Applied Water Science (2022) 12:73
https://doi.org/10.1007/s13201-022-01593-8

REVIEW ARTICLE

Review on generating optimal operation for dam and reservoir water system: simulation models and optimization algorithms

Saad Mawlood Saab[1] · Faridah Binti Othman[1] · Chee Ghuan Tan[1] · Mohammed Falah Allawi[2] · Ahmed El-Shafie[1]

Received: 30 July 2021 / Accepted: 10 February 2022 / Published online: 21 March 2022

Abstract
Accurate and reliable optimization and simulation of the dam reservoir system to ensure optimal use of water resources cannot be achieved without precise and effective models. Providing insight into reservoir system operation and simulation modeling through a comprehensive overview of the previous studies and expanding research horizons can enhance the potential for accurate and well-designed models. The current research reviews previous studies that have used optimization methods to find optimal operating policies for a reservoir system over the past 20 years. Indeed, successful operating policies cannot be obtained without achieving accurate predictions of the main hydrological parameters in the reservoir system, which are inflow and evaporation. The present study focuses on giving an overview of the applications of AI-based models for predicting reservoir inflow and evaporation. The advantages and disadvantages of both optimization algorithms and predictive models have been summarized. Several recommendations for future research have also been included in the present review paper.

Keywords Inflow · Water losses · Reservoir · Simulation

Introduction

Droughts and floods occur frequently in many parts of the world as a result of climate change. These phenomena pose a challenge to water resources management and planning (Ehteram et al. 2017). Dams and reservoirs are built to control these phenomena and to achieve many purposes such as water supply, water irrigation, hydropower generation, and others. It could be noticed that there are high conflict and competition among reservoir purposes particularly during critical conditions (Labadie 2004). As a result, finding and defining the best operating rules is often a complex problem while managing a reservoir system.

The operation of the dam reservoir is one of the most important challenges facing decision makers and planners in order to make effective use of the available water resources. Accordingly, the focus should be on further studies to enhance the durability and operating efficiency of a dam reservoir system to optimize beneficial uses of the system (Higgins and Brock 1999).

Optimization algorithms are appropriate tools to addresses reservoir operation problem and enhancing management and planning water resources. The past studies employed several optimization models for dam reservoir system operation. The optimization algorithms can be classified into two broad categories: conventional (traditional) and evolutionary methods (Ahmadi et al. 2014; Ashofteh et al. 2015). The traditional approach is useful to determine the proper solution for both maximum and minimum unconstrained of the continuous functions (Wehrens et al. 2000). The first approach includes linear and nonlinear dynamic programming, random search, stochastic programming, and others. These techniques have been applied by many previous studies in reservoir system operation. However, the performance of such conventional approaches is imprecise in addressing the complex operational issue especially with multi-purpose reservoirs (Bozorg-Haddad et al. 2016a).

The evolutionary methods are used to solve the matter of optimal operation of a dam reservoir system. The previous studies reported that evolutionary methods have higher efficiency and reliability than conventional techniques. These

✉ Ahmed El-Shafie
elshafie@um.edu.my

1 Department of Civil Engineering, Faculty of Engineering, Universiti Malaya, 50603 Kuala Lumpur, Malaysia

2 Dams and Water Resources Engineering Department, College of Engineering, University of Anbar, Ramadi 31001, Iraq

KACST Springer

methods provide satisfactory results in handling and solving the multi-objectives functions.

Indeed, the successful management of the dam reservoir operation depends on the accuracy of the hydrological parameters data. The inflow and evaporation parameters have the largest influence among hydrological parameters on the operation procedure. As a result, the development of an accurate predictive model that has ability to predict inflow and evaporation records, is an important issue for obtaining a successful dam reservoir operating policy (Allawi et al. 2019a, b).

Reservoir inflow forecasting is a large and active research area in the water resources field. In fact, there are several meteorological parameters that influence behavior and pattern of the inflow parameter. Accordingly, long- and short-term forecast models are very important for the sustainable management of water resources. The actual inflow time series data are often nonlinear, non-stationary and temporally variable due to the influence of many phenomena such as temperature, wind speed and rainfall on the inflow behavior. The reservoir flow mechanism will likely to be extremely different from time to time and from place to another. Therefore, forecasting reservoir flow with acceptable accuracy is quite complicated (Guo et al. 2011).

In recent years, it has been observed that there has been a significant increase in the type and number of methods developed that can be used to model and predict hydrological parameters, including popular data-driven methods. Traditional black box time series methods such as Auto-Regressive Integrated Moving Average (ARIMA), Linear Regression (LR), Nonlinear Regression (NLR), assume that the data for hydrological parameters are stationarity and linear (Solomatine and Ostfeld 2008). Thus, such methods are often unable to deal with instability and nonlinearity involved in the hydrological process. As a result, the previous studies have paid a lot of attention for developing the models that are capable for modeling non-stationary and nonlinear processes.

Reservoir losses due to evaporation are also a major issue in the operation of the dam and reservoir system. Predicting the amount of surface water losses is a critical aspect of developing a reliable operational policy. An effective modern model for predicting reservoir evaporation is necessary to know the amount of water available in the dam reservoir for each period (Fayaed et al. 2013).

In fact, there are two main approaches for estimating evaporation from an open water body which are direct and indirect methods. The first method involves measuring the evaporation pan such as class U-pan, A-pan, and others (Farnsworth and Thompson 1982; Rosenberg et al. 1983). The indirect approach includes many methods such as water budget (e.g., Guitjens 1982), energy budget (e.g., Fritschen 1966), mass transfer (e.g., Harbeck 1962), combination (e.g., Penman 1948) and measurement (e.g., Young 1947). Although there are a large number of literature studies that have used these equations or methods, most of the proposed methods require a lot of observed meteorological data and are therefore more prone to errors. It is often difficult to use such methods because data are not available all times and places (Bai et al. 2016a; Yu et al. 2017). Moreover, the empirical equations are not as efficient as required and do not produce promising results due to the complex nonlinear pattern of evaporation parameter (Nourani and Fard 2012). Therefore, an efficient and accurate predictive model is needed that is capable of detecting evaporation patterns with a high level of accuracy.

During the last few decades, many modern methods have been developed to forecast the hydrological parameters of a reservoir such as Artificial Intelligence (AI) models. AI methods have received a lot of interest from hydrologists to deal with non-static, dynamic, and stochastic patterns of hydrological database. These computational methods and models have a high capacity to overcome complex simulation of pattern parameters. The AI-based models are characterized by having the ability to handle a large amount of data. The prediction of evaporation and inflow depends on several environmental parameters and these characteristics can experience temporal changes (Nourani et al. 2014).

Recently, there has been a significant increase in the number of data-driven approaches applied to hydrologic modeling, in particular, predicting evaporation and inflow data. Specifically, in the field of forecasting the main hydrological parameters in a reservoir system, there are many AI methods that have been used such as an artificial neural network (ANN), support vector machine (SVM), fuzzy logic (FL), and others.

Objectives

The main aim of the current research is reviewed the previous studies that have been employed classic and modern computational methods for handling management of the dam and reservoir system. Applications of AI methods and others were considered in terms of reservoir operation and forecasting inflow and evaporation component. The presented study addresses of effect of the forecasting models accuracy on the reservoir operation efficiency. The challenges that the scientists experienced while modeling the operating of the reservoir system such as nonlinearity, uncertainty, and multi-purposes are mentioned. The applications of optimization algorithms to operate the reservoir system and their basic theory are given in second section. The evaluation for the performance of such algorithms is addressed in "Evaluation and assessment" section. On the other hand, the concept for AI methods and their implementation to forecast inflow and evaporation parameters are reported in third section.

Assessment of these methods and their advantage and disadvantage are discussed in "Evaluation and assessment" section. Author names, year of publication, type of model, and other details are presented in Tables 1, 2 and 3. Fourth section shows the recommendation for future research. Summary and conclusion of the current research are given in the last section.

Optimization algorithms

Genetic algorithm and genetic programming

In fact, several optimization algorithms were developed to solve reservoir operation problem. It has been reported may advantages and drawbacks for these methods. The most common approaches within optimization algorithm derives from computational intelligence which is evolutionary computation. The genetic algorithm (GA) represents a well example for the evolutionary computation concept. Such algorithm depends on the generation of a population that simulates natural evolution, selection, and natural genetics (Haddad et al. 2011; Ehteram et al. 2017; Yu et al. 2018).

Genetic Algorithm has four basic units which are bit, gene, chromosome, and gene pool. The first unit (bit) is the basic component that could be represented by a digit of 0 or 1. The second unit (gene) is formed by the combination of bits. The attachment of genes generates a chromosome that could be a possible solution for optimization problem. The combination of many chromosomes forms gene pool (Whigham and Crapper 2001; Reddy and Nagesh Kumar 2007; Wafae et al. 2016).

Sharif and Wardlaw (2000) examined the performance of genetic algorithm through application to operate the reservoir system in Indonesia. The study considered the existing development situation in the reservoir basin. The comparison between GA with discrete differential dynamic programming method has been conducted. The results demonstrated that GA provided high-level accuracy for operation rules compared to other methods.

Chang and Chang (2001) integrated the genetic algorithm with adaptive neuro fuzzy inference system (ANFIS) for reservoir operation optimization. They applied the proposed model to generate optimal operation policy for the Shih-Men reservoir in Taiwan. The model performance was more reliable compared to other optimization methods. The genetic algorithm has been also employed by Chang et al. (2003) for determining the flushing operational rules for Tapu reservoir which is located in Taiwan. The performance of GA has been examined by several statistical indicators. The results shown that the GA is superior to original operation results that are using in the reservoir system.

Genetic Algorithm was employed to find the best operation policy of the multi purposes reservoir system by Ahmed and Sarma (2005). The operation policy has been derived based on monthly inflow series of 100-year. The results demonstrated by the GA model have been compared with that derived by stochastic dynamic programming (SDP) method. The efficiency of the proposed models was examined basis of their performance in simulating the reservoir system during 20-year. The study shown that the GA model generated promising and effective operating policies. Such policies could be helpfully utilized for reservoir operation.

Jothiprakash and Shanthi (2006) developed genetic algorithm to obtain best operational rules for storage reservoir. The objective function has been formulated to minimize an annual sum of squared deviation from target water irrigation releases and target storage volume. They found that the water releases volume generated by GA are meet the requirements in many times. It has been concluded that the proposed algorithm could be helpful and effective model when use it for operating the Pechiparai reservoir, located in Tamil Nadu, India.

In 2007, Momtahen and Dariane (2007) used the genetic algorithm as an optimizer model to find best operation rules for the reservoir system. The performance of GA model has been evaluated by comparing with dynamic programming and stochastic dynamic programming method. They concluded that the policies provided by GA model reduced the deficit between water release and demand.

Chen et al. (2007) have developed a new kind of high-level species evolution called Macro Evolutionary Multi-Objectives GA (MMGA) model. The suggested model has ability to avoid premature convergence which could be raised whiling the selection process of traditional GA. MMGA has been employed for optimizing the operation rules of the multi-purpose reservoir system in Taiwan. The proposed model enriches the abilities of genetic algorithm for handling the optimization problem by diversifying the possible solution set. The simulation results indicated that the MMGA model could be a viable alternative for solving the optimization problem in the water resources field.

Li and Wei (2008) have improved the genetic algorithm (GA) by integrating with simulated annealing (SA) method for reservoir operation, the proposed model is named (IGA-SA). The IGA-AS has been utilized for determining optimal policies of the Wujiangdu, Hongjiadu and Dongfeng reservoirs which are located on Yangtze river, China. The results indicated that the IGA-SA model is able to provide high-level accuracy in meeting the water demand.

Chang et al. (2010) introduced constrained genetic algorithm (CGA). Such model was applied to operate the Shih-Men reservoir, located in Taiwan. The evaluation metrics shown that the suggested optimization model attained well performance accuracy compared to other conventional

Table 1 Summary of previous studies that were established to model reservoir operation using optimization algorithms

Authors	Type of optimization algorithm	Case study/location	Research remark
Sharif and Wardlaw (2000)	GA	Brantas Basin/Indonesia	The performance of the proposed algorithm was compared with dynamic programming method
Chang and Chang (2001)	GA	Shih-Men Reservoir/Taiwan	The authors improved the model's efficiency by integrating with ANFIS method
Chang et al. (2003)	GA	Tapu Reservoir/Taiwan	The GA model was employed to find optimal flushing operation rule curves
Ahmed and Sarma (2005)	GA	Pagladia Reservoir/India	The performance of the optimization algorithm was examined by simulating the reservoir system during 20-year
Jothiprakash and Shanthi (2006)	GA	Pechiparai Reservoir/India	The objective function was formulated to reduce the deficit between release and demand
Momtahen and Dariane (2007)	GA	Dez reservoir/Iran	The study confirmed the feasibility of the GA model in providing reliable operating policies
Chen et al. (2007)	GA	Fei-Tsui and Tan-Shui Reservoirs/Taiwan	In this study, the early convergence that might appear during the GA process was avoided by integrating the Macro-evolution technique with the genetic algorithm
Li and Wei (2008)	GA	Wujiangdu, Hongjiadu and Dongfeng reservoirs/China	Integration between genetic algorithm and simulated annealing has been carried out
Chang et al. (2010)	GA	Shih-Men reservoir/Taiwan	The study showed that the GA model is not able to handle operating the dam reservoir for long-term period
Wang et al. (2011)	GA	Shih-Men Reservoir/Taiwan	The research suggested a multitier interactive genetic algorithm. This technology decomposes the long series into many small sub-series to find the best solution more quickly
Hınçal et al. (2011)	GA	Blue Mesa Reservoir/USA	The GA model was used to find optimal operating rules for a system of three different reservoirs
Li et al. (2012)	GA	Three Gorges Reservoir/China	Integration between Incremental Dynamic Programming (IDP) with a genetic algorithm was performed
Li et al. (2014)	GP	Three Gorges Reservoir/China	The operating policies obtained by GP were checked against those provided by ANN model
Kumar and Reddy (2006)	ACO	Hirakud reservoir/India	The study aims to reduce the deficit between irrigation water and water demand and maximize the hydropower production
Afshar et al. (2006)	ACO	Dez reservoir/Iran	The authors presented a good model of identifying and generating a complete set of parameters to monitor any given optimization issue
Jalali et al. (2007)	ACO	Benchmark Problems	The study presents a modern model which is multi-colony technique that has the potential to avoid the probability of losing the global optimum

Table 1 (continued)

Authors	Type of optimization algorithm	Case study/location	Research remark
Madadgar and Afshar (2009)	AC	Dez reservoir/Iran	The AC model evidenced its capability to provide highly accurate operational policies
Afshar et al. (2009)	ACO	Dez reservoir/Iran	The developed optimization algorithm contains a new information exchange policy based on the principle of the multi-colony algorithm
Hossain and El-shafie (2014)	ABC	Aswan High Dam/Egypt	In this research, three different classes of inflow, high, medium and low, are considered to generate operating curves
Hossain and El-Shafie (2014)	ABC	Klang Gate Dam/Malaysia	Three indicators, reliability, resilience and vulnerability were used to evaluate the performance of optimization algorithms
Liao et al. (2014)	ABC	Three Gorges Reservoir/China	The authors presented a local search technique based on chaos theory
Hossain et al. (2015)	ABC	Klang Gate Dam/Malaysia and Aswan High Dam/Egypt	The developed model has demonstrated a high ability to determine successful operation rules for two reservoirs located in two different environmental zones
Chen et al. (2016)	ABC	Zhanghe Irrigation Distict/China	Researchers improved the performance of ABC method by combining it with differential evolution model
Ahmad et al. (2016)	ABC	Timah Tasoh Dam/Malaysia	The performance of ABC model was compared with the robust algorithm that is Gravitational Search Algorithm. It is observed that the ABC shows faster convergence and higher stability
Jia et al. (2016)	DE	Shiguan River/China	Four different flood operation scenarios have been proposed to examine the performance of the model
Reddy and Nagesh Kumar (2007)	PSO	Bhadra Reservoir/India	In this work, the optimization model was developed by incorporating the principles of Pareto dominance into PSO algorithm
Nagesh Kumar and Janga Reddy (2007)	PSO	Bhadra reservoir/India	The authors suggested a modern technique called elitist mutation in order to improve an efficiency of the PSO model
Baltar and Fontane (2008)	PSO	Benchmark Problems	The study presented a multi-objective PSO which evaluates alternative solutions based on Pareto dominance
Mousavi and Shourian (2010)	PSO	Bakhtiari reservoir/Iran	The authors studied two different types of optimization problems namely, optimization design and operational reservoir water release
Afshar (2012)	PSO	Dez reservoir/Iran	Effective operating rules were determined using Partially Constrained Particle Swarm Optimization (PC-PSO)

Table 1 (continued)

Authors	Type of optimization algorithm	Case study/location	Research remark
SaberChenari et al. (2016)	PSO	Mahabad reservoir/Iran	The authors investigated the potential of the PSO model in reducing the amount of deficit between irrigation water and water demand
Bilal et al. (2020)	PSO	Mula Reservoir/India	The authors combined Dynamic Programming (DP) with Particle Swarm Optimization to improve the performance of the optimization model
Garousi-Nejad et al. (2016a)	Firefly Algorithm	Benchmark Problems	A modification of the Firefly algorithm procedure was performed in this study
Garousi-Nejad et al. (2016b)	Firefly Algorithm	Aydoghmoush Dam and Karun-4 Reservoir/Iran	The FA model was used to find operating rules for two long-term reservoir that are operated for irrigation and hydropower generation purposes
Bozorg-Haddad et al. (2015)	Bat Algorithm	Several Benchmark Problems and Karun-4 Reservoir/Iran	The proposed model is applied to solve a mathematical optimization problem and a real case study. The BA provided excellent solutions to both problems
Ahmadianfar et al. (2016)	Bat Algorithm	Benchmark Problems	To enhance the global search capacity, an improvement of the bat algorithm has been made using a hybrid mutation strategy
Bahrami et al. (2018)	Cat Swarm Optimization (CSO)	Benchmark Problems	The reliability and effectiveness of the CSO model was compared with that of the GA model
Hosseini-Moghari et al. (2015a, b)	Cuckoo Optimization Algorithm (COA)	Karun-4 Reservoir/Iran	The operating policies obtained by COA model were checked against those provided by ICA and GA model
Ming et al. (2015)	Cuckoo Search Algorithm	Wujiang Multi-Reservoir/China	The model has been developed for reservoir operation in terms of maximizing hydropower generation
Abedinia et al. (2014)	Shark Algorithm	Benchmark Problems	The model has been developed to operate the reservoir system to maximize hydropower generation
Ehteram et al. (2017)	Shark Algorithm (SA)	Bazoft Reservoir/Iran	The SA model provided reliable operating rules compared to those introduced by GA and PSO model
Allawi et al. (2018)	Shark Algorithm	Aswan High Dam/Egypt	The proposed optimization algorithm was applied to find operating rules for a large reservoir located in a semi-arid region
Allawi et al. (2019a, b, c)	Shark Algorithm	Timah Tasoh Dam/Malaysia	A comprehensive evaluation and analysis of the model's performance has been performed using several statistical indicators. It was reported that the successful and effective operating policies of the reservoir system were obtained by shark algorithm

Table 2 Summary of previous studies that were established to model reservoir inflow forecasting using AI methods

Authors	Developed model	Performance metrics	Time scale	Research remark
Coulibaly et al. (2000)	FFNN	NSE, R^2, RMSE, PFC, CORR	Daily	The proposed FFNN model was applied to forecast inflow in a case study located in Canada
Coulibaly et al. (2001)	DNN	NSE, R^2, RMSE, PFC, LFC	Daily	The inflow data were forecasted in a case study located in Canada
El-Shafie et al. (2009)	RBF-NN	PFC, LFC, FE, RE	Monthly	Aswan High Dam (AHD) located in Egypt was chosen as a case study. The study concluded that the RBF-NN model was very successful in prediction the inflow data for the next few months
El-Shafie and Noureldin (2011)	ENN	RMSE, RE	Monthly	Reservoir Inflow Forecasting was performed in a case study located in Egypt. It has been achieved a good improvement in forecasting accuracy with RNN model
Valipour et al. (2012)	DAR-NN	RMSE, MSE, RE, C_v	Monthly	Dez reservoir located in Iran was selected as a case study. Different architectures were created for the proposed models utilizing two transfer functions, sigmoid and radial basis function
Valipour et al. (2013)	AR-NN	RMSE, MBE, RE, C_v	Monthly	The forecasting accuracy of the dam reservoir inflow has been improved by the predictive model used. The proposed AR-NN model was used to forecast inflow data for a case study located in Iran
Elizaga et al. (2014)	ANN	RMSE, MAE, RRSE, R, RAE	Daily	The authors forecasted daily inflow records in a case study in the Philippine
Chiamsathit et al. (2016)	MLP	NSE, R^2	Monthly	The inflow data were forecasted in a case study located in Thailand. The proposed MLP model evidenced reliable for reservoir inflow records
Apaydin et al. (2020)	RNN	NSE, RMSE, MAE, CC	Daily	The authors predicted the inflow data for a case study located in Turkey
Lee et al. (2020)	MLP	Coefficient S	Monthly	The inflow forecasting model was applied to a case study in Korea
Hadiyan et al. (2020)	NARNN	RMSE, R, R^2	Monthly	The proposed NARNN was applied to forecast inflow data for a case study located in Iran
Zhang et al. (2020)	ANN	NSE	10-day	Six different climate parameters were used as input variables. The case study is Huranren reservoir located in China
Lin et al. (2006)	SVM	RMSE, CORR	Monthly	The study concluded that the SVM-based model could be a promising tool due to its efficiency, robustness and accuracy in forecasting reservoir inflow data. The authors used the predictive model to forecast monthly inflow data for a case study located in China
Lin et al. (2009)	SVR	RMSE, MCE, MCP	Hourly	A comparison was made between the performance of the proposed model and Backpropagation Network (BPN). The Fei-Tsui reservoir located in Taiwan was chosen as a case study
Li et al. (2009)	SVM	Box Plot	Monthly	The authors forecasted the inflow data in a case study located in Taiwan. The SVM-based forecasting framework has been modified to enhance the predictability of the inflow

Table 2 (continued)

Authors	Developed model	Performance metrics	Time scale	Research remark
El-Shafie et al. (2007)	ANFIS	RMSE, RE, R^2	Monthly	The ANFIS method has a high ability to address the uncertainties and ambiguities present in the inflow pattern. The reservoir inflow parameter was forecasted in a case study located in Egypt
Bae et al. (2007)	ANFIS	RMSE, CC	Monthly	The researchers applied the ANFIS model to forecast inflow for a case study in South Korea
Wang et al. (2009a, b)	ANFIS	R, NSE, RMSE, MAPE	Monthly	The monthly inflow data were collected from two different case studies and were used to develop different predictive models investigated in the research. The selected case studies are located in China
Lohani et al. (2012)	ANFIS	RMSE, NSE, R^2	Monthly	The ANFIS model was employed to forecast the reservoir inflow in a case study located in India
Awan and Bae (2013)	ANFIS	RMSE, CC	Monthly	Temperature and Rainfall data have been employed as input variables to train the proposed models. The authors predicted the inflow data for a case study located in South Korea
Bai et al. (2016a, b)	ANFIS	MAPE, NRMSE, R, PPTS	Monthly and yearly	The forecasting accuracy was improved by integrating ANFIS with an Even Gray Model (EGM). The Three Gorges reservoir located in China was selected as a case study
Allawi et al. (2017)	CANFIS	RMSE, MAE, RE, R^2	Monthly	Four training procedures were proposed to examine the performance of the CANFIS model. The inflow records were predicted in a case study located in Egypt
Wang et al. (2009a, b)	WNM	RE	Annual, 10 days, Daily	The proposed WNM was applied to forecast inflow data for a case study located in China
Wang et al. (2010)	SVM-PSO	RMSE, RE	Annual	The PSO algorithm is used to find the optimal internal parameters for SVM model. The inflow data were predicted in a case study in China
Noori et al. (2011)	SVM-PCA	RMSE, R^2	Monthly	Several input selection algorithms have been used to select optimal input combinations for modeling. The case study located in Iran was selected
Jothiprakash and Kote (2011)	M5 Model Tree	MSE, MAE, MRE, NSE, R, AIC, RD	Monthly, Seasonal	The predictive model was used to forecast inflow data for a case study located in India
Jothiprakash and Magar (2012)	LGP	RMSE, NSE, BIC, AIC and R^2	Daily, Hourly	The authors used the LGP model to forecast the inflow data for a case study located in India
Budu (2014)	WNN	RMSE, PFC, MAD, COE, PI, d and R^2	Daily	The predictive model was applied for inflow forecasting for a case study located in India
Kumar et al. (2015)	BWNN	R^2, NSE, RMSE, P_{dv}, MAE	Daily	Daily inflow records were predicted in a case study located in Inia
Cheng et al. (2015)	Hybrid model	RMSE, MAE, MAPE, R^2, NSE	Monthly	The proposed model was employed to forecast inflow data for a case study located in China

Table 2 (continued)

Authors	Developed model	Performance metrics	Time scale	Research remark
Bai et al. (2016a, b)	MDFL	MAPE, PPTS, NRMSE, R^2	Daily	The Three Gorges reservoir located in China was selected as a case study. The MDFL model provided excellent forecasting results
Bozorg-Haddad et al. (2016a, b)	ANN-GA	MSE, NSE, R^2	Monthly	Two different case studies were chosen in the research. The first case study is located in Iran and the second case study is located in China
Moeeni and Bonakdari (2016)	SARIMA-ANN	MARE, R^2, RMSE, BIAS, SI, MSE, AIC, SBC	Monthly	The hybrid model forecasts peak inflow values much better than the classic predictive methods. The inflow records were forecasted in the case study of the Jamishan Dam, located in Iran
Li et al. (2016)	DRBM	MAPE, NRMSE, TS	Daily	The performance of the predictive model was inspected by forecasting inflow in two different case studies, located in China
Hong et al. (2020)	RF-MLP	R, R^2, NSE, RMSE, MAE	Daily	Daily inflow data were forecasted in a case study located in South Korea
Tikhamarine et al. (2020)	SVR-GWO	RMSE, MAE, R, NSE, WI	Monthly	Aswan High Dam located in Egypt was selected as a case study to examine the performance of the proposed model
Afan et al. (2020)	RBFNN-GA	MAPE, MBE, MAE, d, RE, R^2	Monthly	The authors forecasted inflow data for a case study located in Egypt
Osman et al. (2020)	FOS	RMSE, NRMSE, NSE, RE, MBE, R^2	Monthly	The case study was selected located in Egypt

R—Correlation Coefficient, NSE—Nash Sutcliffe Efficiency, RMSE—Root Mean Square Error, AIC—Akaike Information Criteria, BIC—Bayesian Information Criteria, d—Index of agreement, PI—Persistence Index, MAD—Mean Average Deviation, PFC—Peak Flow Criteria, LFC—Low Flow Criteria, FE—Forecasting Error, RE—Relative Error, C_v—Variation Coefficient, MBE—Mean Bias Error, MAE—Mean Absolute Error, RAE—Root Absolute Error, CC—Correlation Coefficient, MCE—Mean Coefficient of Efficiency, MCP—Mean Coefficient of Persistence, PPTS—Peak Percent Threshold Statistics, MAPE—Mean Absolute Percentage Error, NRMSE—Normalized Root Mean Square Error, RD—Coefficient of Determination, MRE—Mean Relative Error, P_{dv}—Percentage Deviation in Peak, MSE—Mean Square Error, MARE—Mean Absolute Relative Error, SI—Scatter Index, SBC—Schwarz Bayesian Criterion, TS—Threshold Statistic, WI—Willmott Index

Table 3 Summary of previous studies that were established to model reservoir evaporation prediction using AI methods

Authors	Developed model	Performance metrics	Time scale	Research remark
Keskin and Terzi (2006)	ANN	MSE, R^2	Daily	Six meteorological parameters including air temperature, RH, SR, WS, sunshine, water temperature, were employed to develop ANN model. The reservoir evaporation data were predicted in a case study located in Turkey
Tan et al. (2007)	ANN	R^2	Daily	The authors predicted evaporation records for a case study located in Singapore
Moghaddamnia et al. (2009a, b)	ANN	RMSE, R^2	Daily	The performance of the proposed models was improved using technique called gamma test. Chahnimeh reservoirs were selected as a case study, which are located in Iran
Tabari et al. (2010)	ANN	R, RMSE, MAE	Daily	Evaporation data were collected form a reservoir located in Iran
Allawi and El-Shafie (2016)	ANN	MAE, RE, MSE, R^2	Monthly	The ANN model was applied to predict evaporation records for a case study located in Malaysia
Malik et al. (2018)	RBF-NN	RMSE, CE, R	Daily	The evaporation data were collected from a case study located in India
Allawi et al. (2019a, b, c)	ANN	RMSE, RE, MAE, NSE, KGE, R^2	Daily, Weekly, Monthly	Prediction of evaporation amounts was performed to a case study located in Malaysia
Moghaddamnia et al. (2009a, b)	SVM	RMSE, MAE, MSE, R^2	Daily	The researchers used the SVM to predict the evaporation data for a case study located in Iran
Baydaroğlu and Koçak (2014)	SVM	MAE, R^2	Daily	The selected data were collected from the Ercan meteorological station
Tezel and Buyukyildiz (2016)	SVM	MAE, RMSE	Monthly	The proposed SVM model was applied to predict evaporation data for a case study located in Turkey
Keskin et al. (2004)	ANFIS	MSE, R^2	Daily	The ANFIS model was applied to predict evaporation records for a case study located in Turkey
Tabari et al. (2012)	CANFIS	RMSE, MAE, PE, R	Daily	The authors predicted evaporation data for a case study located in Iran
Salih et al. (2019)	CANFIS	MAE, RMSE, NSE, MAPE, RE, R^2	Monthly	Evaporation prediction modeling has been established based on several meteorological parameters. Nasser lake was chosen as a case study
Allawi et al. (2020a, b)	CANFIS	RMSE, MAE, MAPE, RE, R^2	Monthly	The evaporation data were predicted for a two case studies located in Malaysia and Egypt
Abghari et al. (2012)	WNN	RMSE, R^2	Daily	The authors predicted evaporation data for a case study located in Iran
Arunkumar and Jothiprakash (2013)	GP	MSE, MAE, RMSE, NSE, %MH, %ML, R	Daily	The predictive model succeeded in providing accurate results with five input climate parameters. The case study located in India has been considered in this research
Izadbakhsh and Javadikia (2014)	FFNN-GA	MSE, MSNE, MAE, P, R, R^2	Daily	The structure of the predictive model was optimized by GA technique. The case study is in Iran

Table 3 (continued)

Authors	Developed model	Performance metrics	Time scale	Research remark
Ghorbani et al. (2017)	MLP-FFA	RMSE, NSE, WI, MAE, Taylor diagram	Daily	Five meteorological parameters have been used to establish the evaporation prediction modeling. The evaporation data were predicted for a case study located in Iran
Allawi et al. (2020a, b)	CANFIS-GA	RMSE, MAE, MAPE, RE, R^2	Monthly	The proposed CANFIS-GA model was applied to predict the evaporation records for two different case studies. The first case study is located in Malaysia and the second case study is located in Egypt
Wu et al. (2020)	ELM	RMSE, MAE, MAPE, NSE, AE, t-statistic, R^2	Monthly	The research was conducted to predict the evaporation records for a case study located in China

RH—Relative Humidity, SR—Solar Radiation, WS—Wind Speed, KGE—Kling-Gupta Efficiency, MSNE—Mean Square Normalized Error, AE—Absolute Error, %MH—Percentage Mean Error in Estimating High values, %ML—Percentage Mean error in estimating Low values, CE—Coefficient Efficiency

models. But the researchers found that the GA model could not handle the complicated matters such as operating the reservoir system for long-term. Wang et al. (2011) tried to solve such issue by improving the modern model (i.e., Multitier Interactive GA). It attained good results in operating a reservoir system during 20-years with reducing the computation time by 80%.

To inspect the efficiency of GA model in finding optimal operating rules of multi-reservoir system, Hınçal et al. (2011) had utilized the performance of GA to operate three reservoirs, located in Colorado river. The objective function of the proposed model is a minimizing the deficit between the water release and water irrigation demand. The study demonstrated that the GA is reliable and applicable tool for identifying optimal operation rules. A combination between Incremental Dynamic Programming (IDP) with genetic algorithm was conducted by Li et al. (2012). They applied the suggested model for operating Three Gorges Dam which is located in China. The study concluded that the operation rules derived by optimization method could be promising model for reservoir system operation.

Genetic Programming (GP) model was employed by Li et al. (2014) to derive operation rules for reservoir system for supplying downstream and hydropower generation. The proposed algorithm has been applied to operate the Three Gorges Dam system which is located in China. The GP method provided accurate and proper decision variables. The operation rules obtained by GP model have been superior to conventional rules and Artificial Neural Network (ANN) rule curves. The study shown that the GP is an applicable tool, flexible, efficient, and significantly accurate.

Ant colony and artificial bee colony

Ant Colony Optimization (ACO) is a meta-heuristic method to solve complicated optimization problems. Ant Colony (AC) algorithm has been firstly introduced by Dorigo (1992). The principle of ACO model is inspired by the behavior of ants which utilize the pheromone as the communication tool. They depend on the pheromone to find the shortest path between food sources and their nest. It is known that ants send the information regarding the short way to the food by putting pheromone trail. Ants leave some pheromone on the ground to identify their path. The new ants could detect and follow the laid pheromone, hence enhancing the path by their pheromone. Thus, the best and short way is that agreed by the most of previous and new ants. In ACO algorithm, the pheromone is considered as a distributed numerical information, that use it by ants to establish possible solutions. Ants could adapt these solutions whiling execution the algorithms to create their search experience.

Kumar and Reddy (2006) examined the performance of Ant Colony Optimization (ACO) model for solving the nonlinear optimization problem. The proposed algorithm has been applied to obtain operation policies for Hirakud reservoir, which is the multi purposes reservoir system located in India. The objectives of the algorithm are to reduce irrigation water deficit and maximizing the hydropower production. The results demonstrated that the ACO performed better than GA, in terms of higher hydropower production and lower deficit between water demand and irrigation.

The new Continuous Ant Colony Optimization (C-ACO) method is employed for reservoir operation. Afshar et al. (2006) presented an elitist strategy for C-ACO model so that the best solution of each iteration is directly copied to the next iteration to enhance the algorithm performance. The efficiency of the C-ACO model has been evaluated by comparing its performance against with some common heuristic methods.

Some of the previous studies reported that the performance of ACO model could be relatively weak to handle the continuous problems. Therefore, Jalali et al. (2007) introduced modern version called multi-colony model that could help in generating large search space to avoid the probability of losing the global optimum. The proposed model efficiency was investigated by operating 10-reservoirs system. The researchers conclude that the suggested algorithm has ability to provide promising operation policies and reliable.

Madadgar and Afshar (2009) improved the AC method for optimization reservoir operation. Such model has been applied to operate single reservoir system. According to the obtained results, the proposed optimization model is slightly robust in determining good solution that could be near to optimal solutions. Multi-objectives optimization utilizing heuristic approaches was introduced as the sub-discipline which merges the heuristic computation field with classical field. Afshar et al. (2009) established the Non-dominated Archiving Ant Colony Optimization (NAACO), that uses multi-colony ant model concept and combines the new information exchange policies. The NAACO method attained reliable optimization results in operating multi-objective reservoir system.

On the other hand, the artificial bee colony algorithm has been also adopted as a proposed tool for studying the reservoir operation. Hossain and El-shafie (2014) have considered the performance of ABC to find the optimal operation policies for the Aswan High Dam, which is located in Egypt. The operation guidelines by ABC have been compared with those derived by GA technique. The performance evaluation was conducted using many statistical indicators. The researchers found out that the Artificial Bee Colony technique able to meet the irrigation water demand during most of the simulation period. It has been concluded that the performance and efficiency of ABC model is higher than GA model.

Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) were used in searching for the reliable operation policies by Hossain and El-Shafie (2014). The objective function for such algorithms is minimizing deficit volume between water release and demand. The operation rules generated by suggested methods were inspected by simulating the reservoir during certain period. Such investigation period emphasizes that the performance of ABC and PSO method is well and much faster in obtaining the best solutions of a reservoir operation. The study also demonstrated that ability of ABC is relatively better that PSO model. The results obviously showed that the determination of the optimal operation rules was obtained by ABC method.

Liao et al. (2014) developed Artificial Bee Colony (ABC) method to find optimal scheduling release curves for Three Gorges Project in China. The results indicated that the proposed method has high ability to operate the reservoir system.

The main concept behind ABC method is to provide general rules regarding distribute multi-dimensional tasks, particularly for complicated and nonlinear problems like reservoir operation optimization problem. Thus, Hossain et al. (2015) have utilized ABC method to search for optimal operation policies for the reservoir system. The ability of ABC method has been investigated by comparing with three popular algorithms namely, PSO, GA, and SDP. The proposed model (i.e., ABC) has been employed to solve the operation optimization problem for two different case studies located in two different environment zones. It has been noted that the study demonstrated that the ABC model is a promising tool in handling the critical cases when there is low flow. The operation policies derived by ABC method is better that obtained by GA, PSO, and SDP.

To solve nonlinear complicated optimization problem, Chen et al. (2016) have enhanced the ABC method by combining differential evolution model and PSO algorithm. The methodology was employed for operating the Zhanghe Irrigation Distict, located in China. Three different algorithms were applied to compare with the ABC. The integrated model proved its applicability and efficiency for reservoir system operation.

Ahmad et al. (2016) developed ABC model to operate dam-reservoir located in Malaysia, the objective was reducing the amount of deficit between demand and water release. The proposed algorithm achieved high reliability and stability, lower vulnerability, and fast convergence. According to such indicators, the ABC is superior to another optimization algorithm which is Gravitational Search Algorithm (GSA). While the resilience indictor showed that GSA is slightly better than ABC.

Differential evolution (DE)

The Differential Evolution (DE) has been first proposed by Storn (1996). DE is an evolutionary algorithm that is no require the optimization function to be continuous and hence differentiable. The principle behind such model is like genetic algorithm concept in selection, crossover and mutation. DF model depends on mutation and solves the optimization problem by maintaining a population of possible solutions and generating new solutions hence selecting the best one among them (Storn and Price 1997).

Jia et al. (2016) applied DE for finding optimal solution of real time flood mitigation operation of multi-reservoir system. The flood problem in Shiguan River Basin (located in China) comprises two reservoirs and three flood control points. Four different flood operation scenarios have been proposed to examine the model's performance. Although DE model showed its capability in operating multi-reservoir system, it has been noted some drawbacks regarding its flexibility and convergence ability. In addition, the weakness of computational efficiency when the system dimensions are further increased like add a greater number of reservoir and flood control points.

Particle swarm (PS)

Kennedy and Eberhart (1995) have firstly introduced the Particle Swarm (PS) model. The mechanism of such model is inspired by the movement fish or bird flock. PS model is considered as evolutionary depended computational approach optimizing the problems iteratively. This model works to solve the optimization problems by considering particles or population as the possible solutions. These particles arounds in the search space based on mathematical formula which defines the particle's velocity and position. The movement of particles is affected by their best local position. The particles adapt themselves according to their experiences. It could be noted that the positions are updated based on the better position is found by other particles. Within the process, the best value which are achieved by all particles is recorded in the memory as well as their coordinates (Nagesh Kumar and Janga Reddy 2007; Chau 2007). The advantages of PS model are low computational cost, high adaptiveness, and simple coding (Chau 2007).

Reddy and Nagesh Kumar (2007) used principle of pareto dominance to improve the efficiency of the PSO model in finding optimal operation rules. They found out that the proposed model has ability in minimizing deficit between water release and demand and maximizing hydropower benefit. In further study, Nagesh Kumar and Janga Reddy (2007) suggested the modern technique called elitist mutation in order to enhance an efficiency of the PSO model. The modern model (EMPS) was utilized to address the optimization problem for multiple-objective reservoir, Bhadra reservoir in India. A comparison between the performance of EMPS with other optimization techniques has been carried out. The results demonstrated that the EMPS can attain optimal solution to draw successful operation policies.

In 2008, Baltar and Fontane (2008) employed PS model to find the optimal rules for reservoir operation. The performance of PS model was reliable for solving the optimization problem. On the other hand, Mousavi and Shourian (2010) applied Particle Swarm Optimization (PSO) method to operate the Bakhtiari reservoir, which is located in Iran. Such method attained good results for finding optimal solution for reservoir operation.

The new model called Partially Constrained Particle Swarm Optimization (PC-PSO) has been used to determine the effective operation rules for the large reservoir by Afshar (2012). The performance of the proposed model has been inspected by simulating the operation of Dez reservoir. The optimal results provided by PC-PSO have been compared with the original PSO and genetic algorithm. The study concluded that the PC-PSO is superior to PSO and GA methods in identifying best solutions and convergence characteristics. The minimization of deficit (i.e., water demand–water release) is primary target of optimization and operation studies, (SaberChenari et al. 2016) employed PSO algorithm to achieve such purpose in Mahabad reservoir. They utilized the proposed model with consideration of decreased the average monthly streamflow magnitude. The PSO model provided good operation rules which can be a proper to draw successful policies for operating the reservoir system under several conditions.

Bilal et al. (2020) integrated Dynamic Programming (DP) with Particle Swarm Optimization (PSO) model. The proposed model has been applied for operating the reservoir system. To examine the performance of the suggested model, two different case studies have been considered. The suggested model provided satisfactory results in terms of finding good operation rules able to address with critical situations.

Recent optimization algorithms

Due to the complicated optimization problem, in the last years, limited number of studies given high attention to develop optimization algorithms for reservoir system operation utilizing advanced swarm intelligence models. Indeed, several such models were used to solve the reservoir operation problem like Shark Machine Learning Algorithm (SMLA), Weed Algorithm (WA), Bat Algorithm (BA), and Fire-Fly Algorithm (FA). The previous studies have demonstrated that the performance of these models is superior to conventional models in finding best operation rules for dam and reservoir system. However, each method faced some drawbacks which negatively affected on the overall method efficiency.

These algorithms have been employed by many previous studies such as; (Garousi-Nejad et al. 2016a, b) employed Fire-Fly technique, (Bozorg-Haddad et al. 2015; Ahmadianfar et al. 2016) employed Bat model. Bahrami et al. (2018) developed cat swarm intelligence algorithm, (Hosseini-Moghari et al. 2015a; Ming et al. 2015) utilized Cuckoo technique and (Abedinia et al. 2014; Ehteram et al. 2017; Allawi et al. 2018, 2019a, b) have used shark machine learning algorithm.

Evaluation and assessment

It is useful to summarize the important details for the previous studies that employed optimization algorithms for solving reservoir operation problems. Table 1 lists out author name, reservoir name and its location, kind of optimization algorithm and research remark. According to Table 1, the past works concentrated on developing and enhancing the evolutionary optimization algorithms. Another remark, the ABC model is highly effective and applicable in operating the reservoir system. The purposes of reservoir, its size and environmental region could influence on the results accuracy level. Thus, selection the appropriate optimization method for behavior of data (i.e., stochastic inflow, release, and demand) could help in providing satisfactory results.

Figure 1 shows number of times that the optimization algorithms were utilized of modeling the operating reservoir system based on the studies reviewed. It could be observed that the number of the studies that have been established to model the operation of the reservoir system has been increased in the past two decades. Although that many research articles were conducted on the use of the optimization algorithms for operating a dam reservoir, there are still several aspects that should be considered and discussed.

The current research has reviewed the previous studies which have employed the optimization algorithms for reservoir system operation. Many observations regarding the performance of such algorithms could be summarized in the following:

1) The past active studies showed that the major significant feature of GA model is high likelihood in finding the global optimal solution. This is due to the GA considers all population as candidate solutions for solving the optimization problems instead of relying on the single solution.
2) It has been noted the traditional models experience by several considerable limitations and drawbacks.
3) The previous studies have reported that the effective optimization method should have considerable acceleration and good inertia to address with the optimization reservoir system operation.
4) There are several advantages and characteristics for the swarm optimization algorithms by comparing with classic methods. These merits are their well performance in recognizing dynamic changes, ability in parallel computational and broad exploration. Also, the swarm algorithms are an applicable and reliable in solving complex mathematical problems.
5) It could be noted that the computational intelligence algorithms are robust and effective methods in determining the optimal operation rules for dam and reservoir system.
6) The current review paper concluded that the swarm optimization models to be more reliable and accurate, leading us to suggest that future studies should give attention on functional and feasible swarm intelligence algorithms.

Forecasting methods

Artificial neural network (ANN)

The most common type of artificial intelligence methods is artificial Neural Network (ANN), which is developed based on the network human brain concept (Haykin 1994). ANN has certain performance characteristics whereby; it is a massively parallel distributed information processing system. Usually, the architecture of ANN is composed of three major parts, input layer, hidden layer, and output layer. The first part includes a several of input nodes, the number of nodes is

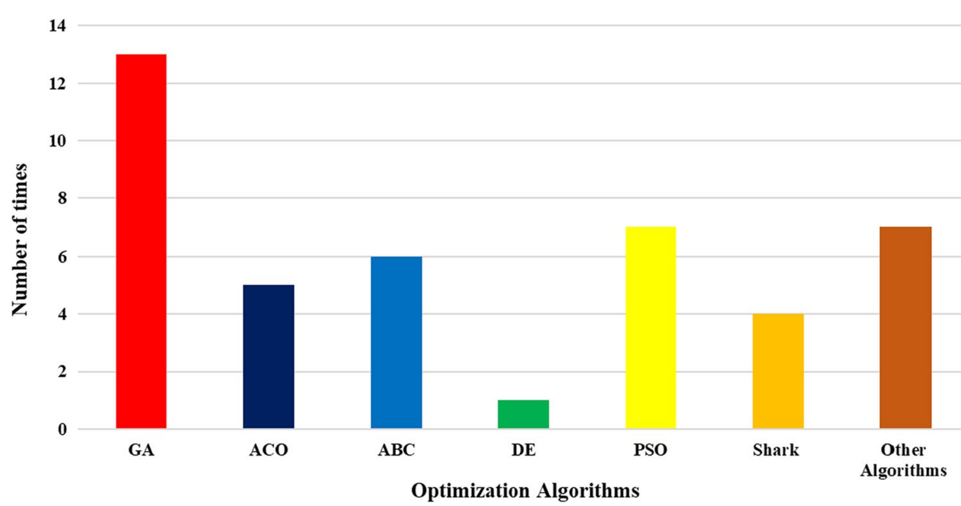

Fig. 1 Number of times that the optimization algorithms have been used for operating reservoir system based on the studies reviewed

depended on numbers of input variables. The second part of architecture has one or more hidden layers that has an activation function, whereas the last part has only one output layer node. There are three different types of ANN namely Feed-Forward Neural Network (FFNN), Radial Basis Function Neural Network (RBNN), and Generalized Neural Network (GNN). FFNN model is widely used in solving engineering problems, which could be considered as a promising nonlinear tool (Hornik et al. 1989). The primary aim of such model is to minimize the calculated error between the predicted and actual records, by finding for the best set of connections weights. RBF-NN was firstly proposed by Broomhead and Lowe (1988). RBF-NN model has a popular activation function called radial basis. Such type of ANN can address with complicated issues such as water resources problems. GRNN was introduced by Specht (1991). This model does not need an iterative training procedure like RBFNN model, but it directly draws the estimation function form the training phase by approximate any arbitrary function between inputs and outputs.

Coulibaly et al. (2000) has evaluated the performance of FF-NN model for reservoir inflow forecasting. The predictive method has been assessed utilizing several statistical indicators. The results showed that the prediction accuracy was improved by FFNN method compared to other prediction models. In a further study, Coulibaly et al. (2001) applied Dynamic Neural-Network (DNN) method to forecast inflow data. Three different types of temporal Neural-Network structures have been inspected with consideration several ingrained representations of temporal information. The methodology performance was compared to multi-Layer Perceptron Neural Network (MLP-NN) method. They found that the DNN could be promising tool in achieving well results for inflow forecasting.

Reservoir inflow forecasting for Aswan High Dam located in Egypt has been carried out by several previous research. In 2009, El-Shafie et al. (2009) developed RBF-NN method to forecast inflow data. The proposed model has been established based on the historical natural inflow data over 30 years which were collected from four different monitoring stations at upstream. A comprehensive analysis has been carried out to evaluate the performance and efficiency of the suggested methodology. The study explored that forecasting accuracy has been improved by 50% during low inflow season. The forecasting error magnitude and its distribution obtained when using RBFNN model are better than other predictive methods.

In another research, El-Shafie and Noureldin (2011) developed two generalized methods called Ensemble Neural Network (ENN) and Regularized Neural Network (RNN) method to overcome the drawbacks of classic ANN. Actual monthly streamflow data during 130 years has been used for train, test and validate the suggested methodology. The results showed that RNN model is superior to ENN and classic ANN models. Good improvement in forecasting accuracy was attained with RNN model.

Development for the Dynamic Auto-Regressive Neural Network has been done by Valipour et al. (2012). The developed model was employed to forecast inflow data for Dez Dam, located in Iran. To examine the validity and reliability of the proposed model, the performance of dynamic autoregressive model was compared to static neural network method. Different architectures have been made for the models used with consideration two transfer functions, sigmoid and radial basis function. The study concluded that using sigmoid function with dynamic model could enhanced the forecasting results. The results supported the performance of dynamic model when compared with other forecasting methods.

For same a case study (Dez Dam), the efficiency of three different models to forecast monthly inflow has been investigated by Valipour et al. (2013). The monthly inflow data from 1960 to 2007 were considered in the study. The observed inflow data over 42 years were utilized to train ARMA, ARIMA and auto-regressive neural network models, the past 5 years were used to test the proposed forecasting models. Several statistical indicators have been adopted to evaluate the performance of methods. The ARIMA method outperformed the ARMA model. Also, the results demonstrated that the dynamic auto-regressive neural network is better than static model. (Elizaga et al. 2014) utilized the neural network-based backpropagation models for reservoir inflow forecasting. According to a comparison between actual and predicted values, the suggested methods provided acceptable prediction accuracy.

Multi-Layer Perceptron Neural Network (MLP-NN) model was applied by Chiamsathit et al. (2016) to forecast one-step-ahead reservoir inflow for Ubol-Ratana Dam located in Thailand. They examined the influence of the forecasting accuracy level on the reservoir operation. The MLP-NN has been modeled based different input variables. Overall, the proposed model can be considered as a proper tool to forecast reservoir inflow.

Recurrent Neural Network (RNN) model has been used to forecast daily inflow data by Apaydin et al. (2020). To verify the predictive model, the performance of the RNN model is compared with classic ANN model. The reliability of proposed model was evaluated using several statistical indictors. The study concluded that the RNN model is more accurate than ANN in forecasting reservoir inflow records.

Lee et al. (2020) investigated the performance of three popular data-driven models, namely MLP, ANN, and SVM, to forecast monthly reservoir inflow. These predictive methods were evaluated using the coefficient S, NSE, and other indicators. The study showed that the developed models could be promising tool to forecast inflow data. Hadiyan et al. (2020) investigated the potential ANN model in forecasting reservoir inflow data. The study provided useful information for to simulate the inflow for the Sefidround reservoir located in Iran.

The main second hydrological parameter in the reservoir system is evaporation. Indeed, there are several previous studies developed many artificial intelligence methods to predict reservoir evaporation values. In 2006, Keskin and Terzi (2006) used Artificial Neural Network (ANN) method for daily evaporation prediction. Numerous climate parameters such as Temperature, Solar Radiation, Humidity, Wind Speed, and others were utilized as input variables. The prediction results indicated that there is good agreement between predicted values obtained by ANN with actual daily evaporation records.

The performance of ANN model has been compared to radiation-based method and temperature-based method by Tan et al. (2007). The proposed methods were applied to predict daily and hourly evaporation data. Analysis for the original evaporation and climate parameters has been conducted. The study showed that there is high correlation between solar radiation with evaporation for both time scales (hourly and daily). Whereas the relative humidity parameter has influence on the daily evaporation scale. The researchers have found out that the efficiency of ANN model is superior to conventional methods.

Moghaddamnia et al. (2009b) have developed two popular AI-based models (i.e., ANN and ANFIS) to predict evaporation data. The performance of such models has been evaluated by comparing with different empirical equations. It is noted that ANN and ANFIS models achieved their aims with some interesting outputs concerning the influence of climate parameters. The study has firstly concluded that the ANN and ANFIS methods provided better results than empirical equations. Secondly, the ANN efficiency is relatively better than ANFIS method. In this study, Gamma Test (GT) technique was utilized to enhance the prediction accuracy by improving the ANN and ANFIS performance. The GT has a good capability to save the effort and time modeling and determining the optimal input variables. The study recommends giving significant attention and the wider experience regarding the input selection approach.

Estimation daily evaporation values for Hamedan province region located in Iran has been carried out by Tabari et al. (2010). They used ANN and Multivariate Nonlinear Regression (MNLR) methods. Five different architectures of proposed models were developed based on several input variables. The study revealed that the wind speed and temperature factors have significant influence on the prediction accuracy. The results demonstrated that the ANN method could be promising tool for evaporation prediction compared to MNLR method.

Allawi and El-Shafie (2016) have studied the possibility of using two AI-based models (i.e., RBF-NN and ANFIS) to predict daily evaporation records. They applied models to predict the evaporation records for Layang reservoir, located in the southeast part of Malaysia. Daily air temperature, humidity, pan evaporation, and solar radiation for 40 years have been used to train and test the proposed models. In this study, the comprehensive analysis for the RBF-NN and ANFIS performance has been conducted. In this context, several statistical indicators were adopted to evaluate and analysis the ability and reliability of the suggested predictive models. The indictors showed that both AI-models have provided acceptable prediction results. By comparing between these models, RBF-NN was better than ANFIS in predicting daily evaporation values.

The RBF-NN, Self-Organizing Map Neural Network (SOMNN), and MLR models were used by Malik et al. (2018) to predict the evaporation data. The prediction modeling was structured based on several meteorological parameters. The predictions obtained by RBF-NN were more accurate compared to those obtained by SOMNN and MLR model. The study reported that the RBF-NN model is effective and robust predictive model in estimating reservoir evaporation records.

In further research, Allawi et al. (2019c) have examined the reliability and efficiency of ANN and SVR models to predict reservoir evaporation. Two different scenarios for the input variables were proposed to verify the applicability of the predictive models. The statistical indexes exhibited that the predictions obtained ANN model is more accurate than those provide by SVR model.

Support vector machine (SVM)

SVM method was popularized as a new statistical learning model and verified to be a robustness and effective method for classification and regression for stochastic data set by comparing its performance with the conventional methods. In fact, the concept of SVM model is based on mapping the input data set in high dimensional feature space to simplify the regression issue and hence re-provide the unknown relationship between the input–output variables. The mechanism of SVM method is simplicity which could be adequately understand by modelers. The further attractive of such model is a remarkable superiority compared to other forecasting methods such as ANN, decision tree, and nearest neighbors. The SVM employs a kernel trick function to establish information regarding the problem type, so that both model complexity and forecasting error are together minimized. Indeed, the predictive ability of SVM model could be understand by several basic concepts including soft margin, separation hyperplane, hard margin, and the kernel function separation hyperplane. Numerous previous studies have employed the SVM-based models to forecast inflow and evaporation parameters.

An accurate reservoir inflow forecasting is an important in managing and scheduling reservoir system. In 2006, Lin et al. (2006) used support vector machine (SVM) to forecast monthly reservoir inflow values. To test the validity of the suggested model, two different forecasting models have been employed for comparison, which are Auto-Regressive Moving Average (ARMA) and ANN method. They have found that SVM-based models are expected to be promising tools due to their efficiency, robustness, and accuracy in forecasting reservoir inflow data.

Effective inflow forecasting models based on the Support Vector Machine (SVM) are introduced by Lin et al. (2009). The SVR has better generalization; the weights of the SVR are guaranteed; SVR is trained much more rapidly. A comparison has been carried out between the performance of the proposed model and Backpropagation Network (BPN) according to several statistical indicators. The obtained results indicated that the proposed SVR-based models are more well reliable and efficiency than BPN-based models. The study recommended that the SVR-based models could be useful to improve the inflow forecasting accuracy and as an alternative to the existing forecasting methods.

Modification for the Support Vector Machine (SVM) model has been carried out by Li et al. (2009) for reservoir inflow forecasting. The modified model was applied to forecast monthly inflow for Shih-Men reservoir, located in Taiwan. The forecasting modeling was established based on several input variables including meteorological parameters. The Genetic Algorithm (GA) was utilized to determine the optimal internal parameters of the SVM model. The SVM-based models achieved well forecasting accuracy. According to a point of view several statistical indicators, the study showed that the modified SVM can be promising model to forecast reservoir inflow.

Temperature, sun radiation, rainfall, and other climate parameters have been embedded to establish the reservoir inflow modeling by Noori et al. (2011). The SVM method has been employed to forecast monthly inflow data. Several input selection algorithms have been used to select the optimal input combinations for modeling. The performance of SVM is compared to classic ANN model. They concluded that the efficiency of the proposed model (SVM) is better than ANN model in forecasting reservoir inflow data. Also, selection the proper input combinations have a considerable role in improving the forecasting accuracy.

The SVM-based models have also been utilized for reservoir evaporation prediction by several previous studies. In 2009, Moghaddamnia et al. (2009a) have combined Gamma Test (GT) technique with SVR method for prediction daily evaporation records. GT technique was used to select the optimal input variables among many meteorological parameters. A comprehensive evaluation and analysis have been done for the proposed model using popular statistical indicators. The performance of SVR was examined by comparing with empirical equations. The results shown that the good prediction accuracy was obtained when using SVR. Utilization of GT with SVR model has improved the predictability of reservoir evaporation.

Reservoir evaporation prediction values based-SVR modeling has been developed by Baydaroğlu and Koçak (2014). Five different input variables have been considered for modeling including Temperature, Wind Speed, Solar Radiation, and time-lag evaporation. The best input combinations to feed the SVR-based models was determined by popular technique called Chaos algorithm. In the study, another two different prediction models were employed, which are ANN and ARIMA models. The best SVR could achieve satisfactory prediction accuracy. The proposed model based on combining (SVR) with Chaos algorithm provided very accurate predictions when compared to the best ANN and ARIMA methods.

Given the complexity of evaporation pattern and the lack of meteorological and hydrological data in reservoir area, the models based on physical process have a limited applicability in predicting the evaporation data. In light of such, Tezel and Buyukyildiz (2016) investigated the efficiency of three different models, including Multi-Layer Perceptron (MLP), RBF-NN and SVR to predict reservoir evaporation data. SVR and RBF-NN models have achieved good prediction accuracy, but the SVR method was a little better than RBF-NN model. The results demonstrated that the SVR model could be more suitable in predicting evaporation data.

Fuzzy logic

The primary aim for designing the mathematical models is to maximize the advantage of such models. To achieve this matter, it should be considering many key features including the model system like credibility, uncertainty, and complexity. It could be observed that allowing more uncertainty could lead to minimize the complexity and then obtaining more reliable results from the model. Based on such concept, Zadeh (1965) has proposed fuzzy theory sets whereby the primary characteristic of such theory is an addressing and studying the uncertain characteristics which could be existing in the parameter patterns. In fact, the fuzzy sets handle the uncertainty by studying the input variables associated with a priority to address modeling vagueness. Furthermore, the system considers the input parameters as a form of interval data not crisp point data. By this way, the system could smoothly solve the modeling ambiguity (Klir and Yuan 1995).

It could be noted that the fuzzy system set has an important part called fuzzification, that addresses with the uncertainties. Several past papers mentioned that the uncertainty feature is existing in the pattern of reservoir inflow and evaporation parameter (Tan et al. 2007; El-Shafie and Noureldin 2011; Cheng et al. 2015). Therefore, the modelers attempted to develop and support the fuzzification part to increase the model ability in handling the ambiguity data. The fuzzy logic models have been employed for mapping between variables in many engineering areas. In this review research, we focus on the fuzzy models' utilization to forecast the reservoir inflow and evaporation.

The ANFIS method was used for monthly reservoir inflow forecasting at Aswan High Dam (AHD) by El-Shafie et al. (2007). The ANFIS method has a high ability to address the uncertainties and ambiguities present in the inflow pattern. The historical data for 130 years were employed to train and test the proposed model. The architecture was established based on multi-lead inflow to enhance the model ability. The proposed modeling developed to be eligible for 3-month-ahead forecasting. The study has shown that the ANFIS-based models exhibited high accurate and harmonious performance to forecast inflow. The ANFIS performance was compared to popular predictive model called MLP-NN. The proposed model outperformed to MLP-NN and has shown super robustness and dependable performance to forecast monthly reservoir inflow.

Bae et al. (2007) have utilized ANFIS-based models to forecast inflow data. They concluded that ANFIS model is a high ability in providing accurate results. The study demonstrated that the ANFIS model outperformed other predictive models.

Wang et al. (2009b) studied the performance of several AI-based models to forecast monthly reservoir inflow records. The monthly inflow data were collected from two different case studies. The research used the collected data to develop different predictive models, namely ANFIS, SVM, ANN, ARAM, and GP technology. Based on several evaluation criteria, the results indicated that the best performance can be obtained by ANFIS, GP, and SVM model.

Lohani et al. (2012) examined the performance of ANFIS model to forecast monthly reservoir inflow by comparing its efficiency with ANN and Auto-Regression (AR) model. The proposed model has been applied to forecast inflow data for Bhakra Dam, located in India. Several popular statistical indicators have been utilized to assess the predictive methods. The obtained results revealed that ANFIS-based models are superior to ANN and AR model for reservoir inflow forecasting.

Awan and Bae (2013) developed predictive model based on ANFIS method to forecast monthly inflow data. Monthly inflow, Temperature, and Rainfall data have been employed as input variables to train the proposed models. Different architectures of proposed model have been considered based on different input combinations. The study showed that using rainfall parameter as input variables improves the forecasting accuracy. The obtained results demonstrated the effectiveness of ANFIS model in forecasting reservoir inflow data.

Monthly and Yearly reservoir inflow forecasting modeling have been developed by Bai et al. (2016b). They adopted the Even Gray Model (EGM) and ANFIS model for forecast both time scales. The proposed models have been applied to forecast the inflow for Three Gorges reservoir, the data are collected from January 2000 to December 2012. The forecast accuracy of reservoir inflow data is improved substantially by the proposed models. To inspect the predictive model, two peer methods, the ANN and auto-regressive integrated moving average method were involved. According to several evaluation indictors, the results showed that the developed predictive model is better that other methods.

Co-Active Neuro Fuzzy Inference System (CANFIS) was modified by Allawi et al. (2017) to forecast monthly reservoir inflow data. The authors applied the proposed CANFIS model for a case study located in Egypt, Aswan High Dam. The comparison has been performed between CANFSI model with other AI-based models. The evaluation criteria demonstrated the superiority of CANFIS model compared to other predictive methods.

Practically speaking, there are difficulties faced by hydrologist when using Class-A pan with regards to the direct measurements. To overcome such difficulties, Keskin et al. (2004) utilized fuzzy logic model for daily pan evaporation prediction. The proposed method has been established by using various meteorological data as input parameters. A comparison of the efficiency of ANFIS method was made with the Penman empirical equation. The study results revealed that the ANFIS model achieved good accuracy and has significant ability to predict evaporation data. The researchers recommended for adopting the ANFIS model to be promising predictive model for reservoir evaporation prediction.

In 2012, Tabari et al. (2012) investigated the ability of the CANFIS model in predicting pan evaporation data for a semi-arid region of Iran. A comparison of the proposed CANFIS model has been carried out with MLP model. The performances of the predictive models were evaluated using several statistical indicators. The study found that the CANFIS model is more reliable in predicting evaporation data compared to MLP model.

In the study of Salih et al. (2019), the CANFIS model was employed to predict monthly evaporation data. CANFIS performance was compared to that of the three AI-based models which are SVR, ANFIS, and ANN model. Several statistical indicators proven the reliability and effectiveness of CANFIS model in predicting reservoir evaporation records.

Co-Active Neuro Fuzzy Inference System method was modified by Allawi et al. (2020a) in order to predict monthly evaporation data. A comparison between the performance of the modified CANFIS with ANFIS, RBF-NN, and SVR model was performed using several evaluation indicators. The study found that a modified CANFIS model can predict evaporation records more accurately than other predictive AI-based models.

Hybrid and other models

Different other predictive models were developed to forecast the hydrological parameters, like combine optimization algorithms or data pre-processing technique with AI methods.

Indeed, there are several editable internal parameters which identify the final shape of the model structure. Over the last decades there have been numerous studies in the development and application of evolutionary algorithms for improving the performance of AI-models. Such algorithms attempt to find the optimal form of internal parameters of AI-models, that could produce the robust and effective modeling.

Many techniques were developed to address the stochastic process involve in the raw data. Wavelet Transform (WT) is the most popular technique for data pre-processing. WT is a significant model for analysis and handle with time series data. The use of this technique has increased dramatically since its introduction in 1984 by Grossmann and Morlet (1984). The primary objective of using the WT approach is to analyze the original data in terms of frequency and non-static, thus producing significant information about the time series data.

The ability of ANN model with WT has been investigated for reservoir inflow forecasting by Wang et al. (2009a). They applied predictive method to forecast the inflow parameter for Three Gorges Dam, located on Yangtze river, China. WNN's performance was evaluated by comparing its efficiency with a common predictive model called TAR model. The study showed that the proposed model attained well results. The forecasting accuracy level is improved when using WNN compared to another model. The researchers concluded that further improvement for WNN procedure could be produce robust and effective predictive model.

In further study, the integration between the PSO with SVM model has been carried out by Wang et al. (2010) to forecast annual inflow data. The objective of the PSO algorithm is to find the optimal parameters of the SVM model. The comparison between the suggested model (PSO-SVM) and ANN model was conducted according to several statistical indicators. The obtained results demonstrated that the PSO-SVM model is better than ANN in forecasting reservoir inflow. The study showed that the PSO-SVM-based model could be an alternative tool for existing forecasting models. The authors recommend that combining the SVM with optimization algorithms can improve the performance and accuracy of a predictive model.

Jothiprakash and Kote (2011) studied the ability of M5 Tree (MT) model to forecast inflow parameter. Two different timelines are considered, monthly and seasonally, to verify model performance. It can be observed that the MT model is superior to Moving Average model. The statistical indicators showed that the proposed model has high effectiveness and reliability. The results of study revealed that the M5 tree model fulfilled accurate predictions using seasonal inflow records.

The ANN, ANFIS, and Linear Genetic Programming (LGP) were employed for multistep-ahead forecasting of inflow data by Jothiprakash and Magar (2012). Daily and hourly inflow data have been utilized to establish the modeling structure. To illustrate the applicability of the proposed models, Koyna river watershed in Maharashtra located in India is chosen as a case study. The proposed model reliability is evaluated utilizing various performance criteria. The study found that the LGP-based model was superior to other models for both daily and hourly time scales.

Integration three predictive models, FFNN, MLP, and RBFNN, with WT technique has been done by Budu (2014), for reservoir inflow forecasting. Research has shown that WT technology performs excellent in improving prediction accuracy. The study recommended adopting WT to enhance the original data to be understandable for the predictive models.

An ensemble model based on WT analysis, bootstrap resampling, and ANN (BWANN) has been proposed by Kumar et al. (2015) to forecast inflow records. For comparison, several peer models including wavelet-based ANN (WANN), Multi Linear Regression (MLR), WMLR, and Bootstrap and Wavelet-based MLR (BWMLR) models, were adopted. Fourteen years of daily reservoir inflow data collected form upstream were used to train and testing the predictive models. Several evaluation indicators were employed to check the reliability and validity of the used models. The study showed that the effectiveness of WANN is better than WMLR, ANN, and MLR methods. Another observation, the BWANN performance is superior to BWMLR model and could be more accurate and useful for daily reservoir inflow forecasting, as requested.

Heuristic methods for monthly reservoir inflow forecasting have been employed by Cheng et al. (2015). The ANN, SVM, and SVM based on genetic algorithm, were applied to forecast inflow at Xinfengjiang reservoir. A comparison has been conducted between the hybrid predictive model and classic ANN and SVM model. The study revealed that three predictive models have satisfactory performance in forecasting monthly inflow values. Five statistical indicators showed that the performance of hybrid model is better than ANN and SVM. It could be concluded that hybrid model is robust tool for the long-term forecasting.

To handle the daily inflow forecasting, Bai et al. (2016a) developed the Multi-scale Deep Feature Learning (MDFL) technique with hybrid methods. In order to extract multi-scale (i.e., random, period, and trend), ensemble empirical decomposition and Fourier spectrum have been utilized. The structure of the proposed modeling was established using the historical daily reservoir inflow series for 12 years. The raw data were collected from the Three Gorges reservoir, located in China. Four different predictive models were adopted to compare with the suggested model. According to the attained results, the present model efficiency overwhelmed all the peer methods for the same task. The minimum forecasting error and maximum correlation between the forecasted and actual data, have been obtained using the proposed predictive model.

In 2016, Bozorg-Haddad et al. (2016b) coupled GA technique with ANN model to forecast inflow data. Historical data of two case studies were utilized to evaluate the proposed ANN, 80% of the data were used to train and 20% of the original data were used to test the suggested model. The obtained results demonstrated that the proposed hybrid model (ANN-GA) is applicable and effectiveness to forecast monthly inflow data.

The combination of a linear seasonal auto-regression integrated moving average (SARIMA) model with an ANN, is conducted by Moeeni and Bonakdari (2016). They examined the performance of the proposed predictive model to forecast inflow records of a dam reservoir. In this research, the Jamishan Dam located in Iran was chosen as a case study. The efficiency of hybrid model (SARIMA-ANN) was compared with SARIMA and ANN models. The study investigated the effect of changing the forecasting period length on the accuracy level of models. The results showed that the hybrid model forecasts peak inflow values much better than the classic predictive methods. Moreover, the SARIMA model is more accurate in forecasting the low records compared to other AI-based models. Overall, the forecasting error minimizes when utilizing the hybrid model more compared to other predictive models. The correlation magnitude between forecasted and actual data is high with hybrid model.

Li et al. (2016) have introduced two different predictive models, Deep Restricted Boltzmann Machine (DRBM), and Stack Auto-Encoder (SAE), to forecast inflow data. The proposed models have been employed for daily reservoir inflow forecasting at Three Gorges reservoir and Gezhouba located in China. The study evaluated the performance of models by comparing with classic FF-NN, ARIMA. Both categories Deep Neural Network (DNN), are established by integrating FF-NN with DRBM (i.e., DRBM-NN) and SAE (i.e., SAE-NN). It could be noted that the effectiveness and robust of two DNN models overwhelm the FF-NN and ARIMA methods in forecasting inflow data.

In 2020, Afan et al. (2020) used Genetic Algorithm to select the proper input combination for the predictive model. The integration has been made between RBF-NN with GA to forecast monthly reservoir inflow. The results showed that the proposed RBFNN-GA model outperformed other predictive models.

Six machine learning models including MLP, DT, RNN, Radom Forest (RF), and Gradient Boosting (GB), were employed for inflow forecasting by Hong et al. (2020). According to several statistical indicators, the MLP model attained best prediction results compared to other predictive models. On the other hand, the study found that the GB and RF performed better than MLP model when the inflow volume is less than 100 m^3/s. Therefore, combination between MLP and those models (i.e., GB-MLP and RF-MLP) has been carried out. The developed model achieved high-level forecasting accuracy.

The performance of three AI-based models was improved by Tikhamarine et al. (2020), to provide the robust and effective predictive model. The improvement of the forecasting accuracy has been carried out by integrating SVR, ANN, and MLP with the Gray Wolf Optimization (GWO) algorithm. The results show, the hybrid models are more accurate and reliable compared to classic AI-based models. Moreover, the efficiency of SVR-GWO model in forecasting monthly inflow data is better than ANN-GWO and MLP-GWO models.

In the study of Zhang et al. (2020), three different data-driven models including ANN, ANFIS, SVM, were employed to forecast reservoir inflow. Several climate parameters have been used as input variables for the predictive models. The results indicated that the predictive model is reliable and effective in forecasting inflow compared to other models used.

Osman et al. (2020), Fast Orthogonal Search (FOS) method was adopted to forecast monthly inflow data. The study reported that the FOS method has ability to avoid the over-fitting problem. It was observed that the forecasting accuracy has been highly improved using FOS method.

Instead of utilizing popular sigmoid activation function in MLP-NN model, Abghari et al. (2012) employed Wavelet function as activation function. Two different Wavelet types have been considered namely Mexican Hat and polyWOG1. The suggested models are applied for daily pan evaporation prediction. According to the obtained results, Mexican hat wavelet NN presented 98.35% and 96.04% accuracy whiling training and testing sessions, respectively. Whereas PolyWOG1 wavelet NN presented 95.92% and 91.03% accuracy during training and testing phases, respectively. The MLP model with standard sigmoid function provided 90.6% accuracy in training period and 87.63 within testing period. It has been observed that the MLP with Mexican hat Wavelet achieved well performance accuracy.

In the research of Arunkumar and Jothiprakash (2013), the reservoir evaporation data were predicted using three different AI-based models including ANN, model tree, GP model. The daily reservoir evaporation records for a period of 49 years were employed to develop the prediction modeling. The evaluation criteria showed that the GP model is better than model tree and ANN model in predicting the evaporation parameter.

Izadbakhsh and Javadikia (2014) coupled the FF-NN model and GA technology to predict evaporation data of a dam reservoir. Feed-Forward Neural Network (FF-NN) with Genetic Algorithm (GA) to predict evaporation data from the dam reservoir. The performance of the hybrid predictive model (FFNN-GA) is compared with classic FF-NN model. Several meteorological parameters including wind speed, sunshine, and temperature, are employed as input variables for modeling. The researchers found the proposed predictive model (i.e., FFNN-GA) is an accurate and reliable in predicting evaporation data, compared to classic FF-NN model. The FFNN-GA could be promising predictive tool for reservoir evaporation prediction.

A hybrid model consisting MLP with Fire-Fly Algorithm (FFA) was adopted by Ghorbani et al. (2017) to predict pan evaporation records. The performance of MLP-FFA model was examined by comparing the accuracy of its predictions with stander MLP and SVM methods. The results demonstrated that the hybrid predictive model outperformed other models. The study found that the FFA technique improves the accuracy of the forecasted evaporation data.

Allawi et al. (2020b) developed new predictive method called Co-Active Neuro Fuzzy Inference System (CANFIS) to predict monthly reservoir evaporation records for two different case studies. Genetic algorithm has been employed to obtain optimal internal parameters of the proposed model. The performance of the GA-CANFIS in predicting evaporation data was inspected by comparing with GA-SVR, GA-ANFIS and GA-RBFNN models. A hybrid model (GA-CANFIS) succeeded in achieving minimal prediction errors and a high agreement level between predicted and actual data. The results show that the developed model could be excellent tool to predict the reservoir evaporation data.

In a recent study, Wu et al. (2020) predicted monthly evaporation data by coupling Extreme Learning Machine (ELM) with two different heuristic algorithms namely, Whale Optimization Algorithm (WOA) and Flower Pollination Algorithm (FPA). The applicability of the proposed models has been compared with ANN, Differential Evolution algorithm optimized ELM (DEELM) and M5 model Tree (M5T). The study demonstrated that the hybrid model (i.e., FPAELM) achieved high-level prediction accuracy, followed by WOAELM model. Further, hybrid predictive models are superior to conventional methods.

Evaluation and assessment

Since the emergence of AI-models in hydrology field, research activity in the field of modeling, analysis, forecasting, and estimation of water quality and quantity has increased significantly. AI techniques have been employed in modeling various hydrological parameters. The current review research has focused on application of AI-models to forecast the main hydrological parameters in reservoir system which are inflow and evaporation. It is noted that hydrologists have paid much attention to the forecasting of reservoir inflow, with fewer studies being done on modeling of reservoir evaporation.

According to the effectiveness and good efficiency of AI techniques regarding address with the nonlinear and stochastic natural of hydrological processes, a considerable understanding and capability to forecast inflow and evaporation could be attained. The obtained results of numerous studies reviewed in this paper have indicated the high effectiveness of integrated or hybrid models in forecasting inflow and evaporation as an accurately, compared with single or classic AI-models. Such enhancements in forecasting inflow and evaporation parameters can lead to the better interpretation for the behavior of these phenomena and hence give proper policies for development water resources management.

The last sections reviewed the previous works which applied AI-based models to forecast the reservoir inflow and evaporation. One of the more important matters that was explored, is fuzzy logic models can best fit with the specific hydrologic processes.

The past studies reported that the ANN models suffered by some limitations and shortcoming like low-speed learning, local minima and over-fitting problem. There are three major types of ANN method namely MLP, RBF-NN and FF-NN model. Based on the past papers, the RBF-NN model has high efficiency and ability in forecasting hydrological parameters compared to other models. It is due to that the RBF-NN model is characterized faster convergence and high robustness (Fernando and Jayawardena 1998; Valipour et al. 2012; Allawi and El-Shafie 2016). In same time, some of research paper reported that the RBF-NN model has some weak points and shortages, where the RBF-NN model suffers to provide acceptable accuracy when using short period of raw data.

Further remarkable, the DNN methods are superior to the static neural network models in forecasting the inflow and evaporation parameters. Indeed, the concept of DNN methods is that the neuron depends not on the present signal of input only, but also based on the prior states of the neurons. Thus, the DNN models characterized by robustness and high efficiency in reducing the learning time. Moreover, the DNN methods have the exceptional ability for mapping the relationship between input–output variables because of its high capability to adjust the network weights, as quested (Coulibaly et al. 2001; Valipour et al. 2013).

It was also found that SVM-based models with optimization algorithms are more efficient that ANN and ANFIS models in monitoring peak values. It is observed that peak values in inflow and evaporation time series, that occur in periodic patterns, could be detected using SVM-based models with optimization techniques more accurately. The classic models could attain good forecasting results for short-term real time forecasting (i.e., hourly, or daily). But the hybrid or integrated AI-models could achieve high-level accuracy for long-term time scale (i.e., seasonally, or monthly). Moreover, type of data has a significant role in selecting of the reliable and effective model. For example, for modeling the highly stochastic process, the probabilistic based pre-processing could be useful for obtaining satisfactory results.

The noteworthy according to the past studies, one of the most important steps that could influence on modeling performance is that choose a suitable transfer function. The transfer function is employed to mapping the nonlinear relationship. Selection appropriate function could improve the forecasting accuracy. Several papers have concluded that the tangent sigmoid transfer function is better than other functions in terms of ability to understanding the pattern of inflow and evaporation parameters. The review demonstrated that most past studies attained their objectives as high accurately using sigmoid function like (Moghaddamnia et al. 2009a; Tabari et al. 2010; Hidalgo et al. 2015; Chiamsathit et al. 2016; Allawi and El-Shafie 2016).

Authors' names, type of AI-based models, timescale and others information around the past studies that have addressed inflow forecasting, are presented in Table 2. It is noted that most of the reviewed papers have used monthly time scale for modeling inflow forecasting. Referring Table 2, the ANN-based models have received high attention from modelers. Many hydrologists attempted to improve the performance of AI methods by integrating them with optimizer techniques.

Table 3 summarizes the major details of the reviewed studies which employed AI-based models for modeling evaporation prediction. Type of the predictive model, timescale, research remark, author's name, and evaluation criteria were presented in Table 3. It is observed that the researchers are concerned with selecting the appropriate input combination for modeling. The performance of predictive models could be enhanced in case include the effective climate parameters like temperature and humidity, with modeling. Through Table 3, the majority of the researchers utilized daily time scale for evaporation prediction modeling. It is found that the long-term scales like monthly are used with large reservoirs. The evaporation prediction modeling has been mostly established based on ANN models. It was observed that RMSE, MAE, and R^2 were the mainly used to evaluate the prediction accuracy.

Figure 2 shows number of times that the artificial intelligence methods were utilized of modeling the prediction of reservoir inflow and evaporation based on the studies reviewed. It is remarkable that prediction modeling was constructed many times based on hybrid models. Artificial Neural Network (ANN) method was widely employed for modeling the prediction of the main hydrological parameters in the reservoir system. It is worth to mention, the CANFIS model could be a predictive candidate model for development the prediction modeling for inflow and evaporation parameters. The development of the CANFIS model procedure may yield accurate prediction results.

To enrich the review study, the major points can be summarized as the following:

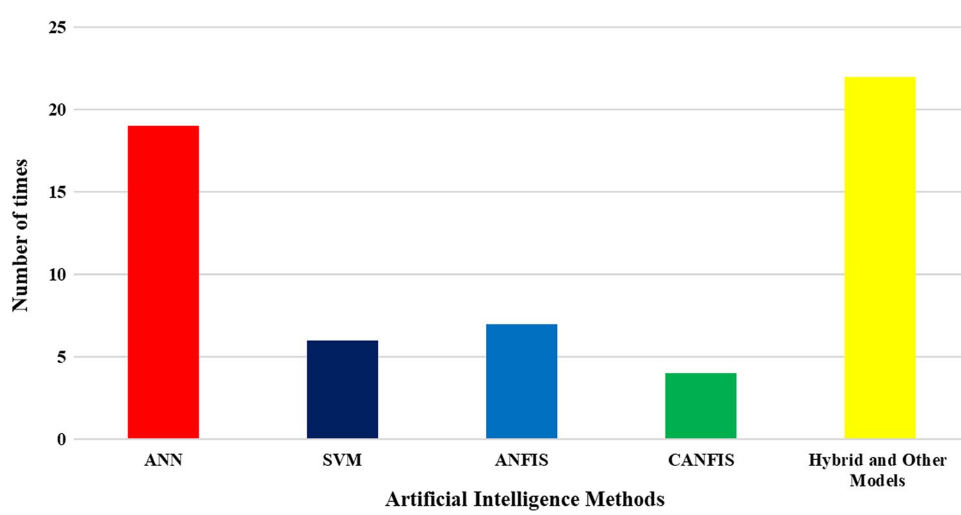

Fig. 2 Number of times that the AI methods have been used for predicting reservoir inflow and evaporation based on reviewed studies

i. The optimization techniques have improved the performance of predictive models. The optimizer is used to find the optimal internal parameters for the model's structure and then selected the proper final shape of the modeling.
ii. In general, the pre-processing techniques such as WT have reduced the data noising. With employing WT, the predictive model can understand the behavior of data as better, hence provide high accuracy level.
iii. The hybrid models achieved acceptable accuracy to forecast inflow parameter whether short-term or long-term.

Recommendation for future research

According to the previous research papers conclusions, there are several advantages and drawbacks of the AI-based models. To address such shortcomings and enhance the advantages, recommendations for future research are suggested, as follows:

1. Identification the adoption of proper input selection techniques is the one of the major concerns in hydro-climatological methods. In a study on ANN models, (Maier and Dandy 2000) reported two disadvantages of AI-based hydrologic modeling. The evaluating the relationship between input–output variables is the first deficiencies, secondly, exploring the effective input parameters and avoiding redundant inputs even if these variables could help the ANN-based models. Such variables may lead to increase the complicated and uncertainty of model. These two matters could appear with other AI-based models. Thus, the attention should be given to reduce an uncertainty and hence improve the performance of the predictive models. In this regard, pre-processing techniques such as Wavelet Transform (WT), Fast Orthogonal Research (FOS), and other techniques can address the two aforementioned issues.
2. Due to the limited number of research studies in the field of modeling reservoir evaporation using integrated models, we recommend that additional studies should be conducted on this topic.
3. One of the most important issues for the designers is choosing the relevant input variables that influence the output outcome. Input selection is an essential step in building model to achieve the highest prediction accuracy. Enhancements made to the AI-model could focus on finding a suitable input selection method. In fact, there are intelligent input selection methods that automatically identifies the input and give the best harmony and relevant inputs for better prediction accuracy. In this context, this study recommends utilizing the input selection methods such as a genetic algorithm and global harmony search method to determine the most effective input variable on the accuracy of the model output.
4. Most of the existing research papers are focused on deterministic hydrological and climate parameters. In fact, few of these studies attempted to improve the reliability and efficiency of operation in dynamic environment. It is useful introducing modern methodologies which able to help the decision makers they are facing the environment uncertainty. With such modern model, it could be provided the applicable and reliable operation policies able quickly handle the unexpected disturbance, as requested. The current optimization algorithms are employed to generate operation rules for dam and reservoir system based on the main hydrological parameters pattern and other constraints. Indeed, the simulation procedure of algorithms is conducted by adopting the hydrological parameters as deterministic variables. Such operation procedure considers that the perfect forecasting for hydrological parameters is available, which is unrealistic. In this context, the present study recommends reimplementing and enhancing the reservoir operation procedure to be under realistic conditions. The proposed operation procedure could be attained by integrating the predictive model with optimization algorithms. Given the parameters values are unknown, the AI-based model will forecast the required data at the beginning of each step (i.e., daily, monthly, seasonally, etc.) whiling an operation procedure. Hence, more realistic and dynamic operating policies for the reservoir system can be obtained.

Conclusion

The present study reviewed previous research papers dealing with simulation and operation of the reservoir system. Applications of optimization algorithms of the reservoir operation have been studied for the past twenty years. Previous studies that used AI-based models to predict reservoir inflow and evaporation were also explored as key components in reservoir simulation. The hydrologists give significant attention through conducting many effective research papers to handle such issue. The optimization algorithms provided acceptable solutions for optimization reservoir operation. Based on the obtained results by several literature studies, the evolutionary algorithms presented satisfactory operation policies. However, there are some drawbacks and shortcoming points for these techniques that can be observed during employ them.

This research demonstrated the efforts which were made to develop the predictive models based on AI methods. It is illustrated that the AI-based models have ability to predict inflow and evaporation parameters with good level of accuracy. The modern models such as integrated predictive models have high effectiveness and more reliable compared to the classic model version. More recommendations to develop predictive model able to handle the inflow and evaporation forecasting have been listed. In order to operate the reservoir system under realistic conditions, a new simulation procedure has been proposed. This procedure involves combining a predictive model with an optimization algorithm while searching for optimal operating rules and evaluating their performance.

Author contributions The first draft of the manuscript was written by Saad Mawlood Saab. The manuscript version has edited and revised by Mohammed Falah Allawi. Supervising and reviewing have been made by Ahmed El-Shafie, Faridah Binti Othman and Taun Chee Ghuan.

Funding The research has no funding.

Availability of data and materials Not applicable.

Declarations

Conflict of interest The authors declare no conflict of interest.

Ethical approval We acknowledge that the current research has been conducted ethically and the final shape of the research has been agreed by all authors.

Consent to participate The authors consent to participate in this research study.

Consent to publish The authors consent to publish the current research in EMAS journal.

References

Abedinia O, Amjady N, Ghasemi A (2014) A new metaheuristic algorithm based on shark smell optimization. Complexity 21:97–116. https://doi.org/10.1002/cplx.21634

Abghari H, Ahmadi H, Besharat S, Rezaverdinejad V (2012) Prediction of daily pan evaporation using wavelet neural networks. Water Resour Manag 26:3639–3652. https://doi.org/10.1007/s11269-012-0096-z

Afan HA, Allawi MF, El-Shafie A et al (2020) Input attributes optimization using the feasibility of genetic nature inspired algorithm: application of river flow forecasting. Sci Rep 10:1–15. https://doi.org/10.1038/s41598-020-61355-x

Afshar MH (2012) Large scale reservoir operation by Constrained Particle Swarm Optimization algorithms. J Hydro Environ Res 6:75–87. https://doi.org/10.1016/j.jher.2011.04.003

Afshar A, Sharifi F, Jalali MR (2009) Non-dominated archiving multicolony ant algorithm for multi-objective optimization: application to multi-purpose reservoir operation. Eng Optim 41:313–325. https://doi.org/10.1080/03052150802460414

Afshar M, Ketabchi H, Civil ER-IJ of, 2006 undefined (2006) Elitist continuous ant colony optimization algorithm: application to reservoir operation problems. ijce.iust.ac.ir 4:274–285

Ahmad A, Razali SFM, Mohamed ZS, El-shafie A (2016) The application of artificial bee colony and gravitational search algorithm in reservoir optimization. Water Resour Manag 30:2497–2516. https://doi.org/10.1007/s11269-016-1304-z

Ahmadi M, Haddad O, Mariño M (2014) Extraction of flexible multiobjective real-time reservoir operation rules. Water Resour Manag

Ahmadianfar I, Adib A, Salarijazi M (2016) Optimizing multireservoir operation: hybrid of bat algorithm and differential evolution. J Water Resour Plan Manag 142:5015010. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000606

Ahmed JA, Sarma AK (2005) Genetic algorithm for optimal operating policy of a multipurpose reservoir. Water Resour Manag 19:145–161. https://doi.org/10.1007/s11269-005-2704-7

Allawi MF, El-Shafie A (2016) Utilizing RBF-NN and ANFIS methods for multi-lead ahead prediction model of evaporation from reservoir. Water Resour Manag 30:4773–4788. https://doi.org/10.1007/s11269-016-1452-1

Allawi MF, Jaafar O, Mohamad Hamzah F et al (2017) Reservoir inflow forecasting with a modified coactive neuro-fuzzy inference system: a case study for a semi-arid region. Theor Appl Climatol. https://doi.org/10.1007/s00704-017-2292-5

Allawi MF, Jaafar O, Mohamad Hamzah F et al (2018) Operating a reservoir system based on the shark machine learning algorithm. Environ Earth Sci 77:366. https://doi.org/10.1007/s12665-018-7546-8

Allawi MF, Jaafar O, Mohamad Hamzah F et al (2019a) Forecasting hydrological parameters for reservoir system utilizing artificial intelligent models and exploring their influence on operation performance. Knowl Based Syst 163:907–926. https://doi.org/10.1016/J.KNOSYS.2018.10.013

Allawi MF, Jaafar O, Mohamad Hamzah F, El-Shafie A (2019b) Novel reservoir system simulation procedure for gap minimization between water supply and demand. J Clean Prod 206:928–943. https://doi.org/10.1016/J.JCLEPRO.2018.09.237

Allawi MF, Othman FB, Afan HA et al (2019) Reservoir evaporation prediction modeling based on artificial intelligence methods. Water 11:1226. https://doi.org/10.3390/W11061226

Allawi MF, Ahmed ML, Aidan IA et al (2020a) Developing reservoir evaporation predictive model for successful dam management. Stoch Environ Res Risk Assess. https://doi.org/10.1007/s00477-020-01918-6

Allawi MF, Aidan IA, El-Shafie A (2020b) Enhancing the performance of data-driven models for monthly reservoir evaporation prediction. Environ Sci Pollut Res 28:8281–8295. https://doi.org/10.1007/s11356-020-11062-x

Apaydin H, Feizi H, Sattari MT et al (2020) Comparative analysis of recurrent neural network architectures for reservoir inflow forecasting. Water 12:1500. https://doi.org/10.3390/w12051500

Arunkumar R, Jothiprakash V (2013) Reservoir evaporation prediction using data-driven techniques. J Hydrol Eng 18:40–49. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000597

Ashofteh P-S, Haddad OB, Loáiciga HA (2015) Evaluation of climatic-change impacts on multiobjective reservoir operation with multiobjective genetic programming. J Water Resour Plan Manag 141:4015030. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000540

Awan JA, Bae D (2013) Application of adaptive neuro-fuzzy inference system for dam inflow prediction using long-range weather forecast. In: Eighth international conference on digital information management (ICDIM 2013). IEEE, pp 247–251

Bae D-H, Jeong DM, Kim G (2007) Monthly dam inflow forecasts using weather forecasting information and neuro-fuzzy technique. Hydrol Sci J 52:99–113. https://doi.org/10.1623/hysj.52.1.99

Bahrami M, Bozorg-Haddad O, Chu X (2018) Application of cat swarm optimization algorithm for optimal reservoir operation. J Irrig Drain Eng 144:4017057. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001256

Bai Y, Chen Z, Xie J, Li C (2016a) Daily reservoir inflow forecasting using multiscale deep feature learning with hybrid models. J Hydrol 532:193–206. https://doi.org/10.1016/j.jhydrol.2015.11.011

Bai Y, Xie J, Wang X, Li C (2016) Model fusion approach for monthly reservoir inflow forecasting. J Hydroinfor 18:634–650

Baltar AM, Fontane DG (2008) Use of multiobjective particle swarm optimization in water resources management. J Water Resour Plan Manag 134:257–265. https://doi.org/10.1061/(ASCE)0733-9496(2008)134:3(257)

Baydaroğlu Ö, Koçak K (2014) SVR-based prediction of evaporation combined with chaotic approach. J Hydrol 508:356–363. https://doi.org/10.1016/j.jhydrol.2013.11.008

Bilal RD, Pant M, Jain SK (2020) Dynamic programming integrated particle swarm optimization algorithm for reservoir operation. Int J Syst Assur Eng Manag 11:515–529. https://doi.org/10.1007/s13198-020-00974-z

Bozorg-Haddad O, Karimirad I, Seifollahi-Aghmiuni S, Loáiciga HA (2015) Development and application of the bat algorithm for optimizing the operation of reservoir systems. J Water Resour Plan Manag 141:4014097. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000498

Bozorg-Haddad O, Janbaz M, Loáiciga H (2016a) Application of the gravity search algorithm to multi-reservoir operation optimization. Adv Water Resour 98:173–185. https://doi.org/10.1016/J.ADVWATRES.2016.11.001

Bozorg-Haddad O, Zarezadeh-Mehrizi M, Abdi-Dehkordi M et al (2016b) A self-tuning ANN model for simulation and forecasting of surface flows. Water Resour Manag 30:2907–2929. https://doi.org/10.1007/s11269-016-1301-2

Broomhead D, Lowe D (1988) Radial basis functions, multi-variable functional interpolation and adaptive networks. 2:327–355

Budu K (2014) Comparison of wavelet-based ANN and regression models for reservoir inflow forecasting. J Hydrol Eng 19:1385–1400. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000892

Chang L-C, Chang F-J (2001) Intelligent control for modelling of real-time reservoir operation. Hydrol Process 15:1621–1634. https://doi.org/10.1002/hyp.226

Chang F-J, Lai J-S, Kao L-S (2003) Optimization of operation rule curves and flushing schedule in a reservoir. Hydrol Process 17:1623–1640. https://doi.org/10.1002/hyp.1204

Chang L-C, Chang F-J, Wang K-W, Dai S-Y (2010) Constrained genetic algorithms for optimizing multi-use reservoir operation. J Hydrol 390:66–74. https://doi.org/10.1016/j.jhydrol.2010.06.031

Chau KW (2007) A split-step particle swarm optimization algorithm in river stage forecasting. J Hydrol 346:131–135. https://doi.org/10.1016/j.jhydrol.2007.09.004

Chen L, McPhee J, Yeh WW-G (2007) A diversified multiobjective GA for optimizing reservoir rule curves. Adv Water Resour 30:1082–1093. https://doi.org/10.1016/j.advwatres.2006.10.001

Chen S, Shao D, Li X, Lei C (2016) Simulation-optimization modeling of conjunctive operation of reservoirs and ponds for irrigation of multiple crops using an improved artificial bee colony algorithm. Water Resour Manag 30:2887–2905. https://doi.org/10.1007/s11269-016-1277-y

Cheng C-T, Feng Z-K, Niu W-J, Liao S-L (2015) Heuristic methods for reservoir monthly inflow forecasting: a case study of Xinfengjiang Reservoir in Pearl River, China. Water 7:4477–4495. https://doi.org/10.3390/w7084477

Chiamsathit C, Adeloye AJ, Bankaru-Swamy S (2016) Inflow forecasting using Artificial Neural Networks for reservoir operation. Proc Int Assoc Hydrol Sci 373:209–214. https://doi.org/10.5194/piahs-373-209-2016

Coulibaly P, Anctil F, Bobée B (2000) Daily reservoir inflow forecasting using artificial neural networks with stopped training approach. J Hydrol 230:244–257. https://doi.org/10.1016/S0022-1694(00)00214-6

Coulibaly P, Anctil F, Aravena R, Bobée B (2001) Artificial neural network modeling of water table depth fluctuations. Water Resour Res 37:885–896. https://doi.org/10.1029/2000WR900368

Dorigo M (1992) Optimization, learning and natural algorithms. Politecnico di Milano, Italy

Ehteram M, Karami H, Mousavi S-F et al (2017) Optimizing dam and reservoirs operation based model utilizing shark algorithm approach. Knowl Based Syst 122:26–38. https://doi.org/10.1016/j.knosys.2017.01.026

Elizaga NB, Maravillas EA, Gerardo BD (2014) Regression-based inflow forecasting model using exponential smoothing time series and backpropagation methods for Angat Dam. In: 2014 international conference on humanoid, nanotechnology, information technology, communication and control, environment and management (HNICEM). IEEE, pp 1–6

El-Shafie A, Noureldin A (2011) Generalized versus non-generalized neural network model for multi-lead inflow forecasting at Aswan High Dam. Hydrol Earth Syst Sci 15:841–858. https://doi.org/10.5194/hess-15-841-2011

El-Shafie A, Taha MR, Noureldin A (2007) A neuro-fuzzy model for inflow forecasting of the Nile river at Aswan high dam. Water Resour Manag 21:533–556. https://doi.org/10.1007/s11269-006-9027-1

El-Shafie A, Abdin AE, Noureldin A, Taha MR (2009) Enhancing inflow forecasting model at Aswan High Dam utilizing radial basis neural network and upstream monitoring stations measurements. Water Resour Manag 23:2289–2315. https://doi.org/10.1007/s11269-008-9382-1

Farnsworth R, Thompson E (1982) Mean monthly, seasonal, and annual pan evaporation for the United States

Fayaed SS, El-Shafie A, Jaafar O (2013) Reservoir-system simulation and optimization techniques. Stoch Environ Res Risk Assess 27:1751–1772. https://doi.org/10.1007/s00477-013-0711-4

Fernando DAK, Jayawardena AW (1998) Runoff forecasting using RBF networks with OLS algorithm. J Hydrol Eng 3:203–209. https://doi.org/10.1061/(ASCE)1084-0699(1998)3:3(203)

Fritschen LJ (1966) Energy balance method. In: Proceedings, American Society of Agricultural Engineering conference Evapotranspiration its role Water Resour Manag, pp 34–37

Garousi-Nejad I, Bozorg-Haddad O, Loáiciga HA (2016a) Modified firefly algorithm for solving multireservoir operation in continuous and discrete domains. J Water Resour Plan Manag 142:4016029. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000644

Garousi-Nejad I, Bozorg-Haddad O, Loáiciga HA, Mariño MA (2016b) Application of the firefly algorithm to optimal operation of

reservoirs with the purpose of irrigation supply and hydropower production. J Irrig Drain Eng 142:4016041. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001064
Ghorbani MA, Deo RC, Yaseen ZM et al (2017) Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (MLP-FFA) model: case study in North Iran. Theor Appl Climatol. https://doi.org/10.1007/s00704-017-2244-0
Grossmann A, Morlet J (1984) Decomposition of hardy functions into square integrable wavelets of constant shape. SIAM J Math Anal 15:723–736. https://doi.org/10.1137/0515056
Guitjens JC (1982) Models of alfalfa yield and evapotranspiration. J Irrig Drain Div 108:212–222
Guo J, Zhou J, Qin H et al (2011) Monthly streamflow forecasting based on improved support vector machine model. Expert Syst Appl 38:13073–13081. https://doi.org/10.1016/j.eswa.2011.04.114
Haddad O, Afshar A, Mariño M (2011) Multireservoir optimisation in discrete and continuous domains. Proc
Hadiyan PP, Moeini R, Ehsanzadeh E (2020) Application of static and dynamic artificial neural networks for forecasting inflow discharges, case study: Sefidroud Dam reservoir. Sustain Comput Inform Syst 27:100401. https://doi.org/10.1016/j.suscom.2020.100401
Harbeck GE (1962) A practical field technique for measuring reservoir evaporation utilizing mass-transfer theory
Haykin S (1994) Neural networks: a comprehensive foundation. Macmillan Coll Publ Co Inc
Hidalgo IG, Barbosa PSF, Francato AL et al (2015) Management of inflow forecasting studies. Water Pract Technol 10:402. https://doi.org/10.2166/wpt.2015.050
Higgins JM, Brock WG (1999) Overview of reservoir release improvements at 20 TVA dams. J Energy Eng 125:1–17. https://doi.org/10.1061/(ASCE)0733-9402(1999)125:1(1)
Hınçal O, Altan-Sakarya AB, Metin Ger A (2011) Optimization of multireservoir systems by genetic algorithm. Water Resour Manag 25:1465–1487. https://doi.org/10.1007/s11269-010-9755-0
Hong J, Lee S, Bae JH et al (2020) Development and evaluation of the combined machine learning models for the prediction of dam inflow. Water 12:2927. https://doi.org/10.3390/w12102927
Hornik K, Stinchcombe M, White H (1989) Multilayer feedforward networks are universal approximators. Neural Netw 2:359–366. https://doi.org/10.1016/0893-6080(89)90020-8
Hossain MS, El-shafie A (2014) Performance analysis of artificial bee colony (ABC) algorithm in optimizing release policy of Aswan High Dam. Neural Comput Appl 24:1199–1206. https://doi.org/10.1007/s00521-012-1309-3
Hossain MS, El-Shafie A (2014) Evolutionary techniques versus swarm intelligences: application in reservoir release optimization. Neural Comput Appl 24:1583–1594. https://doi.org/10.1007/s00521-013-1389-8
Hossain MS, El-Shafie A, Wan Mohtar WHM (2015) Application of intelligent optimization techniques and investigating the effect of reservoir size in calibrating the reservoir operating policy. Water Policy 17:wp2015023. https://doi.org/10.2166/wp.2015.023
Hosseini-Moghari S-M, Morovati R, Moghadas M, Araghinejad S (2015a) Optimum operation of reservoir using two evolutionary algorithms: imperialist competitive algorithm (ICA) and cuckoo optimization algorithm (COA). Water Resour Manag 29:3749–3769. https://doi.org/10.1007/s11269-015-1027-6
Hosseini-Moghari S, Morovati R, Moghadas M (2015b) Optimum operation of reservoir using two evolutionary algorithms: imperialist competitive algorithm (ICA) and cuckoo optimization algorithm (COA). Water Resour
Izadbakhsh MA, Javadikia H (2014) Application of hybrid FFNN-genetic algorithm for predicting evaporation in storage dam reservoirs. Agric Commun 2:57–62
Jalali M, Afshar A, Marino M (2007) Multi-colony ant algorithm for continuous multi-reservoir operation optimization problem. Water Resour Manag
Jia B, Simonovic SP, Zhong P, Yu Z (2016) A multi-objective best compromise decision model for real-time flood mitigation operations of multi-reservoir system. Water Resour Manag 30:3363–3387. https://doi.org/10.1007/s11269-016-1356-0
Jothiprakash V, Kote AS (2011) Effect of pruning and smoothing while using M5 model tree technique for reservoir inflow prediction. J Hydrol Eng 16:563–574. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000342
Jothiprakash V, Magar RB (2012) Multi-time-step ahead daily and hourly intermittent reservoir inflow prediction by artificial intelligent techniques using lumped and distributed data. J Hydrol 450:293–307. https://doi.org/10.1016/j.jhydrol.2012.04.045
Jothiprakash V, Shanthi G (2006) Single reservoir operating policies using genetic algorithm. Water Resour Manag 20:917–929. https://doi.org/10.1007/s11269-005-9014-y
Kennedy J, Eberhart R (1995) Particle swarm optimization. In: Proceedings of ICNN'95 - international conference on neural networks. IEEE, pp 1942–1948
Keskin ME, Terzi Ö (2006) Artificial neural network models of daily pan evaporation. J Hydrol Eng 11:65–70. https://doi.org/10.1061/(ASCE)1084-0699(2006)11:1(65)
Keskin ME, Terzi Ö, Taylan D (2004) Fuzzy logic model approaches to daily pan evaporation estimation in western Turkey/Estimation de l'évaporation journalière du bac dans l'Ouest de la Turquie par des modèles à base de logique floue. Hydrol Sci J. https://doi.org/10.1623/hysj.49.6.1001.55718
Klir G, Yuan B (1995) Fuzzy sets and fuzzy logic
Kumar DN, Reddy MJ (2006) Ant colony optimization for multi-purpose reservoir operation. Water Resour Manag 20:879–898. https://doi.org/10.1007/s11269-005-9012-0
Kumar S, Tiwari MK, Chatterjee C, Mishra A (2015) Reservoir inflow forecasting using ensemble models based on neural networks, wavelet analysis and bootstrap method. Water Resour Manag 29:4863–4883. https://doi.org/10.1007/s11269-015-1095-7
Labadie JW (2004) Optimal operation of multireservoir systems: state-of-the-art review. J Water Resour Plan Manag 130:93–111. https://doi.org/10.1061/(ASCE)0733-9496(2004)130:2(93)
Lee D, Kim H, Jung I, Yoon J (2020) Monthly reservoir inflow forecasting for dry period using teleconnection indices: a statistical ensemble approach. Appl Sci 10:3470. https://doi.org/10.3390/app10103470
Li X-G, Wei X (2008) An improved genetic algorithm-simulated annealing hybrid algorithm for the optimization of multiple reservoirs. Water Resour Manag 22:1031–1049. https://doi.org/10.1007/s11269-007-9209-5
Li P-H, Kwon H-H, Sun L et al (2009) A modified support vector machine based prediction model on streamflow at the Shihmen Reservoir. Taiwan Int J Climatol 30:1256–1268. https://doi.org/10.1002/joc.1954
Li F-F, Wei J-H, Fu X-D, Wan X-Y (2012) An effective approach to long-term optimal operation of large-scale reservoir systems: case study of the three gorges system. Water Resour Manag 26:4073–4090. https://doi.org/10.1007/s11269-012-0131-0
Li L, Liu P, Rheinheimer DE et al (2014) Identifying explicit formulation of operating rules for multi-reservoir systems using genetic programming. Water Resour Manag 28:1545–1565. https://doi.org/10.1007/s11269-014-0563-9

Li C, Bai Y, Zeng B (2016) Deep feature learning architectures for daily reservoir inflow forecasting. Water Resour Manag 30:5145–5161. https://doi.org/10.1007/s11269-016-1474-8
Liao X, Zhou J, Ouyang S et al (2014) Multi-objective artificial bee colony algorithm for long-term scheduling of hydropower system: a case study of China. Water Util J 7:13–23
Lin J-Y, Cheng C-T, Chau K-W (2006) Using support vector machines for long-term discharge prediction. Hydrol Sci J 51:599–612. https://doi.org/10.1623/hysj.51.4.599
Lin G-F, Chen G-R, Huang P-Y, Chou Y-C (2009) Support vector machine-based models for hourly reservoir inflow forecasting during typhoon-warning periods. J Hydrol 372:17–29. https://doi.org/10.1016/j.jhydrol.2009.03.032
Lohani AK, Kumar R, Singh RD (2012) Hydrological time series modeling: a comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. J Hydrol 442:23–35. https://doi.org/10.1016/j.jhydrol.2012.03.031
Madadgar S, Afshar A (2009) An improved continuous ant algorithm for optimization of water resources problems. Water Resour Manag 23:2119–2139. https://doi.org/10.1007/s11269-008-9373-2
Maier HR, Dandy GC (2000) Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environ Model Softw 15:101–124. https://doi.org/10.1016/S1364-8152(99)00007-9
Malik A, Kumar A, Kisi O (2018) Daily pan evaporation estimation using heuristic methods with gamma test. J Irrig Drain Eng 144:4018023. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001336
Ming B, Chang J, Huang Q et al (2015) Optimal operation of multi-reservoir system based-on cuckoo search algorithm. Water Resour Manag 29:5671–5687. https://doi.org/10.1007/s11269-015-1140-6
Moeeni H, Bonakdari H (2016) Forecasting monthly inflow with extreme seasonal variation using the hybrid SARIMA-ANN model. Stoch Environ Res Risk Assess. https://doi.org/10.1007/s00477-016-1273-z
Moghaddamnia A, Ghafari M, Piri J, Han D (2009a) Evaporation estimation using support vector machines technique. Int J Eng Appl Sci 5:415–423
Moghaddamnia A, Ghafari Gousheh M, Piri J et al (2009b) Evaporation estimation using artificial neural networks and adaptive neuro-fuzzy inference system techniques. Adv Water Resour 32:88–97. https://doi.org/10.1016/j.advwatres.2008.10.005
Momtahen S, Dariane AB (2007) Direct search approaches using genetic algorithms for optimization of water reservoir operating policies. J Water Resour Plan Manag 133:202–209. https://doi.org/10.1061/(ASCE)0733-9496(2007)133:3(202)
Mousavi SJ, Shourian M (2010) Capacity optimization of hydropower storage projects using particle swarm optimization algorithm. J Hydroinform. https://doi.org/10.2166/hydro.2009.039
Nagesh Kumar D, Janga Reddy M (2007) Multipurpose reservoir operation using particle swarm optimization. J Water Resour Plan Manag 133:192–201. https://doi.org/10.1061/(ASCE)0733-9496(2007)133:3(192)
Noori R, Karbassi AR, Moghaddamnia A et al (2011) Assessment of input variables determination on the SVM model performance using PCA, Gamma test, and forward selection techniques for monthly stream flow prediction. J Hydrol 401:177–189. https://doi.org/10.1016/j.jhydrol.2011.02.021
Nourani V, Hosseini Baghanam A, Adamowski J, Kisi O (2014) Applications of hybrid wavelet–Artificial Intelligence models in hydrology: a review. J Hydrol 514:358–377. https://doi.org/10.1016/j.jhydrol.2014.03.057
Nourani V, Fard M (2012) Sensitivity analysis of the artificial neural network outputs in simulation of the evaporation process at different climatologic regimes. Adv Eng Softw
Osman A, Afan HA, Allawi MF et al (2020) Adaptive Fast Orthogonal Search (FOS) algorithm for forecasting streamflow. J Hydrol 586:124896. https://doi.org/10.1016/j.jhydrol.2020.124896
Penman H (1948) Natural evaporation from open water, bare soil and grass. Proc R Soc Lond
Reddy MJ, Nagesh Kumar D (2007) Multi-objective particle swarm optimization for generating optimal trade-offs in reservoir operation. Hydrol Process 21:2897–2909. https://doi.org/10.1002/hyp.6507
Rosenberg N, Blad B, Verma S (1983) Microclimate: the biological environment, 2nd edn. Wiley, Hoboken
SaberChenari K, Abghari H, Tabari H (2016) Application of PSO algorithm in short-term optimization of reservoir operation. Environ Monit Assess 188:667. https://doi.org/10.1007/s10661-016-5689-1
Salih SQ, Allawi MF, Yousif AA et al (2019) Viability of the advanced adaptive neuro-fuzzy inference system model on reservoir evaporation process simulation: case study of Nasser Lake in Egypt. Eng Appl Comput Fluid Mech 13:878–891. https://doi.org/10.1080/19942060.2019.1647879
Sharif M, Wardlaw R (2000) Multireservoir systems optimization using genetic algorithms: case study. J Comput Civ Eng 14:255–263. https://doi.org/10.1061/(ASCE)0887-3801(2000)14:4(255)
Solomatine DP, Ostfeld A (2008) Data-driven modelling: some past experiences and new approaches. J Hydroinform, 3–22
Specht DF (1991) A general regression neural network. IEEE Trans Neural Networks 2:568–576. https://doi.org/10.1109/72.97934
Storn R, Price K (1997) Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. J Glob Optim 11:341–359. https://doi.org/10.1023/A:1008202821328
Storn R (1996) On the usage of differential evolution for function optimization. In: Biennial conference of the North American fuzzy information processing society - NAFIPS. IEEE, pp 519–523
Tabari H, Marofi S, Sabziparvar A-A (2010) Estimation of daily pan evaporation using artificial neural network and multivariate nonlinear regression. Irrig Sci 28:399–406. https://doi.org/10.1007/s00271-009-0201-0
Tabari H, Hosseinzadeh Talaee P, Abghari H (2012) Utility of coactive neuro-fuzzy inference system for pan evaporation modeling in comparison with multilayer perceptron. Meteorol Atmos Phys 116:147–154. https://doi.org/10.1007/s00703-012-0184-x
Tan SBK, Shuy EB, Chua LHC (2007) Modelling hourly and daily open-water evaporation rates in areas with an equatorial climate. Hydrol Process 21:486–499. https://doi.org/10.1002/hyp.6251
Tezel G, Buyukyildiz M (2016) Monthly evaporation forecasting using artificial neural networks and support vector machines. Theor Appl Climatol 124:69–80. https://doi.org/10.1007/s00704-015-1392-3
Tikhamarine Y, Souag-Gamane D, Najah Ahmed A et al (2020) Improving artificial intelligence models accuracy for monthly streamflow forecasting using grey Wolf optimization (GWO) algorithm. J Hydrol 582:124435. https://doi.org/10.1016/j.jhydrol.2019.124435
Valipour M, Banihabib ME, Behbahani SMR (2012) Monthly inflow forecasting using autoregressive artificial neural network. J Appl Sci 12:2139–2147. https://doi.org/10.3923/jas.2012.2139.2147
Valipour M, Banihabib ME, Behbahani SMR (2013) Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir. J Hydrol 476:433–441. https://doi.org/10.1016/J.JHYDROL.2012.11.017

Wafae EH, Driss O, Bouziane A, Hasnaoui MD (2016) Genetic Algorithm applied to reservoir operation optimization with emphasis on the Moroccan context. In: 2016 3rd international conference on logistics operations management (GOL). IEEE, pp 1–4
Wang W, Jin J, Li Y (2009a) Prediction of inflow at three gorges Dam in Yangtze River with wavelet network model. Water Resour Manag 23:2791–2803. https://doi.org/10.1007/s11269-009-9409-2
Wang WC, Chau KW, Cheng CT, Qiu L (2009b) A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series. J Hydrol 374:294–306. https://doi.org/10.1016/j.jhydrol.2009.06.019
Wang K-W, Chang L-C, Chang F-J (2011) Multi-tier interactive genetic algorithms for the optimization of long-term reservoir operation. Adv Water Resour 34:1343–1351. https://doi.org/10.1016/j.advwatres.2011.07.004
Wang W, Nie X, Qiu L (2010) Support vector machine with particle swarm optimization for reservoir annual inflow forecasting. In: 2010 international conference on artificial intelligence and computational intelligence. IEEE, pp 184–188
Wehrens R, Buydens LMC, Wehrens R, Buydens LMC (2000) Classical and nonclassical optimization methods. In: Encyclopedia of analytical chemistry. Wiley, Chichester, UK
Whigham PA, Crapper PF (2001) Modelling rainfall-runoff using genetic programming. Math Comput Model 33:707–721. https://doi.org/10.1016/S0895-7177(00)00274-0
Wu L, Huang G, Fan J et al (2020) Hybrid extreme learning machine with meta-heuristic algorithms for monthly pan evaporation prediction. Comput Electron Agric 168:105115. https://doi.org/10.1016/j.compag.2019.105115
Young AY (1947) Evaporation from water surface in California: summary of pan records and coeffcients
Yu P-S, Yang T-C, Chen S-Y et al (2017) Comparison of random forests and support vector machine for real-time radar-derived rainfall forecasting. J Hydrol 552:92–104. https://doi.org/10.1016/J.JHYDROL.2017.06.020
Yu Y, Wang P, Wang C, Wang X (2018) Optimal reservoir operation using multi-objective evolutionary algorithms for potential estuarine eutrophication control. J Environ Manag 223:758–770. https://doi.org/10.1016/J.JENVMAN.2018.06.044
Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353. https://doi.org/10.1016/S0019-9958(65)90241-X
Zhang X, Wang H, Peng A et al (2020) Quantifying the uncertainties in data-driven models for reservoir inflow prediction. Water Resour Manag 34:1479–1493. https://doi.org/10.1007/s11269-020-02514-7