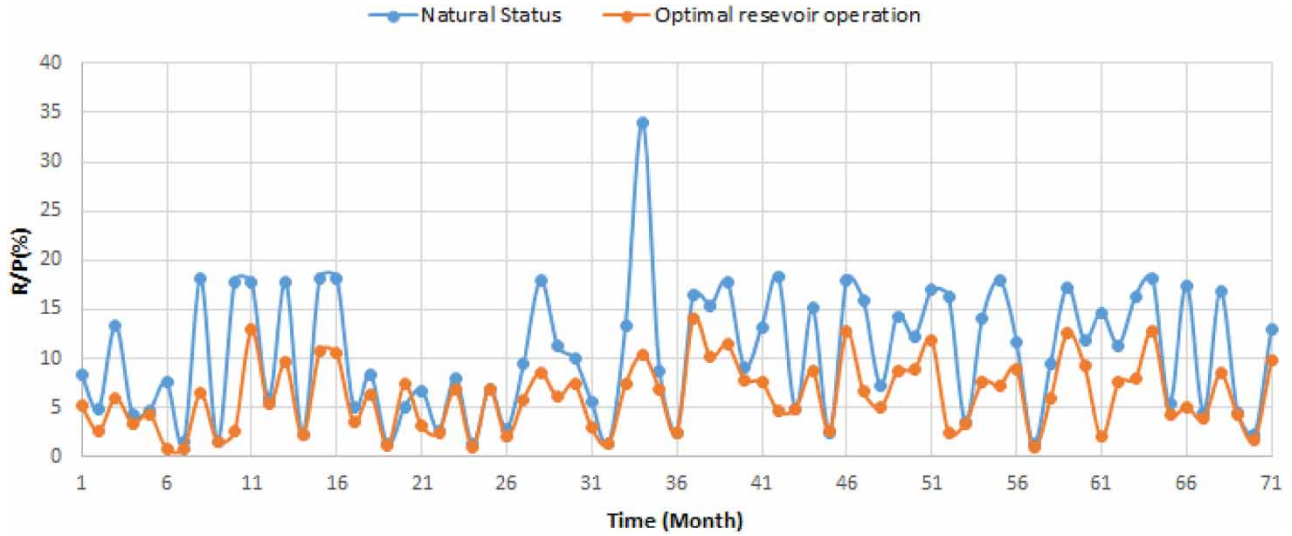


Figure 19 | R/P at optimal release and natural flow in the simulated period by BBO.

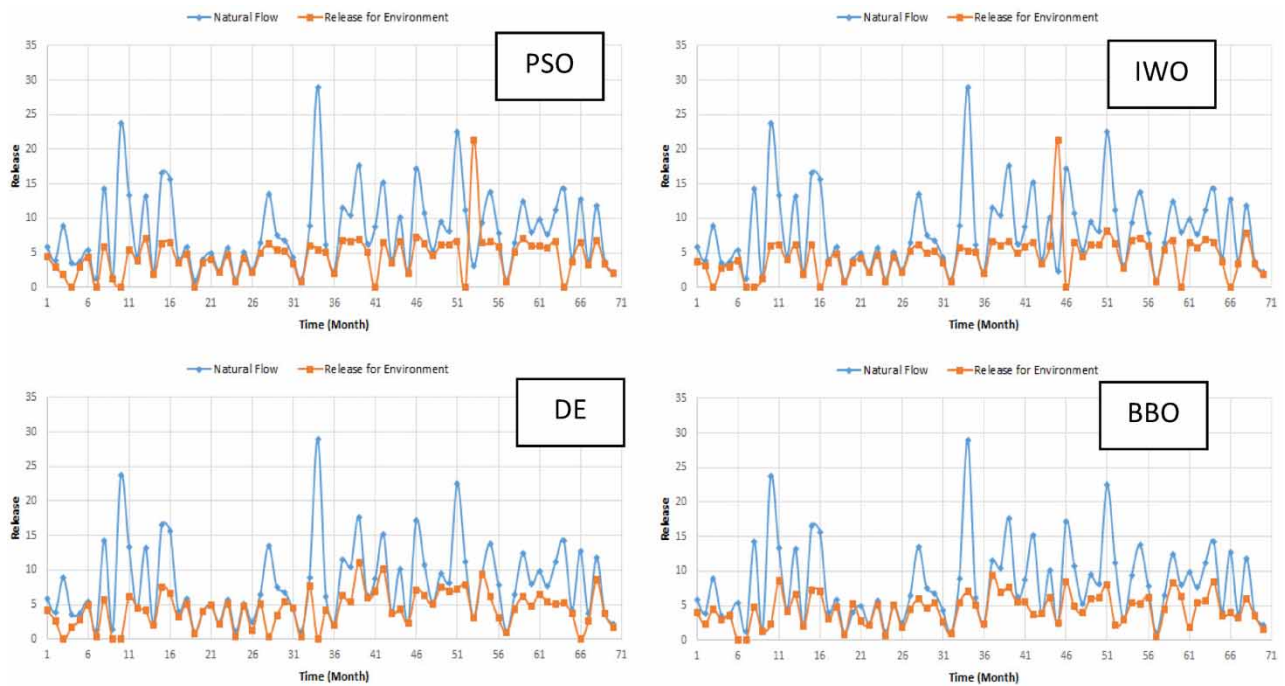


Figure 20 | Optimal release for environment by different optimization algorithms (million cubic meters).

demonstrates that difference between area of riffles and runs in an optimal release and natural flow are close. Hence, biological role of these habitats would be protected for all species. It should be noted that mesohabitats might have biological role for all the species including fishes and benthos. Most ecological environmental flow methods such as physical habitat simulation are based on target species. This might raise uncertainties regarding suitability of environmental flow for other species. However, using environmental flow methods for different species is not possible practically due to the need for considerable field studies including abiotic parameter measurement and biological sampling. In other words, we need inexpensive methods to assess environmental flow downstream of reservoirs. This issue is very important especially in developing countries due to lack of sufficient budget for environmental studies. However, an inexpensive method should be reliable. It should be able to support all the species based on ecological needs. The most important advantage of the proposed method is low cost

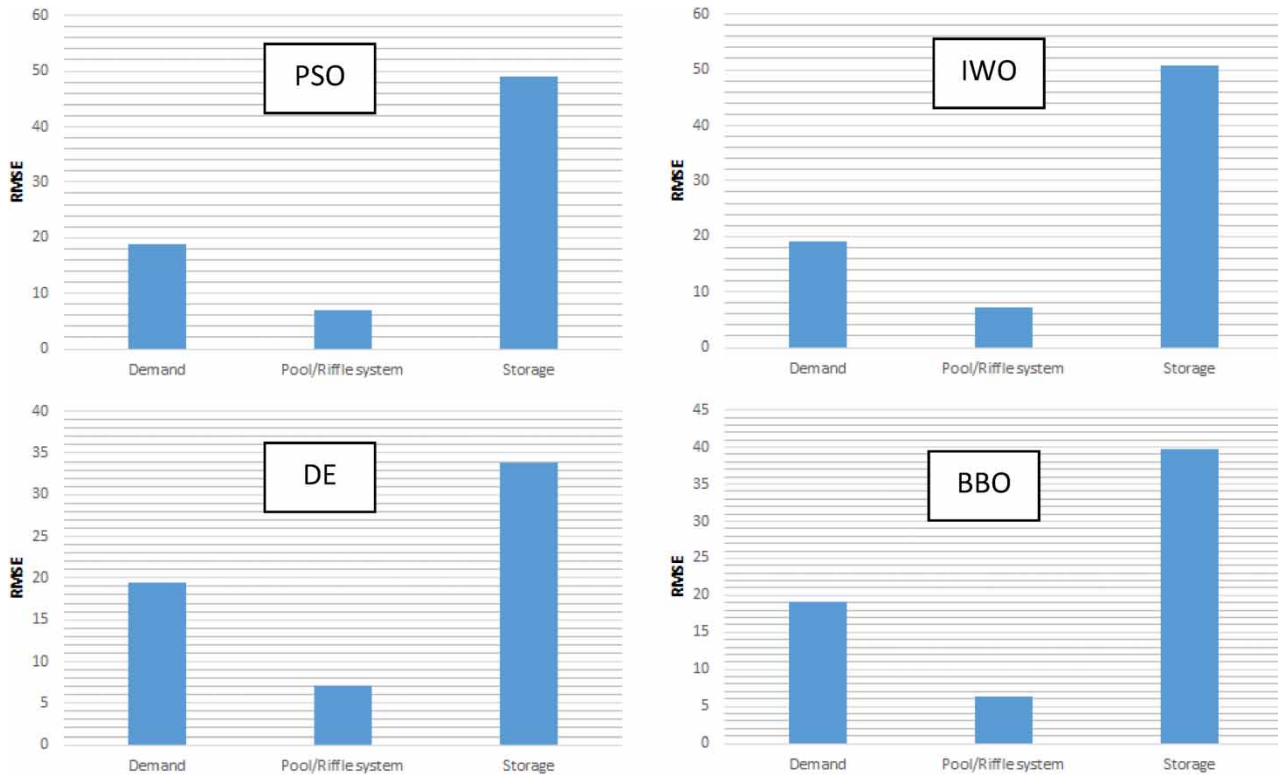


Figure 21 | RMSE for different algorithms in terms of water demand supply, mitigation of environmental flow and storage loss.

and high reliability for different species. We do not claim that the proposed method is the most reliable available method. However, it is able to assess environmental flow based on average suitability for all of the species.

Another advantage of using mesohabitat modeling is the possibility of linking to a reservoir operation model. In fact, if an environmental method is not able to be linked with the reservoir optimization model, it will not be reliable for practical applications. One of the challenges in the assessment of environmental flow is the absence of the ability to integrate benefits from the reservoir with the environmental flow method. In other words, it is a challenge in the negotiations between stakeholders and environmental advocates, because stakeholders might believe that environmental flow might considerably reduce the benefits. The proposed method in the present study is able to minimize negotiations between stakeholders and environmental advocates. In fact, it is a multipurpose method to optimize reservoir operation in terms of benefits and environmental impacts. However, reduction of benefits and environmental impact is inevitable.

RMSE for release of water demand indicates that performance of all algorithms is similar. Differences between optimal release for demand could be observed based on the plotted time series. However, closeness between mean error of the algorithms demonstrates that their performance is approximately similar. Figure 21 displays the reliability index of water demand for comparing algorithms. As presented in the previous section, reliability of supply of water demand should be noted as a key factor for the reservoir operation, because the main responsibility of the reservoir is supply of irrigation demand in the case study. It should be noted that Rajaie reservoir is not the only water resource for defined water demand in the present study. Hence, measuring the reliability of the water supply would be helpful to assess how much water demand could be supplied by the reservoir. Figure 22 displays that reliability for all of the algorithms is less than 50%, which means the role of other alternatives for supply of water demand is significant. Results demonstrate that either PSO or IWO has the same reliability for supply of water demand. Either DE or BBO has slightly lower reliability. It should be noted that the difference between algorithms is negligible.

Moreover, it is required to investigate the performance of algorithms in terms of storage by RMSE index. Figure 21 demonstrates that DE is the best method regarding storage benefits in the reservoir. Either PSO or IWO are the weakest methods in terms of storage benefits. It seems that DE is the best method for reservoir operation optimization in the present study. The performance of algorithms is very similar in terms of water demand and mitigation of environmental impacts. However, there

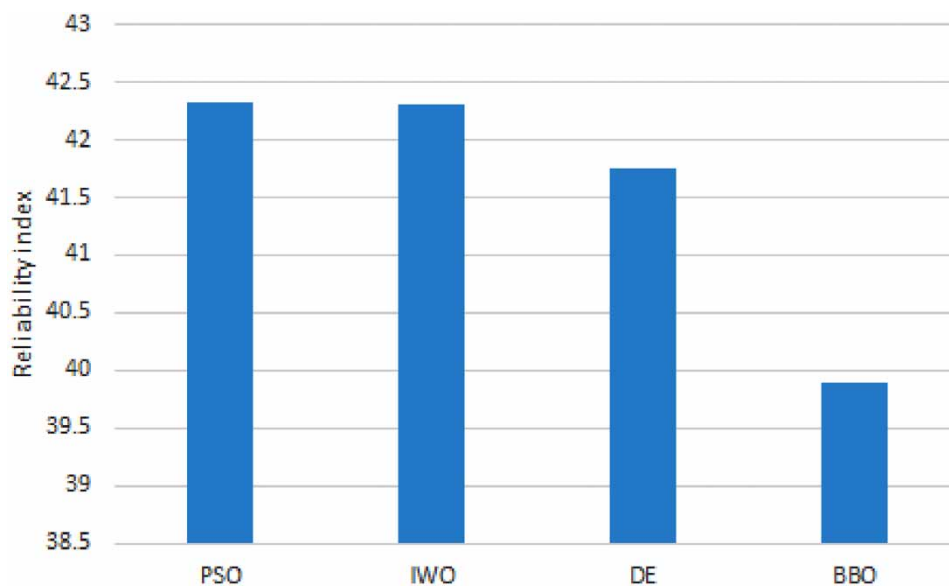


Figure 22 | Reliability index of water demand supply for different algorithms.

is slight difference between methods in terms of storage benefits. Hence, DE is the best method to optimize reservoir operation, because it has the lowest RMSE for the storage benefits. We recommend using the proposed method in the future reservoir operation studies in which reducing environmental impact at downstream river habitats is targeted. In fact, the proposed method is able to minimize negotiation between stakeholders and environmental advocates.

The proposed method might be highly effective on the improvements of the environmental degradation downstream of the reservoirs. In fact, the conventional method of optimization in which the environmental flow is not considered in the structure of the optimization might not be able to manage the environmental degradations downstream properly. The conventional methods such as the hydrologic desktop method might consider a constant flow as the environmental flow downstream of the reservoir without considering dynamic assessment of the mesohabitats in the structure of the optimization model, which might be highly important in the biological activities of the aquatics. For example, some aquatics need to move to the riffles to search for food or to pools as shelters. Previous methods of reservoir operation optimization are not able to consider these ecological complexities in the management of the flow. However, the proposed method is able to link the water management in the reservoir system and the ecological management of the river in an integrated framework. In other words, the proposed method might be able to improve the ecological status of the river ecosystem, which is remarkably advantageous compared with the conventional operation models in which ecological assessment is not considered in the optimization framework.

4. CONCLUSIONS

The present study proposed a linked mesohabitat model-reservoir operation optimization method to simultaneously reduce environmental impact at downstream river habitats and maximize benefits from the reservoir. Based on results, the proposed method is able to mitigate mesohabitat suitability loss. In other words, difference between mesohabitat suitability in the natural flow and optimal release is minimized. Moreover, the results demonstrate that environmental requirements might reduce the reliability of water supply considerably. Differential evolution algorithm was the best method to optimize reservoir operation in the present study. The main advantage of the proposed framework is reduction of negotiation between stakeholders and environmental advocates due to mitigating environmental impacts and reservoir operation losses simultaneously.

CONFLICT OF INTERESTS

None

DATA AVAILABILITY STATEMENT

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

REFERENCES

- Afshar, A., Haddad, O. B., Mariño, M. A. & Adams, B. J. 2007 Honey-bee mating optimization (HBMO) algorithm for optimal reservoir operation. *Journal of the Franklin Institute* **344** (5), 452–462.
- Afshar, A., Shafii, M. & Haddad, O. B. 2011 Optimizing multi-reservoir operation rules: an improved HBMO approach. *Journal of Hydroinformatics* **13** (1), 121–139.
- Altinbilek, D. 2002 The role of dams in development. *Water Science and Technology* **45** (8), 169–180.
- Booker, D. J., Sear, D. A. & Payne, A. J. 2001 Modelling three-dimensional flow structures and patterns of boundary shear stress in a natural pool–riffle sequence. *Earth Surface Processes and Landforms: The Journal of the British Geomorphological Research Group* **26** (5), 553–576.
- Cai, W., Zhang, L., Zhu, X., Zhang, A., Yin, J. & Wang, H. 2013 Optimized reservoir operation to balance human and environmental requirements: a case study for the Three Gorges and Gezhouba Dams, Yangtze River basin, China. *Ecological Informatics* **18**, 40–48.
- Ehteram, M., Karami, H., Mousavi, S. F., El-Shafie, A. & Amini, Z. 2017 Optimizing dam and reservoirs operation based model utilizing shark algorithm approach. *Knowledge-Based Systems* **122**, 26–38.
- Ehteram, M., Karami, H., Mousavi, S. F., Farzin, S., Celeste, A. B. & Shafie, A. E. 2018 Reservoir operation by a new evolutionary algorithm: kidney algorithm. *Water Resources Management* **32** (14), 4681–4706.
- Fuentes-Aguilera, P., Caamaño, D., Alcayaga, H. & Tranmer, A. 2020 The influence of pool-riffle morphological features on river mixing. *Water* **12** (4), 1145.
- Horne, A., Kaur, S., Szemis, J., Costa, A., Webb, J. A., Nathan, R., Stewardson, M., Lowe, L. & Boland, N. 2017 Using optimization to develop a ‘designer’ environmental flow regime. *Environmental Modelling & Software* **88**, 188–199.
- Jahandideh-Tehrani, M., Haddad, O. B. & Loáiciga, H. A. 2015 Hydropower reservoir management under climate change: the Karoon reservoir system. *Water Resources Management* **29** (3), 749–770.
- Jowett, I. G. 1993 A method for objectively identifying pool, run, and riffle habitats from physical measurements. *New Zealand Journal of Marine and Freshwater Research* **27** (2), 241–248.
- Jowett, I. G. 1997 Instream flow methods: a comparison of approaches. *Regulated Rivers: Research & Management: An International Journal Devoted to River Research and Management* **13** (2), 115–127.
- Karami, H., Ehteram, M., Mousavi, S. F., Farzin, S., Kisi, O. & El-Shafie, A. 2019 Optimization of energy management and conversion in the water systems based on evolutionary algorithms. *Neural Computing and Applications* **31** (10), 5951–5964.
- Kennedy, J. & Eberhart, R. 1995 Particle swarm optimization. In *Proceedings of ICNN’95-International Conference on Neural Networks*, Vol. 4. IEEE, pp. 1942–1948, doi:10.1109/ICNN.1995.488968.
- Labadie, J. W. 2004 Optimal operation of multireservoir systems: state-of-the-art review. *Journal of Water Resources Planning and Management* **130** (2), 93–111.
- Liang, Y., Liu, H., Qian, C. & Wang, G. 2019 A modified genetic algorithm for multi-objective optimization on running curve of automatic train operation system using penalty function method. *International Journal of Intelligent Transportation Systems Research* **17** (1), 74–87.
- Mahdade, M., Moine, N. L. & Moussa, R. 2018 Wavelet and index methods for the identification of pool–riffle sequences. *Hydrology and Earth System Sciences Discussions* 1–30.
- Mehrabian, A. R. & Lucas, C. 2006 A novel numerical optimization algorithm inspired from weed colonization. *Ecological informatics* **1** (4), 355–366.
- Najafabadi, E. F. & Afzalimehr, H. 2020 Comparison of two-and three-dimensional flow and habitat modeling in pool–riffle sequences. *Iranian Journal of Science and Technology. Transactions of Civil Engineering* **44** (3), 991–1000.
- Qin, A. K., Huang, V. L. & Suganthan, P. N. 2008 Differential evolution algorithm with strategy adaptation for global numerical optimization. *IEEE Transactions on Evolutionary Computation* **13** (2), 398–417.
- Reis, L. F. R., Bessler, F. T., Walters, G. A. & Savic, D. 2006 Water supply reservoir operation by combined genetic algorithm–linear programming (GA-LP) approach. *Water Resources Management* **20** (2), 227–255.
- Sedighkia, M. & Abdoli, A. 2021 Efficiency of coupled invasive weed optimization-adaptive neuro fuzzy inference system method to assess physical habitats in streams. *SN Applied Sciences* **3** (2), 1–13.
- Sedighkia, M., Ayyoubzadeh, S. A. & Hajiesmaeli, M. 2017 Modification of Tennant and wetted perimeter methods in Simindasht basin. Tehran Province. *Civil Engineering Infrastructures Journal* **50** (2), 221–231.
- Simon, D. 2008 Biogeography-based optimization. *IEEE Transactions on Evolutionary Computation* **12** (6), 702–713.
- Tharme, R. E. 2003 A global perspective on environmental flow assessment: emerging trends in the development and application of environmental flow methodologies for rivers. *River Research and Applications* **19** (5-6), 397–441.
- Wegscheider, B., Linnansaari, T. & Curry, R. A. 2020 Mesohabitat modelling in fish ecology: a global synthesis. *Fish and Fisheries* **21** (5), 927–939.
- Yaseen, Z. M., Allawi, M. F., Karami, H., Ehteram, M., Farzin, S., Ahmed, A. N., Koting, S. B., Mohd, N. S., Jaafar, W. Z. B., Afan, H. A. & El-Shafie, A. 2019 A hybrid bat–swarm algorithm for optimizing dam and reservoir operation. *Neural Computing and Applications* **31** (12), 8807–8821.
- Yin, X. A., Yang, Z. F. & Petts, G. E. 2012 Optimizing environmental flows below dams. *River Research and Applications* **28** (6), 703–716.