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Estimation of River-Suspended Sediments using Anns and ANFIS Methods with Modeling in MATLAB (Case study: Dez River in Khuzestan)

Seyed Mohsen Mousavi[1], Heeva Elmizadeh[2]*, Mohamad ali Sakiani[2] and Amin Zoratipour[3]

[1]*Department of Environmental Planning and Design, Shahid Beheshti University, Iran*

[2]*Department of Marine Geology, Khorramshahr University of Marine Science and Technology, Iran*

[3]*Department of Nature Engineering, Agricultural Sciences and Natural Resources University of Khuzestan, Iran*

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Corresponding author: Heeva Elmizadeh, Department of Marine Geology, Khorramshahr University of Marine Science and Technology, Iran

Abstract

Modeling and analyzing the suspended sediment load in rivers, particularly in arid and semi-arid regions, is crucial due to its impact on river morphology changes and the intricate, non-linear relationships among factors influencing various hydrological phenomena. This analysis serves as a fundamental tool in water resources management and the development of hydraulic structures. This research focuses on estimating the suspended sediment load of the Dez River at the hydrometric station of the Dezful regulatory dam through the application of artificial neural network (ANNs) and ANFIS (adaptive neuro-fuzzy inference systems) models. MATLAB software was utilized for model implementation, and the evaluation of model performance was conducted using criteria such as R^2, RMSE, NS coefficient, STDVE, and MAE. A comparative analysis was performed to assess the similarities between these models. In this process, data about concentration measurements or sediment discharge, along with their corresponding flow rates over the specified period, were transformed onto a logarithmic axis. By establishing a relationship between river discharge and sediment discharge, and then extending this relationship to encompass river flow statistics, a best-fitting line was derived. The least squares method was employed to pass the line through the points and extract the optimal fit. The findings indicate that both ANNs and ANFIS methods yield highly accurate estimations. Furthermore, through data segregation based on varying precipitation and flow conditions, enhanced homogeneity was achieved, thereby refining the sediment measurement curve with heightened precision. Additionally, the results underscore the potential of the ANFIS algorithm for estimating and forecasting suspended sediment levels in other rivers across the country. In conclusion, the study suggests that for the prediction of erosion variables, sedimentation, and runoff volume—recognized as complex hydrodynamic and ecological challenges—the intelligent and nonlinear ANFIS model stands out due to its proficiency in capturing intricate nonlinear relationships. Hence, it is recommended for employment in the study area and analogous basins nationwide, owing to its heightened efficacy and capability.

Keywords: Modeling; ANFIS; Neural network; Suspended river load; Dez River

Introduction

Alluvial rivers undergo erosion and sediment transfer throughout their evolutionary phases. Consequently, estimating suspended sediment load emerges as a crucial factor in comprehending hydrological, geomorphological, and hydraulic parameters related to river sediments [1,2]. This aspect represents a pivotal issue and forms the foundational basis for effective water and soil resource management within watersheds [3-7]. In contemporary research, various factors such as non-linear properties, the inherent uncertainty in sediment estimation, the necessity for extensive data, and the complexity of physical models have led researchers to employ intelligent methods for predicting non-linear phenomena. Among these methods, adaptive neuro-fuzzy inference systems (ANFIS) and Artificial Neural Networks (ANN) hold prominence [8-11].

Modeling and novel computational methods play a crucial role in estimating suspended sediments in rivers, addressing engineering challenges, and predicting output responses from intricate systems [12,13]. These methods rely on data and offer flexibility, enabling them to tackle ambiguous and complex issues, particularly those that cannot be readily expressed through mathematical relationships. In this context, artificial neural networks have emerged as a novel and potent tool in addressing hydrological challenges, particularly in predicting suspended sediment loads [14]. They represent simulation models employed in nonlinear system modeling, capable of depicting reality with considerable accuracy. Their predictive capabilities closely align with real-world observations, making them invaluable in hydrological modeling endeavors. Additionally, the ANFIS, commonly referred to as fuzzy logic-based systems, integrates fuzzy inference with neural network principles. In ANFIS, membership function parameters are adjusted using the backpropagation method alone or in conjunction with the least squares method. Linguistic expressions are employed to establish a link between system inputs and observable outputs, facilitating a comprehensive understanding of the system's behavior [15]. The ANFIS model is recognized as a fusion of neural networks and fuzzy inference systems, effectively addressing the limitations of each while capitalizing on their respective strengths. In this paradigm, neural networks serve as determinants for fuzzy system parameters, enabling a comprehensive integration of both methodologies [16].

In recent years, the use of intelligent systems has become common to increase the accuracy of river sediment estimation [17-21]. In this context, Duan et al. [22] utilized the SPARROW method to model the production and transfer of suspended sediments in the Ishikari basin. They concluded that this method exhibits high efficiency and accuracy in both modeling suspended sediments and managing water resources. Furthermore, Eshghi et al. [23] examined the effectiveness of intelligent models, including artificial neural network methods and support vector machine models, in estimating river-suspended sediments. Their findings indicated a strong agreement between these methods and the measured values. In their study, Sattari et al. [24]. employed statistical measures including correlation coefficient, root mean square error, and mean absolute error to model suspended sediments in the Aharchai River. Their research findings underscored the high accuracy achieved through data mining methods. Additionally, the ANFIS model has been applied in diverse areas, including predicting rainfall patterns [25], forecasting reference evaporation and transpiration [26], and predicting daily suspended sediment concentration [27].

Buyukyildiz & Kumcu [28] utilized a fuzzy inference system based on adaptive networks, support vector machines, and artificial neural network models to estimate suspended sediment load. Patel et al. [29] demonstrated the strong performance of neural networks in solving complex nonlinear regression problems. Additionally, Adib & Jahanbakhshan [30] as well as Adib & Mahmoodi [31] applied artificial neural network models combined with genetic algorithms to predict suspended sediment loads in the Karun and Marun rivers. They employed genetic algorithms to optimize input parameters, connectivity, and the number of hidden layer neurons in the ANN, achieving high accuracy in estimating suspended sediment load concentrations. Srinivas & Singh [32] evaluated an advanced fuzzy frequency-based simulation model aimed at studying river basin sedimentation. The outcomes highlighted the effectiveness of this model in devising optimal water resource management scenarios. In this context, the Dezful Tantimi dam, located north of Dezful city along the Dez River, primarily serves to regulate and direct river water into the drainage channels of the Dezful irrigation network. Due to various topographical factors along the Dez River's flow path, such as slope, bedrock type, velocity, and vegetation cover, significant amounts of sediment -amounting to thousands of tons annually - flow from upstream areas to the dam. Mismanagement of water resources and associated issues could lead to a reduction in the lake's capacity behind the dam and cause irreparable damage to its drainage channels. Therefore, given the critical importance of sediment and its associated challenges in this region, researching to estimate sediment levels in the Dez River becomes imperative. Thus, this study delves into the Dez River basin to estimate and model suspended sediments using data gathered from the hydrometric station of the Dezful regulatory dam. Specifically, artificial neural network models and ANFIS structures are simulated and compared. Notably, this research extends beyond traditional approaches by incorporating the Echel parameter (water height) alongside discharge and sediment parameters of the Dez River, thereby exploring new avenues in fuzzy modeling and neural networks.

Materials and Methods

The studied area encompasses the final segment of the Dez River watershed, which ranks among the largest watersheds of Karun Bogor, spanning an area of 6288 square kilometers. This region traverses through the agricultural lands of Dezful and Shush cities (Figure 1). As the Dez River exits the Dez Dam, it gradually transitions from mountainous terrain to the Khuzestan Plain and the plains of the Dezful-Andimeshk study area. Within this expanse, 2496 square kilometers comprise plains, while 3792 square kilometers consist of highlands. The highest elevation within the range reaches 2639 meters above sea level in the northern reaches of the basin, while the lowest elevation stands at 20 meters at the basin's outlet. The primary inflow into the study area originates from the north, stemming from two significant rivers, Caesar and Bakhtiari, which serve as the primary branches of the Dez River [33].

In this study, we employ monthly data on precipitation (mm), sediment discharge (tons per day), and flow rate (cubic meters per second) collected from the hydrometric station situated at the Dezful Regulatory Dam along the Dez River. This location is strategically chosen as it represents the river's conditions before reaching the Dez Dam. Our objective is to estimate the suspended

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sediment load of the Dez River. In this context, discharge and sediment data from the Dezful regulatory dam station were acquired and subjected to monthly quality control measures. Following the removal of incomplete or outlier data and subsequent reconstruction of the dataset, efforts were made to standardize the type and range of the data. Before model training, the input data underwent normalization. Subsequently, 70% of the dataset (404 data points) was allocated for network training, 15% (86 data points) for testing, and the remaining 15% (86 data points) for validation and evaluation purposes. These data were randomly selected, and the results were analyzed accordingly. Consequently, the network inputs about the Eshel (water height) and discharge variables are associated with the hydrometric station located at the Dezful regulatory dam. The corresponding monthly sediment quantity at this station was designated as the network output. Through this configuration, the factors influencing sediment volume were identified and analyzed. In this study, MATLAB software was utilized to assess the model estimation outcomes. The data of sediment concentration or discharge, along with their corresponding flow rates over a specific period, were transformed onto a logarithmic axis. Subsequently, the relationship between river discharge, and sediment discharge, and the generalization of this relationship to river flow statistics was examined. A best-fitting line was then generated through the application of the least squares method to the data points. Subsequently, artificial neural network models and neuro-fuzzy systems (utilizing fuzzy neural inference) were employed to evaluate the results, comparing them with regression estimates. These models were simulated, and various evaluation criteria including determination coefficient (R2), root mean squared error (RMSE), Nash-Sutcliffe coefficient (NS), standard deviation (STDVE), and mean absolute relative error (MAE) were employed. The goal was to identify the model with the least error and optimal performance [34].

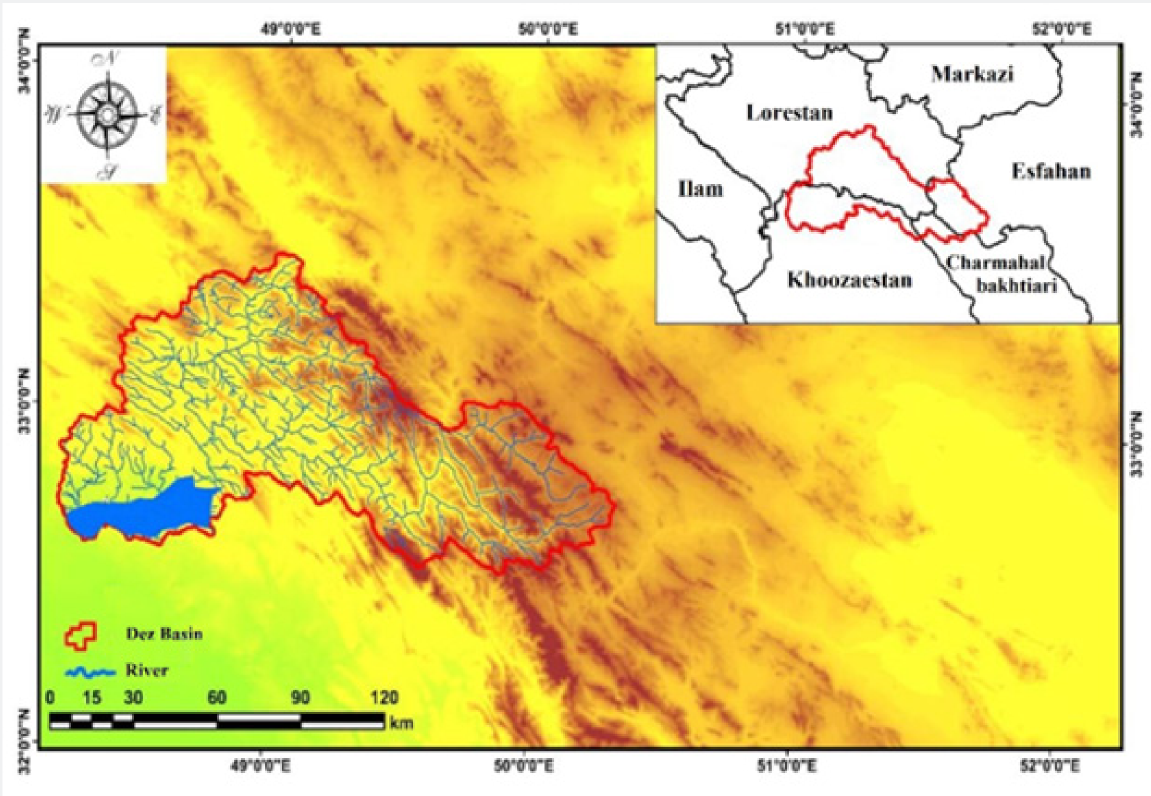

Figure 1: Geographical location of the study area.

Results

In this study, a Multilayer Perceptron (MLP) neural network employing a supervised learning method was utilized for sediment modeling and prediction. Specifically, the Luneberg-Marquette (LM) algorithm was employed, as summarized in Table 1. In the ANN method, the factors influencing the specific sedimentation rate are initially identified. Subsequently, steps are taken to format the matrix for input into the multilayer perceptron network. In this process, the inputs of the network, such as Eshel (water height) and discharge variables, are associated with the hydrometric station at the Dezful regulatory dam. The corresponding monthly sediment amount at this station is then chosen as the output of the network. "In the validation stage, the performance of the neural

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network method was assessed by testing it against the 15% of data that were set aside for testing purposes. Additionally, the specifications of the ANFIS model for predicting the sediment amount at the Dezful dam station are outlined in Table 2 [35-43].

Table 1: Details of the neural network used for sediment prediction.

Parameter	Amount
Type of neural network	MLP
The structure of the neural network	2×6×5×1
The number of input layer neurons	2
The number of neurons in the first hidden layer	6
The number of neurons in the second hidden layer	5
The number of neurons in the output layer	1
The driving function of the first layer	Tansig (Sigmoid tangent)
The driving function of the second layer	Logsig (sigmoid)
The driving function of the third layer	Purlin (Liner)
Training data	70%
Validation data	15%
Test data	15 [illegible]
Training algorithm	LM
Number of repetitions	2000
Target value	1e-8

Table 2: Specifications of ANFIS model for sediment prediction.

Parameter	Amount
Type of FIS system	Sogno
The number of inputs	2
Number of outputs	1
AND method	Multiplication
OR method	Maximum
De-fuzzification method	Maximum
Implication	Multiplication
De-fuzzification of mean centers	Maximum
Number of rules	25

Table 3: Criteria for determining errors in ANFIS and ANNs methods.

Acceptable value	ANFIS	ANNs	Error determination criterion
It changes between zero and one, and its optimal value is one.	0.74226	0/69526	R^2
It varies between zero and infinity. Its optimal value is 0.	0.033795	0/038569	RMSE
It is the best method and has the least error. The lower the amount the better.	0.057053	0/099198	MAE
It is between zero and infinity. The smaller the value, the closer the data is to the average.	0.31498	0/58199	STD
It is between negative infinity and one, and its optimal value is positive one. If the coefficient is higher than 0.5, the model has a good simulation.	-22.1105	-0.70/852	NS

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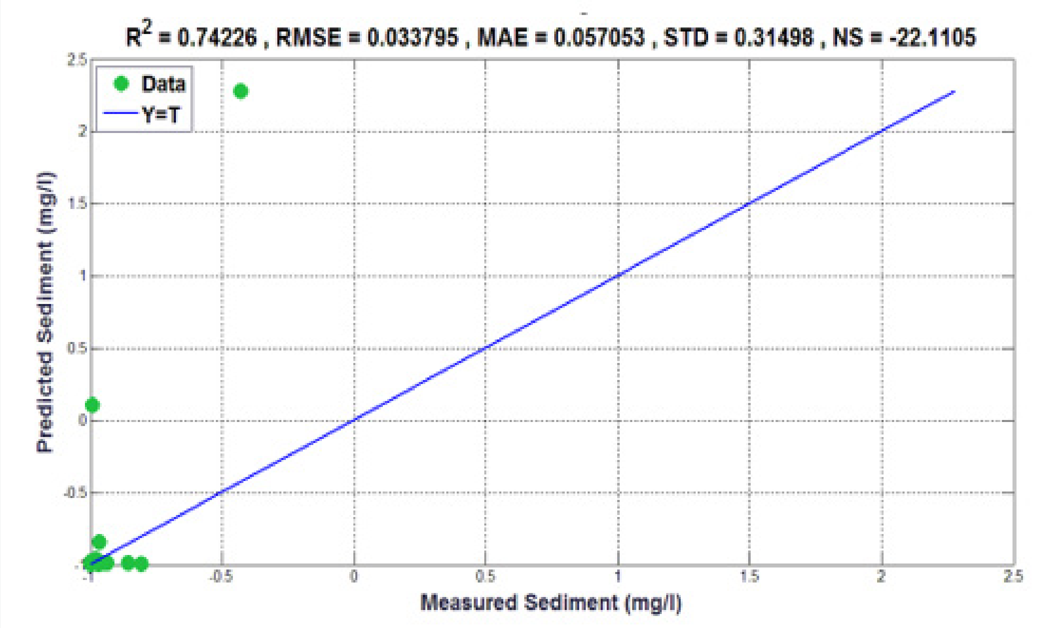

Figure 2: Distribution between the measured and predicted sediment values by ANFIS.

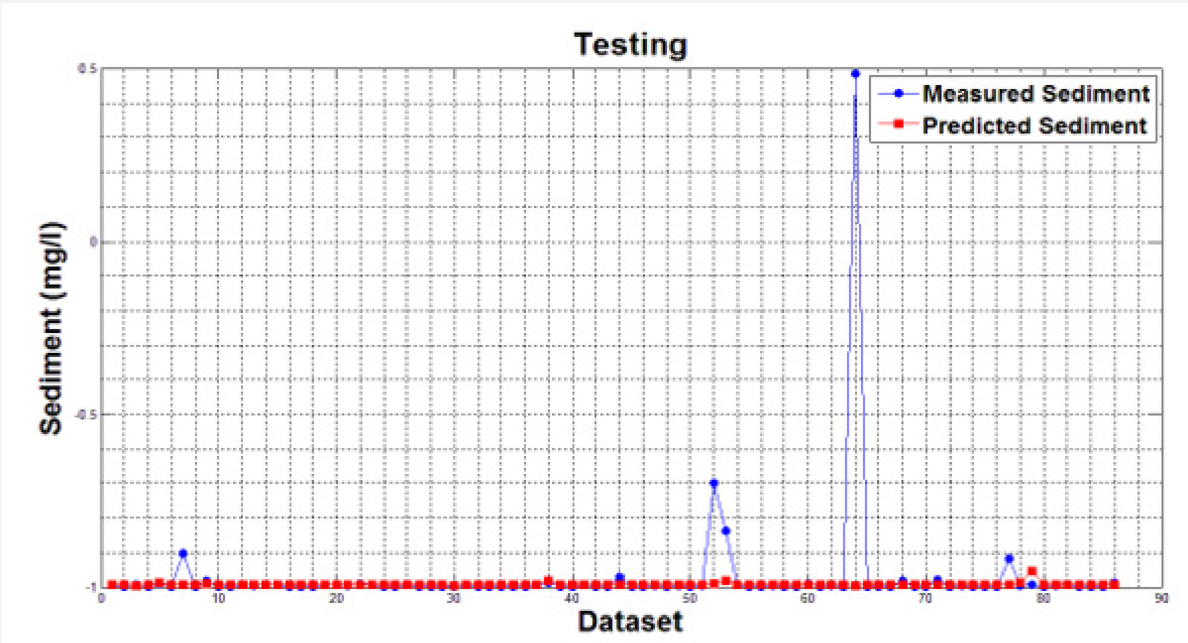

Figure 3: Distribution between the measured and predicted sediment values by ANNs.

Figures 2 & 3 depict the distribution diagrams related to ANFIS and artificial neural network models during the test phase. In these diagrams, the blue line represents the bisector of the first quadrant in both the vertical and horizontal axes. The measured sediment values are plotted on the X-axis, while the predicted sediment values are plotted on the Y-axis. The proximity of these values to the first quadrant (blue line) signifies an excellent fit and accurate estimation of the outputs of both ANFIS and ANNs, indicating more precise sediment prediction. As observed from the figure, a significant proportion of sediment values closely align with the bisector of the first quadrant. Additionally, the criteria for determining errors in the ANFIS network method are presented in Table 3.

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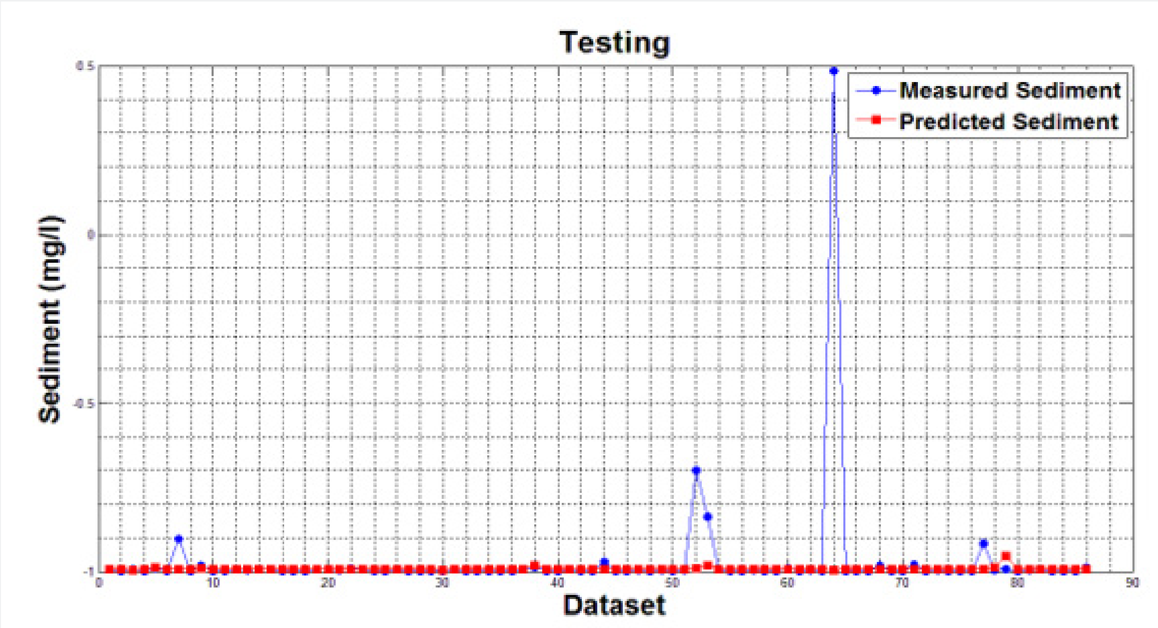

Figure 4: Sediment amounts measured and predicted by ANFIS.

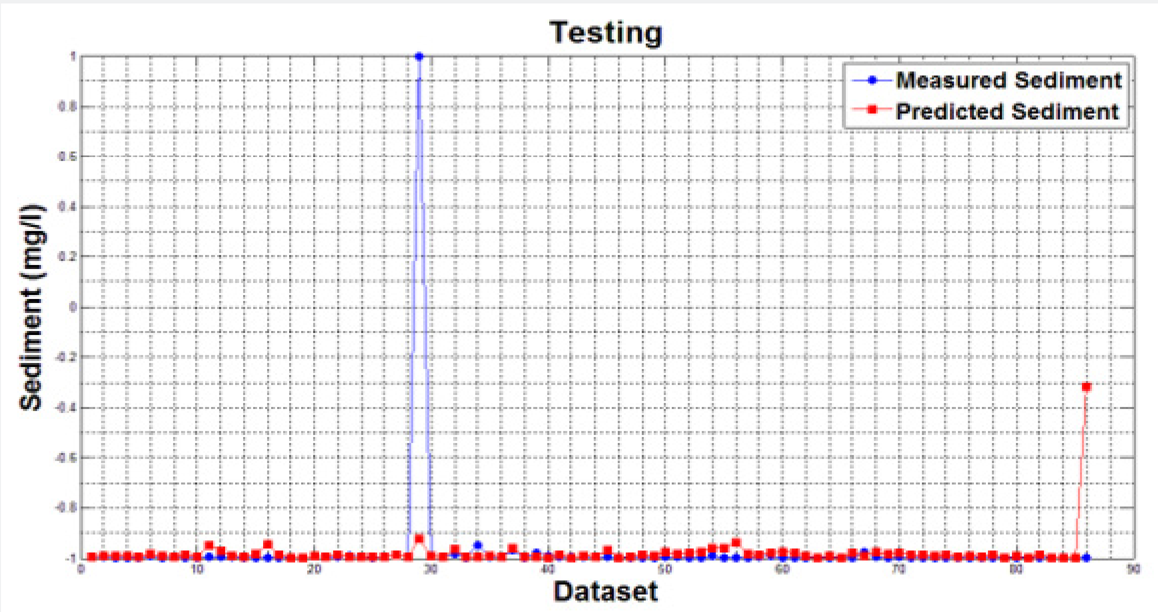

Figure 5: Sediment amounts measured and predicted by ANNs.

In Figures 4 & 5, the level of adjustment and consistency between observed and predicted values of monthly precipitation during the testing stage by ANFIS and ANNs is illustrated. The graphs demonstrate that these models have operated with remarkable accuracy in estimating monthly precipitation values, as the predicted values closely align with the actual ones.

Discussion and Conclusion

Modeling and estimating the suspended sediment load in rivers are crucial due to their profound influence on altering river morphology. This necessity stems from the intricate, non-linear relationships among factors affecting various hydrological phenomena. Such modeling serves as a fundamental and critical

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tool in water resource management, hydraulic structure operation, and dam dead volume calculation. With a comprehensive understanding and prediction of sediment transport dynamics, stakeholders can make informed decisions regarding river management, infrastructure maintenance, and flood control measures. Ultimately, this ensures the efficient and sustainable utilization of water resources and the optimal performance of hydraulic structures. In the majority of studies simulating river-suspended sediments, researchers often rely solely on the flow rate as the variable to estimate sediment quantity. However, it's essential to note that the flow rate alone fails to comprehensively account for the variability of river sediment, particularly across different seasons throughout the year. This research aims to address this limitation by incorporating additional parameters such as runoff, shale content, and sediment characteristics. By doing so, we aim to provide a more nuanced understanding of sediment dynamics across various seasonal conditions. Based on the findings, it can be inferred that ANFIS offers a more suitable approach for forecasting suspended sediments in the Dez River. The results suggest the superiority of FIS over artificial neural networks in this context. Specifically, FIS models demonstrate greater efficacy in capturing the stochastic behavior of hydrological variables and accounting for forecast uncertainty, which is essential for accurate predictions. Unlike neural network models, which excel primarily in point forecasts, FIS models can incorporate non-explicit values in defining climate predictors. Moreover, they enable the generation of long-term predictions in the form of possible intervals rather than precise values, thus accommodating the inherent uncertainty in hydrological forecasting. Additionally, FIS models can capture the non-linear relationships between independent and dependent variables more effectively, further enhancing their predictive performance in complex systems such as river sediment dynamics. Therefore, the use of FIS models represents a valuable approach for improving the accuracy and reliability of suspended sediment forecasts in river systems like the Dez River.

The analysis of results comparing ANN models with ANFIS revealed that the latter demonstrated remarkable performance. Specifically, the ANFIS model successfully accounted for 85% of peak flow changes and 99% of runoff volume changes. By employing a cluster separation method characterized by minimal error and a high-efficiency coefficient, the ANFIS model effectively estimated suspended sediment levels within the study area. This robust performance underscores the efficacy of ANFIS in capturing the complex relationships inherent in hydrological processes and highlights its potential as a valuable tool for sediment prediction and management in river systems. As the percentage of training data increases relative to the test data, the ANFIS method tends to yield more accurate and appropriate results.

The disparity between these two approaches lies in their methodologies for ascertaining the membership function. In instances where the number of input variables is limited, the network separation method proves advantageous for efficient data classification. Conversely, when confronted with a large number of input variables, the adaptive neural-fuzzy network employing cluster separation demonstrates superior training speed compared to its counterpart utilizing network separation. Given that this research also dealt with a substantial number of variables, the cluster separation method exhibited notable performance improvements over the network separation approach. The research findings demonstrate that incorporating flow rate alongside ash and sediment variables as influential factors in estimating suspended sediments within the basin significantly enhances modeling efficiency. Notably, the location of the Dezful regulatory dam station at the basin's lowest point, coupled with its steep slope directed towards the station, and the predominantly sedimentary and calcareous bedrock of the river's tributaries, contribute to heightened suspended sediment levels. Consequently, these elevated sediment levels exacerbate erosion issues and downstream sedimentation problems as the river transitions into areas with reduced slopes. The river's course exhibits diverse geomorphological features, including numerous meanders and alluvial terraces. In this context, employing multiple simple models developed based on the aforementioned criteria can yield more accurate estimates of suspended sediment levels in the river compared to a singular model that does not differentiate the data. Overall, the outcomes of this research, along with the employed modeling framework, can serve as a viable model for estimating or predicting suspended sediment levels in other rivers across the country. In conclusion, it is evident that for predicting erosion, sediment, and runoff volume variables, which represent some of the most intricate hydrodynamic and ecological challenges, neural network and neuro-fuzzy models exhibit superior capability and efficiency compared to traditional regression models. Hence, it is recommended to utilize intelligent and nonlinear neural network models for simulating erosion and runoff in the study area and analogous basins across the country due to their remarkable proficiency in discerning nonlinear and complex relationships.

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