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REVIEW ARTICLE

Review on applications of artificial intelligence methods for dam and reservoir-hydro-environment models

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Abstract

Efficacious operation for dam and reservoir system could guarantee not only a defenselessness policy against natural hazard but also identify rule to meet the water demand. Successful operation of dam and reservoir systems to ensure optimal use of water resources could be unattainable without accurate and reliable simulation models. According to the highly stochastic nature of hydrologic parameters, developing accurate predictive model that efficiently mimic such a complex pattern is an increasing domain of research. During the last two decades, artificial intelligence (AI) techniques have been significantly utilized for attaining a robust modeling to handle different stochastic hydrological parameters. AI techniques have also shown considerable progress in finding optimal rules for reservoir operation. This review research explores the history of developing AI in reservoir inflow forecasting and prediction of evaporation from a reservoir as the major components of the reservoir simulation. In addition, critical assessment of the advantages and disadvantages of integrated AI simulation methods with optimization methods has been reported. Future research on the potential of utilizing new innovative methods based AI techniques for reservoir simulation and optimization models have also been discussed. Finally, proposal for the new mathematical procedure to accomplish the realistic evaluation of the whole optimization model performance (reliability, resilience, and vulnerability indices) has been recommended.

Keywords Hydrological parameters · Predictive models · Optimization models · Environmental

Introduction

Background

The operating of reservoir system is a significant issue for decision-makers in the water recourses management field. The decision process for selecting the optimal operational rules to operate the reservoir system is often complexed by conflicts existing between the multi-objectives for the reservoir. The reservoirs are constructed for serving several purposes such as water irrigation, hydropower generation, water supply, flood control, and other objectives. Although there are some degrees of commensurability among these purposes, there is more conflict and competition particularly during the flood and drought seasons. For example, in case the inflows volume is over the reservoir capacity, this leads for occurring the dam spillage, hence an unexpected flood to occur in the downstream. On the other hand, the reservoir may sometimes need to release an extra volume of water to match the downstream requirements during drought seasons, which leads to the low storage capacity for the reservoir. To handle these problems, the decision makers should have the ability in determining the optimal policies for water management. Accordingly, the focus must be on redoubling efforts to enhance the operational efficiency and effectiveness of the reservoir system for optimization of the beneficial uses of these projects. Furthermore, some of the adverse

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impacts of a large storage project could be reduced by improving operational management and with added facilities (Higgins and Brock 1999).

Dam optimization models

Optimization methods are the proper tools for addressing reservoir operation problems and improving water resources management. The previous studies developed several optimization methods of operating the reservoir system, classified methods into classic and evolutionary algorithm approaches (Ahmadi et al. 2014; Ashofteh et al. 2015). The conventional approaches are helpful of determining the suitable solution for unconstrained maxima and minima of the continuous functions (Wehrens et al. 2000). This category comprises random search technique; linear, dynamic, and stochastic programming; and other techniques. Although many types of research have used these methods in reservoir operation, the classic approaches have not been successful (have not performed well) in handling complex problems, particularly with multipurpose reservoir (Bozorg-Haddad et al. 2016a). In fact, the evolutionary algorithms were developed to tackle such complex problems. Most of the previous studies reported that the evolutionary algorithms have much superior capability compared to classical methods and they could effectively address several objective functions, including multi-purpose reservoirs. In reality, the success of optimization methods depends on the accuracy of the required data such as water inflows and evaporation from a reservoir during a certain period. The forecasting accuracy of the inflow and evaporation is a significant issue in achieving successful management of the reservoir operation. Measuring these hydrological parameters is necessary and hence selecting a reliable predictive model that is able to provide accurate and explicit information for optimization models is crucial.

Hydrological parameters for reservoir simulation models

The reservoir inflow, whether long-term or short-term, is not easily predictable because the inflow pattern is characterized by high complexity, non-stationary, high stochastic, and nonlinearity. Thus, the inflow modeling is very crucial for water resources planning and management. Long-term inflow forecasts are significant for water resource decisions such as operational optimization of reservoir systems, hydropower generation, scheduling releases, water irrigation decisions, and other applications. Short-term inflow forecasts are important for reliable operation of the flood warning systems and for the mitigation. As a result, several methodologies have been developed to improve long-term inflow forecasts. It is a well-known fact that the behavioral aspects of reservoirs are different. Hence, there is no single model which could be adopted that can provide good performance equally for all reservoirs.

The conventional methods such as autoregressive moving average (ARMA), autoregressive (AR), moving average (MA), linear regression (LR), autoregressive integrated moving average (ARIMA), multi-linear regression (MLR), and ARIMAX have been applied for inflow forecasting (Salas 1980; Wu et al. 2009; Valipour et al. 2012; Valipour 2015). These models are incapable of capturing stochastic, nonlinearity involved in hydrological processes. As such, scholars have conducted studies for developing methods which are able of overcoming the drawbacks and limitations of the classical methods.

The evaporation from the reservoirs is also a significant matter for reservoir management. Estimating the amount of losses from surface water in the reservoir system is a highly crucial aspect in the water resource planning and management. An accurate predictive model for evaporation prediction is required to determine the volume of water available in a reservoir system. The effect of losses is considered through the design of water distribution systems. The evaporation leads to losing certain amounts of water from a reservoir, and hence the evaporation rate must be known in order to handle the amount of water lost from a reservoir at any period of time. The successful evaporation modeling facilitates in ensuring sufficient amount of water distribution in the reservoir system (Fayaed et al. 2013).

The measurement of actual evaporation is conducted using several indirect methods such as Priestley-Taylor, energy budget method, Thornthwaite equations, Penman-Monteith, Blaney-Criddle, and other methods (Terzi 2013). In addition, the evaporation from a reservoir can be estimated using direct methods, which comprise the application of pan measurements such as class A pan, class U pan, and other types of measurements. The performance of those conventional methods was unsuccessful in achieving satisfactory results because of the stochastic nature, nonlinearity, and complexity in the evaporation pattern (Nourani and Sayyah Fard 2012). As a result, there is need for providing accurate models capable of addressing the estimation of evaporation rate.

In the last two decades, the data-driven techniques of artificial intelligence (AI) have received considerable attention from researchers in addressing significant dynamicity and the natural stochastic characteristics concealed in a hydrological database. Some characteristics of AI methods are suitable for solving reservoir inflow and evaporation modeling problems. Numerous AI-based models have been broadly used, such as optimization algorithms, classification methods, as well as probability and statistical learning models (Luger 2005). Among the widespread implementation of AI techniques, fuzzy logic, neural network, genetic algorithm, support vector machine, and genetic programing have been significantly utilized in several hydrologic domains (Nourani et al. 2014). Since the emergence of AI-models in water resources field, the efficacy of their performance has been reported in hydrological applications broadly (e.g., rainfall-runoff; precipitation, inflow, evaporation rate, water quality, sediment, etc.).

Objectives

The primary goals of this review paper are categorizing AI methods comprehensively and enumerating their new application in reservoir system management in terms of operation optimization, inflow forecasting, and evaporation rate prediction. Furthermore, apart from AI approaches in optimization system, other classical models applied in reservoir system operation are also evaluated. The current review also focuses on the effect of the reliability of the inflow modeling and evaporation rate on the efficiency of reservoir operation optimization models. This review covers various articles published in high impact factor journals. The challenges faced by researchers in the operation of reservoir systems such as uncertainty, nonlinearity, and multi-objectives are presented here. Details of the selected studies, including authors, year of publication, AI approaches, and other information, are given in Tables 1, 2, and 3. Discussion of the basic concepts of each AI technique for inflow and evaporation modeling and reviews on the applications reported in previous articles are presented in "Applications of AI-modeling in forecasting evaporation and reservoir inflow" section. Evaluation and assessment of the application of AI methods in simulation hydrological parameters (inflow and evaporation) in a reservoir are given in "Evaluation and assessments for predictive models" section. The basic theory behind the concepts of the optimization methods and their implementation in reservoir operation are presented in "Applications of optimization models in operating the reservoir" section, while the assessments of the optimization methods are discussed in "Evaluation and assessments for optimization models" section. The recommendations for future research are given in "Recommendations for future research" section. The last section of the review paper addresses the summary and conclusions of the study.

Applications of AI-modeling in forecasting evaporation and reservoir inflow

Artificial neural networks

The artificial neural networks (ANNs) are a set of densely interconnected processing units which handles parallel-distributed information system and has the same concept as that of the biological neural networks of the human brain (Haykin 1999). The development of ANN method based on several rules are (a) the information processing that exists at several single elements called neurons or nodes; (b) signals are transferred between neurons by connection links; (c) the connection link has a certain weight, which is representing its connection intensity; and (d) typically, each node of the architecture of ANN applies a nonlinear transformation (activation function) that determines output signals for the input variables (Task and Neural 2000). Feed forward neural networks (FFNN), radial basis function neural networks (RBFNN), and generalized regression neural network (GRNN) techniques are examples of the types of ANN method that utilize inflow and evaporation modeling. An overall review of the implementation of ANN method to solve different engineering problems has been developed by (Coulibaly et al. (1999), Maier and Dandy (2000), and Dawson and Wilby (2001)). We reported the previous studies which used the ANN for reservoir inflow forecasting and evaporation prediction.

FFNN technique has been developed by Coulibaly et al. (2000). They have utilized the developed model for daily reservoir inflow forecasting. The proposed model has been designed to avoid over and under fitting during training phase by taking advantage of the Levenberg Marquardt back-propagation (LMBP) and cross-validation technique. The accuracy of the proposed model was compared to benchmarks from the statistical model and the operation conceptual model. The new ANN structure provided good results for modeling reservoir inflow.

One year later, Coulibaly et al. (2001) utilized the deep neural network (DNN) model for addressing the detection of the reservoir inflow pattern. They have examined the accuracy of three types of temporal neural network structures with different inherent representations of temporal information. The IDNN model has been used to forecast inflow data. Also, the performance of regularized neural network (RNN) model with and without time-delays was investigated for reservoir inflow forecasting. The accuracy result of these models was compared with the performance of conventional multi-layer perceptron (MLP) technique. The results showed that the dynamic neural network models demonstrated significant improvement in forecasting accuracy compared to the conventional MLP model. The study concluded that the performance of the RNN method is more accurate compared to other suggested models.

El-Shafie et al. (2009) conducted a study to forecast reservoir inflow data at Aswan High Dam (AHD) using the inflow data of the oversight stations at upstream of the AHD. The natural inflow values collected during the 30-year period at four oversight stations were analyzed to determine their cross- and auto-correlations patterns. They developed reservoir inflow forecasting modeling using ANN model. The researchers found out that the ANN modeling succeeded in forecasting inflow data for a few months ahead with

Table 1 Summarizing of the reviewed studies that utilized AI-models for reservoir inflow forecasting, including a type of AI techniques, authors, methods, input variables, and the used time scale

No.	Type of AI-models	Authors	Methods	Variables	Time scale
1	ANN	Coulibaly et al. 2000	FFNN	Inflow, Temperature, Precipitation	Daily
2		Coulibaly et al. 2001	RNN, DNN, MLP	Inflow, Precipitation	Daily
3		Muluye and Coulibaly 2007	BNN, RMLP, TLFN, MLP	Inflow, Temperature, Precipitation	Seasonal
4		El-Shafie et al. 2009	RBF-NN, MLP	Inflow	Monthly
5		El-Shafie and Noureldin 2011	RNN, ENN	Inflow	Monthly
6		Valipour et al. 2012	MLP-NN	Inflow	Monthly
7		Valipour et al. 2013	MLP-NN	Inflow	Monthly
8		Elizaga et al. 2014	FFBP	Inflow	Daily
9		Hidalgo et al. 2015	FFNN	Inflow	Daily Monthly
10		Chiamsathit et al. 2016	MLP	Inflow	Monthly
11	SVM	LIN et al. 2006	SVR	Inflow	Monthly
12		Lin et al. 2009	SVR	Inflow	Hourly
13		Li et al. 2009	SVR	Inflow, Precipitation	Monthly
14		Noori et al. 2011	SVR	Inflow, Rainfall, Temperature, Sun radiation	Monthly
15	Fuzzy logic	El-Shafie et al. 2007	ANFIS	Inflow	Monthly
16		BAE et al. 2007	ANFIS	Inflow, Rainfall, Temperature	Monthly
17		Lohani et al. 2012	ANFIS	Inflow	Monthly
18		Awan and Bae 2013	ANFIS	Inflow, Rainfall, Temperature	Monthly
19		Bai et al. 2016b	ANFIS	Inflow	Monthly
20	Integrated and other AI-models	Wang et al. 2009	WANN, TAR	Inflow	Annual, 10 days, Daily
21		Wang et al. 2010	SVM-PSO	Inflow	Annual
22		Jothiprakash and Kote 2011	M5 model tree	Inflow	Seasonally and Monthly
23		Jothiprakash and Magar 2012	LGP	Inflow, Rainfall	Hourly, Daily
24		Budu 2014	WRBF, WMLP	Inflow	Daily
25		Kumar et al. 2015	WANN, WMLR, BWNN BWMLR	Inflow, Rainfall	Daily
26		Cheng et al. 2015	SVM-GA	Inflow	Monthly
27		Bai et al. 2016a	MDFL	Inflow	Daily
28		Bozorg-Haddad et al. 2016b	ANN-GA	Inflow, Temperature, Precipitation, Evapotranspiration	Monthly
29		Moeeni and Bonakdari 2016	SARIMA-ANN	Inflow	Monthly
30		Li et al. 2016	DRBM-NN	Inflow	Daily

significant accuracy. Furthermore, this work had introduced a technically sound model regarding the Aswan High Dam operation policy to formulate the reservoir policies to serve the water users in Egypt.

In order to identify the optimal input pattern and overcome the over-fitting problem which could occur during the training period, El-Shafie and Noureldin (2011) suggested an autocorrelation and cross-correlation as a technique for finding the optimal input pattern. Two generalized models were used to avoid over-fitting of the training data, namely RNN and ensemble neural network (ENN) approaches. The natural inflow data over 130 years at Lake Nasser was utilized to train and test the suggested predictive model. The authors found that the RNN model was superior to the non-generalized neural network and traditional autocorrelation model and it was able to introduce inflow forecasting with high accuracy.

Valipour et al. (2012) investigated the ability of a dynamic autoregressive artificial neural network modeling to forecast monthly reservoir inflow forecasting. Comparison between the predictive model with the well-known technique called static autoregressive ANN has been conducted. The developed modeling has been applied for forecasting inflow data at Dez dam, located in a semi-arid region. The researchers provided different architectures of the static and dynamic models and in conjunction with two transfer functions, namely

Table 2 Summarizing of the reviewed studies that utilized AI-models for evaporation prediction, including a type of AI techniques, authors, methods, input variables, and the used time scale

No.	Type of AI-models	Authors	Methods	Variables	Time Scale
1	ANN	Keskin and Terzi 2006	MLP	Evaporation, Temperature, Sunshine, Solar radiation, Air pressure, Relative humidity, Wind speed	Daily
2		Tan et al. 2007	FF-NN	Evaporation, Relative humidity, Solar radiation, Wind speed, Temperature	Hourly, Daily
3		Moghaddamnia et al. 2009b	MLP	Evaporation, Temperature, Wind speed, Vapor pressure, Relative humidity	Daily
4		Tabari et al. 2010	FF-NN, MNR	Precipitation, Temperature, Wind speed, Relative humidity, Solar radiation	Daily
5		Allawi and El-Shafie 2016	RBF-NN	Evaporation, Temperature, Solar radiation Relative humidity	Daily
6	SVM	Moghaddamnia et al. 2009a	SVR	Evaporation, Temperature, Wind speed, Relative humidity	Daily
7		Baydaroğlu and Koçak 2014	SVR	Evaporation, Temperature, Wind speed, Solar radiation, Relative humidity	Daily
8		Tezel and Buyukyildiz 2016	SVR	Temperature, Relative humidity, Wind speed, Precipitation	Monthly
9	Fuzzy logic	Keskin et al. 2004	ANFIS	Temperature, Relative humidity, Solar radiation, Pressure, Sunshine, Wind speed	Daily
10	Integrated and other	Abghari et al. 2012	WNNs	Evaporation, Temperature, Relative humidity, Solar radiation, Sunshine	Daily
11	AI-models	Izadbakhsh and Javadikia 2014	FFNN-GA	Temperature, Wind speed, Sunshine	Daily

radial basis function and sigmoid function. The authors recommended that the autoregressive ANN with sigmoid activation function model would be able to forecast for the next 5 years with high accuracy compared to other models.

Table 3 Summarizing of the reviewed studies that utilized optimization modeling, including a type of optimization techniques, authors, methods, reservoir name, location, and compared models

No.	Authors	Method	Reservoir	Location	Compared with
1	Chang and Chang 2001	GA	Shihmen	China	ANFIS
2	Li and Wei 2008	IGA-SA	Wujiangdu, Dongfeng, Hongjiadu	China	GA, SA
3	Chen et al. 2007	MMGA	Fei-Tsui	China	GA
4	Li et al. 2012	IDP-GA	TGP-GZB	China	IDP, GA
5	Momtahen and Dariane 2007	GA	Dez	Iran	ISO, SDP, DP
6	Kerachian and Karamouz 2007	SVLGAQ	Ghomrud	Iran	SDP, SVLGA
7	Chang et al. 2003	GA	Tapu	China	–
8	Chang et al. 2010	CGA	Shih-Men	China	Historical operations
9	Wang et al. 2011	MIGA	Shihmen	China	GAs
10	Hınçal et al. 2011	GA	Bulue Mesa, Morrow, Crystal	USA	Historical operations
11	Reddy and Nagesh Kumar 2007	EM-MOPSO	Bhadra	India	NSGA
12	Mousavi and Shourian 2010	PSO	Bakhtiari	Iran	GA
13	Afshar 2012	FPCPSO	Dez	Iran	GA, UPSO, PCPSO
14	Nagesh Kumar and Janga Reddy 2007	EMPS	Bhadra	India	DPSA, DDDP, PSO, GA
15	SaberChenari et al. 2016	PSO	Mahabad	Iran	PSO with different K value ($K = 0, -0.25, -0.5, -0.75$)
16	Ahmad et al. 2016	ABC	Timah Tasoh	Malaysia	GSA
17	Chen et al. 2016	ABC	Zhanghe	China	PSO
18	Liao et al. 2014	MOABC	Gorges, Gezhon	China	ABC with different parameters
19	Hossain and El-shafie 2014a	ABC	Nasser	Egypt	GA
20	Hossain and El-Shafie 2014b	ABC	Klang gate dam	Malaysia	GA, PSO
21	Shi-Mei Choong 2016	ABC	Chenderoh	Malaysia	ABC with different parameters
22	Khan et al. 2012	GA	Tarbela	Pakistan	GA with different parameters

Comparison between the performance of ARMA, ARIMA, and ARANN models was conducted by Valipour et al. (2013). The proposed methodology had been applied to forecast monthly inflow of the Dez dam reservoir, whereby the inflow forecasting of the reservoir during testing phase showed that the ARIMA model gave a better performance compared to the ARMA model. In addition, the dynamic autoregressive ANN that was used in this study proved to be superior to the static autoregressive ANN model. In this study, the authors had addressed the effects of choosing the proper number of neurons as well as the activity function, and they concluded that the appropriate number of hidden layer neurons for dynamic and static neural networks was 17 and 6, respectively, while the sigmoid activity function was the best function to obtain high accuracy.

Elizaga et al. (2014) studied daily inflow forecasting using an artificial neural network-based back-propagation method. Many statistical indicators have been utilized for evaluating the methods performance such as RMSE, RRE, correlation coefficient (R), and MAE. The results indicated that the ANN method has the best inflow forecasts with high correlations between the actual and forecasted and provided minimum errors.

To explore measures for managing reservoir inflow forecasting studies with a particular module, Hidalgo et al. (2015) provided an architecture which facilitated the analysis of water inflow forecast models. Several mathematical approaches based artificial neural network, linear regression, and hydrologic simulation have been applied to forecast daily and monthly inflows. These models have been developed to achieve benefits in analyzing four situations, i.e., (a) water inflow forecasting, (b) performance evaluation of a specific model, (c) research tool for inflow forecasting, and (d) comparison tool for distinct models. The researchers concluded that the application of the proposed model introduced a helpful tool to manage reservoir inflow forecasting and analysis methods.

Chiamsathit et al. (2016) checked the ability of multi-layer perceptron (MLP) technique to forecast 1-month-ahead inflow for the Ubonratana reservoir, which is located in Thailand. They investigated the effect of forecast inflows in the operation of the reservoir in terms of the simulations that were carried out according to the systems rule curves. Comparison during simulation was conducted for four inflow situations, namely (1) type A, which considered the inflow as known and assumed to be historical; (2) type B (inflow known and assumed to be forecasted); (3) type C (inflow known and assumed to be historical average for a month); and (4) type D, this situation considered the inflow as unknown, with the release-water decision only conditioned in starting reservoir storage. The results demonstrated that type B inflow led to obtaining the best performance.

Artificial neural network (ANN) models were utilized to predict daily evaporation by Keskin and Terzi (2006). They considered the meteorological data as input variables such as solar radiation, air temperature, air pressure, air water temperature, wind speed, and humidity. The results indicated that the ANN models during the testing period were able to provide high accuracy in predicting daily evaporation rate.

The radiation-based models, temperature-based models, mass transfer-based models, and ANN models have been proposed by Tan et al. (2007). They suggested models for predicting daily and hourly water losses by way of evaporation. The authors found that solar radiation correlated best with pan evaporation during both of time-scales, while the relative humidity factor was a significant parameter on a daily time scale. They concluded that the ANN models were better than the simplified models in estimating evaporation values in each time scale, either hourly or daily.

The same comparison had been carried out by Moghaddamnia et al. (2009b). The researchers explored the efficiency of the ANN and ANFIS techniques for evaporation prediction. The ability of AI-models was compared with other empirical equations. It has been demonstrated that the performance of AI-models attained their objectives with some interesting findings regarding the meteorological parameters. The authors found that the ANN and ANFIS models gave much better performance compared to the other empirical formulas. In addition, it was found that the ANN technique was slightly better than the ANFIS model. To improve the accuracy of the AI-models, gamma test (GT) has been utilized. GT has the ability to save a great amount of time and efforts for models for selecting the best input combinations. The researchers recommended that a wider experience regarding the input selection method and how it could be utilized should be gained in order to evaluate the effectiveness of the data.

In mapping the complex relationship between input and output sets, Tabari et al. (2010) utilized the power of ANN and multivariate nonlinear regression (MNR) techniques to estimate daily evaporation from surface water. Five different ANN and MNLR models comprising several climate variables were developed. The authors revealed by a sensitivity analysis that the estimated evaporation values were more sensitive to temperature and wind speed parameters. The study showed that the ANN model was more suitable to predict daily evaporation compared to the MNLR model.

Allawi and El-Shafie (2016) explored the potential of the RBF-NN and ANFIS models to predict daily evaporation from the reservoir. The meteorological data had been utilized as input variables to improve the performance of the proposed methodology. The results revealed the robustness of RBF-NN model and its ability to achieve high accuracy compared to ANFIS model. The researchers found that despite the proposed models being a suitable tool to fit the evaporation phenomenon and providing good accuracy, the models showed some shortcomings for the prediction of peak values. In this context, there is a necessity to explore a new model as a crucial tool in predicting evaporation. Allawi and El-Shafie (2016) recommended that a method with highly nonlinear polynomial as an explicit mathematical method should be introduced to achieve an acceptable level of accuracy. In addition, the AI-models should be combined with a proper optimization technique to re-adjust the parameters of the method used.

Support vector machine method

In recently years, support vector machines (SVMs) have been developed as a modern statistical learning approach. SVMs approach proved to be a sturdy and high-efficiency algorithm for classification (Vapnik 1995) and regression (Drucker· et al. 1996; Collobert and Bengio 2001) for a stochastic data, compared with the performance of traditional messy methods. The SVM is characterized in two ways: it is simple enough, allowing for researchers to learn its mechanism easily. Secondly, SVM is an efficient tool in providing high predictive accuracy superior to the performance of several approaches, such as nearest neighbors, ANNs, and decision tree. The principal ideas behind SVM method are creating relationship between the original data set into high or infinite dimensional feature space in order to simplify the classification problems in the feature space, as well producing a certain relationship between variables. SVMs techniques utilize the experience of a Kernel trick to acknowledge the problem, so that the model complexity is minimized together with prediction errors. Conceptually, the performance of the SVM technique as the predictive model could be known by addressing many basic concepts, for instance, the soft margin of SVM, experience of Kernel function, as well as the separating hyperplane (Cristianini and Shawe -Taylor 2000). Several models were explored by experts and researchers to learn the behavior of reservoir inflow and evaporation from a reservoir and to forecast values accurately.

Efficacy of the models based on the SVMs to forecast hourly reservoir inflow was developed by Lin et al. (2009). Based on statistical theory, the SVMs have three characteristics, i.e., (i) SVMs have a better generalization ability, (ii) SVMs are trained rapidly, and (iii) the weights and structures of the SVMs are guaranteed to be optimal and unique. Comparison with back-propagation networks (BPNs) was conducted to clearly demonstrate these three characteristics. The results showed that the SVMs-based model's performance was superior to the BPN-based models. In addition, the researchers have added typhoon characteristics to the models used to improve the long-term forecasting during typhoon warning terms. The authors concluded that the addition of typhoon characteristics significantly improved the accuracy of forecasting compared to the results that were obtained without typhoon characteristics.

LIN et al. (2006) evaluated the performance of SVM in forecasting reservoir inflow. The authors compared the proposed methodology with ARMA and ANN approaches. In conclusion, the support vector machine (SVM) was proven to be an excellent tool for the inflow forecasting. In another study, Li et al. (2009) modified the support vector machine to enhance the predictability of the inflow for Shihmen reservoir, located in Taiwan, by utilizing meteorological parameters from an earlier period. They used genetic algorithm (GA) to determine the procedure for the SVM parameters in order to recognize nonlinearity in climate systems pattern. Bagging was utilized to build different SVM models to minimize variance in the prediction by averaging predictions obtained from the models. The proposed models proved its high efficacy and robust performance in predicting the inflow values through all of the adopted evaluation indicators.

Noori et al. (2011) adopted the SVM approach to predict one-step-ahead of monthly reservoir inflow. The proposed model was constructed based on 18 input variables of the climatic parameters, i.e., monthly minimum, average, and maximum temperatures; rainfall; inflow; and monthly sun radiation with three temporal delays belonging to t, t-1, t-2. Thereafter, forward selection (FS), principal component analysis (PCA), and gamma test (GT) methods were utilized to minimize the number of inputs data. Upon minimizing from 18 to 7 inputs by FS and five variables by PCA and GT methods, these were than fed to SVM method, and ANN model based on PCA method was developed. The researchers compared among PCA-SVM, GT-SVM, and PCA-ANN models and the results indicated that the performance of PCA-SVM model during testing period outperformed PCA-ANN and GT-SVM models.

To develop the modeling accuracy in predicting daily evaporation, Moghaddamnia et al. (2009a) used gamma test to select the best input combination of meteorological data. The study applied SVR model to predict daily evaporation from free surface water in the semi-arid region. Comparison between the proposed model and empirical formulas had been carried out and several statistical indexes were considered to evaluate the models. According to the values of performance criteria, the ability of SVM model was superior to empirical equations in capturing evaporation values accurately.

In 2014, Baydaroğlu and Koçak (2014) predicted evaporation amounts from surface water using support vector regression (SVR) method. Temperature, wind speed, relative humidity, solar radiation, and evaporation time series were utilized to predict water losses. The concept of SVR is dependent on the computation of the linear regression in a multi-dimensional feature space. The input variables of SVR model were prepared utilizing another powerful approach, namely chaos approach. To utilize of the characteristics of chaos theory, it is essential to remodel the phase space utilizing observations. Both the univariate and multivariate time series embedding techniques have been applied to observations, and the results showed clearly that SVR model was the most effective technique for predicting evaporation compared to modern and conventional techniques such as ANN and ARIMA methods.

Multi-layer perceptron (MLP), RBFNN, and SVR techniques have been investigated to predict monthly pan evaporation by Tezel and Buyukyildiz (2016). Air temperature, wind speed, precipitation, and relative humidity data were utilized as input variables. The Romanenko and Meyer methods had also been considered for the comparison, and the authors concluded that the SVR and ANN algorithms have similar performance, while the SVR and ANN methods were better than the Romanenko and Meyer approaches.

Fuzzy logic

The main target in designing any mathematical model is to maximize the utility of the model. To accomplish this purpose, numerous key features for each system of models have to be considered such as uncertainty, credibility, and complexity. Broadly, allowing more uncertainty leads to minimize complex and providing more reliable in results of the model. In 1965, Zadeh (1965) explored the theory of fuzzy sets, the major feature of which was studying the uncertainty characteristics that existed in a pattern of variables. The fuzzy system solves the uncertainty problem by two methods, namely (a) studying input data associated with the priority to solve modeling vagueness, or (b) studying an input as a form of interval data, not crisp point data, in order to handle modeling ambiguity (Klir and Yuan 1995). The fuzzy system sets were recognized as a global tool to address complexity in a system's behavior when systematic modeling of a system does not exist because of an ambiguity and inaccuracy for the input variables (Kreinovich and Mukaidono 2000). The fuzzification existing in logic fuzzy models addresses the uncertainty data that characterized the hydrological parameters. The previous studies reported that the uncertainties exist in inflow and evaporation data. The researchers attempted to support the fuzzification to ascertain that modeling can address ambiguity in the time series data. ANFIS, batch least squares, and gradient least squares are examples of the fuzzy models. These models have been used to achieve mapping between variables in several engineering domains with various sources. The last studies that applied fuzzy logic methods for evaporation and inflow forecasting are listed as follows.

El-Shafie et al. (2007) proposed ANFIS approach for monthly inflow forecasting for Aswan High Dam reservoir. The ANFIS technique is distinguished by the capability in handling uncertainty and ambiguity in the raw inflow data. ANFIS separates space of input variables into fuzzy subspaces and determines an output data utilizing the different linear functions. The historical data of water inflows for 130 years was utilized in training and verification of the proposed model. An architecture of ANFIS was established by multi-lead inflow in order to improve the capability of the method, which would be able to introduce a forecast accurately for three-steps ahead. The proposed methodology exhibited high accuracy and harmonious performance for inflow forecasting, and in addition, the results showed that ANFIS could capture extreme values and provide significant accuracy better than those by MLP-NN method. The ANFIS approach showed super robustness and dependable performance for water inflow forecasting under various reservoir inflow patterns.

The ability of autoregressive (AR), ANN, and ANFIS models in forecasting monthly inflows was examined by Lohani et al. (2012). They considered the effects of monthly periodicity in the water inflows data, and cyclic terms were also included in the AR, ANN, and ANFIS approaches. The ANFIS approach had provided high accuracy to forecast monthly inflow at Bhakra Dam located in India, and the ANFIS performance was superior to both AR and ANN models.

In order to explore the deterministic effect of the climatic parameters on the ANFIS model performance, BAE et al. (2007) and Awan and Bae (2013) incorporated Korea meteorological administration monthly rainfall forecast and other parameters as inputs for ANFIS model. The subtractive clustering approach had been utilized to determine an optimal set of fuzzy rules. The researchers attempted to obtain suitable ANFIS architecture through tuning with various values of cluster radius for subtractive clustering. The proposed methodology was applied to forecast inflows for three major reservoirs in South Korea, and the authors concluded that the use of monthly rainfall forecast provided significant enhancement in the reservoir inflow forecast.

A model fusion approach had been established to forecast reservoir inflow by Bai et al. (2016b). They considered the characteristics of the Three Gorges reservoir inflows in various time scales, namely the monthly scale and yearly scale series. The adaptive neuro-fuzzy inference system (ANFIS) and even gray models were adopted to forecast monthly and yearly inflow patterns, respectively. The researchers utilized gray relation analysis (GRA), where the water inflow patterns at the different scale series were normalized and incorporated to provide the final inflow forecast results. The proposed model was compared with back-propagation neural network (BPNN) and auto-regressive integrated moving average (ARIMA), and the results showed that the proposed methodology exhibited high accuracy according to evaluation indicators during both time scales.

Practically speaking, there are some difficulties of a class A pan for the direct measurements that emerged due to the subsequent implementation of coefficients based on the measurements from the small tank to large bodies of open water. Keskin et al. (2004) used the fuzzy logic reasoning and alternative models to overcome these difficulties. The researchers have focused on achieving three objectives, namely (i) developing fuzzy models to predict daily evaporation using meteorological data as input factors for the models, (ii) comparing the proposed method with the widely used Penman method, and (iii) evaluating the potential of fuzzy models in such applications. The fuzzy models have been developed through the centroid method of defuzzification processing of the output membership functions for finding crisp values. During the testing period, the fuzzy models proved their capabilities in estimating evaporation values accurately. They recommended that the fuzzy models were a suitable tool for predicting and estimating the missing daily pan evaporation values.

Integrated and other AI-models

In fact, there are several other models that have been developed to forecast reservoir inflow parameter, such as hybrid model, integrated optimization algorithms with AI-models, and data prepressing model. Firstly, the hybrid models are combining several models in one framework in order to provide powerful modeling able for detecting natural inflow and evaporation data.

In the last two decades, several active types of research works have been introduced by researchers for integrating AI-models with several optimization methods. Broadly, the evolutionary computation is represented as one branch of optimization methods which is categorized into two main streams, namely swarm intelligence algorithms including ant colony optimization (ACO) (Dorigo et al. 1996) and particle swarm optimization (PSO) (Kennedy and Eberhart 1995) and, secondly, evolutionary algorithms such as genetic algorithm (GA) (Holland and John 1975), evolutionary programming (EP) (Fogel et al. 1966), and genetic programming (GP) (Koza 1992). It is a known fact that the artificial intelligence methods have numerous variables which would change the performance of a model. Therefore, identification of the optimal variables would provide a powerful model able to handle complex problems such as the stochastic nature in the evaporation and inflow values. Recently, evolutionary computing algorithms have proven their abilities in identifying the proper parameters for the AI methods through integrated (EC) algorithms with AI-based models.

On the other hand, several prepressing models have been developed recently. The wavelet transform (WT) integrated with AI-based models is considered as a prepressing model. Wavelet transform is a considerable method for analysis of time series data, and recently, WT approach has increased in popularity and usage since its theoretical development in 1984 by Grossmann and Morlet (1984). In fact, the major purpose of using wavelet transform is the analysis raw data in terms of frequency domain and providing significant information regarding the behavior of original time series data.

As a modern method in signal pre-processing, WT could be dependable in removing any shortcomings of the AI-based models in handling non-stationary behavior of signals. Furthermore, a mathematical approach of WT provides helpful decompositions of hydrological data so as to improve the performance of the AI-models by holding helpful information on a different resolution. The two types of methods of wavelet transform are discrete WT (DWT) and continuous WT (CWT). The first approach uses mother functions such as a trous or the Mallat algorithms, which would work on scales having discrete numbers. On the other hand, CWT approach runs on a smooth continuous function that could be recognized and decomposes signals with different scales. The main drawback of CWT is that its construction is inverse and more complex. In practice, this shortcoming may be undesirable because it needed a reconstruction of signals (Fugal 2009). The recommended literature for a thorough information about the WT was provided by Labat (2005), Sang (2013), and Nourani et al. (2014). In fact, a significant record of articles has been devoted for prediction models in order to understand the dynamics of inflow or evaporation and fundamental progress have been made in this domain. Several types of research works have achieved high accuracy results with robust models utilizing the combined WT- and AI-based models. Hereafter, the present study reported the previous studies that developed several models in forecasting two hydrological parameters (i.e., inflow and evaporation).

The multi-resolution characteristics of WT analysis and the nonlinear ability of ANN models were highlighted by Wang et al. (2009). The proposed model was applied for inflow forecasting at the Three Gorges Dam in Yangtze River, located in China. The comparison between the WNM and TAR models had been carried out, and the results showed that the WNM had outperformed the TAR model. The researchers suggested that future studies should concentrate on developing WNM to provide high accuracy in forecasting inflow volume and other hydrological parameters.

In another research, Wang et al. (2010) explored the effectiveness of the PSO in improving the SVM in annual inflow forecasting. The objective of their research was to find out the appropriate parameters value of the SVM model. Suitable parameters of the SVM model were adopted in the testing phase to obtain the optimal results in forecasting, and the integrated optimization technique with AI-model (SVM-PSO) was compared with the artificial neural network (ANN) model. The authors concluded that the SVM-PSO model had succeeded in forecasting water inflows accurately. They indicated that the proposed methodology was a valid alternative tool for use in annual inflow forecasting and recommended that the SVM models should be combined with other advanced searching techniques.

Jothiprakash and Kote (2011) developed the M5 model tree (MT) to forecast reservoir inflow data. The study considered two different time-scales namely monthly and seasonally. The comparison between the proposed model (i.e., M5 model tree) has been conducted with the conventional univariate autoregressive integrated moving average (stochastic) models. It was quite clear that the stochastic models were unable to provide forecasts with high level accuracy. Several statistical indicators revealed that the M5 model tree has high ability in providing reliable results for reservoir inflow forecasting. It was found that the developed models attained high accuracy when using seasonal data compared to monthly values.

Jothiprakash and Magar (2012) had used lumped and distributed data for artificial intelligence techniques and developed combined models for multi-time-step reservoir inflow prediction. They utilized ANN, ANFIS, and LGP methods to forecast daily and hourly intermittent reservoir inflow. Several performance criteria were used to evaluate the models' ability, and the results showed that the performance of LGP models was better than other suggested models for both time-scales.

Budu (2014) applied two types of approach, i.e., the wavelet transform and moving average (MA) in integration with FF-BP, RBF-NN, and MLP models to predict daily inflow. Daily data for 11 years inflow, rainfall, and streamflow at an upstream of the Malaprabha reservoir in Belgaum have been used, and the results of the research exhibited the excellent performance of WT prepressing method and indicated that the WNN performed better compared to ANN and MLR models. He recommended that more future research using data from different areas might be required to support those conclusions.

In an endeavor to handle a nonlinear relationship and stochastic time series data problems, Kumar et al. (2015) developed an ensemble modeling method based on bootstrap resampling, wavelet analysis, and ANN (BWNN) for inflow forecasting. The proposed model has been compared with wavelet analysis based on artificial neural network (WANN), wavelet-based multi-linear regression (WMLR), and bootstrap and wavelet analysis based on standard ANN, multilinear regression (BWMLR), and standard MLR. The original data have been decomposed utilizing wavelet transformation into wavelet sub-series to develop WANN models instead of the standard data used for development of ANN model. They concluded that the efficiency of a proper selection of wavelet functions and suitable model might be required for wavelet-based methodology development. Furthermore, the results obtained using BWANN models were more reliable, accurate, and likely to be useful for operational inflow forecasting compared to other models.

The developed modeling based on support vector machine (SVM) and ANN was established by Cheng et al. (2015). The proposed model had been used to forecast water inflow at Xinfengjiang reservoir. The process of the predictive model was divided into two stages, i.e., (1) utilizing ANN and SVM methods to find the complex nonlinear analysis relationship among the input data and the output set, while at the same time, applying the genetic algorithm (GA) approach to search for proper parameter values of the SVM, and (2) the results obtained by means of ANN and SVM were considered as input variables for the new ANN model, which provided the final results. The performance of the developed model has been compared with the ability of the classic ANN and SVM. According to five statistical indictors, the proposed model was an efficient method for the long-term inflow forecasting.

A multi-scale deep feature learning (MDFL) with other models was investigated by Bai et al. (2016a) for forecasting daily inflow. In order to enhance accuracy results, three aspects were considered in the combined models, namely:

(a) The multi-scale feature extraction, three feature terms S, T, and P were extracted using the ensemble empirical mode decomposition (EEMD), and were reconstructed using Fourier transform (FT) method.
(b) Deep feature learning, three deep belief networks (DBNs) were subsequently applied to learn the corresponding feature terms.
(c) In fact, three deep neural networks (D-NNs) were created by the weight of the trained DBNs, where they were used to forecast multi-scale features.

The capacity of the models to forecast daily reservoir inflow was compared with wavelet-based ANN (WANN) model, D-NN, back-propagation neural network (BPNN), and least support vector regression (LSVR) model. The researchers concluded that the proposed methodology exhibited the best performance among all peer models.

Most recently, Bozorg-Haddad et al. (2016b) have used genetic algorithm coupled with ANN method for inflow simulation and forecasting. The GA was applied to identify the parameter values of the ANN model, such as a number of neurons and hidden layers. In addition, the GA approach was used to determine the appropriate architecture of the ANN and efficacy of the hydrologic and meteorological parameters for the objective of inflow simulation and forecasting. The authors found that the ANN-GA model was capable of determining desirable values for the considered parameters. The proposed model could be utilized by the decision-maker as a rapid and effective tool for the better simulation and forecasting of normal phenomena such as water inflows.

To enhance the forecasting accuracy of reservoir inflow, a linear seasonal autoregression integrated moving average (SARIMA) model combined with ANN model was proposed by Moeeni and Bonakdari (2016). The proposed hybrid model (SARIMA-ANN) was applied to predict monthly inflow, and the hybrid model proved that its performance in predicting peak flood was superior to those of the individual models. On the other hand, SARIMA model is better than other models in predicting low values. In conclusion, the evaluation indexes demonstrated that the hybrid model could minimize the forecast error more compared to SARIMA and ANN models.

Two deep feature learning architectures, namely deep restricted Boltzmann machine-based NN (DRBM-NN) and stack autoencoder-based NN (SAE-NN), were introduced by Li et al. (2016). The proposed models were applied for reservoir inflow forecasting. The model's performance was evaluated by comparing with the ARIMA and basic feed forward neural network (FF-NN) methods. Based on statistical indicator values, it is found that the D-NN models were powerful in providing high accuracy, superior to those of the other models.

Abghari et al. (2012) explored various types of mother wavelet as activation function instead of a sigmoid function for identifying the significant differences in the results of daily pan evaporation prediction. The study used two mother wavelets, namely Mexican Hat and polyWOG1 for developing the prepressing model (WNNs). The authors compared between the prepressing model, multi-layer perceptron neural network (MLPNN), and the standard sigmoid function. During verification period of the wavelet network for daily pan evaporation prediction, the results showed that the method could be functional, and they concluded that Mexican Hat and polyWOG1 wavelet networks could be alternative functions to sigmoid neural networks (MLP) in predicting daily evaporation. On the other hand, the statistical indicators showed that the efficiency of Mexican Hat wavelet neural networks in predicting evaporation losses was superior to that of polyWOG1 wavelet networks.

Integrated feed forward neural network (FFNN) method with the genetic algorithm (GA) for predicting evaporation losses from the storage dam reservoir was developed by Izadbakhsh and Javadikia (2014). The primary model estimated evaporation rate based on conventional feed forward technique and compared its performance with an integrated optimization model with AI-modeling (FFNN-GA). Daily meteorological data such as minimum and maximum temperatures, wind speed, and sunshine were used as input variables to the proposed model. The best structure of the FFNN method had been selected through the genetic optimizer. In conclusion, the results showed that the capability of FFNN-GA model to predict evaporation values was superior to the traditional feed forward neural network technique.

Evaluation and assessments for predictive models

The review of the previous studies that used AI-models for evaporation prediction and inflow forecasting has been conducted by previous sections. Several studies explored that the ANNs models suffered from some limitations and apparent shortcomings, such as over-fitting problem, local minima, low-speed learning. Further, the modelers intervention in selecting some parameters had an effect on the model's efficiency. It is known that ANNs have several types of approaches, for instance, RBF-NN and FF-NN methods. According to last studies, the RBF-NN method has high accuracy in forecasting reservoir-hydro-environment parameters compared to other types methods. This is because the RBF-NN characterized higher reliability, faster convergence, and smaller extrapolation errors (Fernando and Jayawardena 1998; Valipour et al. 2012; Allawi and El-Shafie 2016). However, several researches reported that the RBF-NN has some limitations and weak points. The major shortcoming of the RBF-NN is incapacity for providing high accuracy for reservoir inflow forecasting or evaporation prediction using the short period of database.

Remarkably, the previous studies demonstrated that the DNN technique outperformed the static neural network in both evaporation and reservoir inflow modeling, especially in the peak points. In fact, the principle behind DNN method is that the state of neurons depend not on the current input signal only but also on the prior states of the neuron. Therefore, the dynamic neural network has effectiveness for reducing the network's input dimension and thus reducing the learning time. Furthermore, the DNN method has the exceptional capability to learn the relationship between input and output variables due to the feature of the adjustment weights network (Coulibaly et al. 2001; Valipour et al. 2013).

The significant step that was noted through a previous works is choosing a proper transfer function. The transfer function is employed for providing the nonlinear mapping potential. Hence, selecting the proper transfer function leads to improving the performance of the modeling. The literature studies reported that the tangent sigmoid transfer function could capture the nonlinear relationship between the variables better than other types of transfer functions. Consequently, most research achieved their objective with high accuracy utilizing tangent sigmoid transfer function such as Moghaddamnia et al. (2009a), Tabari et al. (2010), Hidalgo et al. (2015), Chiamsathit et al. (2016), and Allawi and El-Shafie (2016).

Through the assessment of the literature studies which used support vector machine (SVM) method, it can be seen that SVM succeeded for long-term inflow forecasting better than short-term. Also noted is that the SVM is unable to provide a high performance in predicting the low values of the evaporation. This is because selecting the optimal parameter values concerning the architecture of SVM is a difficult issue. The main advantage of SVM method is reducing the popularize error of model addition a mean square error during a training phase. According to Mercer's theory, symmetric optimization problems are convex, therefore they are not local minima point (LIN et al. 2006; Li et al. 2009; Baydaroğlu and Koçak 2014; Tezel and Buyukyildiz 2016).

It is noteworthy that based on the previous studies that used SVM, the radial basis function (RBF) kernel could recognize the nonlinear relationship between class labels and attributes better than other types of transfer functions. This is because the tuning parameters which would effect on the complex model selection are fewer with RBF kernel compared with other transfer functions such as sigmoid and polynomial kernels. Furthermore, the RBF kernel tends to provide very well performance with general smoothness presumptions. Accordingly, most of the previous papers have reported that the RBF is a proper kernel function to forecast the water inflow and evaporation. In conclusion, the SVM model performs better for long-term evaporation prediction and it needed more information (input variables) to capture low values. The SVM method was able to attain high accuracy result for reservoir inflow forecasting more than evaporation prediction for both long- and short-term.

Throughout the reviewed studies concerning the utilization of fuzzy logic approach in predicting evaporation data and inflow, the ANFIS technique has been commonly used owing to its ability in handling imprecise, insufficient, and complicated natural data (i.e., inflow and evaporation). The ANFIS has been introduced as having high effectiveness in mapping between variables based on obtainable data. Indeed, events of a reservoir inflow and the evaporation are very complex phenomena of a precise and detailing, and hence convergent in the fuzzy set technique provides sensible and tractable models.

The literature shows that owing to the advantages of ANFIS model, it was able to capture low, average, and high values of the evaporation and the water inflow with high accuracy according to outstanding statistical measurement. In addition, several scholars stated that the ANFIS could deal with the hydrological time series parameters, including their vagueness and uncertainties and stochastic values (Keskin et al. 2004; BAE et al. 2007; El-Shafie et al. 2007; Lohani et al. 2012). Despite the high efficiency of the ANFIS method for learning the nonlinear relationship, few studies utilize ANFIS approach to predict evaporation rate from the dam reservoir.

To enrich the review process, an assessment of the many studies used in the application of several models, respectively evaporation modeling and reservoir inflow, reveals the following:

(i) It is noteworthy that the integration of evolutionary computational approaches such as GA, artificial bee colony (ABC), and other approaches with AI-based models showed high capability for capturing the relationship between meteorological parameters and evaporation pattern in various continents and climatological zones.
(ii) The advantages in applying GA approach combined with AI-model are high ability in mapping mathematical expression among the variables data. In addition, the GA could optimize the parameters of the AI-models such as SVM method and finding the appropriate structure for ANN methods. Accordingly, most of researches reported that integrated GA with AI-based models would provide a powerful and useful model in forecasting hydrological parameters.
(iii) Several previous studies have used the wavelet transform (preprocessing technique). However, it is observed that the preprocessing approach was applied more for reservoir inflow forecasting than evaporation prediction. This indicates that the stochastic nature of the data in the evaporation time series is less than inflow values.
(iv) It can be concluded that the wavelet transform approach could enhance the performance of the inflow modeling with various time scales; this enhancement is grater for the larger time-scales such as monthly data compared with other scales (weekly, daily, or hourly).
(v) In general, the hybrid model, integrated AI-models with optimization techniques modeling and prepressing modeling attained high accuracy level for inflow forecasting in both of long- and short-term. Further, the reviewed studies reveal that those models could be introducing very well accuracy to predict evaporation from the reservoir with various time scales.

Table 1 lists out the details of the reviewed papers, including author name, type of AI techniques, time scale for inflow prediction and forecasting, and other information. One of the more significant aspects for dealing with the type of AI techniques to achieve the best performance in handling the inflow pattern is selecting the suitable time scale. It is observed that most of the previous researches have utilized monthly scale for reservoir inflow forecasting. Referring to Table 1, the ANN approach has received considerable attention from hydrologists regarding the inflow modeling. It is demonstrated that the researchers attempted to develop AI-models by integrating these models with several optimization algorithms.

The details of the previous studies that used AI methods for evaporation prediction are presented in Table 2. This table summarizes the most information concerning the previous studies whether a type of predictive model used input variables for modeling and other. It appears that the authors are concerned with choosing the proper input variables in evaporation modeling (Table 2). Based on the review, a number of studies have concluded that the prediction model can be improved if other climatological data that affect the evaporation rate are included, such as temperature, wind speed, and relative humidity. It also found that a majority of the authors applied daily scale to a modeling of the evaporation process. The long-term scales such as on a monthly basis are widely utilized by researchers who deal with large reservoirs. It is quite clear that the ANN model has been mostly utilized in predicting the evaporation from a reservoir.

Throughout the survey, the ANN and fuzzy logic methods have proven to be able to provide robust models with high level of accuracy for inflow forecasting and evaporation prediction. These methods have the ability to trace the events of the input variables, which could enhance future forecasts through the pattern recognition. It is also noteworthy that performance of methods is supported by using optimizer research in determining the proper parameters of the SVM structure could handle well in high noise conditions, by automatically identifying parameters.

Applications of optimization models in operating the reservoir

Genetic algorithm

An increasing number of new optimization methods have been generated in the past years, on which every approach has its advantages and drawbacks based on the types of problems regarding water resources management such as operating the reservoir system. The most popular approaches for optimization method derive from the computational intelligence that is the evolutionary computation (EC), a good example being the genetic algorithm (GA). The GA approach is based on a generation of population which mimics natural evolution, selection, and natural genetics. Major concepts of genetic algorithm are founded on genetic concepts, including selection, mutation, as well as resultant recombination (crossover) in an operator (Affenzeller 2009).

The integration of genetic algorithm and ANFIS was introduced by Chang and Chang (2001). They concluded that the suggested method provided better results in estimating the water deficit and generalized shortage indicator. The performance of the proposed method was used to determine the optimal policy of operation the Shihmen reservoir in Taiwan, China. The genetic algorithm was also utilized by Chang et al. (2003) to determine and optimize the flushing operating rule curves at Tapu Reservoir located in Taiwan, China. This report had combined two models, namely the sediment flushing model and the reservoir simulation model. The proposed model provided higher flushing efficiency (FE) and lower shortage indicator (SI) when compared with the original operational rule in the reservoir.

Li and Wei (2008) took GA to the next level through integrating GA with simulated annealing (SA), and the novel global optimization algorithm was called improved genetic algorithm-simulated annealing (IGA-SA). The IGA-AS method was applied in the case of the Wujiangdu, Dongfeng, and Hongjiadu reservoirs in Yangtze River, China.

Chen et al. (2007) considered the efficacy and efficiency of the macro-evolutionary multi-objective genetic algorithm (MMGA) in finding the release policy of a reservoir. Macro-evolution is a new type of high level development which could avoid premature convergence that might emerge through the selection procedure of conventional GA. The MMGA was utilized for optimizing the rule curves releases of a multi-objective reservoir system in Taiwan. The results showed that the proposed MMGA method was quite competitive and provided an alternative method to solve multi-objective reservoir optimization problems.

Momtahen and Dariane (2007) utilized genetic algorithm as the optimizer approach to identify optimal rules for reservoir operation. The direct search method was applied to a single reservoir system and compared with dynamic programming (DP) and stochastic dynamic programming (SDP). The results showed that the proposed model gave better performance in optimizing different kinds of policies compared to DP and SDP.

The stochastic varying chromosome length genetic algorithm (SVCLGA) method was proposed by Kerachian and Karamouz (2007) to determine optimal operating rules for water quality management in Ghomrud Reservoir system. The authors had shown that the proposed method could reduce the salinity of the allocated water demand, as well as the salinity build up in the reservoir.

The constrained genetic algorithm (CGA) was introduced by Chang et al. (2010). The CGA approach was considered as the optimizer model for the operation performance of the Shih-Men reservoir. The researchers found out through the evaluation indicators that the proposed model gave very good performance, where the genetic algorithm was mostly utilized for reservoir optimization problems. However, GA could not analyze complex issues such as identifying the optimal rules for long-term reservoir. This problem had been solved by Wang et al. (2011) by proposing a new approach called multi-tier interactive genetic algorithm. This method had succeeded in reducing the computation time by 80% for 20 years of long-term reservoir operation.

In order to explore the ability of genetic algorithm in determining the optimal policy of multi reservoirs, Hınçal et al. (2011) had applied genetic algorithm for three reservoirs in the Colorado River Storage project. The optimal values of probability of crossover, probability of mutation, population size, as well as generation number were provided using GA model to the multi-reservoirs. The objective function considered was to meet irrigation demands for irrigation purpose reservoir, and the rules obtained were compared to the historical operational rules of the reservoirs. The researchers concluded that the proposed model was applicable and effective as an alternative tool to other conventional optimization tools. Li et al. (2012) applied the GA in combination with incremental dynamic programming (IDP) for the long-term optimal operation of the Three Gorges Dam, and the authors had also compared the novel method with a conventional genetic algorithm.

Swarm intelligence

Particle swarm optimization

Recently, many researchers have their attention on the use of the particle swarm optimization (PSO) method in various types of research dealing with the optimization problems. PSO was first proposed by Kennedy and Eberhart (1995) and it involved swarm intelligence, which is a modern stochastic optimization algorithm based on a mimic of many existing swarms in nature such as fish schooling and bird flocking. This development approach is mostly a mimic of natural evolutionary patterns such as emergent intelligence, which is generated in the population or collective behavior. The particle swarm optimization simply regulates the trajectory of particles and selects the better solution for each particle, where the algorithm keeps the information regarding the best position visited by each particle. Every particle is moving toward a direction and a certain velocity that will have effect on the algorithm efficiency. Therefore, it is necessary to consider all the parameters such as the particle's velocity and its historical best location, which are limitations of the PSO when solving the problems.

Reddy and Nagesh Kumar (2007) combined the Pareto dominance principle with the particle swarm optimization to improve the multi-objective particle swarm optimization. The results showed the ability of a model maximizing hydropower and minimizing irrigation water deficit, as well as water amount up to satisfactory level requirements in the downstream region. Nagesh Kumar and Janga Reddy (2007) introduced a new strategic mechanism, namely elitist-mutation, to improve the performance of the original particle swarm optimization. The novel approach has been used to handle multiple-objectives of the Bhadra reservoir system in India. The researchers had compared the proposed model with other evolutionary techniques, and the EMPS model showed its capability to give better solutions when compared with other models.

Multiple objective PSO method to optimize multipurpose reservoir was introduced by Baltar and Fontane (2008), who concluded that the model could provide the best performance compared to other models. The particle swarm optimization method had been applied to optimize the operation and design of the Bakhtiari reservoir system in Iran (Mousavi and Shourian 2010). The results indicated that the proposed model was capable of finding good solutions for the dam operation problems.

Partially constrained particle swarm optimization (PCPSO) approach was applied to identify the effective solutions for the large-scale reservoir by Afshar (2012). PCPSO method was utilized to optimize the operation of Dez reservoir and the proposed model results were compared with the genetic algorithm and conventional PSO. The new algorithm provided superior results compared to the genetic algorithm and original PSO method in locating near optimal solutions and convergence characteristics. The PSO model had also been adopted by SaberChenari et al. (2016) to minimize the deficit between water demand and release for Mahabad reservoir Dam, located in the northwest of Iran. The authors applied PSO model with the consideration of the decreased probability of monthly inflow values. They concluded that the PSO model provided release rules that could be an appropriate policy during drought condition for the reservoir.

The artificial bee colony

Artificial bee colony (ABC) algorithm introduced by Karaboga (2005) is a new swarm intelligence method that is capable of providing optimal solutions for handling optimization matter in water resources management lately. This approach mimics the foraging behavior of the bee and the food, which is considered the solution. ABC method consists of several sets that are the employed bee, the onlooker, and the scout. The scout bee is working to handle the exploration process, while the exploitation process is undertaken by the onlookers and the employed bee. The same concept reflects on finding the best solutions as speedily as possible for the engineering problems. The implementations of the bee swarm intelligence have been reviewed by Karaboga and Akay (2009). Several advantages of the bee have been utilized as a model intelligence system, such as the concept of the bee dance, task distribution, communication between bees, a collective system to select the best site for food, and the concept of finding the short path to reach a target.

A study pertaining to the reservoir operation policy by ABC method was proposed by Hossain and El-shafie (2014a). The ABC algorithm was developed to search for optimal guidelines in operating the Aswan High Dam reservoir. The proposed model was compared with the corresponding results from genetic algorithm (GA), and the researchers utilized several indices to evaluate the proposed models such as resiliency, vulnerability, and reliability indicators. The ABC approach succeeded in meeting the demand for about 98% of the total time period. The study showed that the performance of ABC method was better than the GA method.

Hossain and El-Shafie (2014b) explored the efficiency of the evolutionary and swarm intelligence algorithms in searching for the optimal reservoir releases policy. They used GA, PSO, and ABC as optimizer methods with the same objective function for each month. The objective of the methods was reaching the minimum deficit between releases and demand. The verification of the models showed that the ABC and PSO models were very much faster in finding the optimal solution for the reservoir. On the other hand, the simplicity of ABC algorithm was the major attraction compared to the PSO technique. In conclusion, the ABC technique was considered better than the GA and PSO algorithms in determining the optimal reservoir policy.

The multi-objective artificial bee colony (MOABC) algorithm was presented by Liao et al. (2014), where the proposed technique had been applied in the long-term scheduling of the hydropower systems of the Three Gorges Project (TGP), located in china. The conclusion of this research indicated the ability of the MOABC method in solving an optimization reservoir problem and with better convergence ability.

Chen et al. (2016) proposed a new integrated mathematical model to maximize the annual returns for a reservoir pond system. The objective was achieved by utilizing of two models, namely an operating policy model and an allocation model. The first model considers optimizing reservoirs and ponds releases, while the second model optimizes irrigation allocations across crops. ABC algorithm is improved using integrating particle swarm optimization (PSO) algorithm and evolution algorithm to find the optimal solution for the complex optimization problem. The results showed that the proposed model could handle the reservoir management with higher efficiency, particularly for drought years.

The major principle behind the ABC mode is providing general rule concerning multi-dimensional task distribution, especially for the complex and nonlinear issues such as operating the reservoir system. Therefore, Hossain et al. (2015) applied the artificial bee colony (ABC) technique to determine an optimal reservoir policy, and the researchers compared the ABC performance with GA, PSO, and neural network-based stochastic dynamic programming. The methodology was applied to Klang Gates Dam, located in Taman Melawati, Malaysia and the Aswan High Dam, located in Egypt. The authors concluded that the ABC algorithm was able to solve the critical situations of low inflow. In addition, the release policy that was obtained using ABC was superior in terms of lower water loss and high reliability in the case of both of complex reservoirs.

The ABC algorithm was introduced by Ahmad et al. (2016)) to minimize the deficit between water demand and water release for Timah Tasoh Dam reservoir, located in the northern part of Peninsular Malaysia. The ABC algorithm provided lower vulnerability, stability, higher reliability, and faster convergence indicators, and based on these indexes the ABC algorithm performance was considered better than the gravitational search algorithm (GSA). On the other hand, the GSA was better in the resilience index measure.

Recent optimization algorithms

Most recently, limited number of researches has been shown an interest for developing optimization models for the dam and reservoir operations using advanced swarm intelligence algorithms due to its complexity. In fact, there are many other swarm intelligence algorithms that have been utilized to handle the optimization reservoir operation problems such as bat algorithm, weed algorithm, firefly algorithm, shark algorithm. Such advanced swarm intelligence algorithms outperformed traditional methods in generating optimal operation rules for dams and reservoirs; however, each algorithm experienced particular drawbacks that negatively influenced the overall model performance. Several studies used these algorithms for obtaining optimal policies for a reservoir system such as bat algorithm (Bozorg-Haddad et al. 2015; Ahmadianfar et al. 2016), weed algorithm (Asgari et al. 2016; Azizipour et al. 2016), firefly algorithm (Garousi-Nejad et al. 2016a, b), Cuckoo algorithm (Hosseini-Moghari et al. 2015; Ming et al. 2015), shark algorithm (Ehteram et al. 2017a, b), and cat warm intelligence algorithm (Bahrami et al. 2018). However, the results indicated that advanced swarm intelligence algorithms may trap the local optimums for solving multi-reservoir problems and required more computation time for obtaining converged solutions, and hence, there is a need to improve these algorithms before it could be generalized.

Simulation-optimization model

Although the current evolution relies on the use of optimization models, in practice, however, simulation techniques are one of the strategic tools for the reservoir management and the planning system studies. The first diagram of the simulation-optimization technique was introduced by Carson and Maria (1997) as shown in Fig. 1. The predictive technique provides a suitable output which will be utilized through the optimization process to identify optimal solutions that would lead to better input to the simulation techniques. Mays (1989) studied the integration of simulation with optimization in water resources applications, such as real-time flood operation, groundwater management, and distribution system. The researcher suggested a close gap between practice and theory through coupling of nonlinear Optimization and Simulation.

Wurbs (2005) conducted the comparison review on a generalized river and reservoir simulation-optimization technique, and a study highlighted some of the abilities and weak points of the reviewed studies. The report is considered as an important reference for researchers and water managers wanting to identify a better program for reservoir modeling.

Mayer and Muñoz-Hernandez (2009) described the integrated water resources optimization models (IWROMs), in which the researchers presented the different techniques undertaken to find and maximize the economic benefits of withdrawing water for different purposes that utilized various categories in IWROM applications. They described the hydrologic simulations utilized in IWROM implementations, and the mathematical approaches utilized in solving the optimization problems. It is proposed that the IWROMs mimic the effect of water resources management strategies on the

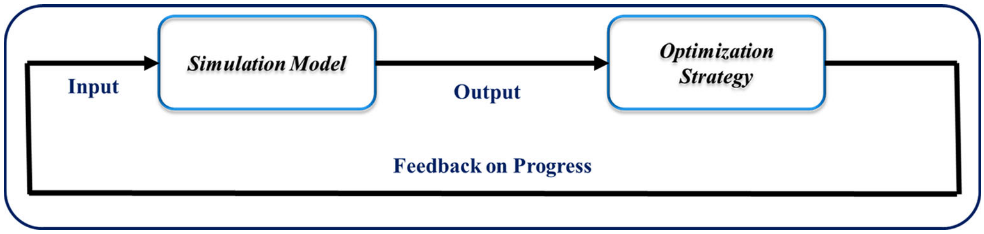

Fig. 1 Simulation-optimization model procedure

environment around of basin scale, simulation and assessment for policies and strategies management for water resources, and it could support basin-wide decision makers, particularly for water-scarce areas. The authors found it necessary for improvements to be made in solving model uncertainty, considering different environmental parameters, and the effect of water allocations among users.

The reservoir optimization-simulation with sediment evacuation (ROSSE) technique was applied by Khan et al. (2012) to minimize the irrigation deficit in Tarbela reservoir, located in Pakistan. The authors have conducted calculations through a sensitivity analysis to select the appropriate values of different GA parameters required for run the modeling. They conclude that the GA optimization model is capable to determine the optimal policy for a reservoir with high reliability under different conditions. Yazdi and Salehi Neyshabouri (2012) proposed the simulation-optimization technique to find the optimal design of the multi reservoir flood control though the combining of the MIKE-11 hydrodynamic technique with non-dominated sorting GA (NSGA-11) method.

Evaluation and assessments for optimization models

The present paper has reviewed in the current section many previous studies that utilized optimization algorithms in operating the reservoir system. The literature review has revealed several observations that can be summarized briefly as follows:

(i) The conventional optimization methods suffer from several limitations and drawbacks. These methods are powerless in catching a global optima and slow speed for solving reservoir operation problems.
(ii) It is noteworthy that the main remarkable feature of the GA search procedure is the higher probability in capturing the global optimal solution because it considers all of its population for possible solutions rather than depending on a single solution.
(iii) It was explicit that the swarm intelligence methods have high capability in solving optimization problems. This is due to several advantages that characterize those methods compared to the conventional optimization models. Such advantages are high performance in the exploration and exploitation, broad robust applicability to dynamic changes, capability in parallel computing, and handling optimization problems with complicated mathematical properties.
(iv) Most of the reviewed papers reported that the successful algorithm in handling optimization problems should have acceleration and high inertia.

A summary of the previous studies undertaken by many researchers to develop several optimization models in solving different types of optimization problems has been presented in Table 3. Table 3 shows a summary of the reviewed studies, including types of optimization techniques, name of reservoirs, locations, and comparison of methods. Based on the review, the researchers are concentrating on developing the evolutionary and intelligence swarm algorithms, and it is observed that the artificial bee colony is more appealing to the hydrologists in reservoir management. The behavior of the reservoir varies according to its size, purpose, and environment, and it appears that choosing the proper algorithm to suit the case study could facilitate in providing high accuracy. Reservoir optimization algorithms could be classified into many types as shown in Fig. 2, which exhibits more advanced classification of the optimization methods. Computational intelligence (CI) methods are more advanced algorithms in finding the optimal rules policy for reservoir management.

Recommendations for future research

It is known that the prediction modeling consists of four steps to obtain the target (output), namely (1) determining the suitable training period to train the AI-models, (2) selecting the significant input parameters for modeling to improve the predictive model's performance, (3) data prepressing for eliminating noises data and error to simplify data for AI-models, and (4) developing the flexible predictive model to handle the nonlinear relationships between input-output variables and providing significant results. Based on the reviewed papers, we are attempting to introduce several suggestions that could facilitate in enhancing the accuracy level. The proposed improvement procedures for each step are as follows:

a) The time series data is considered as random values, while the training period is a significant phase in the modeling process. The training period provides several information to AI-models, concerning the pattern of hydrological data.

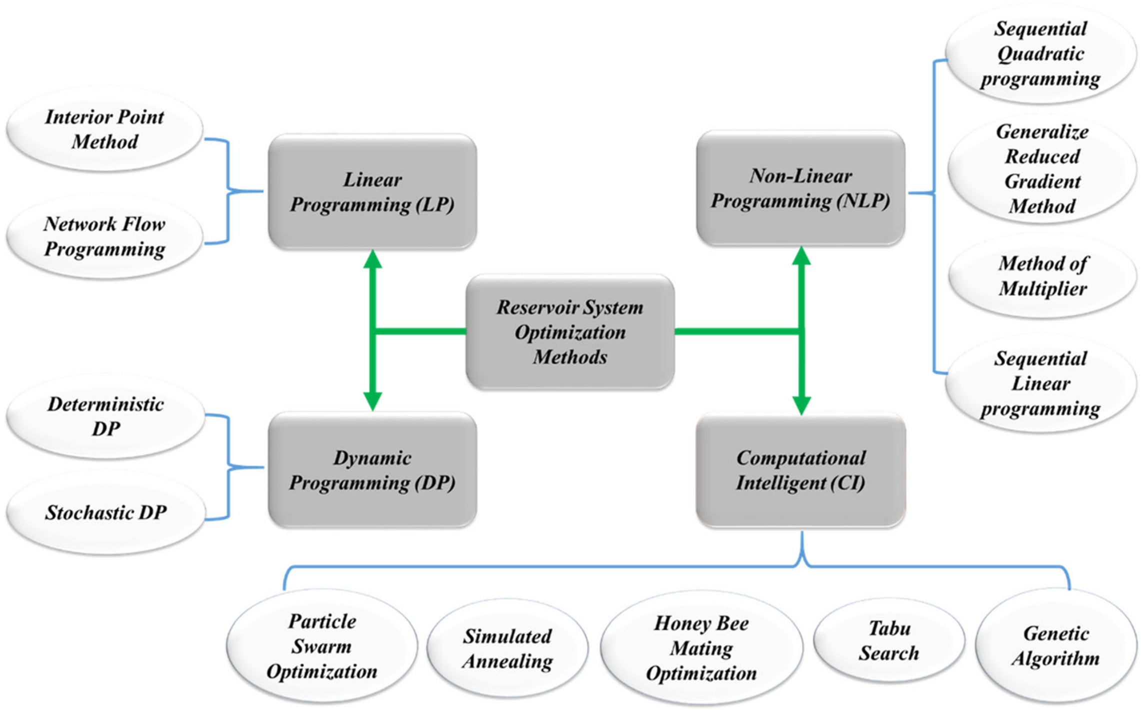

Fig. 2 Optimization models classifications based on previous studies

After that, the predictive model provides the decision (output) based on these information that were obtained during training period. Therefore, it is necessary to identify a certain term comprising most events that have occurred during the study period. The suggested way to address this problem is by considering splitting the data approach, and then determining the best distribution of data that introduces significant information to the models.

To construct the modeling, the raw data should have divided into two distinct sets: training and testing set. The current study (as shown in Fig. 3) proposed examining the performance of predictive models using four different training procedures (i.e., four splitting data) to provide a robust modeling based on AI-models. In the first procedure, the partitioned data with 75% of all available values are allocated to train the predictive model and 25% of raw data used for testing. The second procedure aimed to provide modeling structure based on 80% of the data utilized during training phase and 20% of the data used to test the trained models. The third procedure allocated 15% of the natural data for testing the performance of the developed models and utilizing the remainder 85% of the data within training phase. In the fourth procedure, the 90% of all available data are allocated to train the modeling and the remainder 10% of the raw data utilized during testing period.

b) The results accuracy for AI-models is based on the type of input variables (Maier and Dandy 2000). Therefore, determining the suitable input for modeling leads to enhance the performance of suggested models. In this context, this study recommends selecting the proper input parameters for modeling using one of the optimization such as a genetic algorithm or other optimizer models or using the global harmony research method. These approaches would enhance the performance of the predictive model by determining correlated antecedent values and neglecting other lag-time. Furthermore, these methods can find the effective parameters on prediction modeling and disregard those parameters which do not improve the accuracy of results.
c) The preprocessing methods showed good results for reducing noise, randomness, and stochastic nature of the original data. In this context, the wavelet transform method proved its capability to decompose time series. However, the present study recommends using a new approach that uses high-resolution spectral analysis based on fast orthogonal research (FOS) methods. FOS is developed for nonlinear modeling which finds functional expansions utilizing arbitrary sets of non-orthogonal candidate functions. The advantages of the suggested technique are as follows: FOS provides persimmons sinusoids series exemplification by first finding the considerable sinusoids components. Another advantage is that the frequencies of the sinusoids determined are not necessarily proportional nor integral double of the essential frequency of symmetry to the record length.
d) According to Li and Sankarasubramanian (2012), there are several sources of errors which emerge through a

modeling processing. This is because of the inclusion of uncertainty, non-stationary, and stochastic input-output variables and due to a model architecture, itself. To obtain the robust modeling, the current study recommends integrating the fuzzy-logic method with optimization techniques. The optimization techniques attempt to optimize several structure modeling parameters. This modeling leads increasing ability to capture the uncertainties, non-stationary and stochastic characteristics in the modeling variables by two ways, namely (i) controlling the associated input variables with preferences to handle modeling vagueness, or (ii) considering input variables in the form of interval data. The proposed model with a new scheme to enhance the stages for prediction modeling is shown in Fig. 3.

The dominant interpretation of stochastic models improves the accuracy of reservoir optimization performance; however, the results would be highly unreliable when the system operation performance indexes have thresholds, and hence, most likely to introduce inaccurate estimates. Accordingly, the attempts to integrate the reservoir real-time inflow or evaporation forecasting with proper optimization techniques for finding optimal policy are undeniably vital. The reservoir parameters prediction such as evaporation and inflow are giving better definition of the reservoir release policy. A real-time optimization takes advantage of the accurate prediction of reservoir parameters to enhance the reservoir operation efficiency, and therefore meet the downstream requirements to consider power generation management and reduce flood peak.

Practically, two major steps are considered for providing reservoir operation modeling: (1) determining the optimal rules or scheduling time for releasing water, taking into consideration all constraints of reservoir and downstream requirements; and (2) simulation (evaluation) of these rules during certain periods to check the performance of the model with several conditions by statistical indicators. The previous studies have only considered deterministic inflow and evaporation data with those steps to find the optimal scheduling time for a reservoir, while it is necessary to consider the real-time concept for exploring the behavior of models under realistic conditions.

The uncertainties commonly associated with the reservoir operation such as evaporation and inflow lead to further ambiguity regarding the situation of the reservoir with realistic conditions. Besides, these complexities are increasing through their dynamic features as well as an interactive relationship between release and water demand. These complexities have placed major challenges for the decision maker to face in handling a reservoir management when presented with updated parameters values. Determining (i.e., perfect forecast) of the inflow or evaporation is inherently uncertain, thus, using perfect forecast with optimization models leads that the reservoirs system faces operational risk and may sometimes even exposes the dams and reservoirs to operational failure. The updating of hydrological parameters during operating the reservoir and tracing the uncertainties associated with the evaporation and inflow into reservoir could help in gaining information regarding decision making for dams. Hence enhancing the system operation efficiency and minimizing drought and flood risk under different conditions. Considering the stochastic nature of inflow and evaporation from the reservoir with optimization model may provide more robust and reliable model and most importantly is reflecting the real management for the reservoir.

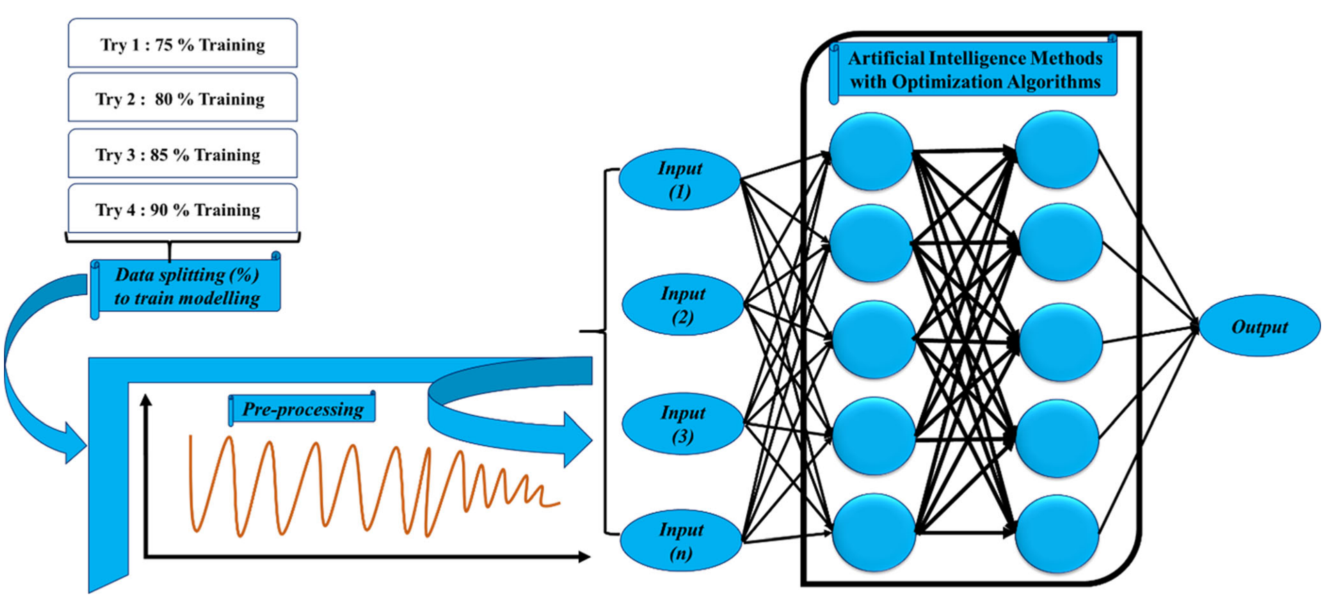

Fig. 3 The proposed predictive model to forecast evaporation and reservoir inflow parameters

To obtain a practical and successful application on water allocation, there is a need to predict the available water in the reservoir. This issue leads to strengthening optimization models, and hence, providing the model performance that matches with realistic conditions. It is important to avoid simulation models based on deterministic data whether for the inflow or evaporation due to the high stochastic nature and fluctuations of these parameters. For this reason, the current work recommended to combine artificial intelligence methods such as ANFIS and CANFIS with artificial swarm intelligence techniques such as artificial fish swarm algorithm or artificial bee colony during the simulation and optimization procedures. The proposed model improves the efficiency of current reservoir optimization operation based on the accurate forecast for evaporation and inflow. The primary purpose of the proposed model is developing an automated and intelligent technique that could determine different possible events that could happen in the reservoir rather than depending on the perfect forecasting. The proposed model for combining AI-based models with optimization algorithms is illustrated in Fig. 4.

The second step in the evaluation of the optimization model considered the prediction of hydrological parameters (inflow and evaporation) to match with the first step as shown in Fig. 5).

The following new procedure is recommended to operate the reservoir system under realistic conditions:

1. To use the operational rules that were obtained by optimization techniques, there is a need to obtain the storage of the reservoir and the type of inflow value for each step (i.e., day, month, season, etc.).
2. The inflow and evaporation values are predicted by AI-models at the beginning of step.
3. The storage of reservoir in the beginning of the step is determined by Eq. (1)

$$S(t) = Si + Ip - Ep \tag{1}$$

Where Si, Ip, and Ep are initial storage, predicted inflow, and predicted evaporation respectively.

4. After obtaining the beginning storage of the reservoir and the type of inflow value for the first step, the decision for water release volume is taken using the operational rules.
5. At the end of the first step, the storage of reservoir is corrected by Eq. 2 according to the actual inflow and evaporation data, which are obtained after the end step (i.e., day, month, season, etc.). The storage from Eq. 2 represents the initial storage for the next step.

$$S(t) = Si + Ia - Ea - R \tag{2}$$

Where Si, Ia, Ea, and R are initial storage, inflow (actual), evaporation (actual), and decision release, respectively.

The reservoir situation is updated according to the water losses by way of evaporation, inflow volume that is coming into a reservoir, and the decision of water release. The new decisions for water release volume are made based on updated forecast for these hydrological parameters as shown Fig. 5. These processes are repeated from step 1 to N (N is simulation period). The performance indicators are calculated by different equations according to this simulation. The most crucial performance index for any optimization models is a reliability indicator. The reliability provides information regarding how many times during simulation the decision to release is capable of meeting the demand over the whole term, and the reliability of models is calculated by Eq. 3.

$$\text{Reliability} = \frac{\text{number of time period which is meeting demand}}{\text{the simulation period}} \tag{3}$$

The vulnerability is the second criteria to evaluate optimization models during simulation period. A vulnerability is defined as a measure of worst case which could be faced by the reservoir system. The maximum deficit which occurred in simulation term is considered as a vulnerability of a model and represents the percentage demand as shown by Eq. 4.

$$\text{Vulnerability} = \left(\frac{\text{Max (deficit)}}{\text{demand}}\right) * 100 \tag{4}$$

The third indicator which can be abstracted from simulation term is a resiliency of model. A resiliency could be defined as the capability of a system to recover from a failure of meeting demand or, the probability of the reservoir system to recover from experiencing unsatisfactory values. A high resiliency value demonstrates that the reservoir system is regaining the ability to meet demand faster during tough conditions, and Eq. 5 estimated the resiliency value.

$$\text{Resiliency} = \frac{\text{no. of successful period value follows a failure}}{\text{no. of total a failure occurred}} \tag{5}$$

Shortage index (SI) could also be used as a measure of the model efficiency to meet downstream requirements. SI provides information regarding a periodical reliability for model as well as a volume of the deficit which occurred during simulation period. In order to calculate the model efficiency, the shortage index can be used in the following Eq. 6.

$$SI = \frac{100}{T} \sum \left(\frac{\text{deficit}}{\text{demand}}\right)^2 \tag{6}$$

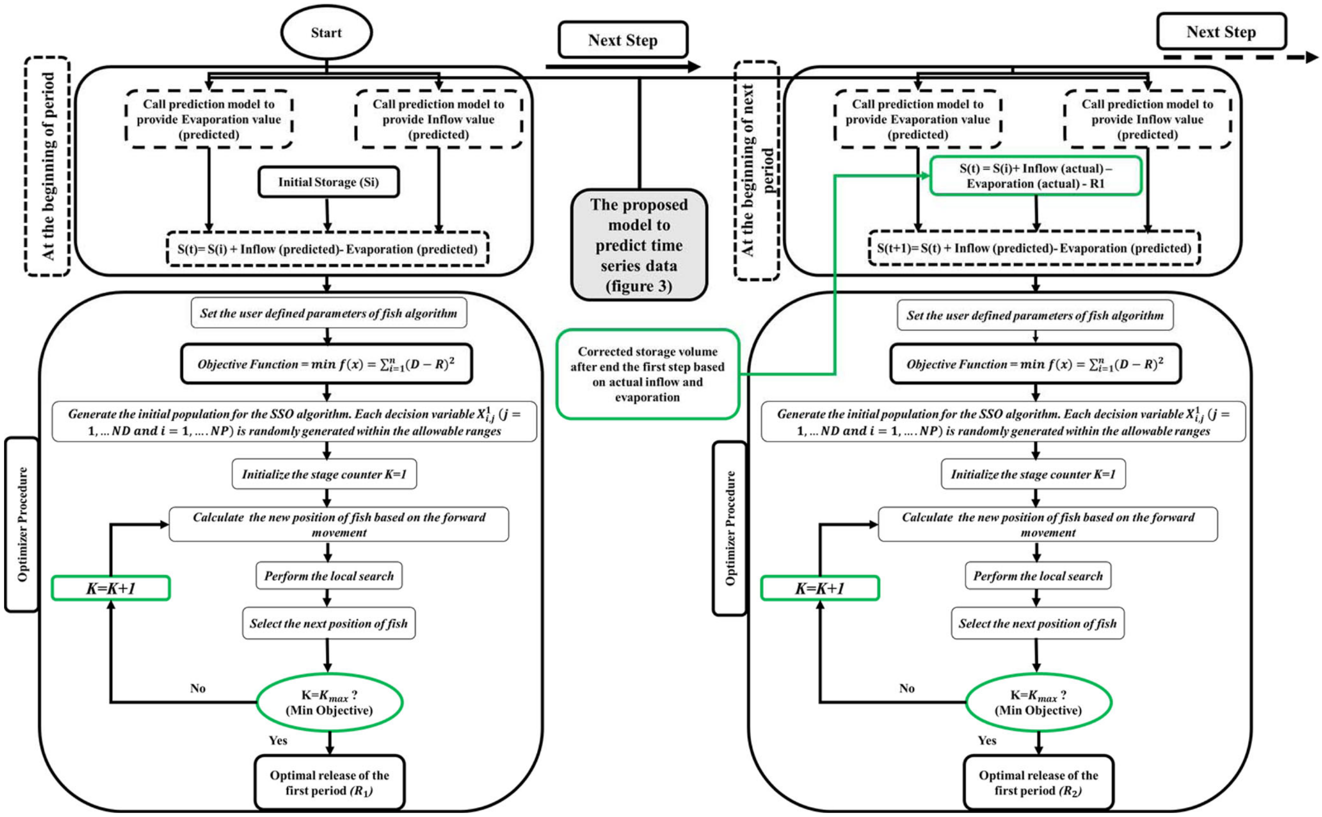

Fig. 4 The developed model which is comprised integrate predictive model with the optimization algorithm

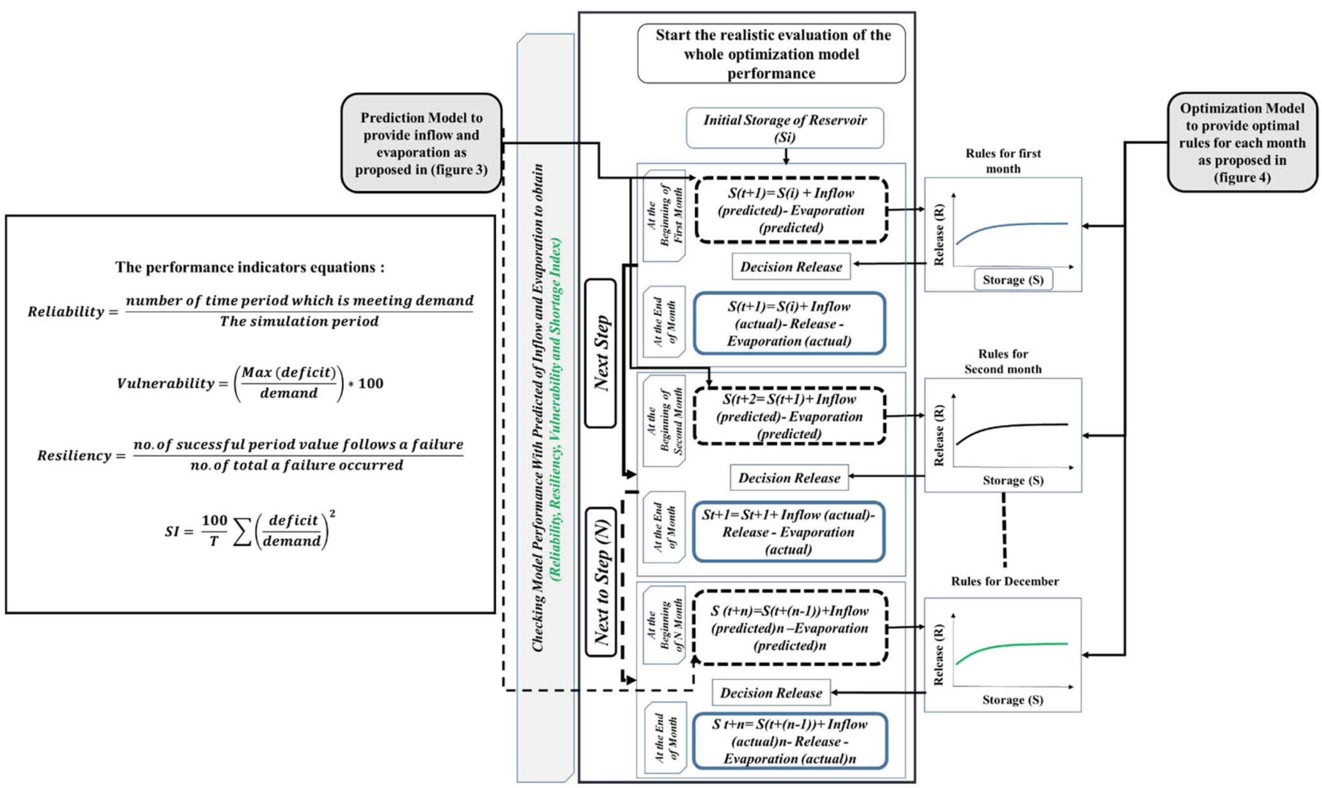

Fig. 5 The new reservoir operation procedure to examine the optimization model's performance under realistic conditions

Conclusion

The current research reviewed the history of developing AI-models in reservoir inflow forecasting and prediction of evaporation from a reservoir as the major components in the reservoir system. Further, this work demonstrates the efforts that have been made during the past decades to develop optimization methods in order to operate the reservoir system. The uncertainty of natural hydrological parameters leads to many problems in simulating the reservoir operation systems. AI techniques have shown considerable progress in predicting and simulating the hydrological modeling and in handling a natural stochastic complexity, nonlinearity, and non-stationary nature of the original database. The reviewed papers have also indicated that prediction model has the primary effect of the optimization methods, which improve the performance of the modeling and provide reliable results for reservoir management. An overall review of the literature studies indicates that very few papers in the evaporation prediction modeling have been published compared to the studies done in addressing reservoir inflow modeling. This study has determined some suggestions for future research, including an innovative method for inflow and evaporation prediction. The pre-processing for time series in the proposed model is based on swarm intelligence (SI) techniques and fast orthogonal search (FOS). The new combination between optimization algorithms and prediction model has also been proposed to be utilized during evaluation stage of the optimization model.

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Compliance with ethical standards

Conflicts of interest The authors declare that they have no conflict of interest.

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