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A simulation–optimization framework for reducing thermal pollution downstream of reservoirs

Mahdi Sedighkia[a,*], Bithin Datta[b] and Saman Razavi[c,d]
[a] ICEDS, Australian National University, Canberra, Australia
[b] James Cook University, Townsville, Australia
[c] Global Institute for Water Security and School of Environment and Sustainability, University of Saskatchewan, Saskatoon, Canada
[d] Institute for Water Futures and Mathematical Science Institute, Australian National University, Canberra, Australia
*Corresponding author. E-mail: mahdi.sedighkia@anu.edu.au

ABSTRACT

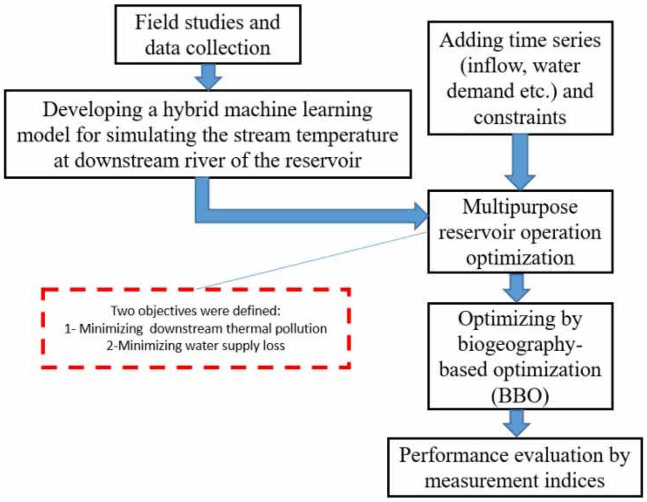
Thermal pollution is an environmental impact of large dams altering the natural temperature regime of downstream river ecosystems. The present study proposes a simulation–optimization framework to reduce thermal pollution downstream from reservoirs and tests it on a real-world case study. This framework attempts to simultaneously minimize the environmental impacts as well as losses to reservoir objectives for water supply. A hybrid machine-learning model is applied to simulate water temperature downstream of the reservoir under various operation scenarios. This model is shown to be robust and achieves acceptable predictive accuracy. The results of simulation–optimization indicate that the reservoir could be operated in such a way that the natural temperature regime is reasonably preserved to protect downstream habitats. Doing so, however, would result in significant trade-offs for reservoir storage and water supply objectives. Such trade-offs can undermine the benefits of reservoirs and need to be carefully considered in reservoir design and operation.

Key words: BBO, hybrid machine-learning model, optimal operation, thermal pollution, water supply

HIGHLIGHTS

- Mitigating thermal pollution of the reservoirs.
- Developing a novel environmental optimization model.
- Using a combination of machine-learning model and optimization system for reducing potential impacts of water temperature on the aquatics.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Large dams are the most important hydraulic structures in river basins and are important suppliers of water and electricity (Di Baldassarre *et al.* 2021). However, the downstream and upstream environmental impacts of large dams are not negligible (Manouchehri & Mahmoodian 2002). Optimal management of these structures to achieve the desired water supply and environmental benefits is important because the construction of a large dam is expensive (Ahmad *et al.* 2014).

Most reservoir design and operation problems have historically been based on a simple loss function to optimize reservoir operation (Ehteram *et al.* 2018). In this loss function, the difference between the target and release is minimized. Generally, the target is defined as the water demand and the release is the actual water supply at each time step. Different methods have been applied for this optimization, including linear programming (LP), non-linear programming (NLP), dynamic programming (DP), and evolutionary algorithms. LP is one of the simpler methods (Reis *et al.* 2006), and NLP and DP methods have been recommended for non-linear functions (Arunkumar & Jothiprakash 2012). The objective function of reservoir operation is complex and, hence, evolutionary algorithms as an advanced method are more appropriate and have been recommended by many studies (Afshar *et al.* 2007, 2011; Asadzadeh *et al.* 2014; Bozorg-Haddad *et al.* 2015a, 2015b; Asgari *et al.* 2016; Ehteram *et al.* 2018; Yaseen *et al.* 2019; Sharifi *et al.* 2021). Different classifications have been proposed for these algorithms: for example, classic algorithms such as genetic algorithms have widely been used for different optimization problems while new algorithms have been proposed to improve the efficiency of the optimization process (Dokeroglu *et al.* 2019); animal-inspired algorithms generally imitate the social behaviour of animals while non-animal-inspired algorithms follow other natural or physical laws (Jahandideh-Tehrani *et al.* 2019).

The protection of river ecosystems is important for the sustainable management of water resources. Reservoirs affect downstream river ecosystems by changing the natural flow regime (Qicai 2011). Water temperature is a key environmental characteristic that affects the biological activities in a river ecosystem, and many such activities (e.g., searching for food and reproduction) are strongly dependent on the thermal regime (Weber *et al.* 2014). Hence, water temperature modelling is important for assessing the ecological status of a river ecosystem. Thermo-hydrodynamic models such as SSTEMP have been used to simulate water temperature in a single reach or river network (Bartholow 1995); however, such models are inflexible in terms of directly linking to reservoir operation optimization models. Data-driven models have shown great promise to simulate environmental systems (Razavi *et al.* 2022); for example, neural networks have been utilized for water quality modelling (Zhu *et al.* 2019). These models can provide a fast and flexible assessment (Razavi 2021), which is especially applicable in water resources models and can be used when an outcome cannot be easily measured (Sreekanth & Datta 2011). A large number of effective inputs might make a system complex and, hence, using a surrogate model can be beneficial. Different types of methods, including neural networks (Mengistu & Ghaly 2008) and Bayesian networks (Shi *et al.* 2012), can be applied to develop a surrogate model.

Large dams alter downstream thermal conditions, which is defined as a type of thermal pollution (Ling *et al.* 2017). Sedighkia *et al.* (2019) reviewed the importance of thermal conditions to biological habitats, confirming that the consideration of thermal regimes is fundamental with respect to maintaining the integrity of freshwater ecosystems (Olden & Naiman 2010). For example, the impacts of large dams on salmon due to changing thermal regimes demonstrate the importance of thermal regime modelling (Angilletta *et al.* 2008). However, thermal models have not yet been integrated into reservoir operation models, which is a significant research gap. The present study proposes a novel framework to optimize the thermal regime downstream of a reservoir. The proposed method links a thermal model to predict the downstream water temperature with a reservoir operation optimization with the aim to reduce downstream thermal pollution while maximizing water supply. This study could lead to new methods of advanced environmental management of reservoirs in which complex computational frameworks are integrated into water resource management models.

2. APPLICATION AND METHODOLOGY

2.1. Study area and methodological overview

We implemented the proposed framework in the Jajrood River Basin, Iran. Some endangered fish species have been observed in this ecosystem and, thus, protecting it is an important task for the regional department of the environment. However, this river plays a key role in satisfying the water demand of Iran's capital region. The Latian Dam was constructed midstream in this river basin to meet these water demands. The water supply is currently achieved using direct pumping from the reservoir, which means satisfying downstream environmental flow is a challenge. Initial ecological studies demonstrate that thermal pollution due to the altered water temperature regime is a main environmental concern with respect to protecting endangered fish species (Sedighkia *et al.* 2019). Ideally, the water temperature regime downstream of the reservoir should be as close as possible to the natural thermal regime (in the absence of the reservoir). Hence, new operational optimization is required to balance environmental needs and demands for water supply. We simulated the downstream water temperature regime and optimized dam operation in this region as a case study. Due to the low available flow in the simulated period, simultaneous satisfaction of environmental and water supply requirements was challenging. Figure 1 shows an overview of the methodology in which the simulation of the downstream water temperature and optimization of the reservoir operation are linked. Figure 2 shows the location of the Latian Dam in the Jajrood River Basin. The capacity of the reservoir is 95 million cubic metres (MCM), with minimum operation storage of 15 MCM and optimal or strategic storage of 70 MCM based on recommendations by the regional water authority.

2.2. Water temperature regime modelling

We utilized the coupled particle swarm optimization-adaptive neuro-fuzzy inference system (PSO-ANFIS) to simulate water temperature in the river downstream of the reservoir. We selected a river reach with a length of 10 km and simulated the downstream water temperature in different cross-sections (intervals between cross-sections were 100–1,000 m). The simulated average water temperature throughout the downstream river reach was then used in each time step of the optimization model. In other words, data from many cross-sections were considered to simulate the downstream water temperature, with the arithmetic mean of these values used as an overall estimation.

Figure 3 displays a simple structure of the ANFIS-based model with two inputs. More details regarding the structure of this model are presented by Awan & Bae (2014). PSO was used as the optimizer. Figure 4 is a flowchart of the PSO-ANFIS approach. In brief, PSO was utilized to train the ANFIS-based model and find the optimal coefficients for connecting neurons in the network because evolutionary algorithms such as PSO can improve the predictive ability (Sedighkia *et al.* 2022). Table 1 displays the main characteristics of the ANFIS-based water temperature model. The water temperature depends on several factors and, hence, data-driven models are a good option to achieve a reasonable simulation of the thermal regime. This data-driven model can be directly applied to reservoir operation optimization. Two known indices – the Nash–Sutcliffe efficiency (NSE) index and root means square error (RMSE) – were applied to evaluate the goodness-of-fit of the hybrid machine-learning model (see Gupta *et al.* (2009) for more details).

2.3. Optimization model

The main component of the optimization model is the objective function. We developed a novel form of the objective function for the reservoir operation with a focus on minimizing thermal pollution. The core of the objective function is the same as the conventional loss function. However, a penalty function method was used to integrate the required constraints into the

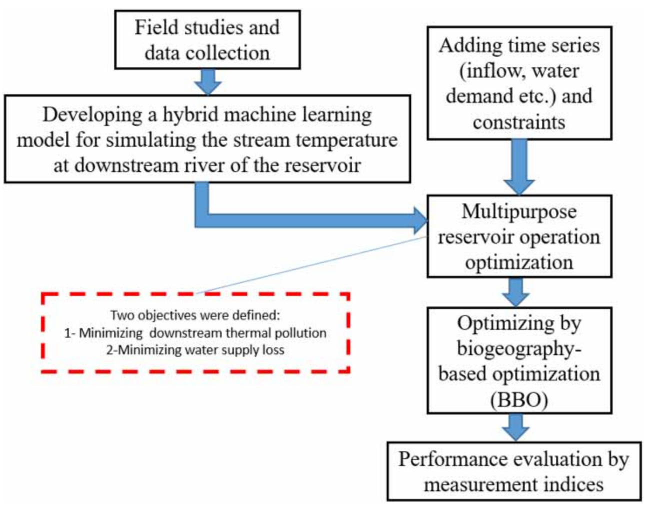


Figure 1 | The workflow of the proposed method.

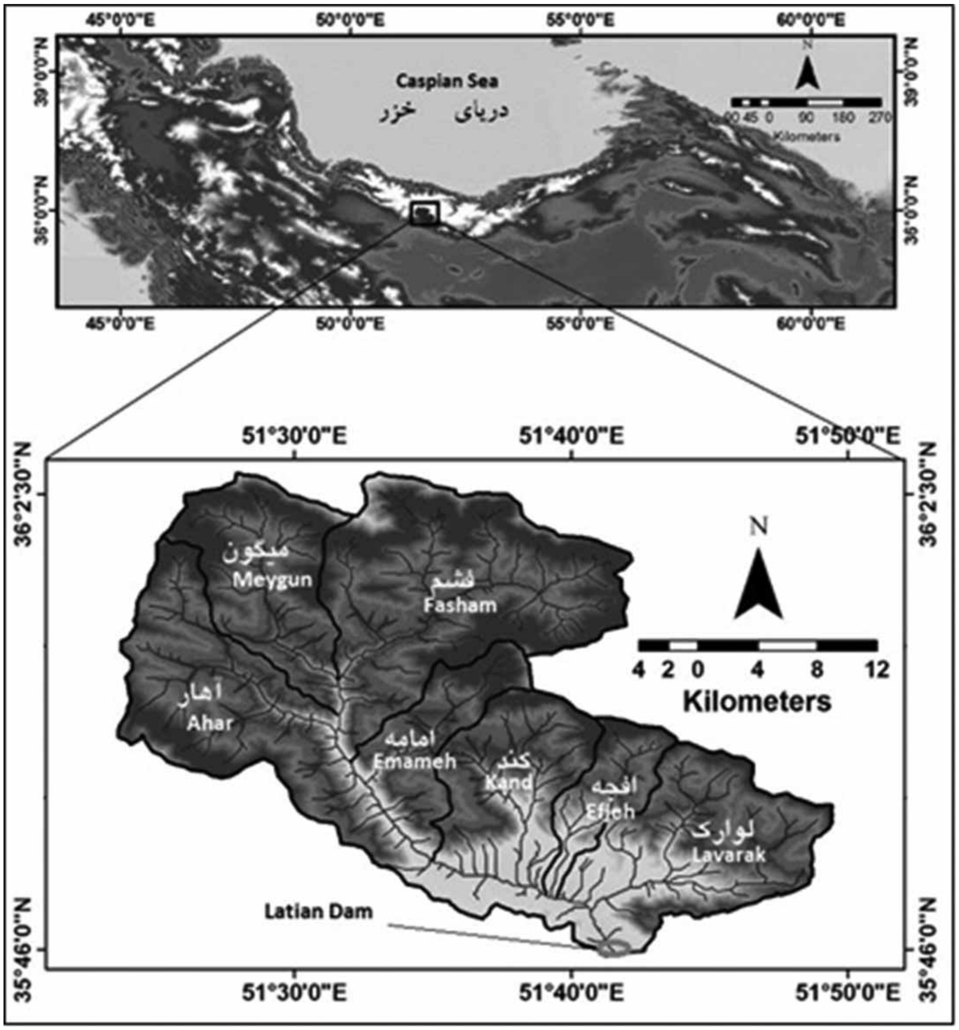


Figure 2 | The location of the Latian Dam in the Jajrood River Basin.

optimization code (Agarwal & Gupta 2005). The objective function employed was:

$$\text{Minimize(OF)} = \sum_{t=1}^{T}\left(\frac{D_t - \text{RD}_t}{D_t}\right)^2 + P1 + P2 + P3 + P4, \tag{1}$$

where D_t is the maximum water demand at time step t, RD_t is the water released from the reservoir at time step t, and $P1 - P4$ are penalty functions. $P1$ and $P2$ are related to the downstream water temperature regime in the optimization model; these penalty functions were developed based on a predetermined target for the water temperature regime. Ideally, the water temperature resulting from the optimal release scenario should mimic resulting from the natural flow. Equation (2) outlines the thermal pollution penalty functions applied in the optimization model as follows:

$$\begin{cases} \text{if } \text{OTW}_t > 1.1\ \text{NTW}_t \rightarrow P1 = c1\left(\dfrac{\text{OTW}_t - 1.1\ \text{NTW}_t}{1.1\ \text{NTW}_t}\right)^2 \\ \text{if } \text{OTW}_t < 0.9\ \text{NTW}_t \rightarrow P2 = c2\left(\dfrac{0.9\ \text{NTW}_t - \text{OTW}_t}{0.9\ \text{NTW}_t}\right)^2 \\ \text{if } \text{RE}_t < \text{minevn} \rightarrow P3 = c3\left(\dfrac{\text{minevn} - \text{RE}_t}{\text{minevn}}\right)^2 \end{cases}, \tag{2}$$

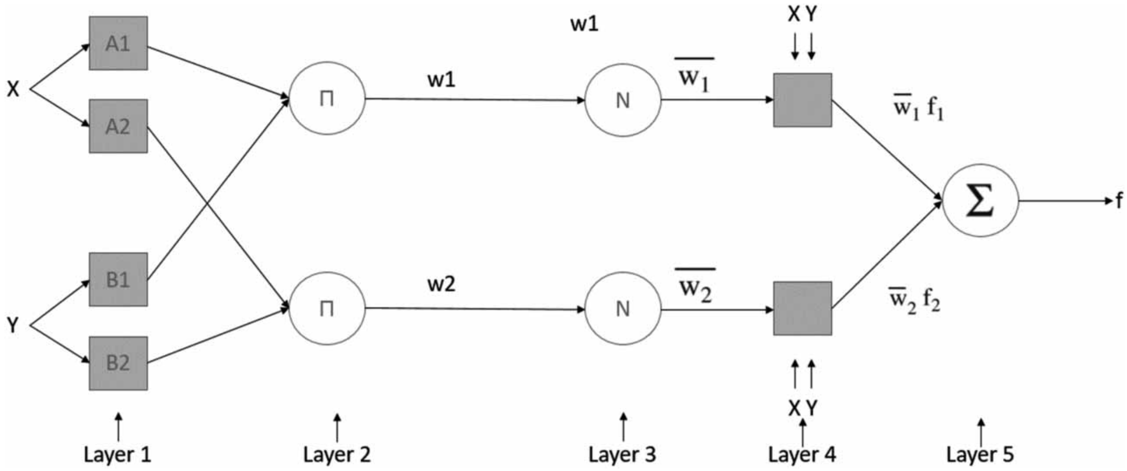


Figure 3 | Simple structure of the ANFIS-based data-driven model.

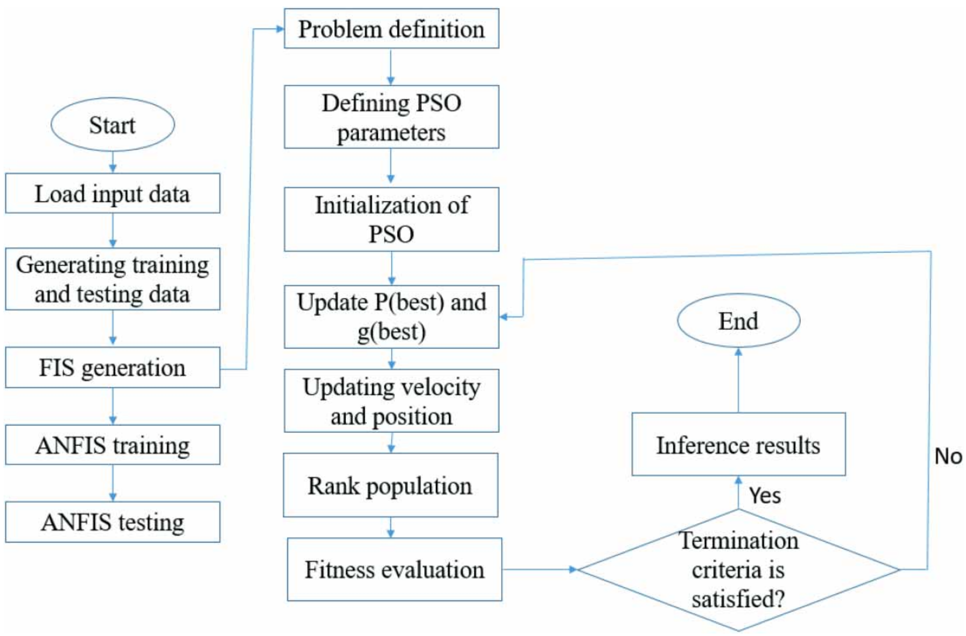


Figure 4 | The PSO-ANFIS flowchart.

Table 1 | Main characteristics of the ANFIS-based downstream water 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); Wetted perimeter (m); Distance from the reservoir (m); Elevation from sea level (m); Water temperature at distance = 0 m (°C); Air temperature (°C)	10	Gaussian	Water temperature at each cross-section	10	Linear	Subtractive clustering

MFs, membership functions.

where NTW is the natural temperature regime, OTW is the optimal temperature regime, RE is the release for the environment, and minenv is the minimum environmental flow requirement. In the case study, minenv was defined as 10% of the mean annual flow based on previous environmental flow studies. An initial ecological survey of the study area indicated a

10% change in temperature might impact river habitats; thus, we considered 10% as the tolerance of the change in downstream water temperature in the penalty function. A minimum environmental flow was also considered. The following equation considers a minimum operational storage penalty function, maximum storage penalty function, and water demand function, i.e., storage in the reservoir should not be less than the minimum operational storage or more than the maximum storage or capacity of the reservoir, and water supply should not exceed water demand:

$$\begin{cases} \text{if } S_t > S_{\max} \rightarrow P4 = c4\left(\dfrac{S_t - S_{\max}}{S_{\max}}\right)^2 \\ \text{if } S_t < S_{\min} \rightarrow P5 = c5\left(\dfrac{S_t - S_{\min}}{S_{\min}}\right)^2 \\ \text{if } \mathrm{RD}_t > D_t \rightarrow P6 = c6\left(\dfrac{\mathrm{RD}_t - D_t}{D_t}\right)^2 \end{cases}, \tag{3}$$

where S_t is the storage at time step t, and $S_{\max}$ and $S_{\min}$ are the maximum and minimum storage, respectively. $c1$–$c6$ are constant coefficients determined based on the sensitivity analysis. The storage of the reservoir must be updated for each time step using the following equation:

$$S_{t+1} = S_t + I_t - \mathrm{RD}_t - \mathrm{RE}_t - F_t - \left(\frac{E_t \times A_t}{1,000}\right), t = 1, 2, \ldots, T, \tag{4}$$

where I_t is the inflow, F_t is the overflow, E_t is evaporation, RE is the downstream release for the environment, and A_t is the surface area of the reservoir. The overflow of the reservoir was calculated using the following equation:

$$\begin{cases} \text{if}\left(S_t + I_t - \left(\dfrac{E_t \times A_t}{1,000}\right)\right) \geq S_{\max} \rightarrow F_t = S_t + I_t - \left(\dfrac{E_t \times A_t}{1,000}\right) - S_{\max} \\ \text{if}\left(S_t + I_t - \left(\dfrac{E_t \times A_t}{1,000}\right)\right) < S_{\max} \rightarrow F_t = 0 \end{cases}. \tag{5}$$

Note that release for water demand is directly pumped from the reservoir and, hence, two releases are defined in the optimization model.

We utilized biogeography-based optimization (BBO) to optimize the monthly downstream water temperature regime (Figure 5). This algorithm, developed by Simon (2008), is an optimization algorithm that follows a natural process pattern inspired by the distribution of biological species through time and space. It works based on the evolution of new species, migration of species (animals, fish, birds, or insects) between islands, and extinction of species. Two migration and mutation operators are utilized.

The performance of each factor in the optimization model (water supply, storage loss, and downstream water temperature regime) was assessed based on selected indices. Due to possibility of the secondary storage and the importance of knowing how much water is supplied by the reservoir (its main purpose) in the simulated period, we used a reliability index α_R to measure the performance of the optimization system in terms of the water supply (see Ehteram *et al.* (2018) for more details):

$$\alpha_R = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t}. \tag{6}$$

Two indices were applied to evaluate the performance of the optimization model in terms of storage loss, the vulnerability index, and RMSE:

$$\mathrm{VI}_{\text{storage}} = \operatorname*{Max}_{t=1}^{T}\left(\frac{S_{\text{optimum}} - S_t}{S_{\text{optimum}}}\right), \tag{7}$$

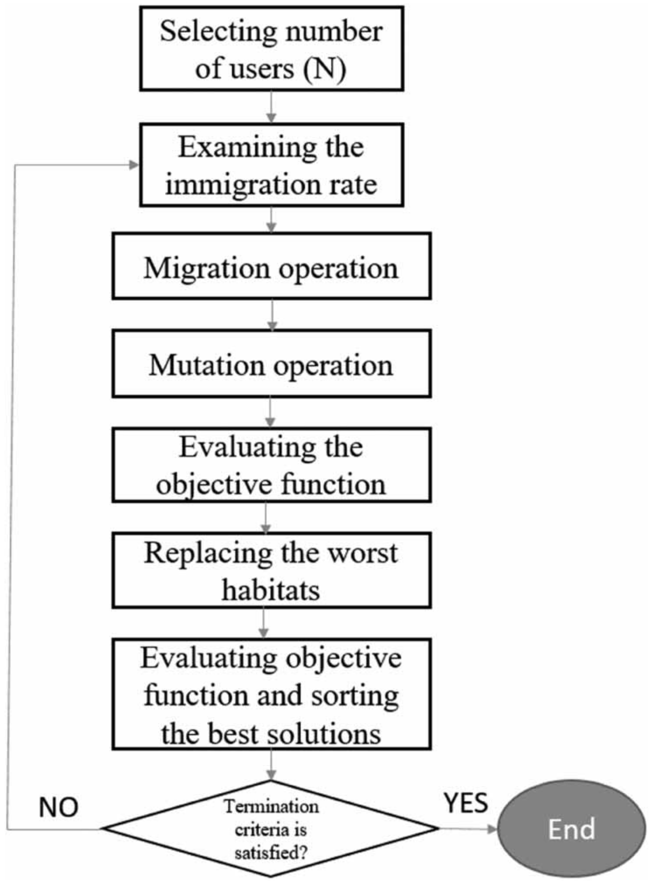


Figure 5 | The flowchart of BBO (Simon 2008).

$$\mathrm{RMSE}_{\mathrm{Storage}} = \sqrt{\frac{\sum_{t=1}^{T} (R_t - S_{\mathrm{Optimum}})^2}{T}}. \tag{8}$$

The reliability index is not recommended to assess storage loss because the storage at each time step is profitable and defining a reliability index for storage is not logical. Finally, two indices were applied to assess the performance of the optimization system in terms of optimal downstream water temperature regime, NSE, and RMSE:

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T} (\mathrm{NTW}_t - \mathrm{OTW}_t)^2}{\sum_{t=1}^{T} (\mathrm{NTW}_t - \mathrm{NTW}_0)^2}, \tag{9}$$

$$\mathrm{RMSE}_{\text{thermal pollution}} = \sqrt{\frac{\sum_{t=1}^{T} (\mathrm{OTW}_t - \mathrm{NTW}_t)^2}{T}}. \tag{10}$$

The NSE measures the difference between observations and the simulation (values >0.5 demonstrate the predictive skills of the model are robust), and can be used to measure the performance of hydrologic models (Gupta *et al.* 2009); it can also be applied to water quality parameters.

3. RESULTS AND DISCUSSION

The first step involved using the results of the data-driven model to simulate the downstream water temperature. We applied 169 recorded water temperature data points to train and test the model (Figure 6). Small differences between observations and simulations indicate that the performance of the data-driven model is robust; this is supported by an NSE for the test period of 0.76. Moreover, the RMSE of 4.01 indicates the mean error is small. The values of these indices corroborate the acceptability of the model for the case study.

Figure 7 displays inflow, water supply, water demand, and optimal environmental flow in the simulated period. Conventional optimization models typically output the minimum difference between release and water demand but do not consider thermal pollution. As such, using a conventional reservoir operation model might markedly increase downstream thermal pollution because the difference between optimal release for the environment and minimum environmental flow can be considerable (0.34 m^3/s in the case study). Notably, previous reservoir operation studies have added environmental flow to the model considering simple hydrological or physical habitat methods (Sedighkia & Abdoli 2022); however, an optimal downstream water temperature regime might require more than the basic environmental flow. We utilized a thermal penalty function in this regard, and therefore the optimal environmental flow is more than the minimum environmental flow for many time steps. At the same time, the water supply is considerably less than the demand for some time steps due to the need to satisfy environmental flows. Thus, environmental considerations might reduce the potential water supply from reservoirs and storage loss might also occur. The results demonstrate how mitigating thermal pollution markedly affects the water supply benefits of the reservoir.

Figure 8 displays the downstream water temperature regime for a natural flow and the optimal regime based on the output of the optimization model. The performance of the optimization model is robust in terms of optimizing the downstream water temperature regime as the optimal and natural temperatures are similar for most time steps. Figure 9 displays the storage time series in the simulated period. The performance of the minimum storage penalty function is not robust but is generally acceptable. The reservoir storage is more than the minimum operational storage for most time steps. Moreover, the performance of the maximum storage penalty function is robust. Due to changes in the reservoir inflow, the available storage at some time steps is critically low. The performance indices for the water supply, storage, and temperature regime are given in Table 2. Interestingly, the reliability index of 10.1% demonstrates that the optimization model is unable to supply more than 90% of the water demand. In other words, managers will pay a high price to satisfy environmental requirements. Values of the VI and RMSE for the storage loss indicate that it is considerable but not as great as the water supply loss. As a challenging period with respect to reservoir inflow is currently occurring, a reduction in storage benefits is expected. The NSE and RMSE

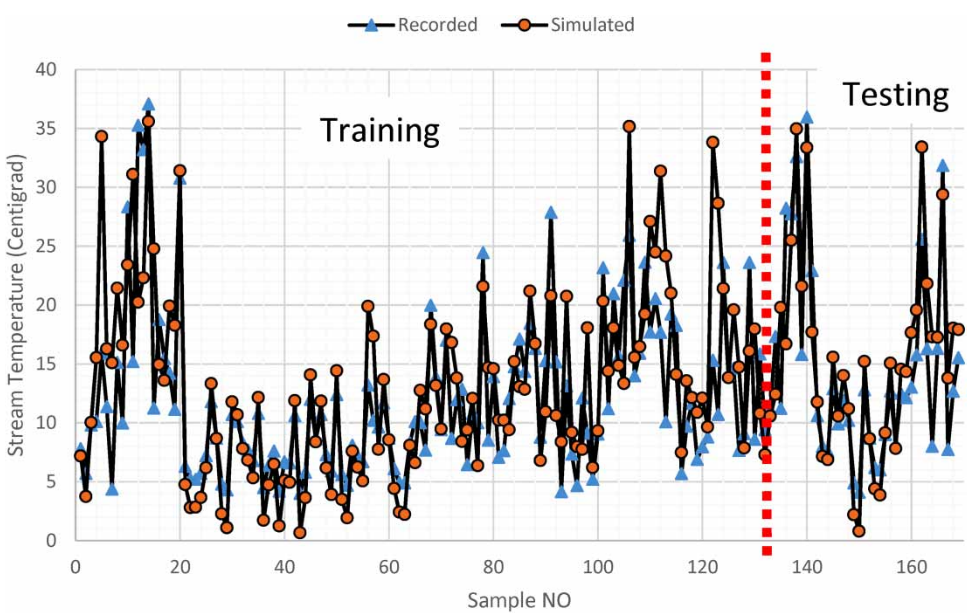


Figure 6 | Data used to train and test the machine-learning model.

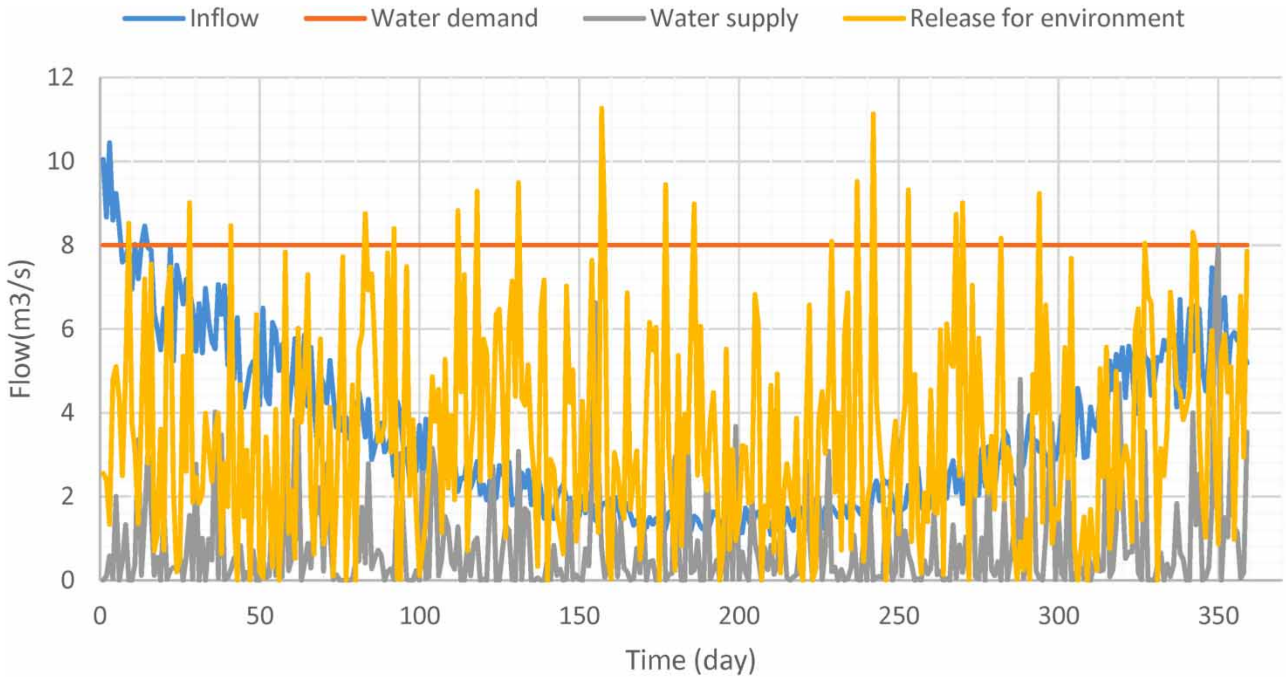


Figure 7 | Optimal water demand and release in the simulated period.

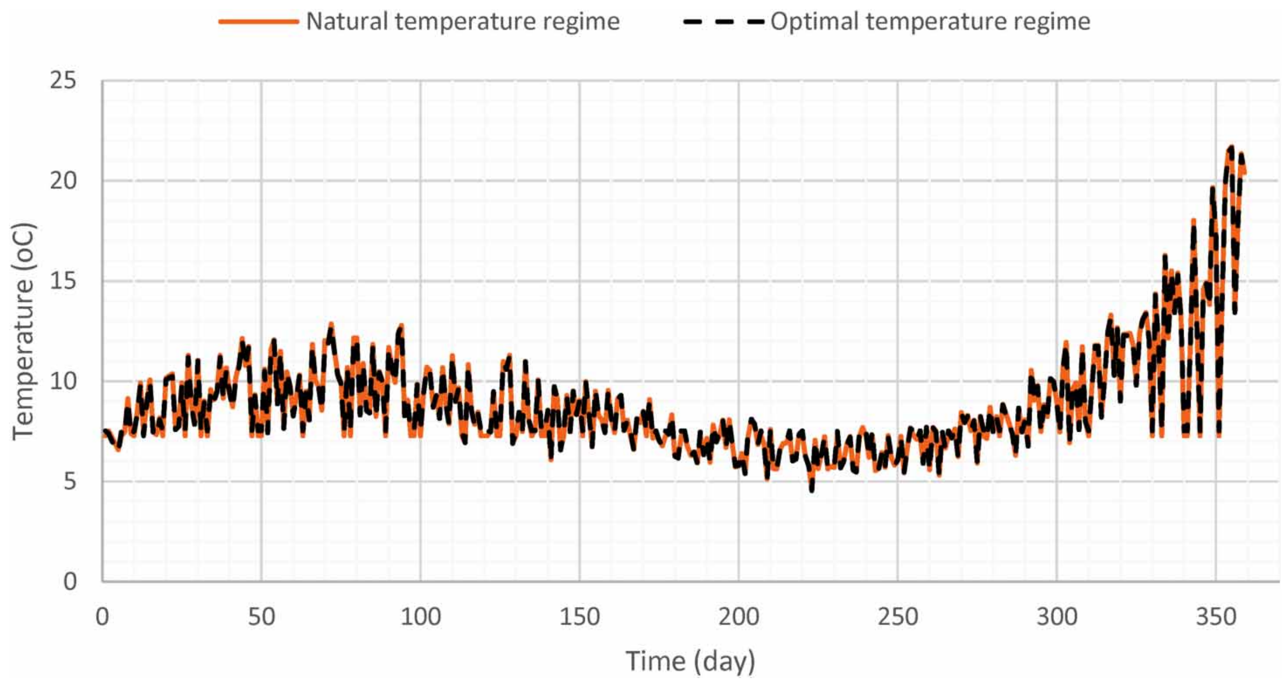


Figure 8 | Optimal downstream water temperature regime and natural temperature regime.

of the downstream water temperature regime indicate that the optimization model is robust in this regard, i.e., the optimal regime is close to the natural regime.

The model is not without limitations. High computational complexity reduces the efficiency of optimization models but is inevitable when simulating a long time period or conducting numerous simulations in practical projects. We applied an ANFIS-based water temperature model, which was good in terms of addressing technical issues but resulted in high

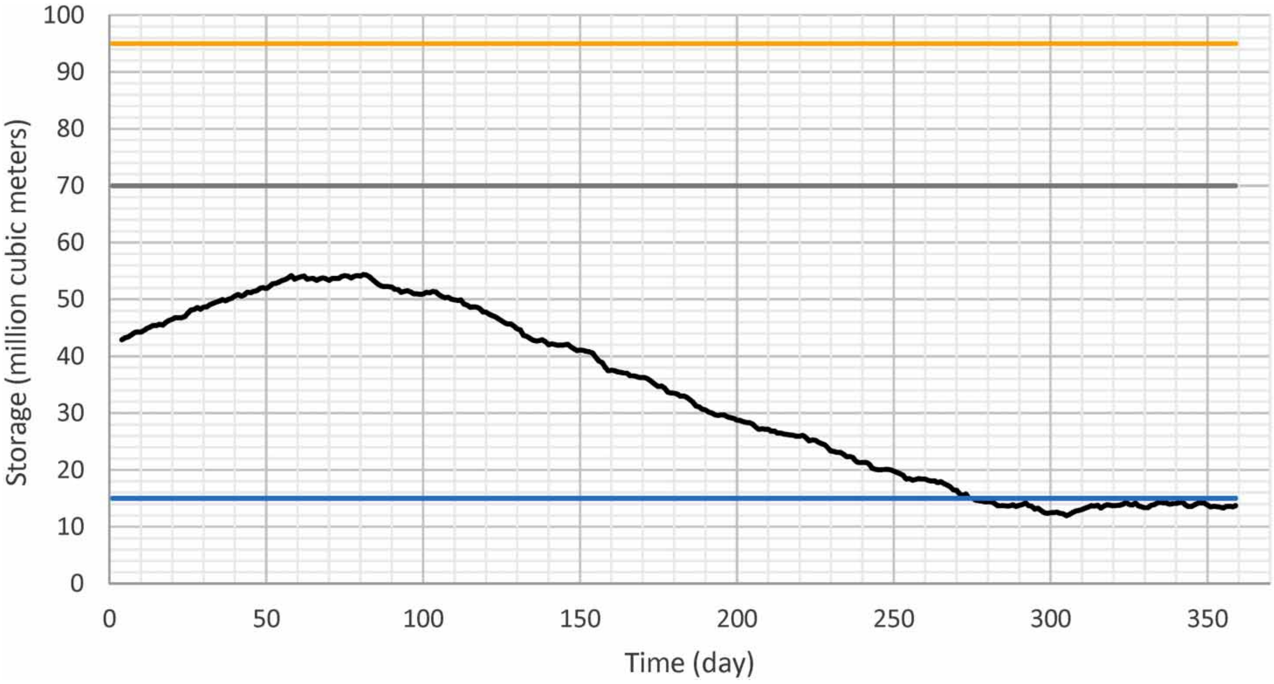


Figure 9 | Optimal storage in the reservoir in the simulated period (blue line: minimum operational storage, yellow line: capacity, grey line: optimum storage, black line: optimal storage time series in the simulated period). Please refer to the online version of this paper to see this figure in color: http://dx.doi.org/10.2166/wqrj.2022.018.

Table 2 | Measurement indices of the optimization model

Model factor	Performance index	Value
Water supply	α_R	10.1%
Storage loss	VI	82%
	RMSE	39.9 MCM
Downstream water temperature regime	NSE	0.971
	RMSE	1.1 °C

computational complexity. This is the main limitation of the proposed method, and future studies should aim to address this aspect to improve the applicability of the model. We utilized BBO in the optimization process, yet many other algorithms available in the literature could be applied to improve the model. The main weakness of all evolutionary methods is the inability to guarantee global optimization for the problem; hence, using a wide range of algorithms to find the best solution is recommended. Ranking the algorithms can be done using a decision-making system. Moreover, a multi-objective model is also an appropriate approach. For example, the use of a multi-objective genetic algorithm or multi-objective PSO has been recommended by some studies (Mansouri *et al.* 2022). However, we applied a single-objective algorithm to reduce the computational complexity. Multi-objective models are inherently more complex but might be able to achieve the objectives by Pareto front visualization. Any such approaches must consider any significant resulting decrease in model efficiency.

Ideally, the downstream water temperature during the optimal operation of the dam should be the same as the natural flow condition. Water temperature in a river is dependent on key factors used in the model, one of which is river flow or release from the reservoir. The release will not be necessarily the same as the natural flow due to the simultaneous impact of different factors. Due to the impacts of a reservoir on water temperature and stratification, simulating water temperature is complex (Table 1). In the proposed simulation–optimization, release is used as the main factor used to adjust the water temperature based on ecological requirements. Stratification was only indirectly taken into account in the model (i.e., selected input parameters were able to cover the possible impact of stratification on the downstream thermal regime). Moreover, many cross-sections were considered to simulate the downstream water temperature. Deviations from suitable temperatures were noted for some cross-sections but, due to the use of average values in the case study, these deviations were not considered in the assessment of the model. Revisiting this issue in future studies is recommended.

The case study used a daily time scale, as a monthly time scale is not appropriate for managing the thermal regime and a time scale of less than a day is not practical with respect to dam operation. Water temperature might be influenced by many environmental factors and we tested different combinations of inputs. Our initial simulations in the case study indicated that the proposed combination of inputs in Table 1 generated the most accurate results. Adding more inputs to the data-driven model increased the computational complexity and reduced model accuracy. However, all case studies are different, and thermal model development should be carried out based on the relevant considerations. For example, here we considered a 10% deviation in temperature as the maximum tolerable change. A fixed temperature could also be selected but might reduce the water supply benefits of the reservoir due to reduced flexibility for managing release. However, a large amount of tolerance (e.g., 10 °C) would certainly be detrimental to aquatic species. Notably, in some cases, reservoir operations that do not consider environmental requirements can be in place for long periods of time. The consequent effect on the downstream water temperature regime can result in irreversible impacts on the river ecosystem akin to the extinction of species.

Despite the limitations noted, the proposed approach could be successfully applied to reservoir operation. The optimization model simultaneously considers the requirements of a successful water supply operation and environmental considerations. Using two appropriate penalty functions for thermal pollution could improve reservoir operation models in terms of environmental concerns. However, the low-reliability index for the water supply demonstrates that considering environmental impacts might markedly reduce the water supply benefits of the reservoir. The results suggest that using secondary storage is necessary for the management of the water supply. For example, if release is used for irrigating lands, storage tanks on farms might be necessary to regulate irrigation supply.

Most studies to date have not included an environmental modelling component in reservoir operation optimization. In recent years, an environmental component has been added but these have typically been superficial and lacked the ability to properly integrate environmental complexities into water resources management. For example, many studies have applied hydrological methods in the optimization of environmental flow but did not consider other effects on habitat degradation (Shaeri Karimi *et al.* 2012). Some studies highlight the need to mitigate downstream water quality challenges but fail to consider thermal pollution (Dhar & Datta 2008). In other words, the ecological component in these models is not sufficiently robust to minimize the difference between natural flow and the altered flow regime. Several methods are available for estimating the natural thermal regime but are beyond the scope of the present study. In the case study, the change of elevation before and after dam construction was not considerable, and historical data demonstrated that the natural thermal regime upstream of the dam could be used to estimate the natural regime downstream.

4. SUMMARY AND CONCLUSIONS

The present study developed a novel framework of reservoir operation in which changes in downstream temperature regimes, water supply loss, and storage loss were minimized in a simulated period. A hybrid machine-learning model was used to simulate the downstream water temperature. The values of two indices, the NSE and RMSE, indicate that the data-driven model was robust with respect to simulating the downstream water temperature. BBO was used to optimize reservoir operation in which the thermal pollution is minimized while the supply benefits are maximized. Indices used to measure the performance of the optimization model included the reliability index, vulnerability index, RMSE, and NSE. The model was not fully able to satisfy water demand (only 10% could be supplied) in the simulated period due to the downstream environmental requirements. However, the temperature regime proposed by the optimization model is close to the natural temperature regime, which indicates the method can minimize environmental impacts but at the expense of water supply and storage. Notably, the storage loss was considerable during the simulation due to a challenging period for the reservoir in terms of inflow.

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DATA AVAILABILITY STATEMENT

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

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Afshar, A., Bozorg-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. & Bozorg-Haddad, O. B. 2011 Optimizing multi-reservoir operation rules: an improved HBMO approach. *Journal of Hydroinformatics* **13** (1), 121–139.

Agarwal, M. & Gupta, R. 2005 Penalty function approach in heuristic algorithms for constrained redundancy reliability optimization. *IEEE Transactions on Reliability* **54** (3), 549–558.

Ahmad, A., El-Shafie, A., Razali, S. F. M. & Mohamad, Z. S. 2014 Reservoir optimization in water resources: a review. *Water Resources Management* **28** (11), 3391–3405.

Angilletta Jr., M. J., Ashley Steel, E., Bartz, K. K., Kingsolver, J. G., Scheuerell, M. D., Beckman, B. R. & Crozier, L. G. 2008 Big dams and salmon evolution: changes in thermal regimes and their potential evolutionary consequences. *Evolutionary Applications* **1** (2), 286–299.

Arunkumar, R. & Jothiprakash, V. 2012 Optimal reservoir operation for hydropower generation using non-linear programming model. *Journal of the Institution of Engineers (India): Series A* **93** (2), 111–120.

Asadzadeh, M., Razavi, S., Tolson, B. A. & Fay, D. 2014 Pre-emption strategies for efficient multi-objective optimization: application to the development of Lake Superior regulation plan. *Environmental Modelling & Software* **54**, 128–141.

Asgari, H. R., Bozorg Haddad, O., Pazoki, M. & Loáiciga, H. A. 2016 Weed optimization algorithm for optimal reservoir operation. *Journal of Irrigation and Drainage Engineering* **142** (2), 04015055.

Awan, J. A. & Bae, D. H. 2014 Improving ANFIS based model for long-term dam inflow prediction by incorporating monthly rainfall forecasts. *Water Resources Management* **28** (5), 1185–1199.

Bartholow, J. M. 1995 The stream network temperature model (SNTEMP): a decade of results. In: *Workshop on Computer Application in Water Management: Fort Collins, CO*. (L. Ahuja, J. Leppert, K. Rojas & E. Seely, eds). Water Resources Research Institute, Colorado State University, Fort Collins, CO, pp. 57–60.

Bozorg-Haddad, O., Karimirad, I., Seifollahi-Aghmiuni, S. & Loáiciga, H. A. 2015a Development and application of the bat algorithm for optimizing the operation of reservoir systems. *Journal of Water Resources Planning and Management* **141** (8), 04014097.

Bozorg-Haddad, O. B., Moravej, M. & Loáiciga, H. A. 2015b Application of the water cycle algorithm to the optimal operation of reservoir systems. *Journal of Irrigation and Drainage Engineering* **141** (5), 04014064.

Dhar, A. & Datta, B. 2008 Optimal operation of reservoirs for downstream water quality control using linked simulation optimization. *Hydrological Processes: An International Journal* **22** (6), 842–853.

Di Baldassarre, G., Mazzoleni, M. & Rusca, M. 2021 The legacy of large dams in the United States. *Ambio* **50** (10), 1798–1808.

Dokeroglu, T., Sevinc, E., Kucukyilmaz, T. & Cosar, A. 2019 A survey on new generation metaheuristic algorithms. *Computers & Industrial Engineering* **137**, 106040.

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.

Gupta, H. V., Kling, H., Yilmaz, K. K. & Martinez, G. F. 2009 Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. *Journal of Hydrology* **377** (1–2), 80–91.

Jahandideh-Tehrani, M., Bozorg-Haddad, O. & Loáiciga, H. A. 2019 Application of non-animal–inspired evolutionary algorithms to reservoir operation: an overview. *Environmental Monitoring and Assessment* **191** (7), 1–21.

Ling, F., Foody, G. M., Du, H., Ban, X., Li, X., Zhang, Y. & Du, Y. 2017 Monitoring thermal pollution in rivers downstream of dams with Landsat ETM+ thermal infrared images. *Remote Sensing* **9** (11), 1175.

Manouchehri, G. R. & Mahmoodian, S. A. 2002 Environmental impacts of dams constructed in Iran. *International Journal of Water Resources Development* **18** (1), 179–182.

Mansouri, M., Safavi, H. R. & Rezaei, F. 2022 An improved MOPSO algorithm for multi-objective optimization of reservoir operation under climate change. *Environmental Monitoring and Assessment* **194** (4), 1–19.

Mengistu, T. & Ghaly, W. 2008 Aerodynamic optimization of turbomachinery blades using evolutionary methods and ANN-based surrogate models. *Optimization and Engineering* **9** (3), 239–255.

Olden, J. D. & Naiman, R. J. 2010 Incorporating thermal regimes into environmental flows assessments: modifying dam operations to restore freshwater ecosystem integrity. *Freshwater Biology* **55** (1), 86–107.

Qicai, L. 2011 Influence of dams on river ecosystem and its countermeasures. *Journal of Water Resource and Protection* **3** (1), 60–66.

Razavi, S. 2021 Deep learning, explained: fundamentals, explainability, and bridgeability to process-based modelling. *Environmental Modelling & Software* **144**, 105159.

Razavi, S., Hannah, D. M., Elshorbagy, A., Kumar, S., Marshall, L., Solomatine, D. P., Dezfuli, A., Sadegh, M. & Famiglietti, J. 2022 Coevolution of machine learning and process-based modelling to revolutionize Earth and environmental sciences: A perspective. *Hydrological Processes* **36** (6), e14596.
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. 2022 Design of optimal environmental flow regime at downstream of multireservoir systems by a coupled SWAT-reservoir operation optimization method. *Environment Development and Sustainability* 1–21. https://doi.org/10.1007/s10668-021-02081-w.
Sedighkia, M., Abdoli, A., Ayyoubzadeh, S. A. & Ahmadi, A. 2019 Modelling of thermal habitat loss of brown trout (Salmo trutta) due to the impact of climate warming. *Ecohydrology & Hydrobiology* **19** (1), 167–177.
Sedighkia, M., Datta, B. & Abdoli, A. 2022 Utilizing classic evolutionary algorithms to assess the Brown trout (Salmo trutta) habitats by ANFIS-based physical habitat model. *Modeling Earth Systems and Environment* **8**, 857–569.
Shaeri Karimi, S., Yasi, M. & Eslamian, S. 2012 Use of hydrological methods for assessment of environmental flow in a river reach. *International Journal of Environmental Science and Technology* **9** (3), 549–558.
Sharifi, M. R., Akbarifard, S., Qaderi, K. & Madadi, M. R. 2021 Comparative analysis of some evolutionary-based models in optimization of dam reservoirs operation. *Scientific Reports* **11** (1), 1–17.
Shi, L., Yang, R. J. & Zhu, P. 2012 A method for selecting surrogate models in crashworthiness optimization. *Structural and Multidisciplinary Optimization* **46** (2), 159–170.
Simon, D. 2008 Biogeography-based optimization. *IEEE Transactions on Evolutionary Computation* **12** (6), 702–713.
Sreekanth, J. & Datta, B. 2011 Comparative evaluation of genetic programming and neural network as potential surrogate models for coastal aquifer management. *Water Resources Management* **25** (13), 3201–3218.
Weber, N., Bouwes, N. & Jordan, C. E. 2014 Estimation of salmonid habitat growth potential through measurements of invertebrate food abundance and temperature. *Canadian Journal of Fisheries and Aquatic Sciences* **71** (8), 1158–1170.
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.
Zhu, S., Heddam, S., Nyarko, E. K., Hadzima-Nyarko, M., Piccolroaz, S. & Wu, S. 2019 Modeling daily water temperature for rivers: comparison between adaptive neuro-fuzzy inference systems and artificial neural networks models. *Environmental Science and Pollution Research* **26** (1), 402–420.

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