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ORIGINAL PAPER

Salinity management of reservoirs by linking hydrodynamic model, surrogate model, and evolutionary optimization

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Abstract
This study proposes a combined system for salinity management of reservoirs in which the lake ecosystem simulation is integrated with the reservoir operation optimization. A finite volume-based depth-averaged model is applied for simulating salinity in the reservoir for a long-term period. Then, a surrogate model is developed by applying outputs of the fluid dynamic model using adaptive neuro-fuzzy inference system. The surrogate model is used in the structure of the optimization model to estimate the average salinity concentration in the reservoir. Two objectives are defined in the reservoir operation optimization including minimizing water supply loss and mitigating salinity impacts on the aquatic habitats in the lake ecosystem. According to case study results, the fluid dynamic model is reliable for simulating salinity distribution in the reservoir, which means it is recommendable for simulating salinity distribution of reservoirs. Moreover, The Nash–Sutcliff coefficient of surrogate model is 0.79, which implies it is reliable for applying in the optimization model as a surrogate model of salinity. Based on the environmental considerations, 0.55 ppt was defined as the average threshold of habitat suitability. Average optimal salinity during the simulated period is 0.52 ppt, which implies the optimization model is able to reduce salinity impacts properly. We recommend using the proposed method for the case studies in which increasing salinity is an environmental challenge for the aquatic species those living in the artificial lakes of large dams.

Keywords Salinity · Fluid dynamic model · Environmental reservoir operation · Adaptive neuro-fuzzy inference system · Optimization

Introduction

The role of reservoirs in water supply has been highlighted in the literature. Moreover, reservoirs might play a role for electricity supply as well (Ho et al. 2017). Due to importance of reservoirs as an expensive hydraulic structures, optimal management of release and storage is crucial (Ahmad et al. 2014). A general loss function, which is applicable to manage downstream release, has been extensively used in the previous studies. This function minimizes the difference between target and release by defining loss as two-sided objective function. It is demonstrated that losses due to deviation from storage and release need to be incorporated in penalty or loss functions associated with real-time operation of reservoir systems. Many methods have been applied for solving the reservoir operation model as an optimization problem. Linear programming (LP) was the simplest method to optimize reservoir operation, which has broadly been addressed in the literature (e.g., Dogan et al. 2021; Lee et al. 2008). Given the complexity of the reservoir operation as a nonlinear function, linear programming was not able to handle it accurately and efficiently. Hence, development of nonlinear programming and dynamic programming was the next step to solve the reservoir operation function which have been highlighted in some studies (e.g., Zhao et al. 2014; Rani et al. 2020). Ahmed et.al 2014 reviewed details of the optimization methods of reservoir operation. Evolutionary algorithms as the efficient and robust methods, which have been applied to optimize the reservoir operation in recent years, might be recommendable in many cases. Either the genetic algorithm (GA) or particle swarm optimization is one of the known classic evolutionary algorithms utilized in the reservoir operation (more details on these algorithm by

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Lambora et al. 2019; Banks et al. 2007). Moreover, hybrid algorithms have been introduced as an improved algorithm as well (Ehteram et al. 2018). As a general classification of these algorithms, an evolutionary method might be animal- or nonanimal-inspired algorithm (Jahandideh-Tehrani et al. 2021) or classic and new generation algorithm (Dokeroglu et al. 2019). For example, ant colony optimization and honeybee algorithms are the known animal-inspired algorithms applied for optimizing the reservoir operation (Jahandideh-Tehrani et al. 2021). Bat algorithm, firefly algorithm, cat swarm, and penguin search algorithms have been used to solve the reservoir operation optimization as well (Ehteram et al. 2018; Moeini and Babaei 2017). Thus, according to the literature, the evolutionary algorithms could be reliable methods for optimizing reservoir operation.

Communities benefit from reservoir in different aspects such as water supply. However, the environmental impacts of reservoirs are challenging, especially for river ecosystems (Cai et al. 2013). A reservoir might change the downstream flow regime as well as water quality parameters. For example, the environmental flow has been introduced as a solution for managing downstream environmental impacts of a reservoir (e.g., Yin et al. 2012; Sedighkia et al. 2021a, 2021b; Suwal et al. 2020). More details on the concept of environmental flow have been addressed in the literature (Kumar and Jayakumar 2021). Moreover, reservoirs have been used as a tool for controlling downstream water quality (e.g., Dhar and Datta 2008; Saadatpour et al. 2021). However, a reservoir itself is an active habitat, which means it is needed to focus on the water quality of the artificial lake as well. The reservoir might be used for some economic activities such as fish cage farming which means suitability of water quality parameters such as salinity is important in a reservoir (Dochin and Stoyneva 2014; Anufriieva 2018). Using fluid dynamic models is popular in the water quality modeling of lakes, which could be applicable for simulating water quality distribution. These models have been utilized for saltwater and freshwater lakes, which implies they are reliable for a wide range of water quality problems and improving water quality management in lake ecosystems. Hydrodynamic models are able to simulate the spatial distribution of water quality parameters, which can visualize the impacts of different scenarios in lakes (Martin et al. 2018; Bek et al. 2010; Toffolon et al. 2006). Several commercial models such as MIKE 21, EFDC+, and FVCOM have been recommended in the literature (e.g., Wu et al. 2019). One of the reliable packages for hydrodynamic modeling is currently TUFLOW, which has been broadly applied in Australia and other countries for a wide range of problems such as flood modeling in floodplains or water quality modelling in coastal and inland basins. In recent years, TUFLOW FV (finite volume version of TUFLOW) is developed and recommended, especially for water quality modeling in water bodies (Madani et al. 2022). Due to abilities and applicability of this model, the present study applies TUFLOW FV for simulating water quality parameters in the artificial lakes of a dam.

It is required to highlight the novelties and purposes of the proposed method in this study. Many previous studies focused on the reservoir operation optimization through a wide range of optimization models. Some studies highlighted downstream water quality in the management of a reservoir. However, it is needed to put the water quality modeling of reservoir itself in the structure of the reservoir operation model because a reservoir is an active habitat for many aquatic species. In other words, large dams might disconnect the relation between downstream and upstream habitats of a river. Hence, many fish species those cannot move toward the downstream might live in a reservoir as a new habitat. Thus, environmental management of reservoirs should be considered in the reservoir operation as well. However, previous studies have proposed no method to integrate water quality requirements of reservoir ecosystem with the operation of reservoir. This issue was identified as a significant research gap which is the main motivation of this study. Due to this research gap, this study develops a novel system for integrating environmental management of reservoirs with the operation optimization in which an advanced two-dimensional fluid dynamic, a surrogate model, and the evolutionary optimization are linked to manage the reservoir with a focus on salinity as one of the important water quality parameters. The proposed methodology was implemented in the Latian reservoir located in the Jajrood river basin, Tehran, Iran, based on available data and field studies in recent decade. This study might open new windows for using advanced hydrodynamic models of lakes in the environmental operation of reservoirs, which is currently a serious need for managing environmental challenges in the river ecosystems.

Materials and methods

Figure 1 shows an overview on the methodology, which might be helpful for the readers to identify the different parts of the proposed method. Our method consists of three main parts including water quality modeling of the lake, surrogate model, and the reservoir operation optimization. As a description on the methodology, available recorded data at the hydrometric station at upstream and downstream of the reservoir as well as recorded data in the reservoir were collected including water quantity and water quality data. Based on the digital elevation model of the region and bathymetry map of the reservoir as well as collected data, 2D hydrodynamic model of the reservoir was developed and calibrated for simulating salinity in the reservoir. However, direct linking of hydrodynamic model and optimization of

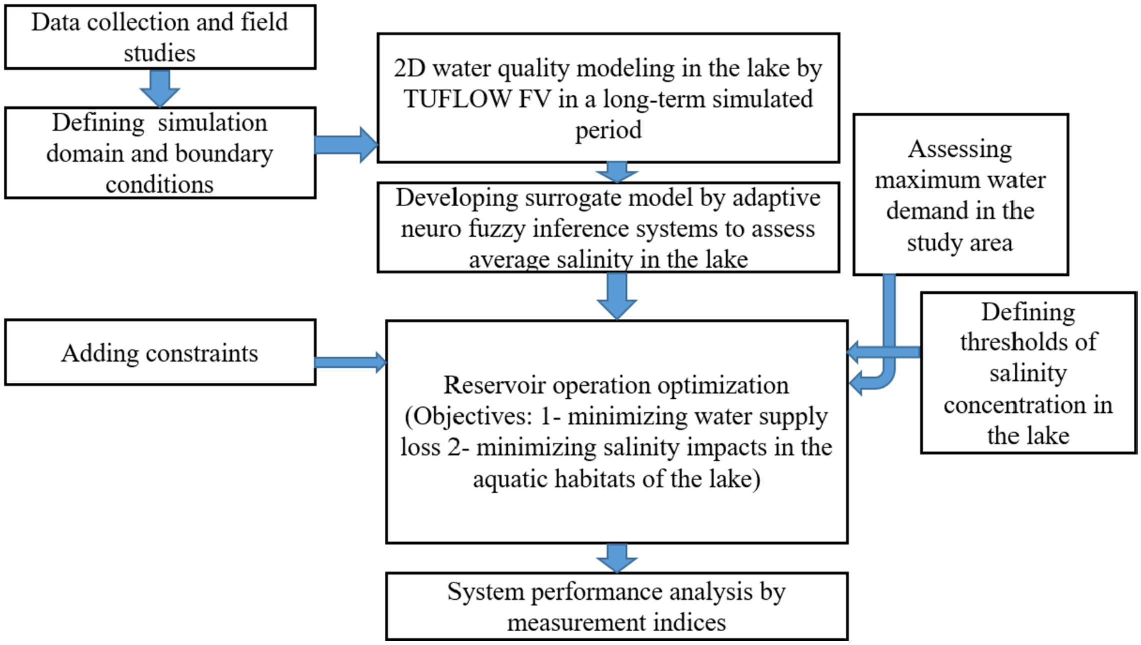

Fig. 1 Workflow of the proposed method

the reservoir is not possible. Hence, the outputs of the hydrodynamic model were considered as the basis of developing a surrogate model to add it in the reservoir operation optimization. Finally, a novel objective function was developed for managing salinity in the reservoir considering water supply and other technical constraints in the reservoir management.

Study area

The proposed method was applied in the Latian reservoir as one of the important dams in the Tehran province, Iran. This dam is responsible for satisfying drinking water and irrigation demand in the capital territory of Iran, which is a key hydraulic structure for the regional water authority. Many native aquatic species are living in the Jajrood river at upstream of the dam which exploit the lake ecosystem for many biological activities. In recent years, due to expanding urban areas at upstream of the reservoir, salinity concentration has increased which means the suitability of the habitats in the lake and the river has been weakened. The regional department of environment is seriously concerned regarding the reservoir operation because the regional water authority is willing to maximize the benefits of the reservoir in terms of water supply without considering requirements of the reservoir ecosystem. Hence, negotiations have been escalated between the stakeholders and the environmental advocators, which might need a new plan for environmental management of the reservoir. Based on this research gap, a novel integrated model was developed in which the water quality modeling of the reservoir with a focus on salinity and the operation model of the reservoir are linked. Initial ecological survey in the study area indicated that salinity is a critical problem for the habitats, which might lead to perishing the aquatic species in the lake ecosystem of the Latian dam. Figure 2 shows the location of the Latian reservoir and upstream catchment. We focus on the one year as the optimization period for indicating the capabilities of the proposed method. Inflow of the reservoir during the simulated period will be displayed in the results. Moreover, another 1-year period was used in the hydrodynamic simulation to develop the surrogate model of estimating average salinity in the reservoir.

Hydrodynamic modeling by TUFLOW FV

TUFLOW FV is a numerical model, which could be applied for solving the one-dimensional (1D) and two-dimensional (2D) shallow water equations (NLSWE). This model solves a wide range of hydrodynamic problems from the open channels design, floodplains, lake, and estuaries modeling to coastal and oceanic modeling. This model is designed in basis of unstructured geometries and is commonly referred to as a flexible mesh model. Advantages/disadvantages of using flexible mesh are highlighted in the literature (Hoch et al. 2018). Moreover, solution scheme of this model has been reviewed in the literature (TUFLOW FV manual, 2019). This model does not have a graphical user interface (GUI) which might be a weakness at the first glance. However, it enhances the flexibility of the model due to possible links with robust platforms as the GUI. Currently, surface

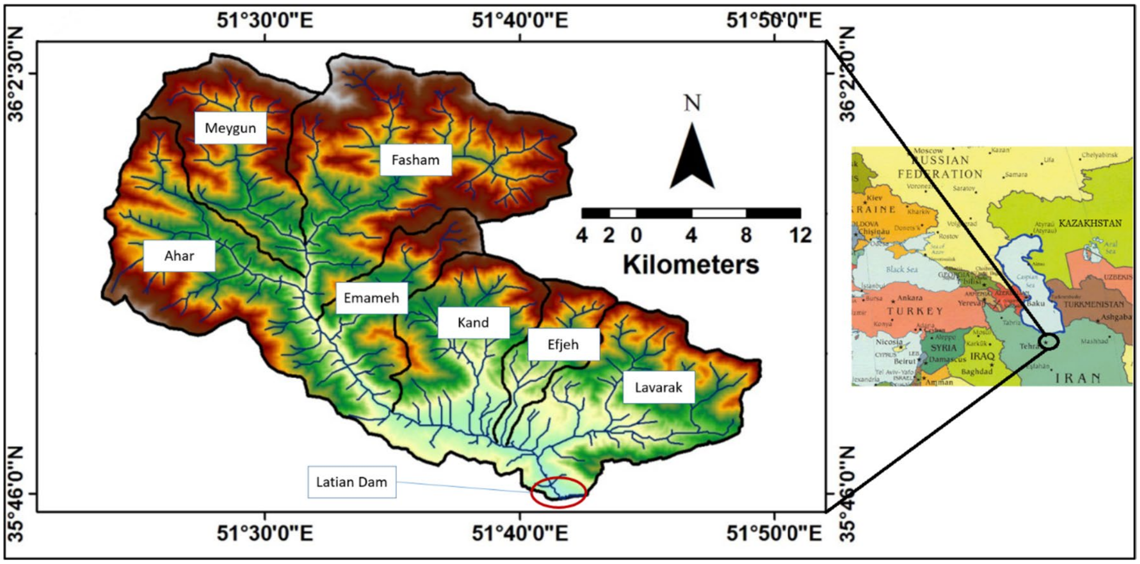

Fig. 2 Location of the Latian reservoir and upstream catchment

water modeling system (SMS) developed by Aquaveo company has been recommended as the best tool for generating computational mesh of the hydrodynamic model. SMS is a software platform which can integrate processes of surface water modeling which can be used for mesh generation to develop water quality model TUFLOW FV. More details regarding SMS have been addressed in the literature (Choi et al. 2008). Figure 3 shows the workflow of the TUFLFOW FV linked with the SMS for water quality modeling in the lake ecosystems.

Table 1 displays the full details of the developed hydrodynamic models in the Latian reservoir. Furthermore, Fig. 4 shows the border of the simulated domain, the location of boundary conditions (inflow and outflow), and two available

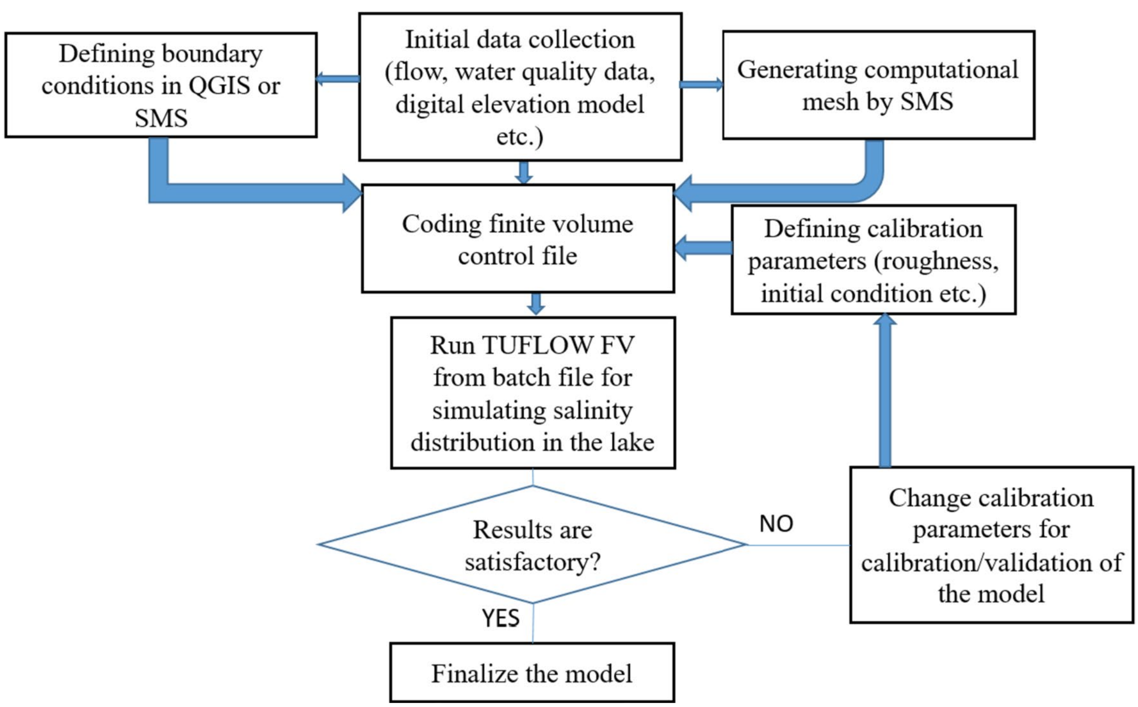

Fig. 3 Workflow of TUFLOW FV for simulating salinity distribution in the lake

Table 1 Main characteristics of developed model in TUFLOW FV (hydrodynamic model)

Initial condition (salinity)	0.15 ppt throughout the Latian reservoir
Initial condition (water temperature)	20 °C throughout the Latian reservoir
Initial condition (water level)	1585 m
Grid type	Curvelinear
Number of grid cells	6881
Model area	0.9762 km^2
Timing (simulated period)	One year (daily-based model)
Time step	0.69 s
External forcing data (flow)	Flow time series in three boundary conditions- two inflows (IN1 and IN2) and one outflow (OUT)
External forcing data (salinity)	Salinity time series in three boundary conditions- two inflows (IN1 and IN2) and one outflow (OUT)
External forcing data (water temperature)	Water temperature time series in three boundary conditions- two inflows (IN1 and IN2) and one outflow (OUT)
External forcing data (atmospheric data including air temperature, wind speed, etc.,)	One time series was used in the simulated period

Fig. 4 Border of simulated domain and location of boundary conditions

points in the reservoir in which the salinity was recorded for calibrating the fluid dynamic model.

Surrogate model

One of the disadvantages of the hydrodynamic models is inflexibility of the model for using in the structure of the water resources management model such as reservoir operation models directly. Hence, it is needed to apply an additional tool for linking the outputs of the hydrodynamic water quality model with the reservoir operation optimization. The purpose of our reservoir operation model is to minimize the average salinity in the reservoir. Hence, the surrogate model was defined to estimate the average salinity of the reservoir in different time steps of the optimization period. As a brief description on the surrogate model, it is an engineering model, which could be applied when the outcome of interest is not easily measurable or computable. In fact, a surrogate model is a statistical or machine learning model, which is able to estimate the outcome considering some key effective inputs (Dasari et al. 2019). We developed a surrogate model based on the outputs of the fluid dynamic or hydrodynamic model to estimate the salinity concentration in each time step of the optimization process. Machine learning models might be a powerful option to develop surrogate models due to high efficiency and capabilities. Neural networks are known and popular data-driven models in the engineering applications, which have been utilized in many previous studies for water quality simulation or many other applications in civil engineering (Cao et al. 2018; da Silva et al. 2021; Huang and Fu 2019; Khan et al. 2018; Salleh et al. 2021). In the present study, we used adaptive neuro-fuzzy inference system (ANFIS) to develop the surrogate model of estimating salinity concentration as one of the recommended forms of the neural network. More details regarding the theory, application, and advantages of the ANFIS-based model have been addressed in the literature (Karaboga and Kaya 2019). Table 2 shows characteristics of the ANFIS-based model for estimating the average salinity concentration in the structure of the optimization model. It should be noted that we tested different combinations of inputs which means selected inputs are results of a trial-error process.

It is required to evaluate the goodness-of-fit of the surrogate model compared with the outputs of the hydrodynamic model. In other words, outputs of the hydrodynamic model were used as the observed data and generated data by the surrogate model were applied as the simulated data in the evaluation process of the surrogate model. Equations 1 and 2 show the mathematical definition of the Nash–Sutcliffe coefficient (NSE) and root mean square error (RMSE) in the present study (more details on these indices by Lin et al. 2017; Willmott and Matsuura 2005; Gupta and Kling 2011) which were utilized as the evaluation indices of the surrogate model.

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T} \left| M_t - O_t \right|}{\sum_{t=1}^{T} \left| O_t - O_m \right|} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{T} \left(M_t - O_t \right)^2}{T}} \tag{2}$$

Reservoir operation optimization

We developed a new form of the objective function in which two objectives were considered. The first objective is to reduce the average salinity concentration of the reservoir to a safe level, which could be helpful for mitigating the environmental impacts in the reservoir ecosystem. Moreover, the objective function is able to minimize losses of water supply as another objective of the optimization model. Equation 3 displays developed objective function in the present study where T_t *i*s target (water demand + environmental flow) in time step t, R_t is release from the reservoir in time step t, FSC is favorite mean salinity concentration in the reservoir, and OSC_t is optimal salinity concentration in time step t in the reservoir. The optimization model minimizes the difference between target and release as well as the difference between mean favorite and optimal salinity concentration in the reservoir in the simulated period. T is time horizon. FSC was defined as 0.55 ppt based on the previous ecological studies and expert opinion (Abdoli et al. 2021). It should be noted that environmental flow was defined as a fixed flow regime which means the portion of environmental flow will be reduced from optimal release in each time step and rest of available water will be allocated to the water demand.

Table 2 Main features of the surrogate model (ANFIS-based model)

Inputs	Number of MFs (inputs)	Type of MFs (inputs)	Outputs	Number of MFs (Output)	Type of MFs (Output)	Clustering method
Average of inflow (m^3/s) in time step *t* to *t*-5 in Jajrood river (IN1 in Fig. 4)	10	Gaussian	Average salinity concentration of the Latian reservoir in time step t	10	Linear	Subtractive clustering
Average of inflow (m^3/s) in time step *t* to *t*-5 in Lavarak river (IN2 in Fig. 4)	10	Gaussian				
Average of outflow (m^3/s) in time step *t* to t-5 from Latian reservoir (OUT in Fig. 4)						
Average of salinity concentration (ppt) in time step *t* to *t*-5 in Jajrood river (IN1 in Fig. 4)	10	Gaussian				
Average of salinity concentration (ppt) in time step *t* to *t*-5 in Lavarak river (IN1 in Fig. 4)	10	Gaussian				

$$\text{minimize(OF)} = \sum_{t=1}^{T}\left(\left(\frac{\text{FSC} - \text{OSC}_t}{\text{FSC}}\right)^2 + \left(\frac{T_t - R_t}{T_t}\right)^2 + P1_t + P2_t + P3_t\right) \tag{3}$$

It is necessary to add constraints of the reservoir management to the model as well. We considered minimum operational storage and capacity of the reservoir as the constraints in the optimization model. Moreover, release for satisfying water demand should not be more than the target as well. We added three penalty functions (Eq. 4) to integrate the constraints in the optimization model of the reservoir operation where $S_{\max}$ is maximum available storage in reservoir, $S_{\min}$ is minimum operational storage, and S_t is storage in each time step. C1, C2, and C3 are penalty coefficients estimated based on the sensitivity analysis.

$$\begin{cases} \text{if } S_i > S_{\max} \rightarrow P1 = c1\left(\frac{S_t - S_{\max}}{S_{\max}}\right)^2 \\ \text{if } S_i < S_{\min} \rightarrow P2 = c2\left(\frac{S_{\min} - S_t}{S_{\min}}\right)^2 \\ \text{if} R_t > D_t \rightarrow P3 = c3\left(\frac{\text{RE}_t - \text{TE}_t}{\text{TE}_t}\right)^2 \end{cases} \tag{4}$$

Moreover, it is mandatory to update storage in each time step by Eq. 5 in which the overflow could be calculated by Eq. 6.

$$S_{t+1} = S_t + I_t - F_t - R_t - \left(\frac{\text{EV}_t \times A_t}{1000}\right), \quad t = 1, 2, \ldots, T \tag{5}$$

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_t is area of reservoir surface. RE_t is release for environmental flow, F_t is overflow in each time step, and T is time horizon.

$$\begin{cases} \text{if}\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) \geq S_{\max} \rightarrow F_t = S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right) - S_{\max} \\ \text{if}\left(S_t + I_t - \left(\frac{E_t \times A_t}{1000}\right)\right) < S_{\max} \rightarrow F_t = 0 \end{cases} \tag{6}$$

In the present study, we applied the evolutionary optimization to optimize the reservoir operation. Many algorithms have been used in the reservoir operation optimization in recent years. The biogeography-based optimization has been recommended in the previous studies to optimize the reservoir operation. Hence, we applied this algorithm in this study as well. The flowchart of this algorithm to find the best solution is shown in Fig. 5. More details regarding the methodology of this algorithm for finding the optimal solution have been addressed in the literature (Simon 2008).

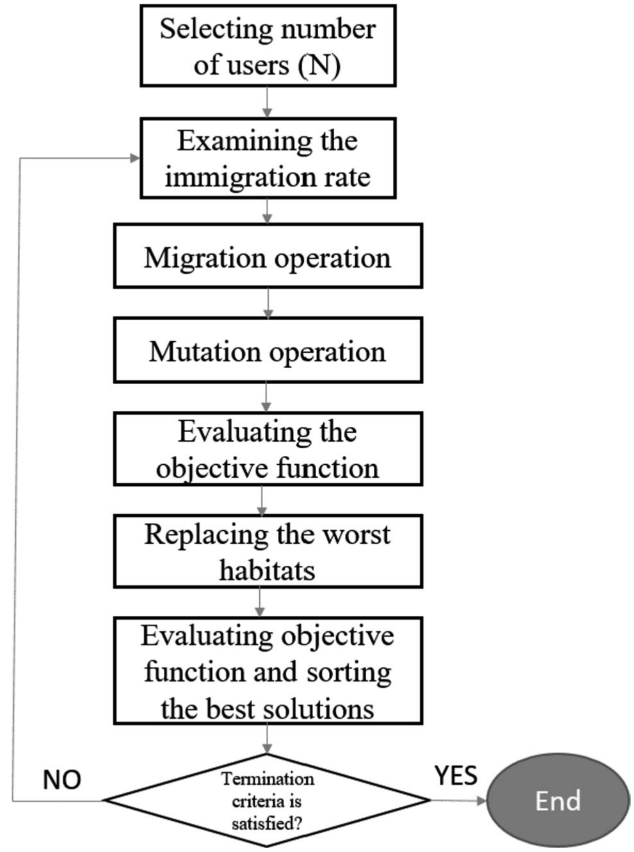

Fig. 5 Flowchart of biogeography-based optimization (BBO) (Simon 2008)

The performance of each optimization system should be evaluated using some indices. In the present study, water supply and salinity management were defined as the purposes of the optimization. Hence, three indices were considered including two indices for evaluating the salinity in the reservoir and one index for evaluating water supply. As displayed in the following equations, reliability index (RI) was used for evaluating water supply in the simulated period. Moreover, root mean square error (RMSE) and average salinity index (ASI) were applied to evaluate the salinity in the reservoir.

$$\text{RI} = \frac{\text{total optimal release for water demand}}{\text{Total water demand}} \tag{7}$$

$$\text{If OSC}_t > \text{FSC} \rightarrow \text{RMSE} = \sqrt{\frac{\sum_{t=1}^{T}(\text{OSC}_t - \text{FSC})^2}{T}} \tag{8}$$

$$\text{ASI} = \frac{\frac{\sum_{t=1}^{T}(\text{OSC}_t)}{T}}{\text{FSC}} \tag{9}$$

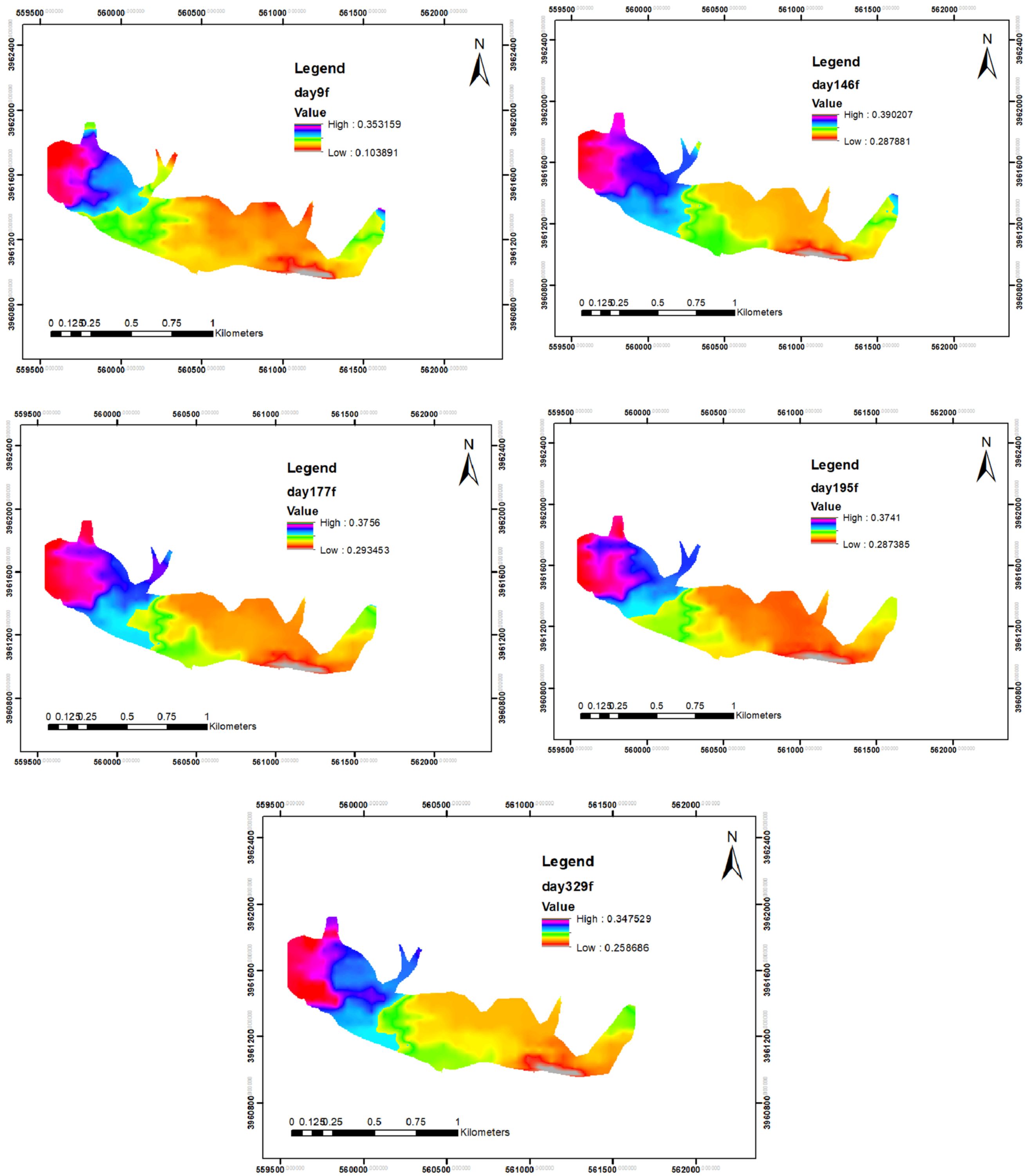

Fig. 6 Salinity distribution in the reservoir (lake) in some sample days of the simulated period (salinity in parts per thousand (ppt))

Results and discussion

In the first step, it is essential to display the results of the hydrodynamic modeling by TUFLOW in the case study. Based on calibrated and validated outputs of the TUFLOW FV in the case study, Fig. 6 shows some sample results. As presented, we simulated 365 days by the TUFLOW FV. In other words, average daily flows were used in daily modeling of salinity in the reservoir. Based on Fig. 7, salinity distribution is considerably distinctive in different locations of the reservoir. For example, the salinity concentration near to the outflow of the reservoir is highly lower than other locations of the simulated area. The sample results of the hydrodynamic modeling of salinity indicate that using 2D hydrodynamic models for simulating and managing the salinity of the reservoir ecosystem is necessary because salinity distribution is nonuniform in different locations of the lake.

The outputs of the hydrodynamic modeling in all simulated days were used to develop the surrogate model. Figure 7 shows the results of developing the surrogate model in which training and testing process of the model are observable. Based on computing NSE and RMSE as the measurement indices, the surrogate model is robust to estimate the salinity considering some key inputs. According to the literature, the maximum NSE is 1 which means the simulation and the observations are the same. However, developing a perfect model is not possible in practice. In the present study, simulation and observation mean the simulated average salinity by the surrogate model and the hydrodynamic model, respectively. NSE more than 0.5 has been considered as the acceptable threshold in the literature. In the developed model, NSE is 0.79, which implies the model is reliable for simulating the average salinity of the reservoir. Moreover, RMSE is too low which means the mean error of the model is negligible for practical modeling of the salinity in the optimization model. In the next step, it is required to present the outputs of the optimization model. Figure 8 shows the key inputs and the proposed outputs or optimal solutions by the reservoir operation model. Based on the results, the reservoir is not able to supply considerable part of water demand because defined water demand is beyond the potential capacity of the river basins. Hence, using other available water resources is essential. Currently, regional water authority can satisfy demands by two other dams and groundwater resources. Storage time series indicates that optimization model keeps available water in the reservoir to reduce salinity concentration based on the defined purposes in the model. In other words, defining environmental impacts in the reservoir operation model might reduce reliability of water supply during the operational period. RI is 8% which means the Latina reservoir by the proposed operation is only able to supply a small portion of the requested water demand for the capital territory, and using other resources or reducing water consumption is very important for managing the demands. Moreover, ASI is 0.96 which indicates the average of the optimal salinity in the reservoir is less than favorite average salinity. In other words, the optimization model is able to mitigate the environmental impacts of the operation in the lake's habitats by reducing average salinity to a safe level for the aquatic species. RMSE is 0.15 ppt which demonstrates the mean error of the optimization model regarding salinity mitigation is not remarkable during the simulated period.

A full discussion on the technical and computational aspects of this study might be helpful for the readers to apply

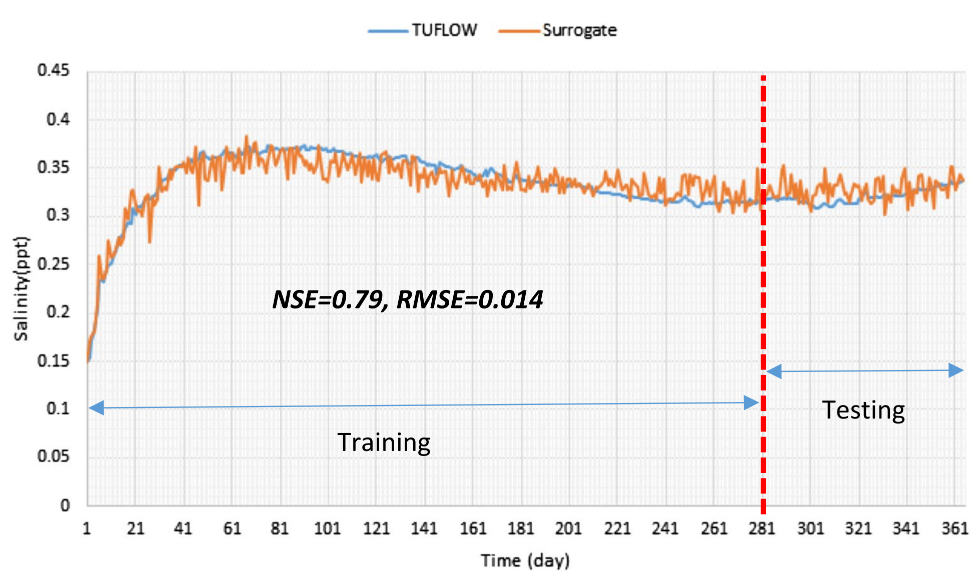

Fig. 7 Training and testing of the surrogate salinity model

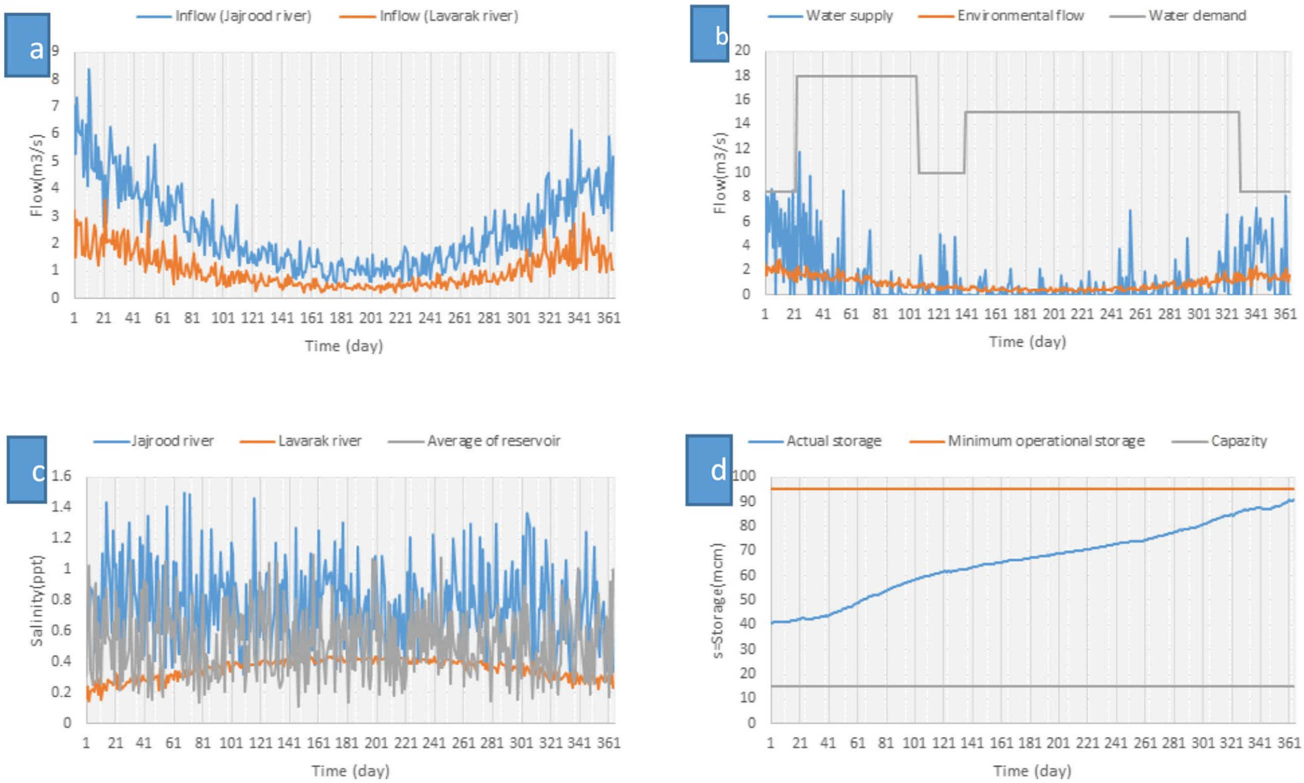

Fig. 8 Key inputs and outputs of the optimization model (**a** inflow, **b** optimal release, **c** salinity concentration, **d** storage time series)

the proposed framework in future studies. We discuss on advantages, limitations, and recommendations for using this method. Moreover, It should be discussed why the proposed mechanism could be useful for improving environmental management of reservoirs compared with the previous proposed methods.

Reservoir operation models do not conventionally apply the environmental components in the optimization system. Some recent studies highlighted the importance of including environmental challenges in the reservoir management. However, they did not consider the river ecosystem itself in the operation of dams. In other words, recent studies highlighted downstream habitats in the reservoir management. The present study proposed a novel framework in which environmental requirements of the reservoir ecosystem have been integrated in the structure of the optimization model of the reservoir. In other words, a novel form of ecological reservoir operation is proposed which might be helpful for reducing the environmental degradations of a dam in the river ecosystem. It should be noted that the large dams disconnect the upstream and downstream habitats of a river, which means the ecological status of the river would be changed. Hence, the role of reservoir ecosystem for providing a suitable environment for the aquatic species at upstream will be important. This study highlighted the salinity management in the reservoir ecosystem as one of the effective water quality factors on the aquatic species such as fish. In fact, initial ecological survey in the case study demonstrated that increasing salinity due to having more urbanized areas at upstream is a serious problem in the lake of the Latian dam, which might threaten several native aquatic species. The proposed method integrates water supply and requirements of the reservoir ecosystem and downstream environmental flow in one optimization model which means it is an integrated environmental water resources model in the reservoir management.

Comparing results of this study with the recent reservoir operation studies is able to highlight the contributions of the novel model. Many previous studies optimized the reservoir operation using a simple loss function in which the difference between water demand and release is minimized. However, this loss function lacks environmental component, which should be avoided in the current condition due to importance of environmental degradations at upstream and downstream of a reservoir. Adding environmental flow model to the reservoir operation has been carried out in recent years which improved the applicability of the model and mitigated downstream environmental degradations (Suwal et al. 2020; Sedighkia and Datta 2022). However, considering environmental flow is not able to overcome upstream environmental challenges. In other words, the previous frameworks have not considered reservoirs as an active habitat which might worsen the environmental impacts of the reservoir operation in terms of upstream habitats in the lake. Linking TUFLOW FV with the reservoir operation model is helpful for managing salinity impacts in the reservoir ecosystem due to water supply as the contribution of this study. This kind of simulation could be helpful in terms of two aspects. First, it is possible to investigate water quality distribution in the actual operation of a reservoir. In other words, when the inflow and outflow of a reservoir are known, this hydrodynamic model is able to provide an accurate assessment on the habitat suitability in terms of water quality parameters. For example, cage fish farming is one of the businesses which is being carried out in some reservoirs. The cages should be located in the suitable habitats in terms of water quality. Using 2D hydrodynamic models would be helpful for better management of cage fish farming in the reservoirs. Moreover, similar to this study, the outputs of the 2D model could be applied in the reservoir operation optimization for developing an ecological operation model.

Computational aspects are important for successful application of the proposed method as well. Hence, it is essential to discuss on the computational advantages and limitation of the method. First, we discuss on the computational aspects of the fluid dynamic model. The computational costs of the fluid dynamic model are the main limitation for applying these models. In fact, considerable run time and memory are needed for simulation of water quality distribution for a long-term period is one of the big challenges in using hydrodynamic models. It might restrict the application of 2D fluid dynamic models in the real reservoir operation projects. Engineers are not willing to apply these models due to increase in the costs of the projects. Moreover, using these models might need professional experts who should be familiar with details and complexities of the models which might be another limitation for applying them in practice. Defining boundary conditions and calibration of the 2D hydrodynamic models might be another complexity in the applications for practical water resources problems. It is needed to define all inflows and outflows as the boundary conditions in which salinity time series should be available. However, availability of the time series in the simulated period might not be achievable in all cases. Hence, it might be needed to carry out some initial hydrological simulation as well. In the case study, the data were available in the simulated period which makes it possible to apply the hydrodynamic models without pre-processing steps. However, it is recommendable to have an initial hydrological simulation in the case studies in which the full time series are not accessible. Furthermore, calibration and validation of the model is a key step for developing a robust model. In the case study, we simulated a small lake which means the limited number of stations in the reservoir in which salinity has been recorded might be adequate. We had data in two locations of the lake which helped us to develop a robust model. However, it is required to have several calibration points in the larger lakes, which might not be available in some cases. In other words, the accuracy of the hydrodynamic model might be weakened in these cases.

The computational aspects of the surrogate model should be discussed as well. Many types of models could be used as a surrogate model. It is recommendable to apply the machine learning models as the surrogate models due to its advantages and robustness. Neural networks are one of the popular models in this regard used in the present study. We applied adaptive neuro-fuzzy inference system due to its advantages. However, other types of neural networks such as feed-forward neural networks might be useable as well. Hence, it is recommendable to apply a wide range of machine learning models in the future studies to investigate the efficiency and accuracy of the models. Moreover, training of the machine learning model is another issue, which should be noted. Many algorithms could be applied in the training of the model. In the present study, we applied the hybrid algorithm (back propagation + least square) which might be appropriate for similar cases. However, some studies recommended other novel algorithms such as particle swarm optimization (PSO) in the training of the ANFIS-based models (Pousinho et al. 2011). It should be noted that training of the neural networks is inherently an optimization problem, which means using novel optimization algorithms is possible as well. It is recommendable to apply evolutionary algorithms in future studies for better assessment of the training methods in development of a surrogate model. Furthermore, other types of regression and classification models might be useable as a surrogate model. There is ample space for applying a wide range of machine learning models as the surrogate model in future studies.

The global optimization is another computational aspect in the optimization process, which should be discussed as a drawback of the evolutionary optimization. These algorithms are not able to guarantee the global optimization which means they might not provide the best answer in the exploration space. Hence, it is recommendable to utilize a wide range of evolutionary algorithms in practical problems. The origin and methodology of the algorithms for finding the best solution are completely different which means using several algorithms is helpful for peace of mind regarding providing the best available solutions. We recommend applying a decision-making method for selecting the best answer among available optimal solutions by different algorithms.

In the present study, the nature of the optimization problem is multi-objective because water supply and salinity management were simultaneously considered. However, we applied an aggregated form of the objective function in which both purposes were defined in one function. It should be noted that using this form of function could have some advantages and disadvantages. The main advantage of the aggregated form is less computational complexity, which might be a key factor for the optimization process. The computational complexity is defined as the required time and memory for finding the optimal solution by an optimization algorithm. In this study, we applied a machine learning model in the structure of the optimization model, which means the computational complexities will be considerably increased. On the other hand, the multi-objective optimization algorithms have more complexities compared with the single-objective models, which implies using a multi-objective algorithm would worsen the computational complexities in the developed model. Hence, applying an aggregated form of the objective function is advantageous in terms of reducing needed time and memory for computing the optimal solution. Moreover, a wide range of singe-objective algorithms is available which means utilizing aggregated form would be beneficial in terms of global optimization.

The proposed method might open new windows for future studies in the reservoir management. First, it is needed to modify available methods in the reservoir operation to integrate the lake ecosystem in the reservoir management. In other words, not only the ecological operation of the reservoir should include the concept of downstream environmental flow, but also the lake ecosystem should be added to the reservoir operation. Secondly, the application of the fluid dynamic model in the reservoir management model should be expanded. The previous studies ignored the useful application of the fluid dynamic models in the environmental management of the reservoir. However, this study demonstrated that using fluid dynamic models can improve water quality management of reservoirs. It is required to present new methods in the reservoir management in which the fluid dynamic model could be applicable for simulating water quality distribution in the lake. It should be noted that climate change is a challenge in the reservoir management in future years, which might need advanced models for overcoming complex impacts in the ecosystem. In other words, we recommend combining the climate change models, fluid dynamic models such as TUFLOW FV, and reservoir operation models in the environmental management scenarios of reservoirs in future studies.

Conclusion

The present study developed a novel system to manage water quality of a reservoir with a focus on salinity in which an advanced two-dimensional fluid dynamic, a surrogate model, and the evolutionary optimization are linked. Based on the results in the case study, defining environmental impacts in the reservoir operation model might reduce reliability of water supply during the operational period. However, the optimization model is able to mitigate the environmental degradations in the lake's habitats by reducing average salinity to a safe level for the aquatic species. Conventional reservoir operation models do not consider reservoir itself as an active habitat which should be protected. However, this study proposes a reliable method to integrate environmental requirements of dams' lake with the reservoir operation as a new method of environmental reservoir operation of large dams.

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Declarations

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Consent to Participate Not applicable.

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