Prediction of daily streamflow using adaptive neuro-fuzzy inference systems and group method of data handling approaches: a case study of kone river, binh dinh province

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Abstract:

Accurate streamflow forecasting plays a vital role in water resource engineering, management, and planning. This study evaluates the performance of the Group Method of Data Handling (GMDH) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models in predicting daily streamflow. Rainfall and streamflow data, collected from rain gauges and hydrological stations in the upstream area of the Kone River in Binh Dinh Province, were used as inputs for the models and tested across various input scenarios. Model performance was assessed using three statistical metrics: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The results revealed that the ANFIS model consistently outperformed the GMDH model, achieving the highest R^2 value of 0.94 and the lowest RMSE (64.6 m^3/s) and MAE (14.2 m^3/s). Additionally, Scenario 1 demonstrated the best predictive performance across both models. This study successfully developed reliable approaches for daily streamflow forecasting and provided valuable insights into the influence of input variables on prediction accuracy.

Key words: *Adaptive neuro-fuzzy inference systems (ANFIS), Group Method of Data Handling (GMDH), daily streamflow, prediction.*

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1. Introduction

In recent years, streamflow prediction has become a critical aspect of hydrology and water resource management. Accurate estimates enhance reservoir operations, support flood prevention, optimize water supply, and assist in the design of hydroelectric projects. Moreover, reliable predictions help mitigate the impacts of climatic events on the environment and improve the overall efficiency of resource management. In Binh Dinh, Vietnam, the Kone River frequently experiences floods, causing significant damage each year. Therefore, accurately predicting its flow is essential for protecting the region.

Over the past decades, daily streamflow forecasting has been the focus of extensive research, leading to the development of various parametric and non-parametric models. With technological advancements, artificial intelligence-based models have become increasingly popular in this field. Techniques such as artificial neural networks (ANN), multiple nonlinear regression (MNLR) [1], support vector machines (SVM) [2] and deep learning models like RNN and LSTM [3] have demonstrated promising results in streamflow prediction.

The Group Method of Data Handling (GMDH) model is an artificial intelligence technique designed to derive fundamental equations for estimating a problem’s target parameters, showing strong performance in complex nonlinear systems. In this model, only the highest-performing outputs from each layer advance to the next, while neurons generating less accurate predictions are discarded. This process optimizes the model’s structure, making GMDH increasingly popular in recent research [4-13].

ANFIS was first introduced by Jang [14]. and has proven to be a powerful data-driven technique for modeling hydrological processes such as rainfall-runoff forecasting and flood risk management. The core structure of ANFIS relies on IF-THEN rules combined with appropriate membership functions to generate input-output pairs. Therefore, these systems have the potential to utilize both expert linguistic information and measured data during the modeling process. The neuro-fuzzy approach has several notable characteristics: (1) the combined advantages of fuzzy logic and artificial neural networks (ANN), (2) the learning and adaptive capabilities of neural networks, and (3) the reasoning method of fuzzy inference mechanisms, which facilitates human-like approximate reasoning. Neuro-fuzzy systems, also known as ANFIS models, can be applied in various fields, such as signal processing, information retrieval, automatic control, and database management, among others. Numerous researchers have successfully applied ANFIS for streamflow prediction, demonstrating its effectiveness in capturing complex hydrological relationships [15-17].

This study aimed to determine the daily streamflow values of Binh Tuong hydrological station located on the Kone river, Binh Dinh. This study developed and applied two different models (ANFIS and GMDH) to asses the efficiency and accuracy of each model in relation to the original data under different scenarios with varying input variables.

2. Study area and data

The Kone River is the longest river in Binh Dinh province, originating from the northern part of An Toan commune in An Lao district. It flows southwest and then south, merging with the Say River at the northern edge of Vinh Son commune in Vinh Thanh district. From there, the river continues southeast through Vinh Thanh district, home to the Vinh Son Reservoir, Vinh Son Hydropower Plant, and Dinh Binh Reservoir. It then passes through Tay Son district, where it joins smaller tributaries from An Khe and Van Canh, forming a larger watercourse.

The Kone River Basin spans across several districts, including An Lao, Vinh Thanh, Tay Son, An Nhon, Tuy Phuoc, and southern Phu Cat. This region is frequently impacted by storms from the East Sea, resulting in heavy rainfall and flooding events, notably in the years 1987, 1996, 2009, 2013, and 2016.

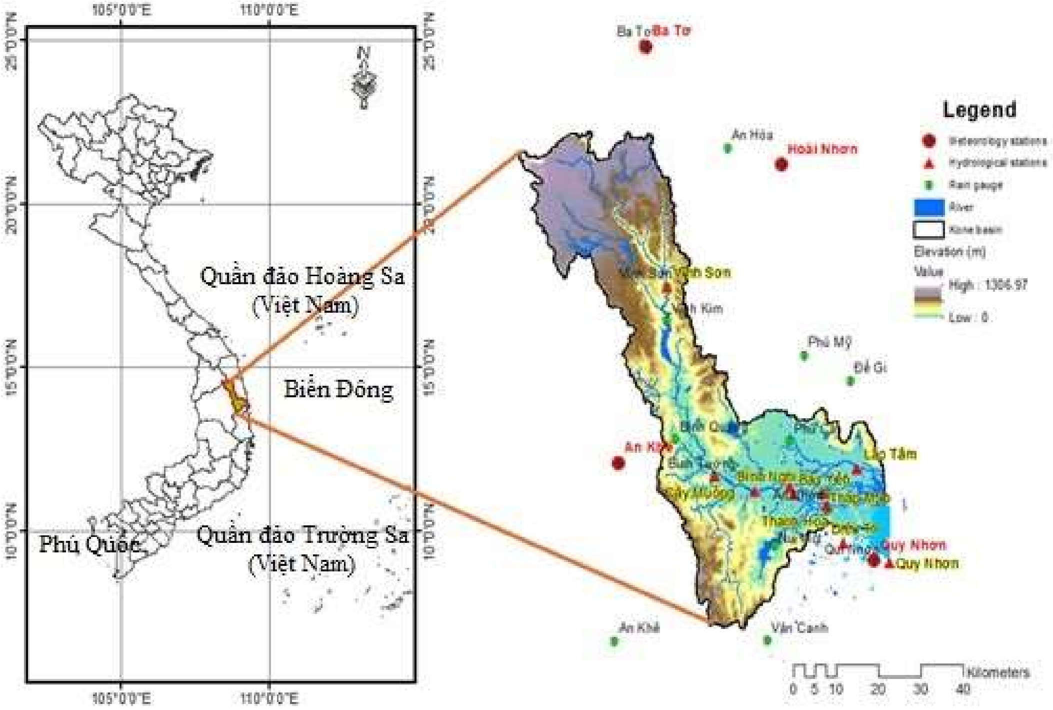

__Figure 8__: The Kone river Binh Dinh and station locations

The aim of this study is to forecast streamflow from the upstream area to the Binh Tuong hydrological station, a region characterized by complex mountainous terrain and numerous regulating reservoirs within the basin. Along the main branch of the Kone River, from the upstream area down to the Binh Tuong hydrological station, there are three rainfall stations: Vinh Son, Vinh Kim, and Binh Tuong. The dataset used in this study consists of daily rainfall and daily streamflow records collected from 2004 to 2009.

3. Methodology

3.1. GMDH model

The GMDH is an iterative self-organizing algorithm that uses polynomial models to identify complex relationships [18]. Its core principle is to generate multiple models, evaluate each based on specific criteria, and select the optimal model [19]. This process gradually adds layers of neurons, where each neuron represents a two-input function fitted using polynomials of a given degree, as shown in Figure 9.

Only the best-performing neurons from each layer (depicted as white neurons in Figure 9) are passed to the next layer, while neurons producing less accurate predictions (illustrated as green neurons in Figure 9) are eliminated. This selection process optimizes the model structure, ensuring that only the most effective neurons are retained. Structural optimization also requires specifying the maximum number of neurons and layers, further enhancing the model's efficiency.

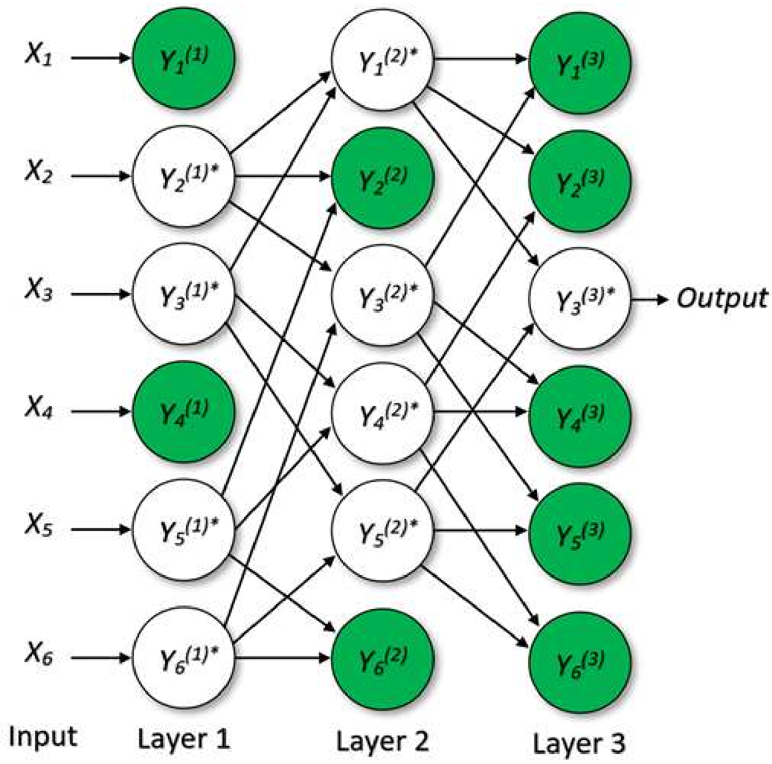

Figure 9: *The structure of GMDH model*

With a time series, GMDH learns the relationships between time lags and then automatically determines the optimal pathway. The mapping of GMDH between input and output variables forms a nonlinear function, given by:

$$\hat{y}(x_1, \dots, x_n) = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_j + \dots + \\ + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ijk} x_i x_j x_k \qquad \text{(Eq - 1)}$$

Where x_i and x_j represent the input variables, and n is the number of samples considered. The coefficients are estimated using the regression method for the pair of input variables (x_i, x_j) as follows:

$$G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i^2 + a_4 x_j^2 + a x_i x_j \qquad \text{(Eq - 2)}$$

Where y represents the observed value, $\hat{y}$ is the predicted value and w is the result of the external criterion, given by:

$$w = \frac{\sum_{n=1}^{P} (\hat{y}_n - y_n)^2}{\sum_{n=1}^{P} (y_n)^2} \qquad \text{(Eq - 3)}$$

Where P represents the number of test sets. If w does not decrease compared to the previous layer, this indicates that the model's prediction error is not reducing, thereby stopping the model expansion and producing the final result.

The coefficients in the polynomial function are calculated using the Least Squares Error (LSE) method. This mathematical technique aims to minimize the sum of squared residuals, thereby reducing the difference between y and $\hat{y}$. The procedure of this fitting method is described as follows:

$$LSE = \begin{cases} \hat{y}(x_1, \dots, x_n) = G(x_i, x_j) \\ e = \sum_{n=1}^{N} (y - \hat{y})^2 \\ \frac{de}{da_k} = 0, k = 1,2,3,4,5 \end{cases} \quad (Eq - 4)$$

3.2. ANFIS model

The ANFIS is a widely-used computational model that combines fuzzy logic, if-then rules, and neural networks. Its structure consists of three main components:

- Rule Base: This component involves selecting fuzzy rules that define the relationships between inputs and outputs.
- Database: It contains the membership functions used in the fuzzy rules, representing the degree to which inputs belong to various fuzzy sets.
- Inference Mechanism: This part performs the reasoning process by applying the fuzzy rules to input data, generating logical outputs.

The ANFIS model updates membership function parameters through two key methods: Establishing the post-distribution status for all parameters, and employing a hybrid approach where input membership function parameters act as antecedents to optimize the output membership functions.These processes help reduce learning errors during training, enhancing the model's accuracy. As a result, most initial membership functions are refined and integrated into the ANFIS model structure, ensuring better performance. The structure of ANFIS is illustrated in Figure 10. The ANFIS model typically consists of two inputs, x and y, and one output, z. In the fuzzy model, the if-then rules are represented as shown in (Eq -5).

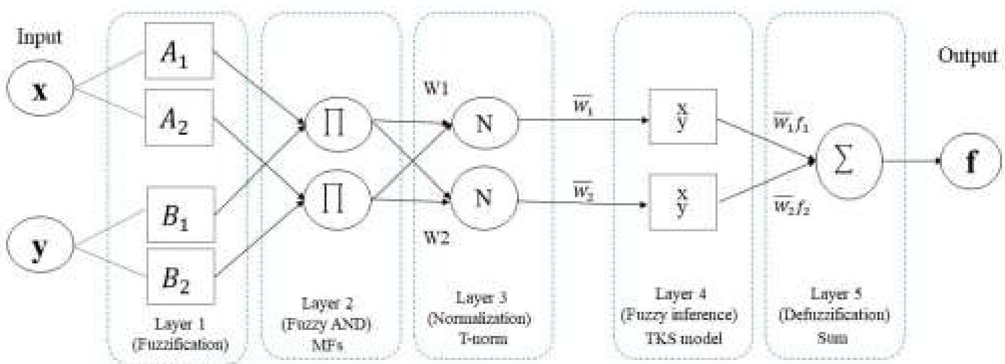

***Figure 10:** The structure of the ANFIS model*

Rule 1: if x is A1 and y B1, then $f1 = p1x + q1y + r1$

Rule 2: if x is A2 and y B2, then $f1 = p2x + q2y + r2$ *(Eq - 5)*

The functions of the ANFIS model are determined as follows:

Layer 1: Each node in this layer represents the degree of membership of the input parameters.

$$o_i^1 = \mu_{Ai}(x) \quad (Eq - 6)$$

Membership functions can be represented as bell-shaped curves, triangles, or trapezoids. The bell-shaped functions are defined as (Eq -7) or (Eq - 8), depending on the membership sets.

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \qquad (Eq\text{ - }7)$$

$$\mu_{Ai}(x) = exp\left(-\left(\frac{x-c_i}{a_i}\right)^2\right) \qquad (Eq\text{ - }8)$$

Layer 2: In this layer, each node is labeled and processes input data based on predefined rules. The output of each node represents the firing strength of its corresponding fuzzy rule, determined by combining the input membership values.

$$W_i = \mu_{Ai}(x)\mu_{Bi}(x), i = 1, 2 \qquad (Eq\text{ - }9)$$

Layer 3: The i-th node of this layer is labeled N, and its output is computed by normalizing the firing strengths from Layer 2. This normalization ensures that each rule's contribution is proportional to the overall firing strength, balancing the influence of different rules.

$$\overline{W_i} = \frac{W_i}{W_1 + W_2}, i = 1, 2 \qquad (Eq\text{ - }10)$$

Layer 4: The data are processed in this layer by

$$o_i^4 = \overline{W_i} f_i = \overline{W_i}\,(p_i x + q_i y + r_i) \qquad (Eq\text{ - }11)$$

Layer 5: The nodes in this layer are labeled z, and the final output is computed by summing all the input data. This aggregation step combines the contributions from all fuzzy rules, producing the overall output of the ANFIS model.

$$o_i^5 = overall\ output = \sum_i \overline{W_i} f_i = \frac{\sum_i W_i f_i}{\sum_i W_i} \qquad (\text{Eq - }12).$$

3.3. Modeling by GMDH and ANFIS

To model a process using GMDH and ANFIS techniques, a series of input and output data is necessary. This data serves as the foundation for training and validating the models, allowing them to learn patterns and relationships within the system. The datasets used to design a GMDH or ANFIS are divided into two categories: training and validation. During the training phase, the network receives both inputs and outputs from the training set and adjusts its parameters accordingly. In contrast, during the testing phase, only inputs are provided to the network, with no prior knowledge of the corresponding outputs. The validation step is crucial to prevent the network from memorizing the training data, ensuring it generalizes well to unseen data. In this study, 75% of the data was selected for training, while the remaining 25% was used for validation.

The GMDH neural network designed in this study consisted of three layers: an input layer, a hidden layer, and an output layer. The key distinction between these layers lay in the number of neurons present in each. To identify the optimal number of neurons in the hidden layer, errors were computed across different network configurations, and the network with the lowest training error was selected as the best model. The parameter value of GMDH model is shown in Table 8.

Table 8: *Parameter value in the GMDH model*

No.	**Parameter**	**Value**
1	α	0.2
2	N-layer	3
3	Max-Neurons	30

In ANFIS modeling, the general structure of the model — including inputs, outputs, and model functions — must be defined initially. Three common methods for neuro-fuzzy system modeling are grid partitioning, fuzzy C-mean clustering, and subtractive clustering. The primary difference between these methods lies in how fuzzy membership functions are determined. In grid partitioning, the user specifies the type and number of input data vector membership functions. Conversely, in subtractive clustering, the neuro-fuzzy inference model automatically determines the membership functions based on the properties and classifications of the input data vector.

In this study, we developed forecasting models corresponding to different input variable scenarios. Four scenarios are presented in Table 9. The input variables selected for the models include rainfall at the Binh Tuong (BT), Vinh Son (VS), and Vinh Kim (VK) stations, as well as the previous day's streamflow at the Binh Tuong hydrological station.

Table 9*: The input scenarios for models*

Scenario	**Input**	**Output**
1	$P_t^{BT}; P_t^{VK}; P_t^{VS}; Q_{t-1}$	Q_t
2	$P_t^{BT}; P_t^{VK}; Q_{t-1}$	Q_t
3	$P_t^{BT}; Q_{t-1}$	Q_t
4	Q_{t-1}	Q_t

The performance evaluation of the forecasting model was conducted using three statistical indicators: the coefficient of determination (R^2), the root mean square error (RMSE) and mean absolute error (MAE). These metrics were employed to assess the model's accuracy and reliability in predicting streamflow.

$$R^2 = \left[\frac{n\sum_{i=1}^{n} S_i O_i - \sum_{i=1}^{n} S_i \sum_{i=1}^{n} O_i}{\sqrt{n(\sum_{i=1}^{n} S_i^2) - (\sum_{i=1}^{n} S_i)^2}\sqrt{n(\sum_{i=1}^{n} O_i^2) - (\sum_{i=1}^{n} O_i)^2}}\right]^2 \qquad (Eq - 13)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - S_i)^2} \qquad (Eq - 14)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - S_i| \qquad (Eq - 15)$$

Where O is observed value and S is simulated value.

The flowchart of this study is presented as Figure 11 below:

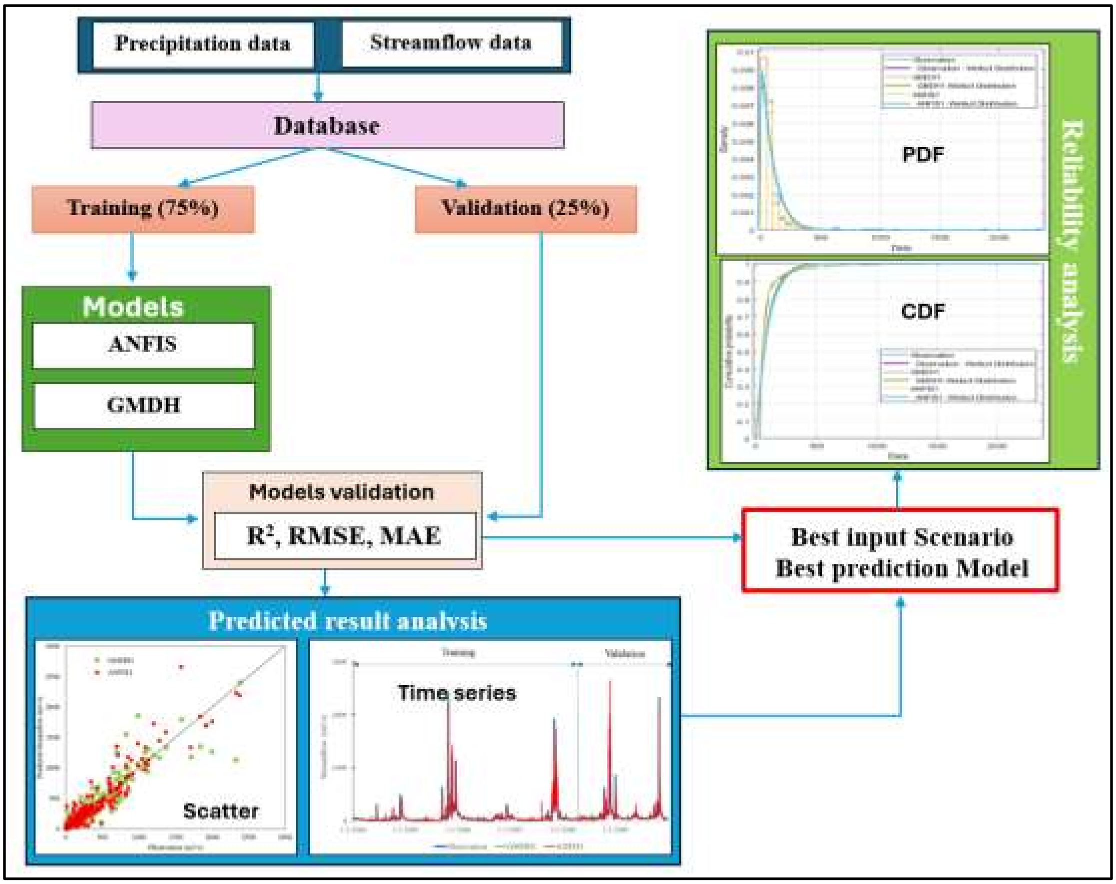

Figure 11: *Flowchart of this study*

4. Rresults and discussion

In this section, the model's performance is presented in Table 10 and Table 11. As shown in these tables, both the GMDH and ANFIS models demonstrate strong performance in forecasting streamflow, with high *R*2 values and low RMSE and MAE. Notably, the ANFIS model produced more accurate results than the GMDH model in both the training and validation processes.

The results show that both the ANFIS and GMDH models perform best in Scenario 1, followed by Scenario 2, while Scenario 4 demonstrates the lowest forecasting performance among the four scenarios. For example, in Scenario 1, the ANFIS1 model achieved $R2$=0.94, RMSE = 39.2, and MAE = 12.2 during the training process, and R2=0.9, RMSE = 64.6, and MAE = 14.2 during the validation process. In contrast, Scenario 4 showed a decrease in R2 to 0.74 and 0.81 for training and validation, respectively, accompanied by a noticeable increase in RMSE and MAE. A similar trend was observed in the GMDH models.

These findings indicate that ignoring rainfall as an input variable leads to a significant increase in model error, particularly when rainfall plays a crucial role in the basin's flow process. Additionally, comparing the ANFIS1, ANFIS2, and ANFIS3 models, as well as the GMDH1, GMDH2, and GMDH3 models, highlights the considerable impact of rainfall data from the Vinh Son and Vinh Kim stations on streamflow at the Binh Tuong station. This comparison provides valuable insights into the importance of incorporating rainfall data when modeling streamflow in this region.

Table 10: *The model's performance for training process*

Model	Training							
	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	ANFIS 1	GMDH 1	ANFIS 2	GMDH 2	ANFIS 3	GMDH 3	ANFIS 4	GMDH 4
R^2	0.94	0.91	0.91	0.90	0.89	0.85	0.76	0.68
RMSE	39.2	48.5	41.3	51.9	55.2	63.5	79.5	96.5
MAE	12.2	15.1	13.3	15.3	16.6	19.7	22.8	24.7

Table 11: *The model's performance for validation process*

Model	Validation							
	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	ANFIS 1	GMDH 1	ANFIS 2	GMDH 2	ANFIS 3	GMDH 3	ANFIS 4	GMDH 4
R^2	0.90	0.86	0.86	0.85	0.83	0.82	0.81	0.79
RMSE	64.6	73.2	68.8	73.7	77.0	80.8	80.3	84.2
MAE	14.2	17.5	18.1	19.3	19.3	23.1	21.6	24.4

The scatterplot comparison of the applied models is presented in Figure 12 for the Kone River in Binh Dinh. The graphs clearly show that the ANFIS model exhibits slightly better predictive performance than the GMDH model across all four scenarios. Figure 13 illustrates the observed and simulated streamflow processes from the GMDH and ANFIS forecasting models. Overall, the rising and falling limbs of the flood hydrographs in the forecasted models align well with the trends of the observed streamflow. This alignment supports the calibration and validation statistical results presented in Table 10 and Table 11. The closer the simulated flood process matches the actual measurements, the higher the correlation coefficient R2.

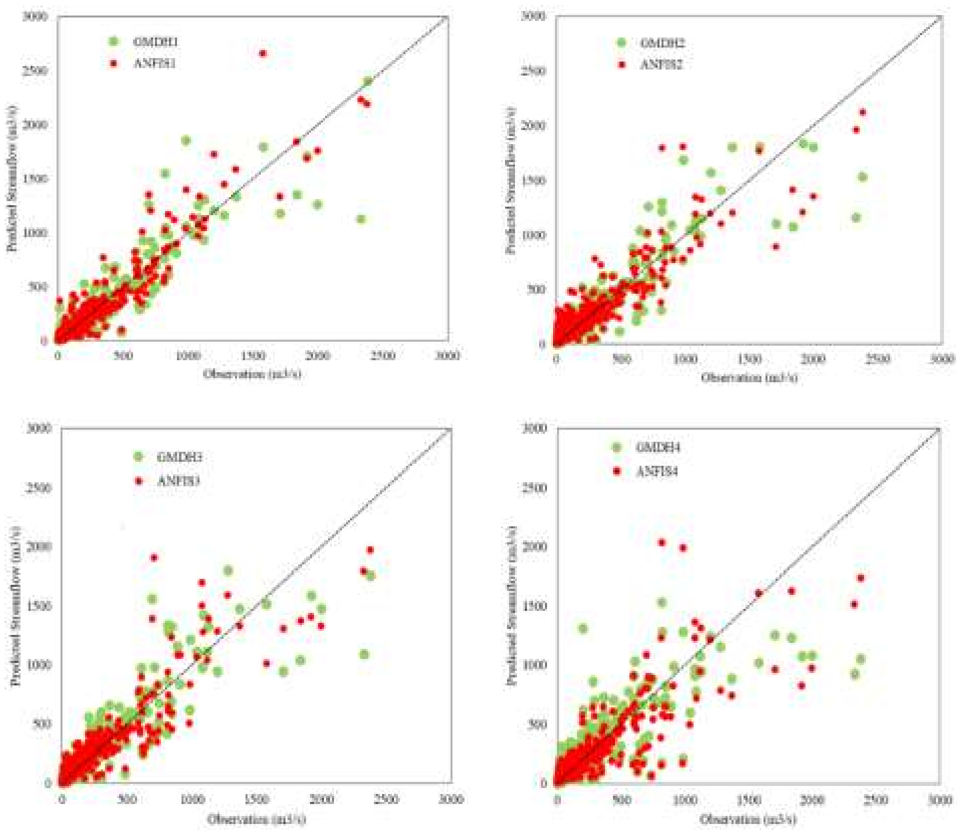

Figure 12: *Scatterplots of the observed and prediected streamflows by GMDH and ANFIS*

To further evaluate the accuracy of streamflow prediction in the Kone River, this study analyzes the Probability Density Function (PDF) and Cumulative Distribution Function (CDF) using the Weibull distribution, which is widely applied to model extreme hydrological events such as peak discharges and maximum annual flows [20]. Observed streamflow data are compared with predictions from the GMDH1 and ANFIS1 models under Scenario 1, as these models demonstrated the highest performance among the four evaluated scenarios.

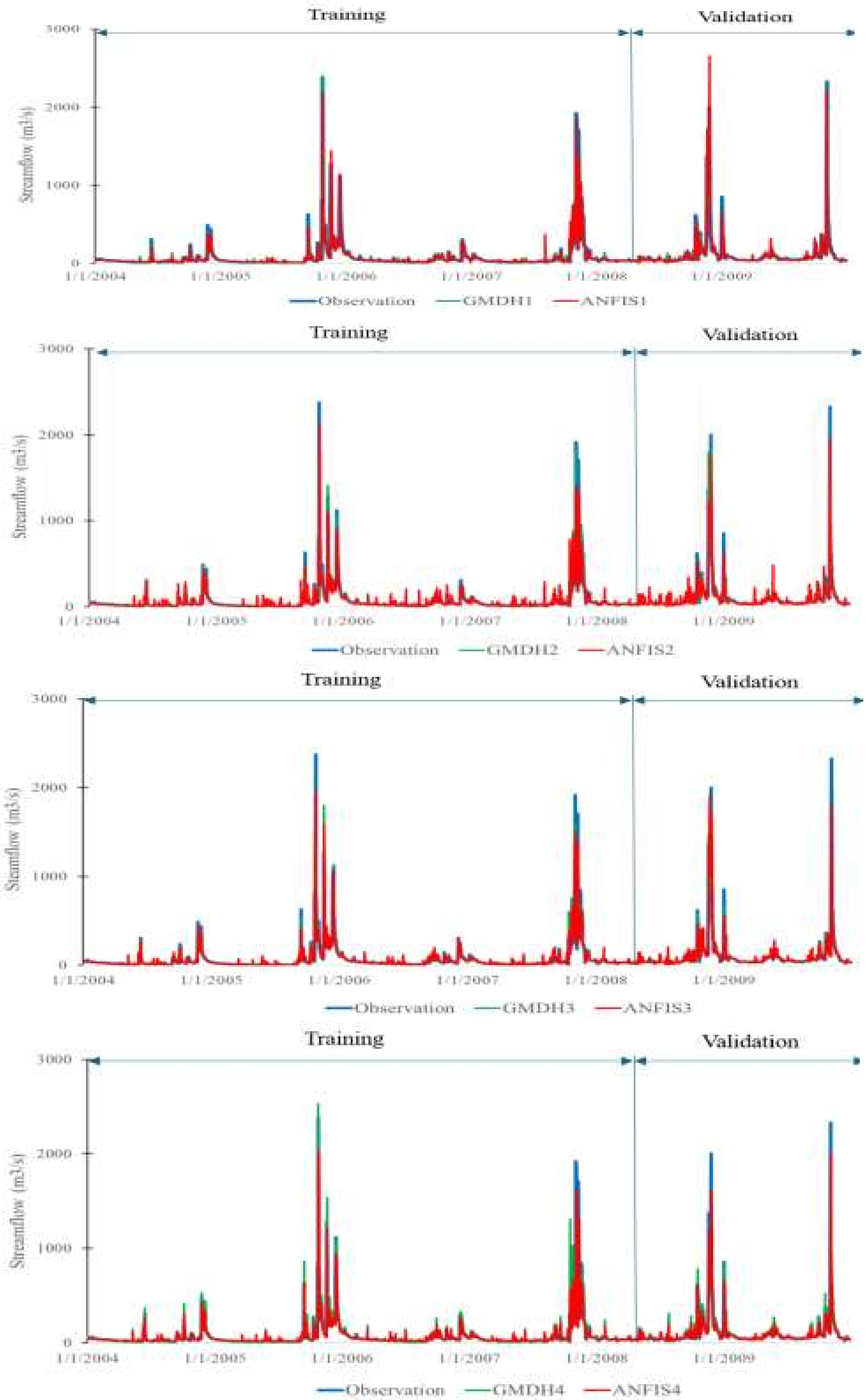

Figure 13: *Time variation graphs of the predicted and observed streamflows by GMDH and ANFIS models.*

As shown in the results (Table 12), the typical streamflow magnitude based on observed data is approximately 96.129 m³/s. In comparison, the GMDH1 model underestimates the streamflow at 91.6463 m³/s, while the ANFIS1 model slightly overestimates it at 96.4265 m³/s, showing better alignment with observed values.

Table 12: *Statistical analysis of streamflow data from observed records and predictions by the GMDH1 and ANFIS1 models using the Weibull distribution.*

Weibull distribution	**Observation**		**GMDH1**		**ANFIS1**	
Log Likelihood	-2017.61		-2002.33		-2024.81	
Mean	93.83		89.73		95.06	
Variance	7789		7242.99		8425.2	
Estimated Weibull Parameter						
	Estimate	**Std. Error**	**Estimate**	**Std. Error**	**Estimate**	**Std. Error**
Scale	96.129	±5.04	91.6463	±4.84	96.4265	±5.19
Shape	1.06377	±0.0339	1.0548	±0.0343	1.0358	±0.0332
Covariance Matrix of Parameters						
	Scale	**Shape**	**Scale**	**Shape**	**Scale**	**Shape**
Scale	25.382	0.059	23.481	0.057	26.951	0.060
Shape	0.059	0.001	0.057	0.001	0.060	0.001

The PDF illustrates the relative likelihood of different streamflow values occurring. As shown in Figure 14, the PDF is slightly right-skewed, indicating a higher probability of moderate discharge values, with a long tail extending toward extreme flood events. The CDF is used to estimate return periods, compare the probability of specific discharge levels between observed and model-predicted data, and evaluate the reliability of predictive models.

In this study, the CDF is applied to assess the performance of the GMDH1 and ANFIS1 models. A close alignment between the predicted and observed CDFs suggests that the model effectively captures the underlying hydrological behavior. As illustrated in Figure 15, the CDF curves of the observed data, GMDH1, and ANFIS1 models exhibit a strong agreement. This consistency indicates that both models are capable of accurately replicating the distribution of streamflow and can be reliably used for flood forecasting.

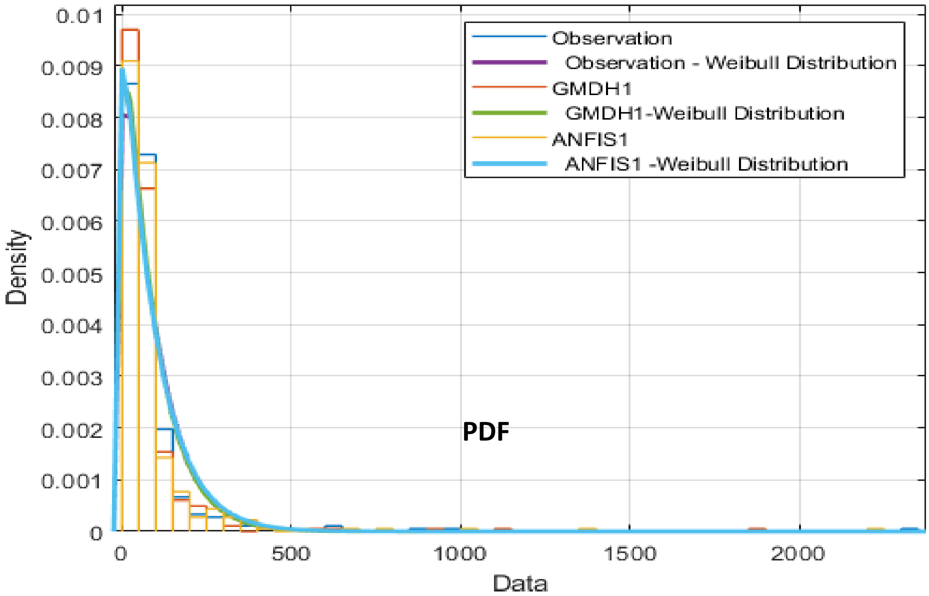

Figure 14: *Probability Density Function (PDF) of streamflow data fitted with the Weibull distribution.*

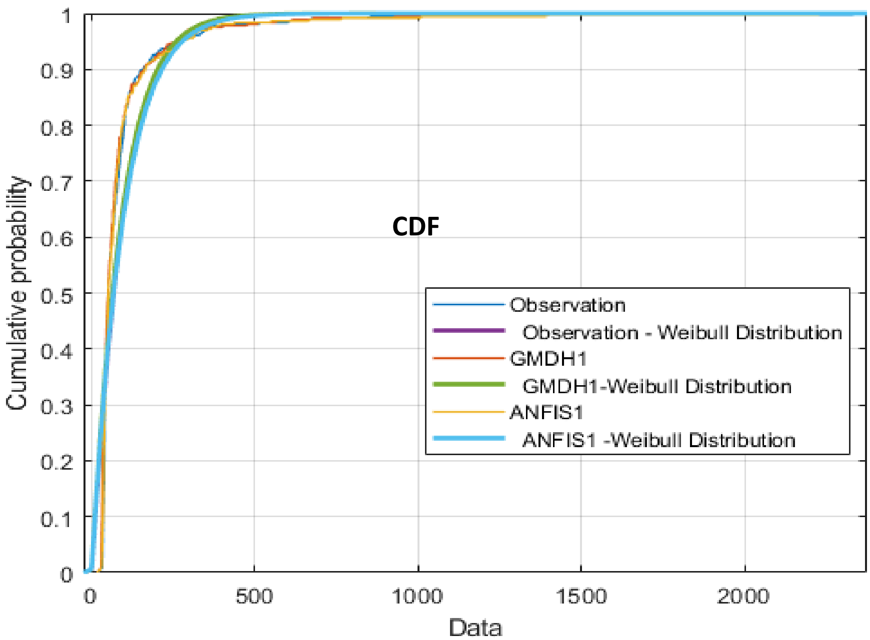

Figure 15: *Cumulative Distribution Function (CDF) of streamflow data fitted with the Weibull distribution.*

5. Conclusion

In this study, GMDH and ANFIS models for daily streamflow forecasting were developed for the Kone River Basin in Binh Dinh, Vietnam. The forecasting performance of these models was compared using three statistical indices: *R*2, RMSE, and MAE. Various input scenarios, incorporating rainfall values from different gauging stations and streamflow data, were tested to assess the predictive accuracy of the selected models. The results showed that both the ANFIS and GMDH models produced reasonably accurate daily streamflow forecasts, with high R2 values and low RMSE and MAE. However, the ANFIS model outperformed the GMDH model. Among the four input scenarios, Scenario 1 delivered the best results, while Scenario 4 produced the least accurate forecasts. The findings also highlighted that the accuracy of a forecasting model depends on the selection of appropriate input variables. This study successfully developed an effective forecasting model that can be applied to real-world flood prediction efforts.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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