A Comparative Analysis of Hidden Markov Model, Hybrid Support Vector Machines, and Hybrid Artificial Neural Fuzzy Inference System in Reservoir Inflow Forecasting (Case Study: The King Fahd Dam, Saudi Arabia)

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Abstract: The precise prediction of the streamflow of reservoirs is of considerable importance for many activities relating to water resource management, such as reservoir operation and flood and drought control and protection. This study aimed to develop and evaluate the applicability of a hidden Markov model (HMM) and two hybrid models, i.e., the support vector machine-genetic algorithm (SVM-GA) and artificial neural fuzzy inference system-genetic algorithm (ANFIS-GA), for reservoir inflow forecasting at the King Fahd dam, Saudi Arabia. The results obtained by the HMM model were compared with those for the two hybrid models ANFIS-GA and SVM-GA, and with those for individual SVM and ANFIS models based on performance evaluation indicators and visual inspection. The results of the comparison revealed that the ANFIS-GA model and ANFIS model provided superior results for forecasting monthly inflow with satisfactory accuracy in both training ($R^2 = 0.924, 0.857$) and testing ($R^2 = 0.842, 0.810$) models. The performance evaluation results for the developed models showed that the GA-induced improvement in the ANFIS and SVR forecasts was matched by an approximately 25% decrease in RMSE and around a 13% increase in Nash–Sutcliffe efficiency. The promising accuracy of the proposed models demonstrates their potential for applications in monthly inflow forecasting in the present semiarid region.

Keywords: reservoir inflow forecasting; artificial neural fuzzy inference system; support vector machine; genetic algorithm

1. Introduction

Reliable inflow forecasting is a highly significant issue for flood and drought mitigation systems, the operation and planning of reservoirs, and hydropower production, especially, in countries with a shortage of water [1–3]. Reservoirs are basically operated on a daily or monthly scale based on operating rules derived utilizing long series of historical inflow records [4–7]. The main objectives of these reservoirs are managing adequate irrigation water, drought and flood mitigation, and hydropower production. Forecasting models are essential for the mitigation of the negative impacts of flood and drought disasters because they can provide early warnings, allowing time for decision-making by reservoir operators [8–13]. In this context, designing and improving reservoir inflow simulation models is of great concern for efficient water resources planning and management [14,15]. For this purpose, there have been numerous studies to improve the modeling and simulation of inflow forecasting. These modeling approaches can be generally categorized into two classes, namely, data-driven and physical models. In physical or conceptual
models, a large amount of hydrological, meteorological, and geographical data are needed for the modeling process. However, in data driven modeling, mathematical functions are used to relate meteorological parameters to inflow without predefinition of basin’s physical characteristics [16]. Univariate and multivariate models are two types of data-driven modeling techniques that are applied for inflow prediction. Univariate models use inflow data as input and multivariate models use several inputs such precipitation, evaporation, temperature, etc. [17].

Data-driven simulations have been employed in several hydrological applications, including inflow forecasting. These models include conventional models such as statistical models (autoregressive, autoregressive integrated, and seasonal autoregressive integrated moving average models—ARMA, ARIMA, SARIMA), or AI-based models such as artificial intelligence models (artificial neural network—ANN, and adaptive neuro-fuzzy inference system—ANFIS) and machine learning models (support vector machine—SVM) [18,19]. The SARIMA model is commonly used in hydrological studies and is recognized as the most efficient statistical linear model in runoff prediction; however, it does not perform well for complex nonlinear problems [20–26]. ANN models, commonly employed due to their high predictive accuracy and flexibility, are the most successful data-driven models [27,28]. According to the literature, the ANN model has been successfully applied to solve a variety of water resources issues [29]. This is because this type of models is capable of accurately simulating and estimating nonlinear functions and complex hydrological data. The ANN is one of the most commonly used data-driven models that has been widely employed for monthly inflow forecasting with reasonable forecasting skill [30–32].

Numerous studies investigated the applicability of ANN against statistical models in inflow prediction. For instance, Mohammadi et al. [33] compared ANN with both AR and ARIMA models in streamflow predicting, and their findings showed that ANN is more reliable. Valipour et al. [34] evaluated the performance of ANN, ARMA, and ARIMA in reservoir inflow forecasting and reported that the ANN was the best. There have been several attempts to combine the benefits of individual models, and, simultaneously, to eliminate the disadvantages of each approach in hybrid modeling. Zhang [35] proposed a hybrid ARIMA-ANN model in which he employed ANN to simulate the residuals of the ARIMA model, and the results confirmed the efficiency of the proposed hybrid model.

The support vector machine (SVM) model is another widely applied data-driven technique, which is commonly employed in the simulation of hydrological data [19,36–38]. The SVM model is a machine learning method for simplifying dynamic systems, simulating nonlinear behaviors, and obtaining the knowledge needed for providing relevant decision. Parsaie et al. [39] evaluated the performance of SVM in the prediction of discharge in compound open channel, reporting that the SVM model could predict discharge with reasonable accuracy. Kisi [40] investigated the reliability of least-squares SVR (LLSVR), ANFIS fuzzy c-means clustering (ANFIS-FCM), and ARMA models in inflow forecasting, revealing that the results of LLSVR outperform those of the ANFIS-FCM and ARMA models. Ghorbani et al. [41] investigated the applicability of SVM and ANN in the simulation of river stage time series, reporting that the two models provided adequate accuracy compared with standard models such as rating curve (RC) and MLR. Chau et al. [42] evaluated the performance of ANFIS and hybrid ANN-GA models in flood forecasting and compared their output with this of the linear regression model (LR), revealing that ANN-GA and ANFIS models were superior to the LR model in terms of performance criteria. The hidden Markov model (HMM) has been applied in several hydrological studies [43–45]; however, inflow forecasting based on the Hidden Markov model has not yet been fully explored in the literature [46–48]. Liu et al. [49] combined HMM and Gaussian Mixture Regression for probabilistic monthly streamflow forecasting using different HMM states, reporting that the proposed model had a good ability score and an acceptable uncertainty distribution. Rolim and de Souza Filho [50] proposed a methodology, using HMM and some other models, to detect and predict the nonlinear low frequency streamflow, revealing that the proposed model enhanced the information about the periods of low frequency streamflow.
The main objective of this project work was to investigate the performance of HMM, multivariate hybrid genetic algorithm GA-SVM, and multivariate hybrid genetic algorithm GA-ANFIS in reliable monthly inflow forecasting at King Fahd dam, Saudi Arabia. To assess the reliability of the proposed models, a detailed comparative study between the established models was carried out using several statistical indices. Forecasting reservoir inflow using hybrid genetic algorithm GA-SVM and multivariate hybrid genetic algorithm GA-ANFIS models has not been widely addressed. Furthermore, the issue on forecasting reservoir inflow at King Fahd dam, Saudi Arabia has not been addressed in the literature. The rest of the article is structured as follows: In the following section, we describe the selected dam for the implementation of the proposed techniques and the study area, followed by a representation of the utilized dataset. A detailed methodology follows in Section 3. A comparative analysis of the ANFIS-GA, HMM, and SVM-GA results and their applications for forecasting reservoir inflow are illustrated in Section 4, followed, finally, by a discussion and concluding remarks in Section 5.

2. Materials and Methods

2.1. Study Area Description and Dataset

Wadi Bisha is one of the largest valleys in the Arabian Peninsula, extending about 250 km from Asir to the Foothill basin (Figure 1). The King Fahd dam, located in Bisha, in the southwest of Saudi Arabia, is one of the biggest concrete dams in the Middle East with a volume of 325 million cubic meters and a catchment area of about 7600 km². The dam was built in 1997 for agriculture management, irrigation of neighboring areas, flood protection, feeding water-bearing sedimentary layers, compensating for groundwater extraction from the region’s groundwater reservoirs, feeding the water treatment plant, and recovering from surface water decreases related to drought in the Bisha valley. More than one hundred tributaries feed the entire valley with water and ensure steady water flow into the dam reservoir. Wadi Bisha extends between 17°30’ N and 20°00’ N in latitude and from 42°00’ E–43°00’ E in longitude, and extends approximately 200 km north of the dam, linking with Tathlith to create the wide Wadi known as Wadi-Ad-Dawasir, which extends as far as 200 km towards RabAl-Khali before ending in Rumeila. The annual rainfall rate in the upper reaches of the Wadi is about 280 mm while it decreases toward the lower end of Wadi Bisha with a rate of 100 mm (Figure 2a). The climate of the study area has in general the characteristics of arid and semiarid regions. The annual total rainfall decreases from the south region towards the northern region, and the peak annual volume of rainfall, 677 mm, was received by Abha station, which is located in the southwest. Furthermore, the Mann-Kendall test identified an overall negative trend in annual rainfall in the study area as the Z-statistics of the test varies from −3.08 to −0.14 (Figure 2b). The data used in this study were made available by the Ministry of Environment, Water and Agriculture in the Kingdom of Saudi Arabia, which is responsible for the operation of the dam. A 52-year time span dataset (1968 to 2019), comprising of monthly inflow to the King Fahd dam and rainfall records of the stations shown in Figure 1, was used as input data to different models employed in this study.

2.2. Hidden Markov Model (HMM)

The Markov chain is a probabilistic model that relies on probability theory and is employed to describe influences between consecutive observations of a random variable [50,51]. HMM is a limited arrangement of states that all have a typically multidimensional probability distribution linked to them and the transition between these states is controlled by transition probabilities. Outcomes or observations are produced in any of these states according to the related probability distribution. HMM comprises the context where the measurement is a probability function of the state, in which case the developed model is a doubled encoded stochastic mechanism with an implicit stochastic process that is hidden and can only be detected by another series of stochastic processes that generate the sequence of measurements [52,53]. In the Markov chain model, the outputs at time
t depend explicitly on the outputs at time t-1, but the outputs in HMM are contingently independent [54]. The implementation of HMM involves the definition of two model parameters (number of states ‘N’ and the number of possible observation objects in each state ‘M’), as well as three likelihood measurements for the entire parameter range of the model, which are given by [55,56]:

\[
\lambda = [A, B, \pi]
\]  

(1)

where \( A \) denotes the transition probability matrix of the states, \( B \) is the emission matrix, and \( \pi \) represents the initial distribution of the states. The following equations are used to determine these parameters:

\[
A = \{a_{ij}\}
\]  

(2)

\[
a_{ij} = P[q_{t+1} = S_j / q_t = S_i] \quad 1 \leq i, j \leq N
\]  

(3)

\[
B = \{b_j(k)\}
\]  

(4)

where:

\[
b_j(k) = P[v_k \text{ at } t / q_t = S_j] \quad 1 \leq j \leq N ; 1 \leq k \leq M
\]  

(5)

\[
V = \{v_1, v_2, \ldots \ldots, v_m\}
\]  

(6)

denotes the observations.

\[
\pi_i = P[q_1 = S_i] \quad 1 \leq i \leq N
\]  

(7)

---

**Figure 1.** Geographic location of the study area.
A trellis diagram of 6 HMM states that describes likelihood calculations of the implemented HMM in this study is shown in Figure 3. Each column in the diagram represents the likely state of reservoir inflow at a given time \( n \). The transition probability represented by \( a_{ij} \) links each state in any specified column to each state in subsequent columns as seen in Figure 3.
2.3. Support Vector Machine (SVM) Model

SVM is a classic machine learning technique focused on mathematical learning theory and it has several benefits in the classification of massive data, feature identification, and regression analysis [46]. The aim of regression analysis with SVR is to estimate a function based on the given dataset \((x, y)\), where \(x\) represents the input vector (in this case, the input vectors \((x)\) refer to lagged precipitation and lagged inflow) and \(y\) represents the output (referring to forecasted values). The SVM regression function can be described as follows:

\[
f(x) = \omega^T \varphi(x) + b \tag{8}
\]

in which \(f(x)\) represents the model’s output, \(\varphi(x)\) is representative of a nonlinear mapping function. \(\omega\) and \(b\) are, respectively, the weight vector and the bias term to be optimized based on the regularized function as follows:

\[
\begin{align*}
\min R(\omega, \xi, \xi^*, \varepsilon) &= \frac{1}{2}||\omega||^2 + C\left[\nu \varepsilon + \frac{1}{l} \sum_{i=1}^{l} (\xi_i + \xi_i^*)\right] \\
\text{subject to} : & y_i - \omega^T \varphi(x_i) - b \leq \varepsilon + \xi_i \\
& \omega^T \varphi(x_i) + b - y_i \leq \varepsilon + \xi_i^* \\
& \xi_i, \varepsilon \geq 0
\end{align*} \tag{9}
\]

in which \(C\) is the penalization parameter used to balance the empirical risk and model regularization term \(||\omega||^2\), \(\xi_i\) and \(\xi_i^*\) represent the positive slack variable. The above SVR model is solved using Lagrange multipliers:

\[
\begin{align*}
\max & R(a, a^*) = \sum_{i=1}^{l} (a_i^* - a_i) - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \left(a_i - a_i^*\right) \left(a_j - a_j^*\right) K(x_i, x_j) \\
\text{subjective to} : & \sum_{i=1}^{l} (a_i - a_i^*) = 0 \\
& 0 \leq a_i, a_i^* \leq \frac{C}{\tau} \\
& \sum_{i=1}^{l} (a_i + a_i^*) \leq C \cdot \nu
\end{align*} \tag{10}
\]

herein \(K(x_i, x_j)\) is the kernel function; \(a_i\) and \(a_i^*\) are the positive Lagrange multipliers, respectively.

Ultimately, the parameters of the SVM model are determined after reaching the desired solution for the objective function, and the regression form for an input vector \(x\) can be represented as follows:

\[
f(x) = \sum_{i=1}^{l} (a_i^* - a_i) \ K(x_i, x_j) + b \tag{11}
\]

2.4. Adaptive Neuro-Fuzzy Inference System

The ANFIS model is a fuzzy inference model (FIS) constructed as ANN, which combines the benefits of FIS with a learning algorithm [57, 58]. ANFIS hypothesizes the FIS model using different output or input data, and then updates its membership criteria using a backpropagation algorithm. In the present study, ANFIS was utilized to derive the relationships between the time of year (months), lagged precipitation, lagged inflow, and the reservoir inflow and to describe them as fuzzy if–then rules as shown in Figure 2. The ANFIS model is mainly comprised of a Sugeno-type FIS of a typical bell input membership function with five functions for each input of the nine inputs, and one output with a linear membership function.
Figure 4 describes the ANFIS system with a multilayered feed-forward design that was connected to an incoherent x and y input network. The Sugeno model (Figure 5) has a rule base that takes the following form:

\[
\text{If } a = A_1 \text{ and } b = B_1 \text{ we have } f_1 = p_1 \times a + q_1 \times b + r_1
\]

(12)

while if \( a = A_2 \) and \( b = B_2 \) we have

\[
\text{if } a = A_2 \text{ and } b = B_2 \text{ we have } f_2 = p_2 \times a + q_2 \times b + r_2
\]

(13)

where \( f_i \) is the output within the inconsistent zone defined by the FIS principle, \( A_i \) and \( B_i \) are the membership magnitudes, \( a \) and \( b \) represent indirect identification function, and \( p_i, q_i, \) and \( r_i \) are the consequential constraints adjusted in the forward passes of the learning algorithm. If the membership functions of the fuzzy sets \( A_i \) and \( B_i \) are \( \mu A_i \) and \( \mu B_i \) correspondingly, the five layers that incorporate ANFIS are described in Figure 6. More details about ANFIS can be found in Abuhasel [58].

![Figure 4. An adaptive neuro-fuzzy inference system (ANFIS) architecture for inflow forecasting.](image)

![Figure 5. Basic structure of ANFIS with a two-rule Sugeno system.](image)
number of premise parameters is equivalent to the summation of the parameters. Consequent parameters are those used in the defuzzification layer, shown in Figure 6 as \( p_i, q_i, r_i \). These parameters are optimized with GA to reduce the difference between the ANFIS output and the measured data to a minimum. In SVM modeling, as the RBF was used, the GA was applied to optimize the parameters \( \sigma, C, \) and \( \varepsilon \) during the training process. The RMSE function obtained with Equation (17) is used to determine the error value of the solution. The RMSE represents the model’s perfect fitting to the datasets and illustrates how the observed data are closely related to the forecasted values.

Figure 6. Schematic diagram of the five layers that incorporate ANFIS.

2.5. Genetic Algorithm

GAs are heuristic search techniques that can be used to solve a variety of practical optimization problems. The basic concepts of GAs were initially introduced by John Holland in the 1970s, and these techniques are based on natural genetics’ evolutionary theory. A basic GA process typically consists of four steps: fitness assessment, selection, genetic operations, and substitution. A population pool of chromosomes persists in a basic GA loop. The chromosomes represent the encoded arrangement of the possible solutions, and these solutions are used for all GA operations excluding the fitness assessment. The population is originally established randomly, and the optimal solutions of all chromosomes are determined by computing the objective function in the decoded form of chromosomes. The GA evolution process starts after the population pool has been initialized. The mating pool is created at the start of each generation by selecting certain chromosomes from the population. The offspring’s fitness results are also assessed, then some chromosomes in the population will be substituted by offspring according to the substitution scheme at the end of the generation. The generation process is iterated until the termination conditions are satisfied. By simulating natural selection and genetic operations, the best chromosomes or optimal solutions can emerge in the final population.

In this study, the GA algorithm was employed to solve the single-objective optimization problem and used for updating two ANFIS parameter types: premise parameters and consequent parameters. Premise parameters correspond to the function of gauss membership described as \( \{a_i\} \) in Figure 6. In all membership functions, the cumulative number of premise parameters is equivalent to the summation of the parameters. Consequent parameters are those used in the defuzzification layer, shown in Figure 6 as \( \{p_i, q_i, r_i\} \). These parameters are optimized with GA to reduce the difference between the ANFIS output and the measured data to a minimum. In SVM modeling, as the RBF was used, the GA was applied to optimize the parameters \( \sigma, C, \) and \( \varepsilon \) during the training process. The RMSE function obtained with Equation (17) is used to determine the error value of the solution. The RMSE represents the model’s perfect fitting to the datasets and illustrates how the observed data are closely related to the forecasted values.
2.6. Performance Evaluation of the Developed Models

To measure the performance of the ANFIS and SVM models in forecasting the reservoir inflow, the following four statistical indicators were utilized:

I. Nash-Sutcliffe efficiency coefficient (NSE) [59], expressed as:

\[
E = 1 - \frac{\sum_{i=1}^{n}(Q_{oi} - Q_{fi})^2}{\sum_{i=1}^{n}(Q_{oi} - \overline{Q})^2}
\]  

(14)

II. The mean absolute error (MAD), expressed as:

\[
MAD = \frac{\sum_{i=1}^{n}|Q_{oi} - Q_{fi}|}{n}
\]  

(15)

III. The absolute variance fraction, \( R^2 \), is calculated as follows:

\[
R^2 = 1 - \frac{\sum_{i=1}^{n}(Q_{oi} - Q_{fi})^2}{\sum_{i=1}^{n}(Q_{oi})^2}
\]  

(16)

IV. The root-mean-square error (RMSE), expressed as:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_{oi} - Q_{fi})^2}{n}}
\]  

(17)

where \( Q_{oi} \) is the measured inflow, \( n \) is the number of data points, \( Q_{fi} \) is the forecasted inflow, and \( \overline{Q} \) is the average of the observed reservoir inflows.

2.7. Methodology

Based on the methods discussed above, the following steps were adopted to carry out this study (Figure 7):

- First of all, the quality of the investigated rainfall records was examined through absolute homogeneity tests to select homogeneous climate data series. These tests included Buishand range test, Von Neumann ratio test, and standard normal homogeneity test. More details about these tests are described by Khadr [60].

- The forecasting model was then selected and, consequently, the required input data.

- The input data of the HMM model included the inflow; however, in SVM and ANFIS models, it included the data shown in Figure 4.

- The input datasets were split into two sets, namely, training (70% of the data) and testing datasets (30% of the data).

- The input variables were identified based on the selected model (HMM, SVM, and ANFIS).

- The process of model training was then performed to obtain the best evaluation parameters.

- The selected forecasting model was then tested, and the model performance was evaluated using the evaluation criteria (Equations (14)–(17)).

- Finally, the historical observed inflow data are compared with the forecasted inflow from HMM, SVM, ANFIS, hybrid SVM-GA, and hybrid ANFIS-GA models.
where \( Q_o \) is the measured inflow, \( n \) is the number of data points, \( Q_f \) is the forecasted inflow, and \( \bar{Q}_t \) is the average of the observed reservoir inflows.

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Figure 7. Schematic diagram of the methodology presented in this study.

3. Results

3.1. HMM

Inflow records were classified for the individual months (January to December), then its relative frequencies were determined, and, eventually, reservoir inflow was forecasted by HMM. Model parameters were then calculated utilizing the training dataset (39 years), and, finally, the forecasting model was validated using the remaining 16 years of data. The HMM modeling process starts with the characterization of states and how they are linked, followed by estimation of the value of parameters, and, finally, transition and emission probabilities. Table 1 represents the six considered states of inflow. The proposed approach was evaluated on various models by adjusting the parameters over appropriate domains and selecting the values that result in the least difference between forecasted and observed values. The forward-back (Baum-Welch) algorithm was employed to estimate the model, as defined in [52]. Figure 8 presents a comparison between historical and forecasted inflow values, and Table 2 demonstrates the performance measures of the proposed HMM and displays the variations in \( R^2 \), RMSE, MAD, and E. For the training phase, the performance measures were \( R^2 = 0.683 \), \( \text{RMSE} = 9.76 \times 10^6 \) m\(^3\), \( \text{MAD} = 3.75 \times 10^6 \) m\(^3\), and \( E = 0.643 \); and these measures for the testing phase were \( R^2 = 0.370 \), \( \text{RMSE} = 1.95 \times 10^7 \) m\(^3\), \( \text{MAD} = 1.04 \times 10^7 \) m\(^3\), and \( E = -0.735 \).
Table 1. Classification of inflow states.

| Months | Jan. | Feb. | Mar. | Apr. | May | Jun. | Jul. | Aug. | Sep. | Oct. | Nov. | Dec. |
|--------|------|------|------|------|-----|------|------|------|------|------|------|------|
| State  |      |      |      |      |     |      |      |      |      |      |      |      |
| 1      | >50  | >100 | >80  | >80  | >140| >45  | >68  | >40  | >29  | >34  | >33  | >31  |
| 2      | 41–50| 81–100| 61–80| 61–80| 112–140| 36–45| 53–68| 31–40| 23–29| 28–34| 27–33| 25–31|
| 3      | 31–40| 61–80| 41–60| 41–60| 81–110| 26–35| 38–53| 21–30| 16–22| 14–20| 13–19| 11–17|
| 4      | 21–30| 41–60| 21–40| 21–40| 51–80 | 16–25| 23–38| 11–20| 9–15 | 14–20| 13–19| 11–17|
| 5      | 10–20| 20–40| 10–20| 10–20| 20–50 | 16–25| 23–38| 11–20| 9–15 | 14–20| 13–19| 11–17|
| 6      | <10  | <20  | <10  | <10  | <20 | <5   | <8   | <2   | <1   | <6   | <5   | <3   |

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3.2. SVM and Hybrid SVM-GA Models

The programming of SVM was performed using MATLAB and the RBF kernel with the parameters (C, $\sigma$, $\epsilon$) was employed for inflow forecasting, with the SVM model’s accuracy being dependent on the identified parameters. During the training process, the optimal selection of the SVM parameters was achieved using GA to optimize the RMSE with a population size of 100, a crossover rate of 0.8, and a mutation rate of 0.01. Once the best
performing SVM model was selected through the training process, the forecast values of the selected performance were estimated, and the forecasted and measured values were compared. Figure 9 illustrates the measured and forecasted inflow and scatter plot for the SVM and SVM-GA models during the training and testing phases. The results showed that further improvements were achieved by the SVM-GA model on forecasted inflow in terms of reduced scatter. The performance criteria show that the SVM-GA model performed better than the SVM. In the case of the SVM model, for the training phase the performance measures were \(R^2 = 0.703\), RMSE = 9.19E + 06 m\(^3\), MAD = 3.71E + 06 m\(^3\), and E = 0.683; and for the testing phase were \(R^2 = 0.581\), RMSE = 1.18E + 07 m\(^3\), MAD = 6.47E + 06 m\(^3\), and E = 0.363. Considering, the performance indices, the SVM-GA model has better accuracy than the SVR model where the performance measures are \(R^2 = 0.73\), RMSE = 7.42E + 06 m\(^3\), MAD = 3.18E + 06 m\(^3\), and E = 0.794 during training; and these values for the testing period are \(R^2 = 0.674\), RMSE = 1.22E + 07 m\(^3\), MAD = 6.98E + 06 m\(^3\), and E = 0.322. A significant drop in the performance level can be observed in Figure 9 in terms of training and test results.

3.3. ANFIS and Hybrid ANFIS-GA Models

The dataset utilized in the SVM and HMM models was employed in the ANFIS models to construct a Sugeno-type FIS using subtractive clustering. The next step involved calculating the corresponding estimate of each rule’s equation to encompass the space of the features using linear least-squares estimates. The forecasted values of the inflow were computed when the model with the best performance was identified through ANFIS.
training. Figure 10 shows the inflow values forecasted by ANFIS versus the observed records for both the training and testing phases. It can be clearly seen that the two curves closely converge, and the trend between the forecasted and measured data is identical, with the exception of a few records that deviate further from the historical recorded values. The high $R^2$ value (0.857) indicates that the forecasted and measured inflow are in complete agreement. The E values in Table 2 are greater than 0.80, indicating that the developed ANFIS model has a perfect match for inflow in both testing and training phases.

Figure 10. Training and testing results of the simulated monthly inflow based on the ANFIS and ANFIS-GA models.

To create the ANFIS-GA model, there were twelve membership functions for each input; a total of 96 functions were composed. Two premise criteria were used in each of the membership functions. Therefore, 192 parameters were successfully optimized. During the network learning process, the optimal selection of the parameters related to the membership functions was achieved using the GA with a population size of 200, a crossover rate of 0.8, and a mutation rate of 0.01. Once the optimal performing ANFIS model was selected through ANFIS training, the forecast values of the selected performance were estimated, then the forecasted and recorded values were compared as presented in Figure 10. Table 2 indicates that the ANFIS-GA model produced accurate results compared with other models. The ANFIS model had a small drop in performance quality ($R^2$, RMSE, and MAD) from the training to the testing phase. A much more distinctive description arises in Figure 6, which illustrates the disparity between the forecasted and measured inflow in the training and testing phases, as well as comparative scatter plots. According
to the time series plots, the ANFIS-GA model was proficient at recognizing the fluctuating pattern of the measured inflow and there was a higher consensus in the forecasted peak values in comparison to their measured records.

4. Discussion and Comparison of the Developed Forecasting Models

This study compared the hydrological performance of five forecasting models in reservoir inflow forecasting, i.e., HMM, SVM, SVM-GA, ANFIS, and ANFIS-GA. The comprehensive analysis performed in the evaluation of the five models (Table 2) identified variety in the performance of these models. The statistical indices utilized to evaluate the developed models ($R^2$, RMSE, MAD, and E) revealed that the ANFIS-GA model outperformed the other four forecasting models, and it produced the highest $R^2$, the minimum RMSE, and maximum value of E. The ANFIS and SVM model showed a slight decrease in the level of performance from the training phase to the testing phase; however, the drop in performance measures obtained by HMM was relatively high. Based on the statistical indices in Table 2, it can be determined that the models combined with GA performed much better than the stand-alone SVM and ANFIS models and GA improves the accuracy of forecasting in both training and testing periods. Consequently, the RMSE values of SVM-GA model have been reduced by 19.26 and 3.38% in comparison with the results of the SVM model at training and test processes, respectively. The RMSE values of ANFIS-GA model have been reduced by 30.40 and 8.48% in comparison with the results of the ANFIS model at training and test processes, respectively. In addition, the $R^2$ values of SVM model have been increased by 4.28 and 11.35% in comparison with the results of the SVM model at training and test processes, respectively. However, the $R^2$ values of ANFIS-GA model have been increased by 8.85 and 4.5% in comparison with the results of the ANFIS model at training and testing processes, respectively. These results indicate the GA-induced improvement in both the SVM and ANFIS model due to the capability of GA in finding the parameters of the optimal solution of SVM and ANFIS models.

To further investigate the models’ performance, an additional statistical evaluation was also carried out using the Taylor diagram, which describes the statistical characteristics of the developed models and their relative positions from the observed dataset during the training and testing phases (Figure 11) based on RMSE and the triangle inequality comparison. Figure 11 illustrates that the ANFIS-GA model performed better than the other model as it was the closest model to the reference line (RMSE) and observed datasets. Few hydrological studies have used hybrid ANFIS and SVM models to predict reservoir monthly inflow.

![Taylor diagram](image)

**Figure 11.** Taylor diagram for HMM, SVM, SVM-GA, ANFIS, and ANFIS-GA compared to the observed data. (a) Training (b) Testing.
The finding of our study supported and agrees with the results previous studies [61–64], which reported that employing hybrid model enhance the forecasting accuracy of the stand-alone model. For instance, Yaseen et al. [61] used firefly algorithm as an optimizer tool to construct a hybrid ANFIS-FFA mode for inflow forecasting. The comparison of their results revealed that the FFA was able to improve the forecasting accuracy of the hybrid, as $R^2$ increased by 0.40% and RMSE decreased by 69.5%. Shafaei and Kisi [62] reported that using of wavelet-ANN in predicting daily river flow increased $R^2$ by 7.38% and 7.40%, and decreased MSE by 56.14% and 55% in comparison with the results of the stand-alone ANN model at training and test processes, respectively. Furthermore, their results revealed that the proposed hybrid ANN model outperforms the ANN and SVM models, according to the comparison data. Zhou et al. [63] proposed a recurrent ANFIS model for multistep-ahead forecasting using a genetic algorithm and least square estimator for parameters optimization. Their results illustrated that the proposed model has the potential to have much more reliable forecasting of the inflow sequence of over a long forecast period compared with the stand-alone ANFIS model as the RMSE values have been decreased by 14.80 and 14.08% at training and test processes, respectively. Su et al. [64] found that the employing GA to optimize the parameters of the SVM improved the accuracy of the monthly inflow forecasting compared with other optimization algorism such as grid search and particle swarm optimization methods. Their results revealed that utilizing GA instead of grid search to optimize the SVM’s parameters increased $R^2$ by 2.04% and decreased RMSE by 78.9% at test process. Furthermore, our work provides new insights into the use of hybrid ANFIS to forecast reservoir monthly inflow.

5. Conclusions

In this study, we examined the potential of the HMM, SVM-GA, and ANFIS-GA models for the one-month-ahead forecasting of reservoir inflow. The constructed models were then evaluated by the historical monthly data of the King Fahd dam, Saudi Arabia. Four statistical measures were utilized to evaluate the performance of the established models and a Taylor diagram was presented to assess the correspondence between the historical inflow output and that of each model. Generally, the results showed that ANFIS and SVM models provided more accurate forecasting than HMM as a statistical model. In terms of the performance outcomes of the developed models, the comparison of the results demonstrated that the ANFIS model is more capable of capturing monthly inflows than the SVM and HMM models. Indeed, employing GA as an add-in optimization algorithm in the ANFIS and SVM models improved the forecasting performance of both models significantly. Based on the results and discussion, the main conclusion of this study is that integrating ANFIS and SVM with GA would result in a highly valuable tool for monthly inflow forecasting in the study area.

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