



Viability of the advanced adaptive neuro-fuzzy inference system model on reservoir evaporation process simulation: case study of Nasser Lake in Egypt

Sinan Q. Salih, Mohammed Falah Allawi, Ali A. Yousif, Asaad M. Armanuos, Mandeep Kaur Saggi, Mumtaz Ali, Shamsuddin Shahid, Nadhir Al-Ansari, Zaher Mundher Yaseen & Kwok-Wing Chau

To cite this article: Sinan Q. Salih, Mohammed Falah Allawi, Ali A. Yousif, Asaad M. Armanuos, Mandeep Kaur Saggi, Mumtaz Ali, Shamsuddin Shahid, Nadhir Al-Ansari, Zaher Mundher Yaseen & Kwok-Wing Chau (2019) Viability of the advanced adaptive neuro-fuzzy inference system model on reservoir evaporation process simulation: case study of Nasser Lake in Egypt, *Engineering Applications of Computational Fluid Mechanics*, 13:1, 878-891, DOI: [10.1080/19942060.2019.1647879](https://doi.org/10.1080/19942060.2019.1647879)

To link to this article: <https://doi.org/10.1080/19942060.2019.1647879>



© 2019 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



Published online: 08 Aug 2019.



Submit your article to this journal [↗](#)



Article views: 752



View related articles [↗](#)



View Crossmark data [↗](#)



Citing articles: 16 View citing articles [↗](#)

Viability of the advanced adaptive neuro-fuzzy inference system model on reservoir evaporation process simulation: case study of Nasser Lake in Egypt

Sinan Q. Salih^a, Mohammed Falah Allawi^b, Ali A. Yousif^c, Asaad M. Armanuos^d, Mandeep Kaur Saggi^e, Mumtaz Alif^f, Shamsuddin Shahid^g, Nadhir Al-Ansari^h, Zaher Mundher Yaseenⁱ and Kwok-Wing Chau^j

^aInstitute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam; ^bDepartment of Civil Engineering, Al-Esraa University College, Baghdad, Iraq; ^cWater Resources Engineering Department, College of Engineering, University of Duhok, Duhok, Iraq; ^dIrrigation and Hydraulics Engineering Department, Civil Engineering Department, Faculty of Engineering, Tanta University, Tanta, Egypt; ^eDepartment of Computer Science, Thapar Institute of Engineering and Technology, Patiala, India; ^fDeakin-SWU Joint Research Centre on Big Data, School of Information Technology, Deakin University, Victoria 3125, Australia; ^gSchool of Civil Engineering, Faculty of Engineering, Universiti Teknologi Malaysia (UTM), Johor Bahru 81310, Malaysia; ^hCivil, Environmental and Natural Resources Engineering, Lulea University of Technology, Lulea 97187, Sweden; ⁱSustainable Developments in Civil Engineering Research Group, Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam; ^jDepartment of Civil and Environmental Engineering, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, People's Republic of China

ABSTRACT

Reliable prediction of evaporative losses from reservoirs is an essential component of reservoir management and operation. Conventional models generally used for evaporation prediction have a number of drawbacks as they are based on several assumptions. A novel approach called the co-active neuro-fuzzy inference system (CANFIS) is proposed in this study for the modeling of evaporation from meteorological variables. CANFIS provides a center-weighted set rather than global weight sets for predictor–predictand relationship mapping and thus it can provide a higher prediction accuracy. In the present study, adjustments are made in the back-propagation algorithm of CANFIS for automatic updating of membership rules and further enhancement of its prediction accuracy. The predictive ability of the CANFIS model is validated with three well-established artificial intelligence (AI) models. Different statistical metrics are computed to investigate the prediction efficacy. The results reveal higher accuracy of the CANFIS model in predicting evaporation compared to the other AI models. CANFIS is found to be capable of modeling evaporation from mean temperature and relative humidity only, with a Nash–Sutcliffe efficiency of 0.93, which is much higher than that of the other models. Furthermore, CANFIS improves the prediction accuracy by 9.2–55.4% compared to the other AI models.

ARTICLE HISTORY

Received 7 June 2019
Accepted 21 July 2019

KEYWORDS

reservoir operation;
evaporation prediction;
artificial intelligent models;
CANFIS; arid environment

1. Introduction

Egypt is facing the challenge of growing water stress owing to limited water resources. It receives a fixed share of water of the Nile River (55.5 billion m³/year) according to the agreement the country made with Sudan in 1959 (Hassan, Ismail, Elmoustafa, & Khalaf, 2018). The water supplied through the Nile is almost the total amount of water available in the country. Lake Nasser is located over the Nile River in Upper Egypt and controls all the water supplied through the Nile (Hassan, 2013). Assessment of the water budget of Lake Nasser is therefore important for better management of water resources of Egypt. The evaporative loss from Lake Nasser is the most significant factor contributing to the lake's water budget. Therefore, it has been taken into account in many previous studies. For the lake management, the authority

considers 7.54 mm/day as the yearly mean of daily evaporation from Lake Nasser, with the highest evaporative loss being 10.8 mm/day in June and the lowest 3.95 mm/day in December (Ebaid & Ismail, 2010). This estimation is based on pan evaporation and the lake's water surface area, which fluctuates both annually and seasonally depending on the net water it receives (Jeuland & Whittington, 2014). Accurate estimation of evaporation losses is crucial for reservoir management (Ghorbani, Deo, Yaseen, Kashani, & Mohammadi, 2018). In semi-arid and tropical areas, lake evaporation is the major factor that needs to be monitored for water resources allocation (Qasem et al., 2019). Thus, accurate estimation of evaporative loss from Lake Nasser is important for water resources allocation and management in Egypt (Elba, Farghaly, & Urban, 2014; Sadek, Shahin, & Stigter, 1997).

CONTACT Zaher Mundher Yaseen  yaseen@tdtu.edu.vn

Evaporation from the lake occurs as a result of the vapor pressure difference between the lake's surface and the atmosphere. It is driven by the availability of energy required for the evaporation process (Burt, Mutziger, Allen, & Howell, 2005; Shirgure & Rajput, 2011). Therefore, a number of meteorological factors influences the evaporation process, including air temperature, water temperature, solar radiation, humidity and wind (Priestley & Taylor, 1972; Sartori, 2000). Numerous models have been implemented for the measurement of evaporative losses from water bodies, which can be categorized as experimental tests, physical methods and artificial intelligence (AI) models. Among the experimental methods, the pan evaporation is most widely used as it is reasonably simple and inexpensive (Koza, 1992). Long-term recordings can be obtained by installing an evaporation pan for a long period, which is considered to provide the most creditable data on evaporation losses (Kisi, 2006). A regression coefficient derived from pan evaporation data is used for measuring the evaporative losses from open water bodies (Cooley, 1983). However, pan evaporation is time consuming and subject to large uncertainties. Considering the limitations of in-situ measurement, many empirical models have been developed for the estimation of evaporation from meteorological variables, which are considered the most suitable methods for the measurement of evaporative loss in the absence of pan evaporation data (Allawi, Jaafar, Mohamad Hamzah, Ehteram, et al., 2018). For example, the Penman equation is especially used to estimate evaporation losses from open water bodies (Penman, 1948). These empirical methods are constructed considering the static initial conditions (Adamala, Raghuvanshi, Mishra, & Tiwari, 2014). Although several empirical models are available for the estimation of evaporation, their potential is not satisfactory owing to the nonlinear association of evaporation with meteorological variables, and non-stationarity and stochasticity in the evaporation process (Baydaroglu & Koçak, 2014). Hence, it is difficult to derive reliable physical-empirical models to represent the physical mechanism of the evaporation process. As a result, new machine learning models to simulate the evaporation process are always being explored by climate and hydrology scientists.

In recent years, AI-based models have emerged as a valuable tool for estimating evaporation losses (Ali Ghorbani, Kazempour, Chau, Shamshirband, & Taherei Ghazvinei, 2018; Kisi & Heddami, 2019; Sebbar, Heddami, & Djemili, 2019). The intelligence systems are advanced technologies for simulating complex natural phenomena (Yaseen, Sulaiman, Deo, & Chau, 2019). Such systems comprehend the knowledge lying beyond the given historical information by mimicking and processing the

actual variability and trend. The AI-based models are simple, versatile and applicable at local scale. A number of studies conducted in different climatic environments and using various meteorological inputs reported higher accuracy of AI models in the prediction of evaporation compared to empirical models (Allawi & El-Shafie, 2016; Hosseinzadeh Talaei, Tabari, & Abghari, 2014; Kisi, 2006; Moghaddamnia, Ghafari, Piri, & Han, 2009). Nourani and Sayyah Fard (2012) used a number of commonly used AI models such as artificial neural networks (ANNs) for the modeling of daily evaporative losses. They compared the results with those obtained using a classical regression model and confirmed the better performance of the ANN model in predicting evaporation from meteorological variables such as air temperature and solar radiation. Deo, Samui, and Kim (2016) compared the performance of support vector regression (SVR) with other AI models, including genetic programming, for the simulation of evaporation. Deo et al. (2016) employed three AI models, namely relevance vector machines, extreme learning machines and multivariate regression spline approaches, for the modeling of monthly evaporation. Both studies reported the significance of AI models for the better prediction of evaporation. Moghaddamnia et al. (2009) compared the performance of ANNs and the adaptive neuro-fuzzy interface system (ANFIS) model in simulating evaporation, and confirmed the improved performance of these models compared to the empirical models. Kisi and Heddami (2019) used fuzzy genetic (FG) techniques to model monthly evaporation losses and compared the performance with ANFIS, ANN and the Stephens Stewart method. The results confirmed the power of FG in modeling evaporation compared to the AI models.

ANFIS, implemented as the base model in the current study, was first suggested as a multiple input-output modeling approach. ANFIS can model highly stochastic patterns by capturing the input-target relationship. The selection of membership functions (MFs) and fuzzy rules is important in designing the optimal ANFIS model and achieving higher prediction accuracy. Therefore, an advanced version of ANFIS, known as the co-active neuro-fuzzy inference system (CANFIS), is proposed in this study for better accuracy in prediction.

The structure of CANFIS allows change in the back-propagation steps and re-evaluation of the membership rule and functions (Malik, Kumar, & Rai, 2018; Pradhan, Kumar, Kumar, & Sharma, *in press*). The CANFIS model is implemented in this study with an improved back-propagation technique to enhance model performance (Chiroma et al., 2013). The model accuracy is enhanced by selecting the numbers of optimal MFs in

both automated and self-adaptive ways. These are the main contributions of the current study.

The performance of the CANFIS model is examined in this study in comparison with other popularly used AI models, namely SVR, radial basis function neural network (RBF-NN) and ANFIS. The proposed CANFIS model is used for modeling monthly evaporation loss from Lake Nasser, Egypt. Several meteorological variables are considered as input attributes for the development of the models. The meteorological variables (sunshine, rainfall and surface pressure) with less influence are initially removed using a simulation-based step-by-step or one-by-one approach to determine the optimal input combination. The rest of the paper is arranged as follows. Section 2 presents a detailed description of the case study area. Section 3 describes the theory of the AI models employed in this study and the statistical metrics used for the assessment of model performance. Section 4 presents the results obtained through the use of the proposed model. The conclusions derived from the results are provided in Section 5.

2. Case study and data description

Aswan High Dam, situated on the upper Nile River in Egypt, was constructed during 1960–1970; afterwards, a lake upstream of the dam, called Lake Nasser, was developed (Figure 1). The reservoir encompasses an area of 6540 km² with a length of about 500 km. The mean width of the lake is approximately 10 km, reaching up to 60 km in the middle. The reservoir has a maximum depth of approximately 90 m and an average depth of 25 m. The total storage capacity of the lake is 162.3 × 10⁹ m³ when the water level reaches its maximum (Omar & El-Bakry, 1981). The reservoir controls the water supply for the whole of Egypt. The climate of the region where the reservoir is situated is hyper-arid. The average annual rainfall in the region is less than 3 mm, while the mean temperature ranges between 17 and 36°C. Low rainfall and high temperature have made the region hyper-arid. The climatological data used in this study are for the period 1969–2010, based on the data availability for Nasser Lake. Data were obtained from the Nile Water Authority and Aswan High Dam Authority, Ministry of Water Resources and Irrigation, Egypt. Historical climate information included evaporation, air temperature, humidity, wind speed and solar radiation.

3. Methodology

3.1. Artificial neural network (ANN)

ANNs were developed using the concept of information processing in the human brain. They are capable

of solving complex nonlinear problems in modeling stochastic time-series data. Through an iterative process, the ANN can determine the optimal hidden neurons and data patterns to predict unknown data (Abraham & Khan, 2004). Owing to their predictive accuracy, ANNs have been used extensively in water resources, hydrology and climate science.

The RBF-NN is an advanced form of ANN. It is composed of three layers of neurons known as the input, hidden and output layers. The number of neurons in the first layer is equal to the number of inputs. The first layer is composed of input data, $X = (x_1, x_2, \dots, x_n)$. The nodes of the second layer (hidden layer) are described on a radial basis. In the RBF, the input (x), a vector having a dimension of I , is transferred to the hidden layer (Ahmed, Noor, Allawi, & El-Shafie, 2018). The activation function, $\emptyset(x)$, in each node of this layer, is a nonlinear function. Thus, the output of the layer is derived according to the radial distance of x and the center of the hidden neurons (c_j), as defined in Equation (1):

$$h_j(x) = \emptyset(x - c_j) \quad (1)$$

Among the different RBFs, the Gaussian function is the most popular. The Gaussian function can be described by Equation (2):

$$\emptyset_j(x) = \exp \left[-\frac{x - c_j^2}{2\rho^2} \right] \quad (2)$$

where x and ρ are the calibration data and the width of the activation function, respectively. The width and the center are related to hidden neurons in the model. The last layer is the output layer, which is linear. It computes all the responses of the network.

3.2. Support vector regression (SVR)

SVR is a neural network based on statistical learning. The input vectors that support the model architecture are chosen through model training, which is detailed as follows. Considering a simple regression problem trained with a data set $\{(x_i + d_i)\}^n$ (x_i denotes input, d_i represents output and n denotes data length), the regression function of SVR can be defined as follows:

$$f(x) = w_i \cdot \emptyset_i(x) + b \quad (3)$$

where w_i and b are the weight and bias, respectively; \emptyset_i is the nonlinear transfer function, which maps the input variables into the high-dimensional feature space, so that linear regression can be used to model the nonlinear regression. Convex optimization with an



Figure 1. Location of Lake Nasser in Upper Egypt (Allawi, Jaafar, Mohamad Hamzah, Mohd, et al., 2018).

ε -insensitive loss function (Vapnik, 1995) can be used to solve Equation (3):

$$\begin{aligned} \text{Minimize : } & \frac{1}{2} \|w\|^2 + c \sum_{i=1}^n (\xi_i + \xi_i^*) \\ \text{Subject to } & \begin{cases} w_i \cdot \phi_i(x) + b - d \leq E + \xi_i \\ i = 1, 2, 3, \dots, N \\ d - w_i \cdot \phi_i(x) - b \leq E + \xi_i \\ i = 1, 2, 3, \dots, N \\ \xi_i, \xi_i^* \geq 0, i = 1, 2, 3, \dots, N \end{cases} \end{aligned} \quad (4)$$

where ξ_i and ξ_i^* are slack variables which are used to assess the deviation of training data beyond the ε -insensitive region. The tolerance range of deviations is depicted by $C > 0$, where C is a constant that defines the penalizing loss in case of a training error. Misfitting of data can be overcome by minimization of $w^2/2$ and $C \sum_{i=1}^n (\xi_i - \xi_i^*)$ in Equation (3).

3.3. Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS is an advanced form of fuzzy logic model. It has gained much attention, particularly in applications

of climate science and hydrology, because of its ability to map highly nonlinear relationships (Jang, 1993). ANFIS employs a hybrid framework that combines back-propagation and least-squares approaches to provide the fuzzy ‘if-then’ rules. This framework, termed the neuro-fuzzy system, includes the integration of the ANN and the fuzzy model, where a multilayer feed-forward network is developed by employing neural network learning models and the fuzzy logic framework to map the input space into the output space (Allawi, Jaafar, Mohamad Hamzah, Abdullah, & El-shafie, 2018).

The common rules with two-fuzzy (i.e. IF-THEN) are realized as shown in Equations (5) and (6):

$$\text{Rule 1: if } u \text{ is } u_1 \text{ and } n \text{ is } n_1 \text{ then } f_1 = p_1 u + q_1 n + r_1 \quad (5)$$

$$\text{Rule 2: if } u \text{ is } u_2 \text{ and } n \text{ is } n_2 \text{ then } f_2 = p_2 u + q_2 n + r_2 \quad (6)$$

where the MFs are represented by u , and n , p , q and r represent the output for the model.

3.4. Co-active neuro-fuzzy inference system (CANFIS)

The CANFIS incorporates the merits of fuzzy systems and neural networks to improve the performance of the neural network system. It has higher capacity to handle input information as the fuzzy system can handle the complete knowledge, which is clearly understood (Aytek, 2009). Two MFs are generally used, namely the general bell and the Gaussian. The procedure also includes the normalizing axon, which aims to normalize the output variables into a range (0, 1). The fuzzy axons are very useful for MF properties, which can be changed through the model of back-propagation (Saemi & Ahmadi, 2008). In the current research, the original CANFIS algorithm is improved. Determination of the optimal internal parameters for the CANFIS model is essential. The selection of an optimal number of MFs is considered as one of the crucial parameters of CANFIS (Lohani, Kumar, & Singh, 2012; Tabari, Talae, & Abghari, 2012).

The selection of MFs during the training phase can provide a suitable mapping of the input-target pattern. The CANFIS allows one additional phase to be added to cover the back-propagation method at the beginning of the fuzzification procedure. To improve the performance of the CANFIS model, the original CANFIS model is modified in this study to enable the back-propagation method to choose the suitable weights in a localized manner. The mentioned modification enhanced the accuracy of the CANFIS model. The procedure used for the development of the CANFIS model in the current research also

helps to sort the functionally classified input variables into different classes of input type with different groups of weights.

It is worth mentioning that the back-propagation approach informs the weight coefficients for each input variable. On the other hand, with the proposed modified CANFIS model, a search algorithm is achieved which can change the MFs, as presented in Figure 2 (dashed line). The classical CANFIS model targets the reduction of prediction error through updating the neural network without changing the fuzzy axons (Figure 2, solid line). The new data processing approach proposed in this study is utilized by the modified CANFIS model to reactivate the fuzzification process with the provided new MFs and also to readjust the fuzzy axons in a self-adaptive model to improve the efficiency of the model.

The CANFIS uses a functional rule which can be applied to the modular network and the input values. Matching the MFs is the target of a number of treatment components, and these are the second component of the proposed CANFIS model. In addition, the number of modular supplied to the learning network is an essential for the prediction accuracy (Hanafy & Hanafy, 2014; Patil & Valunjkar, 2016). In general, the CANFIS network has a combined axon which releases the output of the MFs to an output of the working network (Alexandru & Ishak, 2004; Jang, Sun, & Mizutani, 1997); for example, the outputs are passed to the final output layer. On the other hand, the error is circulated to both the MFs and the employing network. The first layer contains several nodes and handling elements where, in each node, the membership class for a fuzzy set (R_1, R_2, T_1, T_2) is quantified (Allawi, Jaafar, Mohamad Hamzah, Mohd, et al., 2018; Memarian, Pourreza Bilondi, & Rezaei, 2016).

Three MFs describe the fuzzy group. Layer 2 receives the signal produced by each output pair from layer 2 and layer 3, which comprises two components, the upper and lower components (Saemi & Ahmadi, 2008). Finally, the fourth layer produces the final output of the model by providing the final shape of the network output and computing the weighted normalizations of the outputs which are produced in layer 3.

The proposed and the comparative models used in this research were developed using MATLAB and Neuro-Solutions software.

3.5. Performance indicators and model structure

Different statistical metrics are used to evaluate the model's capability (Sanikhani, Deo, Yaseen, Eray, & Kisi, 2018; Sanikhani, Kisi, Maroufpoor, & Yaseen, 2019). The metrics can be used to select the most suitable model

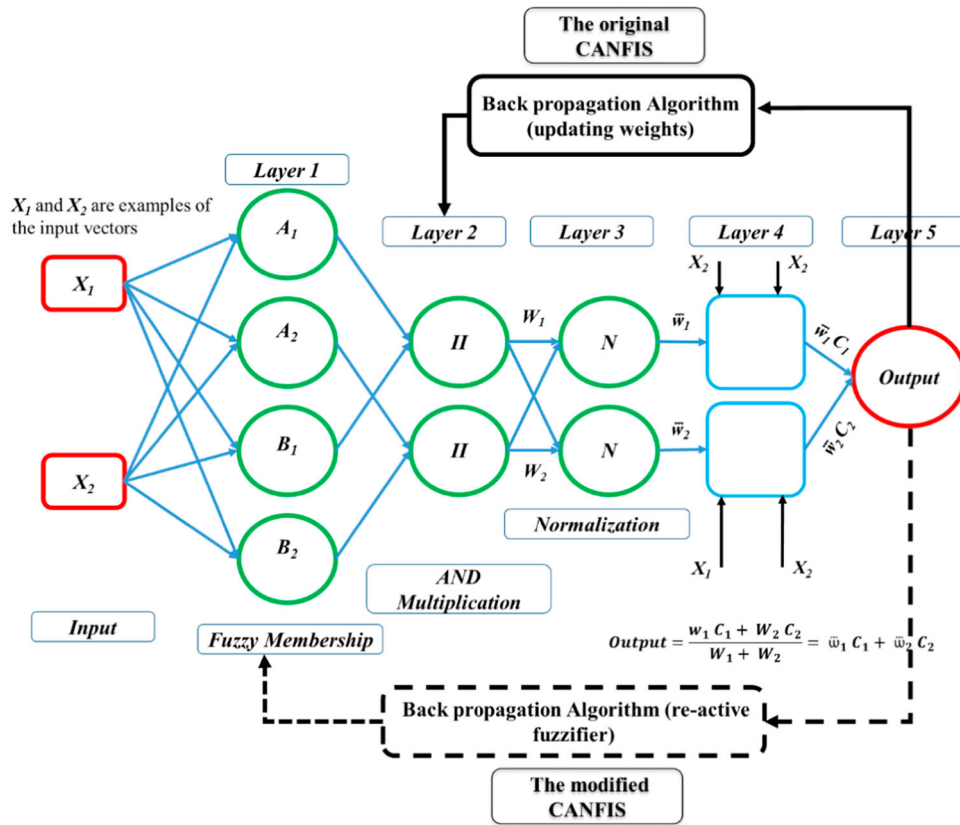


Figure 2. Architecture of the co-active neuro-fuzzy inference system (CANFIS) model with multiple inputs–signal output.

Note: Solid line = procedure of the back-propagation algorithm used in the original CANFIS; dashed line = new procedure of the back-propagation algorithm proposed in this study.

based on its predictive ability. Among those, the mean absolute error (MAE), root mean square error (RMSE), Nash–Sutcliffe efficiency (NSE), correlation coefficient (R^2), mean absolute percentage error (MAPE) and relative error (RE) are the most widely used (Ghorbani, Deo, Karimi, Yaseen, & Terzi, 2018; Yaseen, Kisi, & Demir, 2016; Yaseen, El-Shafie, et al., 2016). These metrics can be expressed as follows:

$$\text{MAE} = \frac{1}{N} \sum_{t=1}^N |F_t - A_t| \quad (7)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{t=1}^N ((F_t) - (A_t))^2} \quad (8)$$

$$\text{NSE} = 1 - \frac{\sum_{t=1}^n (F_t - A_t)^2}{\sum_{t=1}^n (A_t - \bar{F}_t)^2} \quad (9)$$

$$R^2 = \frac{\sum_{t=1}^n [(A_t) - (\bar{A}_t)]((F_t) - (\bar{F}_t))}{\sqrt{\sum_{t=1}^n ((A_t) - (\bar{A}_t))^2 \sum_{t=1}^n ((F_t) - (\bar{F}_t))^2}} \quad (10)$$

$$\text{MAPE} = \frac{1}{N} \sum_{t=1}^N \frac{P_t - A_t}{A_t} \quad (11)$$

$$\text{RE} = \left(\frac{P_t - A_t}{A_t} \right) * 100 \quad (12)$$

where P_t is the predicted value, A_t is the actual value and N is the number of data.

The number of input variables has a significant effect on the model accuracy. Several meteorological variables are initially considered in this study to predict monthly evaporation (Ep), including temperature (Ta), relative humidity (RH), wind speed (Ws) and solar radiation (SR). The historical data are divided into two phases (training and testing). The first 75% of the data is used to train the models, whereas the remaining 25% is used to test the performance of the models. The architectures of the predictive models which are considered in this study to select the best model are as follows:

$$\text{Model 1 : } (Ep = f(Ta)) \quad (13)$$

$$\text{Model 2 : } (Ep = f(RH)) \quad (14)$$

$$\text{Model 3 : } (Ep = f(Ta, RH)) \quad (15)$$

$$\text{Model 4 : } (Ep = f(Ta, SR, RH)) \quad (16)$$

$$\text{Model 5 : } (Ep = f(Ta, SR, RH, Ws)) \quad (17)$$

4. Application results and discussion

4.1. Aswan High Dam

In this study, the SVR is first implemented for modeling monthly evaporation losses from Lake Nasser. The models are developed for all input combinations mentioned in Equations (13)–(17). Five performance metrics are used to assess the accuracy of the SVR models during model calibration and validation. The results are presented in Table 1. It can be observed from the table that the worst prediction results are obtained using Model 1. Model 1 comprises only air temperature as an input to predict

monthly evaporation. This indicates that utilizing temperature alone is not sufficient for evaporation prediction using AI models. The SVR model needs more information to understand the evaporation pattern to provide acceptable results. Table 1 shows that the accuracy in prediction improves significantly when all meteorological variables are considered as inputs (i.e. Model 5).

The second AI model implemented for the prediction of monthly reservoir evaporation is RBF-NN. Different input combinations mentioned in Equations (12)–(16) are used to develop the RBF-NN model to select the model giving the highest predictive accuracy. The performance indicators are computed for different input combinations and presented in Table 2. The prediction accuracy of the RBF-NN models is also affected significantly by different input combinations. It is observed that only the

Table 1. Performance of support vector regression (SVR) models in simulating monthly evaporation losses from Lake Nasser.

Model	Training					Testing				
	MAE	RMSE	MAPE	NSE	R^2	MAE	RMSE	MAPE	NSE	R^2
Model 1	62.53	57.82	0.55	0.61	0.74	63.74	72.45	0.43	0.53	0.52
Model 2	38.23	53.42	0.63	0.69	0.74	41.85	65.67	0.37	0.54	0.55
Model 3	40.71	63.57	0.71	0.67	0.75	41.21	66.82	0.45	0.60	0.58
Model 4	52.87	74.81	0.84	0.69	0.66	55.02	75.77	0.71	0.63	0.59
Model 5*	26.31	35.72	0.34	0.82	0.75	33.87	39.64	0.26	0.65	0.61

Note: Five metrics, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), Nash–Sutcliffe efficiency (NSE) and correlation coefficient (R^2), were used to assess the model performance during model calibration and validation.

*Best performance.

Table 2. Performance of radial basis function neural network (RBF-NN) models in simulating monthly evaporation losses from Lake Nasser.

Model	Training					Testing				
	MAE	RMSE	MAPE	NSE	R^2	MAE	RMSE	MAPE	NSE	R^2
Model 1	55.91	56.73	0.31	0.76	0.80	56.77	65.23	0.26	0.62	0.64
Model 2	35.22	56.87	0.34	0.77	0.82	37.11	62.33	0.18	0.65	0.67
Model 3	49.77	72.42	0.25	0.78	0.75	52.03	74.51	0.23	0.63	0.65
Model 4	34.21	47.58	0.28	0.89	0.86	32.48	34.87	0.16	0.70	0.66
Model 5*	21.72	30.82	0.24	0.85	0.89	30.12	29.24	0.14	0.71	0.69

Note: Five metrics, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), Nash–Sutcliffe efficiency (NSE) and correlation coefficient (R^2), were used to assess the model performance during model calibration and validation.

*Best performance.

Table 3. Performance of adaptive neuro-fuzzy inference system (ANFIS) models in simulating monthly evaporation losses from Lake Nasser.

Model	Training					Testing				
	MAE	RMSE	MAPE	NSE	R^2	MAE	RMSE	MAPE	NSE	R^2
Model 1	51.74	51.74	0.36	0.76	0.83	53.47	69.54	0.33	0.78	0.68
Model 2	29.47	46.37	0.22	0.85	0.85	33.21	67.44	0.21	0.79	0.68
Model 3*	18.82	29.55	0.17	0.86	0.87	22.45	19.47	0.11	0.81	0.77
Model 4	35.24	52.47	0.34	0.84	0.84	25.14	22.11	0.14	0.75	0.71
Model 5	47.28	66.84	0.21	0.82	0.82	45.42	68.54	0.13	0.74	0.75

Note: Five metrics, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), Nash–Sutcliffe efficiency (NSE) and correlation coefficient (R^2), were used to assess the model performance during model calibration and validation.

*Best performance.

RBF-NN Models 4 and 5 are able to attain acceptable prediction accuracy. The minimum RMSE, MAE and mean absolute percentage error (MAPE) are achieved by using three different meteorological variables as inputs (i.e. Model 4). However, the maximum agreement between the predicted and actual evaporation data is obtained by RBF-NN Model 5, where all five meteorological variables are used as inputs for the development of the model.

The performances of ANFIS models during calibration and validation in terms of five performance indicators are presented in Table 3. The performance of ANFIS is found to be different from that of SVR and RBF-NN. The minimum prediction error during testing is obtained using two inputs, the air temperature and relative humidity (i.e. Model 3). Based on the correlation coefficient and NSE coefficient indicators, the maximum

Table 4. Performance of co-active neuro-fuzzy inference system (CANFIS) models in simulating monthly evaporation losses from Lake Nasser.

Model	Training					Testing				
	MAE	RMSE	MAPE	NSE	R^2	MAE	RMSE	MAPE	NSE	R^2
Model 1	23.48	26.57	0.18	0.94	0.92	28.34	28.78	0.27	0.77	0.72
Model 2	42.51	52.73	0.35	0.78	0.78	41.24	47.24	0.32	0.78	0.81
Model 3*	26.47	40.12	0.21	0.91	0.91	18.47	17.66	0.9	0.93	0.97
Model 4	28.24	52.48	0.26	0.82	0.87	30.24	45.23	0.19	0.85	0.85
Model 5	31.77	70.28	0.28	0.75	0.75	37.77	70.21	0.27	0.77	0.77

Note: Five metrics, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), Nash-Sutcliffe efficiency (NSE) and correlation coefficient (R^2), were used to assess the model performance during model calibration and validation.

*Best performance.

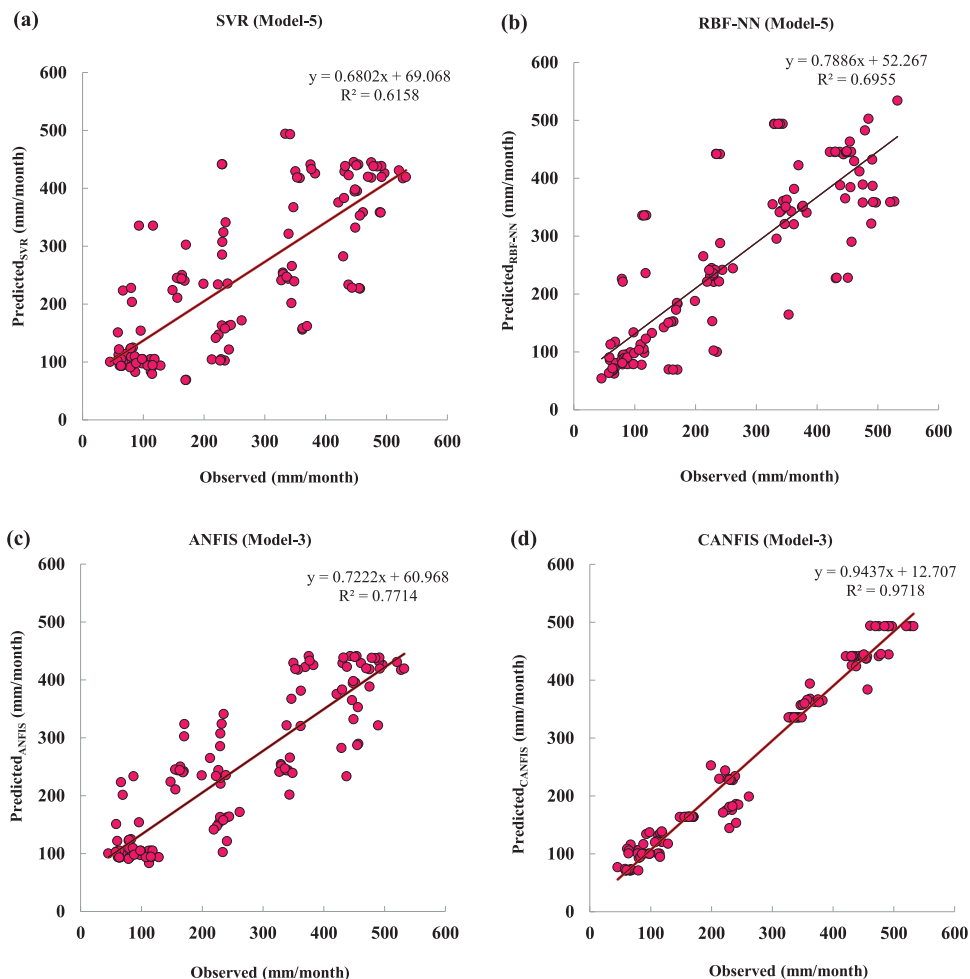


Figure 3. Scatter plots of the actual and the modeled evaporation obtained using support vector regression (SVR), radial basis function neural network (RBF-NN), adaptive neuro-fuzzy inference system (ANFIS) and co-active neuro-fuzzy inference system (CANFIS) models with best input combination.

agreement between predicted and observed evaporation is also found by Model 3. The worst prediction results are shown by Model 1.

Table 4 shows the performance of CANFIS models for different input combinations. The performance of CANFIS models is found to be similar to that of ANFIS models. Model 3 (with temperature and relative humidity as inputs) provides the best prediction result among all of the AI models, while the worst results are obtained using Models 1 and 2. It is also observed that the performance of CANFIS is much better than that of the other models in terms of all statistical metrics. The NSE and R^2 of the prediction are 0.93 and 0.97, respectively, which are much higher than those obtained by the best performing models using other AI methods. The results also revealed temperature and humidity to be the factors with the greatest influence in predicting evaporation from Lake Nasser. The CANFIS model has the highest ability to predict the evaporation pattern from the temperature and humidity.

4.2. Comparison of the performance of the modified CANFIS model with other AI models

The development of models for predicting evaporation from easily available meteorological variables is an important issue for decision makers in water resources management. The results presented in the Section 4.1 indicate that the AI models developed using ANFIS and CANFIS methods can provide a higher level of accuracy in the prediction of evaporation from only two meteorological variables, temperature and relative humidity, whereas the RBF-NN and SVR models provide optimal prediction when all five meteorological variables are considered as inputs. This demonstrates that the SVR and RBF-NN need more meteorological information to understand the behavior of lake evaporation. The performances of different models with the best input combination are compared in this section through graphical presentations.

The scatter plots for the testing of each AI model with the best input combination are presented in Figure 3. This

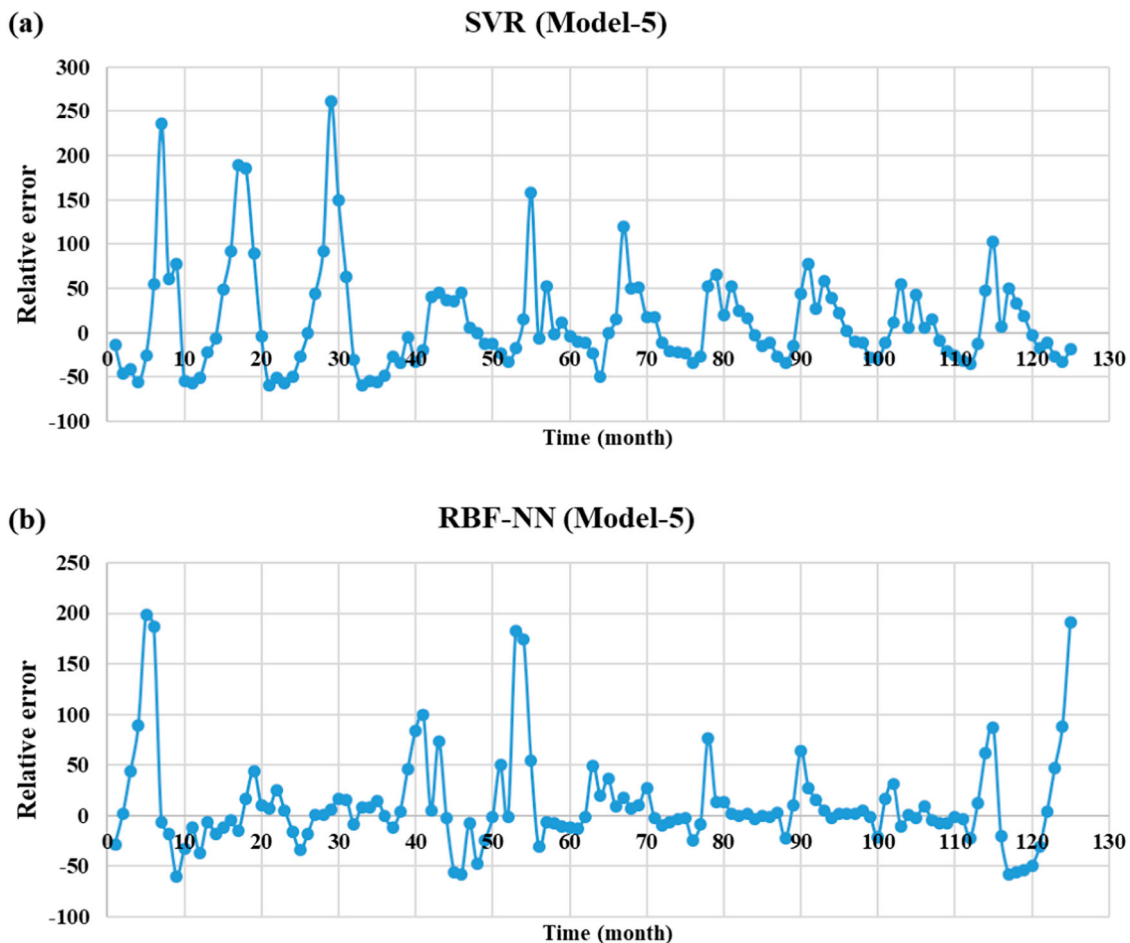


Figure 4. Relative error distribution obtained for support vector regression (SVR) and radial basis function neural network (RBF-NN) models with best input combination.

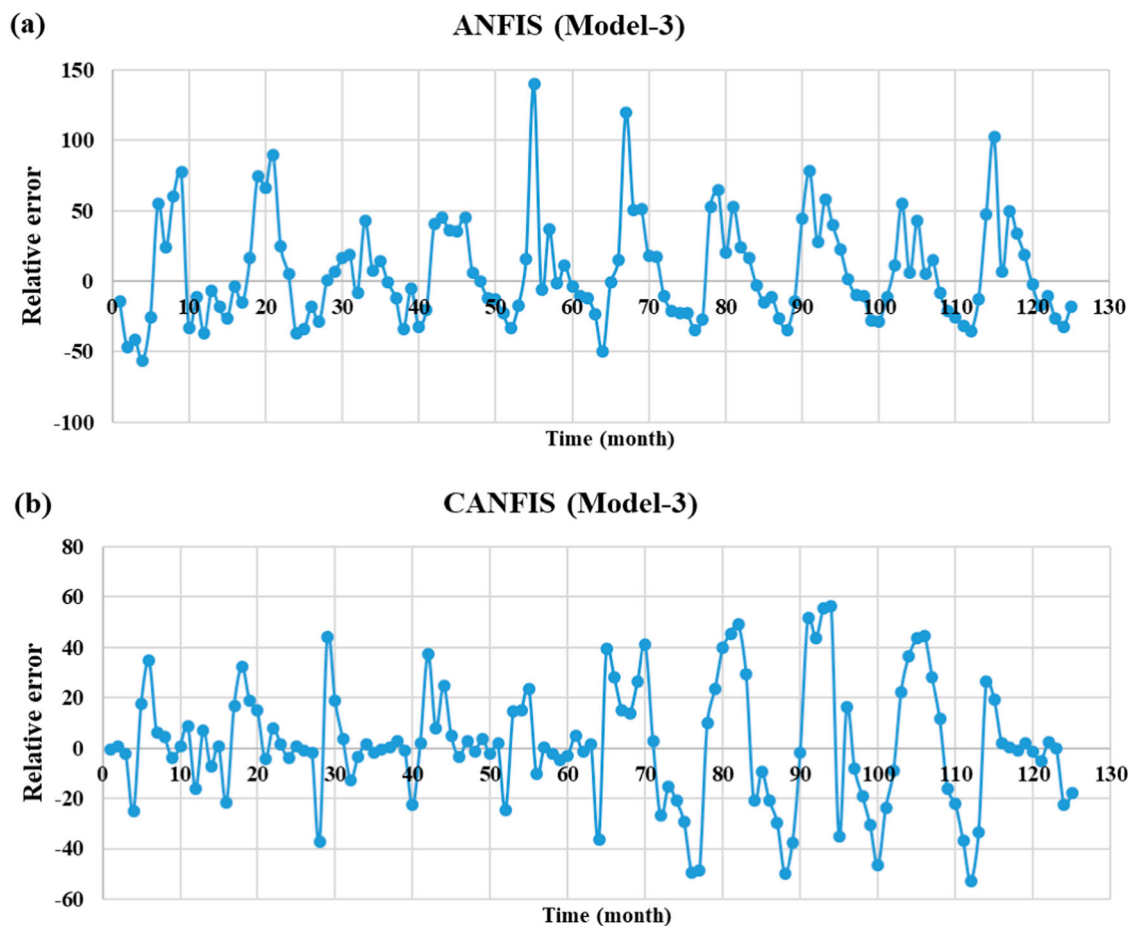


Figure 5. Relative error distribution obtained for adaptive neuro-fuzzy inference system (ANFIS) and co-active neuro-fuzzy inference system (CANFIS) models with best input combination.

figure shows a higher association between the modeled and actual evaporation for CANFIS than for the other models. Agreement between the modeled and actual evaporation for the whole range of values, high, medium and low, is found only for CANFIS. The lowest correlation between the modeled and actual evaporation is observed for RBF-NN.

The most critical indicator generally used to evaluate the capability of AI models is RE. The present study used the percentage RE to evaluate the ability of the models. Figures 4 and 5 illustrate the distribution of RE over the testing period for each AI model with the best input combination. The maximum RE is found for RBF-NN, while CANFIS provides the lowest and the most consistent RE over the testing period. This indicates the higher efficiency of the CANFIS model compared to the other AI models (SVR, RBF-NN and ANFIS), in predicting lake evaporation from meteorological variables. However, some high magnitudes of RE are found for all the models. These high REs could not be minimized using the proposed AI models. The relatively high errors in a few years may be due to the sudden

variability in the climate in those years. This may be solved by integrating the time-series data preprocessing approach with models such as wavelet transformation (Wu & Chau, 2011; Yaseen, El-shafie, Jaafar, Afan, & Sayl, 2015).

Figures 6 and 7 show the time series of the observed and predicted evaporation by all four AI models used in this study. It can be observed from the figure that neither SVR nor RBF-NN is capable of replicating the seasonal variability in the evaporation pattern for all of the years. A shift in the predicted cycle is observed in a few years. The ANFIS model is able to provide acceptable results in detecting the behavior of evaporation. However, the ANFIS model achieves a high level of accuracy only in the prediction of medium values; it cannot successfully replicate the minimum and maximum evaporation (i.e. peaks) in most of the years. On the other hand, the CANFIS model is found to perform best, as it reconstructs the evaporation pattern completely. The results indicate that the CANFIS model can be utilized for the accurate prediction of monthly reservoir evaporation from meteorological variables.

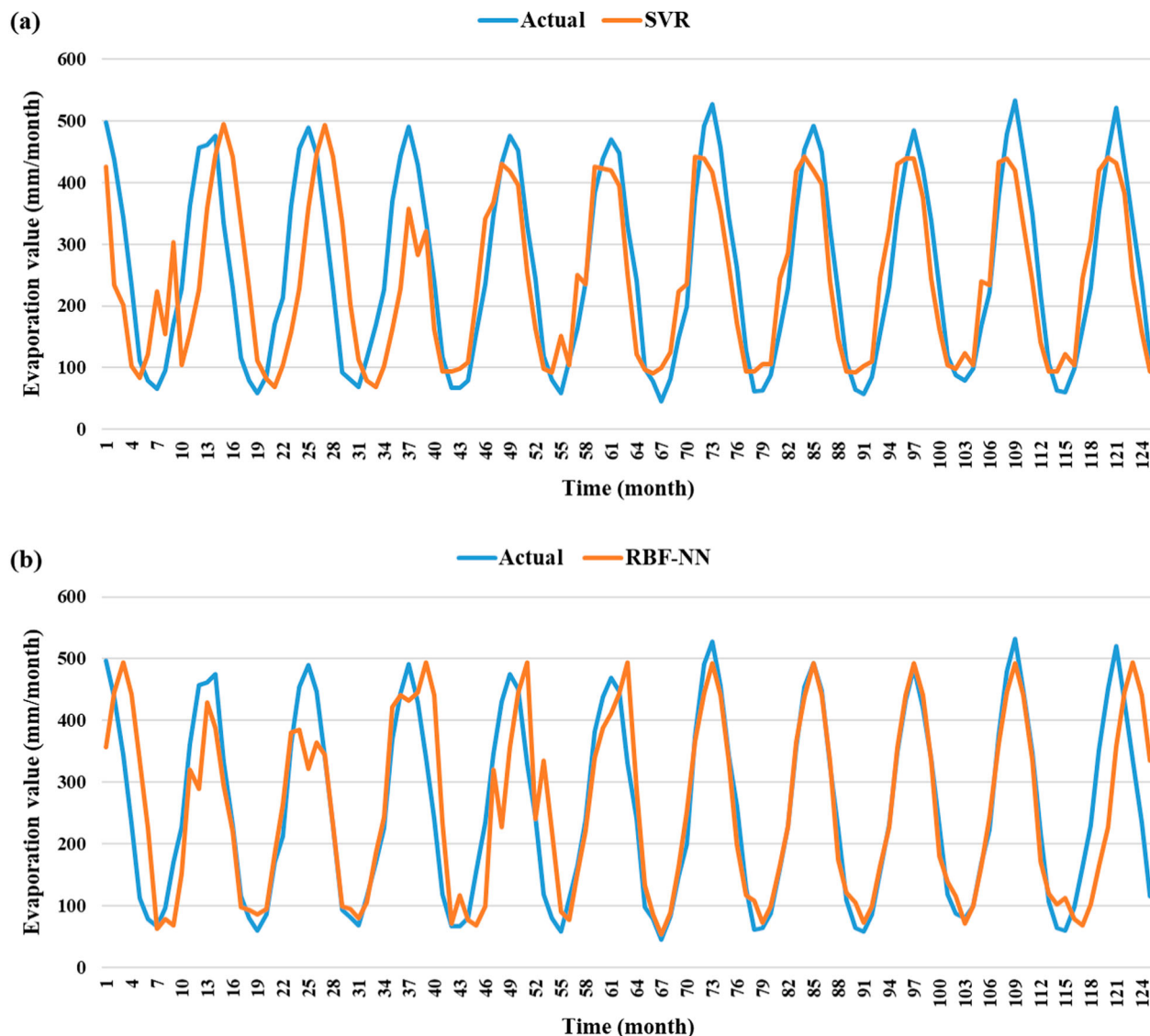


Figure 6. Time series of observed and predicted evaporation by support vector regression (SVR) and radial basis function neural network (RBF-NN) models with best input combination during model validation.

For further analysis of the performance of the AI models, the percentage improvement in accuracy indicator (%IA) using the CANFIS model is computed. The RMSEs are considered to estimate the %IA using Equation (8). The accuracy of the prediction results is found to improve by 55.4%, 39.6% and 9.2% when using CANFIS compared to the SVR, RBF-NN and ANFIS models, respectively. This indicates that the prediction accuracy is highly improved using CANFIS. CANFIS is also found to successfully predict evaporation with a high level of accuracy in terms of all the performance metrics used in this study.

5. Conclusion

The evaporation process plays a crucial role in water resources management, particularly in the management

of lake water. Therefore, the accurate prediction of this hydrological parameter is important for decision making in the planning, development and management of water resources. The ability of a new AI model known as CANFIS to predict lake evaporation is investigated in this study. The performance of the proposed model is compared with three popularly used AI prediction models: ANFIS, SVR and RBF-NN. The developed models are used for the prediction of monthly evaporation losses from Lake Nasser, situated in the hyper-arid region of Egypt. Five meteorological variables are considered to build the prediction models. The optimal input combinations for the models are determined by carefully considering all the possible input combinations. The results reveal that the SVR and RBF-NN models need at least four meteorological variables to provide acceptable prediction accuracy. On the other hand, the

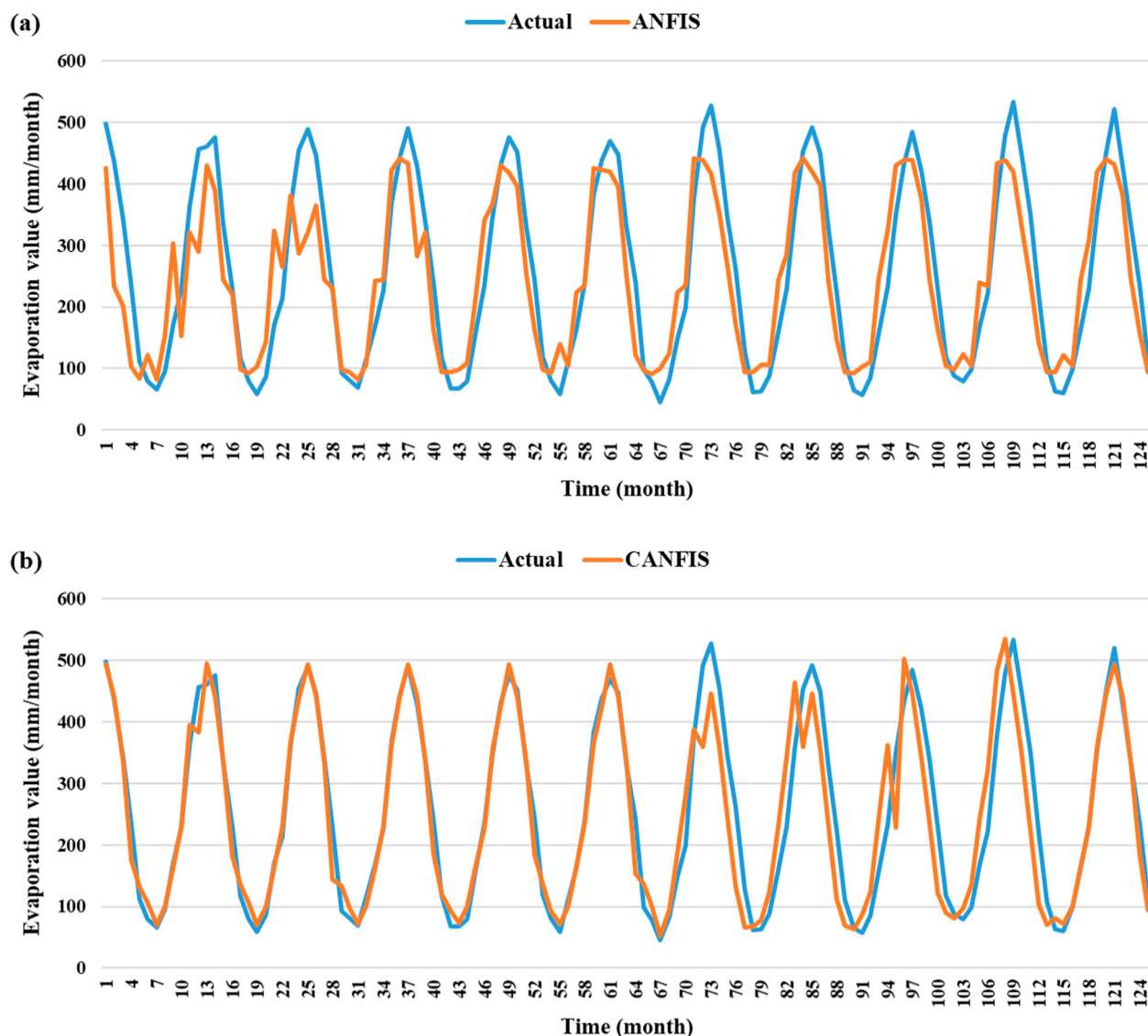


Figure 7. Time series of observed and predicted evaporation by adaptive neuro-fuzzy inference system (ANFIS) and co-active neuro-fuzzy inference system (CANFIS) models with best input combination during model validation.

ANFIS and CANFIS models are able to predict monthly evaporation with good accuracy using only two inputs, namely mean air temperature and relative humidity. The results indicate that temperature and relative humidity are the meteorological factors with the greatest influence in determining the evaporation losses from Lake Nasser. Comparison among the prediction models revealed that the prediction ability could be improved by 55.4%, 39.6% and 9.2% using the CANFIS model compared to the SVR, RBF-NN and ANFIS models, respectively. The newly adopted CANFIS-based evaporation model can be used for reliable estimation of evaporative losses from reservoirs, irrigated crop land, etc., and can also be used for other hydrological applications. As an extension to the current study, a metaheuristic optimization algorithm could be integrated with the CANFIS model for the

tuning of the MF, and the proficiency of the hybrid model in the prediction of evaporation loss could be investigated (Chau, 2017; Moazenzadeh, Mohammadi, Shamshirband, & Chau, 2018).

Acknowledgments

The authors greatly acknowledge the data sets provided by the Nile Water Authority and Aswan High Dam Authority, Ministry of Water Resources and Irrigation, Egypt, and Water Resources Management.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Shamsuddin Shahid  <http://orcid.org/0000-0001-9621-6452>
 Zaher Mundher Yaseen  <http://orcid.org/0000-0003-3647-7137>

References

- Abraham, A., & Khan, M. R. (2004). *Neuro-fuzzy paradigms for intelligent energy management* (pp. 285–314). Berlin: Springer. doi:10.1007/978-3-540-39615-4_12
- Adamala, S., Raghuvanshi, N. S., Mishra, A., & Tiwari, M. K. (2014). Development of generalized higher-order synaptic neural-based ET_o models for different agroecological regions in India. *Journal of Irrigation and Drainage Engineering*, 140(12), 4001–4038.
- Ahmed, A. N., Noor, C. W. M., Allawi, M. F., & El-Shafie, A. (2018). RBF-NN-based model for prediction of weld bead geometry in shielded metal arc welding (SMAW). *Neural Computing and Applications*, 29(3), 889–899. doi:10.1007/s00521-016-2496-0
- Alecsandru, C., & Ishak, S. (2004). Hybrid model-based and memory-based traffic prediction system. *Transportation Research Record: Journal of the Transportation Research Board*, 1879, 59–70. doi:10.3141/1879-08
- Ali Ghorbani, M., Kazempour, R., Chau, K.-W., Shamshirband, S., & Taherei Ghazvinei, P. (2018). Forecasting pan evaporation with an integrated artificial neural network quantum-behaved particle swarm optimization model: A case study in Talesh, Northern Iran. *Engineering Applications of Computational Fluid Mechanics*, 12(1), 724–737. doi:10.1080/19942060.2018.1517052
- Allawi, M. F., & El-Shafie, A. (2016). Utilizing RBF-NN and ANFIS methods for multi-lead ahead prediction model of evaporation from reservoir. *Water Resources Management*, 30(13), 4773–4788. doi:10.1007/s11269-016-1452-1
- Allawi, M. F., Jaafar, O., Mohamad Hamzah, F., Abdullah, S. M. S., & El-shafie, A. (2018). Review on applications of artificial intelligence methods for dam and reservoir-hydro-environment models. *Environmental Science and Pollution Research*, 25(14), 13446–13469. doi:10.1007/s11356-018-1867-8
- Allawi, M. F., Jaafar, O., Mohamad Hamzah, F., Ehteram, M., Hossain, M. S., & El-Shafie, A. (2018). Operating a reservoir system based on the shark machine learning algorithm. *Environmental Earth Sciences*, 77(10), 366. doi:10.1007/s12665-018-7546-8
- Allawi, M. F., Jaafar, O., Mohamad Hamzah, F., Mohd, N. S., Deo, R. C., & El-Shafie, A. (2018). Reservoir inflow forecasting with a modified coactive neuro-fuzzy inference system: A case study for a semi-arid region. *Theoretical and Applied Climatology*, 134(1–2), 545–563. doi:10.1007/s00704-017-2292-5
- Aytek, A. (2009). Co-active neurofuzzy inference system for evapotranspiration modeling. *Soft Computing*, 13(7), 691–700. doi:10.1007/s00500-008-0342-8
- BaydaroÇğlu, Ö., & Koçak, K. (2014). SVR-based prediction of evaporation combined with chaotic approach. *Journal of Hydrology*, 508, 356–363. doi:10.1016/j.jhydrol.2013.11.008
- Burt, C. M., Mutziger, A. J., Allen, R. G., & Howell, T. A. (2005). Evaporation research: Review and interpretation. *Journal of Irrigation and Drainage Engineering*, 131(1), 37–58.
- Chau, K. (2017). Use of meta-heuristic techniques in rainfall-runoff modelling. *Water*, 9(3), 186. doi:10.3390/w9030186
- Chiroma, H., Abdulkareem, S., Abubakar, A., Zeki, A., Gital, A. Y. U., & Usman, M. J. (2013). *Co-active neuro-fuzzy inference systems model for predicting crude oil price based on OECD inventories*. International Conference on Research and Innovation in Information Systems, ICRIS. doi:10.1109/ICRIIS.2013.6716714
- Cooley, K. R. (1983). Evaporation reduction: Summary of long-term tank studies. *Journal of Irrigation and Drainage Engineering*, 109(1), 89–98. doi:10.1061/(ASCE)0733-9437(1983)109:1(89)
- Deo, R. C., Samui, P., & Kim, D. (2016). Estimation of monthly evaporative loss using relevance vector machine, extreme learning machine and multivariate adaptive regression spline models. *Stochastic Environmental Research and Risk Assessment*, 30(6), 1769–1784. doi:10.1007/s00477-015-1153-y
- Ebaid, H. M. I., & Ismail, S. S. (2010). Lake Nasser evaporation reduction study. *Journal of Advanced Research*, 1(4), 315–322. doi:10.1016/j.jare.2010.09.002
- Elba, E., Farghaly, D., & Urban, B. (2014). Modeling High Aswan Dam reservoir morphology using remote sensing to reduce evaporation. *International Journal of Geosciences*, 5(2), 43171. doi:10.4236/ijg.2014.52017
- Ghorbani, M. A., Deo, R. C., Karimi, V., Yaseen, Z. M., & Terzi, O. (2018). Implementation of a hybrid MLP-FFA model for water level prediction of Lake Egirdir, Turkey. *Stochastic Environmental Research and Risk Assessment*, 32(6), 1683–1697. doi:10.1007/s00477-017-1474-0
- Ghorbani, M. A., Deo, R. C., Yaseen, Z. M., Kashani, M. H., & Mohammadi, B. (2018). Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (MLP-FFA) model: Case study in North Iran. *Theoretical and Applied Climatology*, 133(3–4), 1119–1131. doi:10.1007/s00704-017-2244-0
- Hanafy, T. O. S., & Hanafy, T. O. S. (2014). A new algorithm to model highly nonlinear system based coactive neuro fuzzy inference system. *International Journal of Computer Applications*, 94(17), 9–20.
- Hassan, M. (2013). Evaporation estimation for Lake Nasser based on remote sensing technology. *Ain Shams Engineering Journal*, 4(4), 593–604. doi:10.1016/j.asej.2013.01.004
- Hassan, A., Ismail, S. S., Elmoustafa, A., & Khalaf, S. (2018). Evaluating evaporation rate from High Aswan Dam reservoir using RS and GIS techniques. *The Egyptian Journal of Remote Sensing and Space Science*, 21(3), 285–293. doi:10.1016/j.ejrs.2017.10.001
- Hosseinzadeh Talaei, P., Tabari, H., & Abghari, H. (2014). Pan evaporation and reference evapotranspiration trend detection in Western Iran with consideration of data persistence. *Hydrology Research*, 45(2), 213–225. doi:10.2166/nh.2013.058
- Jang, J. S. R. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665–685. doi:10.1109/21.256541
- Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). *Neuro-fuzzy and soft computing, a computational approach to learning and machine intelligence*. Upper Saddle River, NJ: Pearson.
- Jeuland, M., & Whittington, D. (2014). Water resources planning under climate change: Assessing the robustness of real options for the Blue Nile. *Water Resources Research*, 50(3), 2086–2107.
- Kiş, Ö. (2006). Daily pan evaporation modelling using a neuro-fuzzy computing technique. *Journal of Hydrology*, 329(3–4), 636–646. doi:10.1016/j.jhydrol.2006.03.015

- Kisi, O., & Heddami, S. (2019). Evaporation modelling by heuristic regression approaches using only temperature data. *Hydrological Sciences Journal*, 64(6), 653–672. doi:10.1080/02626667.2019.1599487
- Koza, J. R. (1992). *Genetic programming: On the programming of computers by means of natural selection*. Cambridge, MA: MIT Press.
- Lohani, A. K., Kumar, R., & Singh, R. D. (2012). Hydrological time series modeling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. *Journal of Hydrology*, 442–443, 23–35. doi:10.1016/j.jhydrol.2012.03.031
- Malik, A., Kumar, A., & Rai, P. (2018). Weekly pan-evaporation simulation using MLP, CANFIS, MLR and climate-based models at Pantnagar. *Indian Journal of Ecology*, 45(2), 292–298.
- Memarian, H., Pourreza Bilondi, M., & Rezaei, M. (2016). Drought prediction using co-active neuro-fuzzy inference system, validation, and uncertainty analysis (case study: Birjand, Iran). *Theoretical and Applied Climatology*, 125(3–4), 541–554. doi:10.1007/s00704-015-1532-9
- Moazenzadeh, R., Mohammadi, B., Shamsirband, S., & Chau, K. (2018). Coupling a firefly algorithm with support vector regression to predict evaporation in northern Iran. *Engineering Applications of Computational Fluid Mechanics*, 12(1), 584–597. doi:10.1080/19942060.2018.1482476
- Moghaddamnia, A., Ghafari, M., Piri, J., & Han, D. (2009). Evaporation estimation using support vector machines technique. *International Journal of Engineering and Applied Sciences*, 5(7), 415–423.
- Nourani, V., & Sayyah Fard, M. (2012). Sensitivity analysis of the artificial neural network outputs in simulation of the evaporation process at different climatologic regimes. *Advances in Engineering Software*, 47(1), 127–146. doi:10.1016/j.advengsoft.2011.12.014
- Omar, M. H., & El-Bakry, M. M. (1981). Estimation of evaporation from the lake of the Aswan High Dam (Lake Nasser) based on measurements over the lake. *Agricultural Meteorology*, 23, 293–308. doi:10.1016/0002-1571(81)90115-1
- Patil, S., & Valunekar, S. (2016). Utility of coactive neuro-fuzzy inference system for runoff prediction in comparison with multilayer perception. *International Journal of Engineering Research*, 8(1), 156–160. doi:10.17950/ijer/v5i1/036
- Penman, H. L. (1948). Natural evaporation from open water, bare soil and grass. *Proceedings of the Royal Society of London. Series A: Mathematical and Physical Sciences*, 193(1032), 120–145. doi:10.1098/rspa.1948.0037
- Pradhan, S., Kumar, S., Kumar, Y., & Sharma, H. C. (in press). Assessment of groundwater utilization status and prediction of water table depth using different heuristic models in an Indian. *Soft Computing*. doi:10.1007/s00500-018-3580-4
- Priestley, C. H. B., & Taylor, R. J. (1972). On the assessment of the surface heat flux and evaporation using large-scale parameters. *Monthly Weather Review*, 100, 81–92.
- Qasem, S. N., Samadianfard, S., Kheshtgar, S., Jarhan, S., Kisi, O., Shamsirband, S., & Chau, K.-W. (2019). Modeling monthly pan evaporation using wavelet support vector regression and wavelet artificial neural networks in arid and humid climates. *Engineering Applications of Computational Fluid Mechanics*, 13(1), 177–187. doi:10.1080/19942060.2018.1564702
- Sadek, M. F., Shahin, M. M., & Stigter, C. J. (1997). Evaporation from the reservoir of the High Aswan Dam, Egypt: A new comparison of relevant methods with limited data. *Theoretical and Applied Climatology*, 56(1–2), 57–66. doi:10.1007/BF00863783
- Saemi, M., & Ahmadi, M. (2008). Integration of genetic algorithm and a coactive neuro-fuzzy inference system for permeability prediction from well logs data. *Transport in Porous Media*, 71(3), 273–288. doi:10.1007/s11242-007-9125-4
- Sanikhani, H., Deo, R. C., Yaseen, Z. M., Eray, O., & Kisi, O. (2018). Non-tuned data intelligent model for soil temperature estimation: A new approach. *Geoderma*, 330, 52–64. doi:10.1016/j.geoderma.2018.05.030
- Sanikhani, H., Kisi, O., Maroufpoor, E., & Yaseen, Z. M. (2019). Temperature-based modeling of reference evapotranspiration using several artificial intelligence models: Application of different modeling scenarios. *Theoretical and Applied Climatology*, 135(1–2), 449–462. doi:10.1007/s00704-018-2390-z
- Sartori, E. (2000). A critical review on equations employed for the calculation of the evaporation rate from free water surfaces. *Solar Energy*, 68(1), 77–89. doi:10.1016/S0038-092X(99)00054-7
- Sebbar, A., Heddami, S., & Djemili, L. (2019). Predicting daily pan evaporation (Epan) from Dam Reservoirs in the Mediterranean regions of Algeria: OPELM vs OSELM. *Environmental Processes*, 6(1), 309–319. doi:10.1007/s40710-019-00353-2
- Shirgure, P. S., & Rajput, G. S. (2011). Evaporation modeling with neural networks—A research review. *Journal of Artificial Intelligence and Soft Computing Research*, 1(2), 37–47.
- Tabari, H., Talaei, P. H., & Abghari, H. (2012). Utility of coactive neuro-fuzzy inference system for pan evaporation modeling in comparison with multilayer perceptron. *Meteorology and Atmospheric Physics*, 116(3–4), 147–154.
- Vapnik, V. N. (1995). *The nature of statistical learning theory*. New York: Springer. doi:10.1109/TNN.1997.641482
- Wu, C. L., & Chau, K. W. (2011). Rainfall-runoff modeling using artificial neural network coupled with singular spectrum analysis. *Journal of Hydrology*, 399(3–4), 394–409. doi:10.1016/j.jhydrol.2011.01.017
- Yaseen, Z. M., El-Shafie, A., Afan, H. A., Hameed, M., Mohtar, W. H. M. W., & Hussain, A. (2016). RBFNN versus FFNN for daily river flow forecasting at Johor River, Malaysia. *Neural Computing and Applications*, 27(6), 1533–1542. doi:10.1007/s00521-015-1952-6
- Yaseen, Z. M., El-shafie, A., Jaafar, O., Afan, H. A., & Sayl, K. N. (2015). Artificial intelligence based models for stream-flow forecasting: 2000–2015. *Journal of Hydrology*, 530, 829–844. doi:10.1016/j.jhydrol.2015.10.038
- Yaseen, Z., Kisi, O., & Demir, V. (2016). Enhancing long-term streamflow forecasting and predicting using periodicity data component: application of artificial intelligence. *Water Resources Management*, 30(12), 4125–4151. doi:10.1007/s11269-016-1408-5
- Yaseen, Z. M., Sulaiman, S. O., Deo, R. C., & Chau, K.-W. (2019). An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction. *Journal of Hydrology*, 569, 387–408. doi:10.1016/j.jhydrol.2018.11.069