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Associate Prof. Dr. Arif Emre Dursun

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PREFACE

"Engineering is the art of channeling the great sources of power in nature for the use and convenience of humanity."

Thomas Tredgold

The history of engineering is as old as the sense of curiosity in human beings. Our ancestors worked to use and control the materials and forces of nature for the benefit of humanity, just as we do today. These efforts of engineers have led them to undertake a mission to meet the "needs of the society" within the society. Many of the inventions that illuminate our lives have survived to the present day thanks to the successful efforts of researchers who are devoted to engineering. It is obvious that today's research will also shed light on the future, with the diligent work of valuable scientists. Today, some problems arise in every field from law to economy, from health to technology, and solutions are needed by considering these problems. This book presents the theoretical and applied studies from today's technological perspective, blending them with the latest technological innovations and trends in science and engineering.

Associate Prof. Dr. Arif Emre DURSUN

EVALUATION OF NARX, ELMAN-NN, AND CASCADE-NN FOR SUSPENDED SEDIMENT YIELD FORECASTING IN CEYHAN RIVER

Okan Mert KATIPOĞLU[1], Veysi KARTAL[2],
Chaitanya Baliram PANDE[3]

INTRODUCTION

The accurate prediction of the sediment volume is essential during the planning of projects of water resources (Sivakumar, 2006: 31). At the same time, progress and utilization of the river are also significant (Walling, 2009). The sediment deposition in the river has intense impacts on sediment and pollutant transport, lifetime of hydro-electric equipment, dam embankment, channel navigation, fisheries, natural and wildlife habitat, environmental assessment and catchment management (Cigizoglu, 2004: 27). In addition, because of sediment aggradation downstream, the lateral migration of the channel causes severe flooding during severe rainfall due to a significant reduction in channel capacity (Kisi, 2005: 50). Environmental and hydrological problems are complicated by

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sediment transport (ST) and erosion in the rivers (Mirbagheri et al., 1988: 114).

The rise in population, urbanization, and the conversion of forested land for agricultural use have caused watersheds to lose their capacity to absorb water, leading to a rise in flood volume, peak flow, and SL The harmful effects of the increase in sediment load can not be ignored, as it reduces water quality by increasing turbidity and negatively impacts the environment. This impact can be negative and affect various aspects such as fish, and water supply facilities. In addition, the decline in water quality directly impacts the water treatment process, making it more complicated and expensive, which in turn requires additional equipment. The increased suspended sediment load (SL) is a problem that has recently become significant in developing countries (Adib and Mahmoodi, 2017: 21).

LITERATURE REVIEW

Estimating sediment deposition in a river either manually or by an automatic sample machine is challenging since it is troublesome, time-consuming and expensive (Melesse et al., 2011: 98). Sediment rating curve (SRC) and regression have been employed by some researchers to estimate SL (Zhu et al., 2007: 111) and have proved to be inadequate in obtaining the SL. However, AI-based techniques are adequate for predicting complex non-linear cases (Leshno et al., 1993: 6).

AI methods have been applied in a various of studies in hydrology and other fields in recent years (Sirdari et al. 2015: 1; Meshram et al. 2020: 34; Khan et al., 2023; Keshtegar et al., 2023: 15). Artificial neural network (ANN) is one of the generally employed AI-based techniques and has been successfully utilized by several researchers for SL estimation and has shown better results than traditional SRC and MLR methods (Kisi and Yaseen, 2019: 74; Melesse et al., 2011: 98; Yadav et al., 2018: 4).

There have been recently numerous research works in numerous disciplines applying genetic-based multi-objective optimization for NN, attracting popularity among researchers and showing how the hybrid approach can increase the performance of the system (Behzadian et al., 2009: 24; Kant et al., 2013: 23). Yadav et al. (2018: 4) used GA and ANN-based AI models to estimate the load of the SL at the downstream using rainfall, temperature, and flow discharge data. Heuristic and meta-heuristic AI models are also combined in SL prediction (Kisi, 2005: 50; Sahoo and Jha, 2013: 21; Adib and Mahmoodi, 2017: 21).

Optimizing the parameters related to the models is the main difficulty of AI models. Various studies have applied trial-and-error methods in the choice of parameters of AI models to predict SL in a river basin system to obtain quite reasonable results (Melesse et al., 2011: 98; Sharma et al., 2015). Nevertheless, it requires considerable computation time to determine the parameter value and does not ensure an optimum or near-optimal solution to the problem. For this reason, the concurrent optimization of parameters of multiple AI models can tackle the disadvantage of the traditional trial-and-error method by decreasing the computation time and ensuring improved performance (Yadav et al., 2018: 4). In their study, Adib and Mahmoodi (2017: 21) utilized both the ANN algorithm and Markov Chain techniques, which were optimized by Genetic Algorithm (GA), to estimate the SL in the Marun River located in Iran. The analyses indicated that the ANN GA connection model can estimate the SL during floods.

In addition, AI models have been developed by many researchers to estimate SL for a given geographical location by taking into account several temporal parameters such as precipitation, water discharge, and temperature (Kisi, 2005: 50; Melesse et al., 2011: 98; Yadav et al., 2018: 4). However,

previous studies have observed that drainage area and rock type are also important variables affecting SL (Bastia and Equeenuddin, 2016: 144; von Hagke et al., 2016).

Meshram et al. (2019: 33) applied an ANN back-propagation model to predict SL. The reduction in reservoir volume using an ANN was estimated by Iraji et al. (2020: 13). ANN-event-based SL modelling and some studies focusing on sediment concentration have been presented (Rai and Mathur 2007: 22; Singh et al. 2017: 22). Ab Ghani et al. (2011: 1) employed a soft computing technique to estimate sediment loads in three rivers in Malaysia. A distributed feedback ANN architecture was applied to an extensive database collected from measurements in the Langat, Muda and Kurau rivers with no restrictions. SVM, ANFIS, and ANN models were applied by Buyukyildiz and Kumcu (2017: 31) to evaluate load of suspended sediment. Sharghi et al. (2018: 32) demonstrated emotional ANN (EANN) advantages over FFNN. The individual M5 and ANN models with the Wavelet-M5 model were compared by Nourani et al. (2019: 33). The SVM is a machine-learning method applied in hydrology and is an alternative to ANNs. The SVM has been applied for SL (Azamathulla et al. 2010: 38; Ebtehaj et al. 2016: 47) and was shown to outperform ANNs. Ivakhnenko (1968) and Hild and Bozdogan (1995: 20) used regression models, including SVR, M5 tree, and multiple adaptive regression spline (MARS) models for the prediction of SL. Such studies performed modelling of SL and flow estimations. Polynomial regressions were proposed, and MARS was improved to achieve the non-linear behavior of sediment yields and flows by Ivakhnenko (1968) and Hild and Bozdogan (1995: 20). Novelly proposed SVR, M5 tree, and MARS models were applied to estimate SL and river flows in water resources management studies carried out (Malik et al., 2019: 26; Adnan et al., 2019a: 11; Adnan et al., 2019b: 557). The artificial bee colony (ABC)

and MARS model were employed, and the MARS model noted better estimation results than the ABC model as compared to the MARS model (Yilmaz et al. 2018: 639).

Chachi et al. (2016: 61) estimated SL using the fuzzy-based regression models and presented results showing more accuracy for estimation by HMARS-FR model than the other models applied. The algorithms of the M5 tree model were used for sediment prediction along with MLR, ANN, wavelet regression (WR), GEP and SRC and the results demonstrated that the predictive ability of the M5 tree model outperforms the other models (Janga et al. 2009: 18; Goyal, 2014: 28). Senthil et al. (2012: 17) applied hydroclimatic inputs with Levenberg-Marquardt, REPTree, scaled conjugate gradient, M5 tree and SVR models combined with embedded ANN methods and concluded that ANN-LM has better performance of ANN-LM than other models. Tao et al. (2019: 33) applied a radial-based M5 tree (RM5Ttree) combined with a classical M5 tree, an ANN and a response surface method (RSM) to predict the sediments of the Delaware River in the United States. The authors used as input for the models lagged discharge and sediment data and showed that RM5Tree increases the prediction accuracy. The RM5 tree outperformed the classical M5 tree and other models.

The current research aims to investigate the assessment of non-linear autoregressive network with exogenous inputs, Elman, and Cascade-forward neural networks for Suspended SL Forecasting in the Ceyhan River.

MATERIAL AND METHODS

Study Area and Data

It is situated within the borders of Turkey in the semi-arid Eastern Mediterranean region. It lies between 35°15′ to 37°43′ East longitude and 36°33′ to 38°44′ North latitude (Table 1). To the south, the Asi Basin forms a border for it, while to the west

and northwest, it is bordered by the Seyhan Basin, and to the east and northeast, it is bordered by the Euphrates Basin. Based on the information presented in Figure 1, it can be concluded that the drainage area is roughly 21,670 km^2. In the basin, there are different climate zones, the lower part of the basin is located in the Mediterranean climate zone, while the upper and middle parts of the basin are under the continental climate.

The region where the study area is located falls under the Mediterranean Macroclimate region. The Azores' high-pressure area and the Mediterranean climate impact the region during the summer season; conversely, in winter, the Polar air descends southwards, thereby dominating the region. The Mediterranean Basin experiences varying climatic conditions, which are determined by factors such as altitude, orography, land-sea interactions, smaller-scale processes, seasonal oscillations, and dominant pressure systems (Trigo, 2002: 130). The climate tends to be changeable in both basins, exhibiting mean yearly temperatures ranging between 20°C and 25°C in the downstream regions and dropping to 8°C to 7°C as you move upstream, owing to the higher elevation and greater distance from the sea. This phenomenon is known as continentality. According to Altın et al. (2020: 139), the months of July and January are considered the hottest and coldest months, respectively, with mean temperatures of 28°C recorded during the summer months, while the winter months experience a range of temperatures from 9°C in lowlands to 4°C in highlands.

Table 1: The location of the study area

Name of Basin	Station no	Location	Years	The mean distribution of sediment particles	Mean volume of sediment (m^3/year)	Mean gravity of sediment (t/m^3)
Ceyhan	E20A004	353803E-365728N	45	Clay and silt 46.4% Sand 53.6%	953.787 m^3/year	1.33

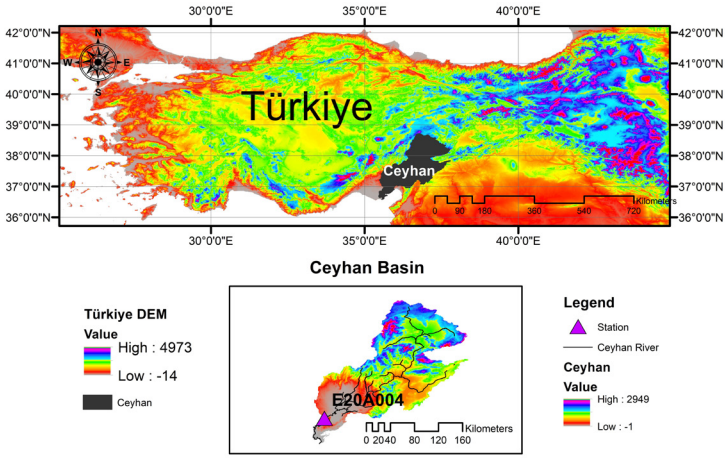


Figure 1: The Geographical Coordinates and Hydrography Map of the Study Area

Cascade Forward Neural Network (CFNN)

The Demuth's (2009) suggestion is a multi-layer feed-forward neural network (FFNN). The structure of a CFNN comprises input, output, and one or more hidden layers, coupled with two additional connections. Incorporating supplementary links can augment the distribution of data on the NN, consequently bolstering the generalization of the neural network (Gao et al. 1996: 2). NN with one hidden layer is enough to solve most problems of estimation and classification (Cybenko 1989: 2; Patuwo et al. 1993: 24).

In Eq. (1), $u^{(k)}_{i}$ is the total input of the j^{th} hidden neuron at k time.

$$net_{h_j}^{(k)} = \sum_{i=1}^{M} w_{i,j}^{1} u_i^{(k)} \; for \; 1 \leq j \leq M \tag{1}$$

in which k is the moment. M is the nodes number in the input layer. $W^{1}_{i,j}$ refers to the weight connect i. $u^{(k)}_{I}$ is the input of the neural network. net_{hj} refers to input of j in the hidden layer.

The output of the j^{th} hidden neuron at time k for a hidden layer of the CFNN network is presented in the following:

$$O_h_j^{(k)} = f\left(net_{h_j}^{(k)}\right) \quad (2)$$

in which O_hj is the output of node j in the hidden layer. $f(*)$ is linear or non-linear output function of hidden layer $f(*)$ is permenantlı within the range [−1, 1]. The CFNN outputs with one hidden layer can be written from Eqs. (1) and (2),:

$$y_n^{(k)} = g\left(\sum_{i=1}^{L} w_{jn}^2 O__h_j^{(k)} + \sum_{i=1}^{M} w_{i,n}^3 u_i^{(k)}\right) for\ 1 \le n \le N \quad (3)$$

in which L refers to the output layer's number. N refers to nodes' numbers in the hidden layer. $W^3_{i,n}$ is the weight connecting node i in the input layer to n in the output layer. W^2_{jn} refers to the weight connecting j in the hidden layer to n in the output layer. $y^{(k)}_n$ is the output of the neural network.

In Eq. (3), remember that when i=0, the second term will denote the input and weight for the bias input.

Elman Neural Network (ENN)

It was introduced by Elman (1990: 14). The ENN is a regular FFNN consisting of an input, output and hidden layer. Every neuron in one layer is associated with every neuron in the next layer. Furthermore, it is a FFNN in which the hidden layer is fed back through an additional set of context nodes.

The second is also referred to as the context layer. It keeps the hidden layer's output and then supplies it back to the hidden layer. The first iteration initializes the output of the context layer and adjusts it to an arbitrary constant value as in Eq. (4)

$$O_c_i^{(k)} = net_c_i^{(k)} \quad (4)$$

The net_ci is the input of context node i.

The input of the i^{th} neuron in the hidden layer is written as follows.

$$net_{h_j}^{(k)} = \sum_{i=1}^{M} w_{i,j}^{1}\, u_i^{(k)} + \sum_{i=1}^{L} w_{i,j}^{3}\, O_c_i^{(k)} \quad for\ 1 \le j \le L \tag{5}$$

where *O_ci* refers to the context node's output. Equation (6) presents the total output of the j^{th} hidden neurons at *k* time.

$$O_h_i^{(k)} = f\left(net_{h_j}^{(k)}\right) \quad for\ 1 \le j \le L \tag{6}$$

The ENN output with one hidden layer can be written from Eqs. (5) and (6).

$$y_n^{(k)} = g\left(\sum_{j=1}^{L} w_{jn}^{2}\, O__h_j^{(k)}\right) for\ 1 \le n \le N \tag{7}$$

The same computation method is employed for the second iteration, except for the context nodes, where the hidden units' values are duplicated to the related context units via a unit delay (D-1). For this reason, the input of context nodes in the second iteration can be represented in Eq. (8). It can be applied to static and dynamic problems. The ENN for dynamic issues has proved to give better performance in several projects, such as control (Liu et al. 2009), speech recognition (Elman 1990: 14), and many other applications (Wang et al., 2006).

$$net_c_i^{(k)} = O_h_i^{(k-1)} \tag{8}$$

Non-linear Autoregressive Network with Exogenous Inputs (NARX)

The NARX represents a major category of discrete-time non-linear systems. Besides being computationally powerful in theory, NARX neural networks have various practical benefits. As an illustration, a report suggests that gradient descent learning could be more effective for NARX networks in comparison to other recurrent architectures with hidden states, as stated by Horne and Giles (1994: 7). The predicted value of

the output in the NARX model at $(k+1)^{th}$ instance, $\hat{w}(k+1)$, is written as below:

$$\hat{w}(k+1) = F(\hat{w}(k), \ldots, \hat{w}(k-q+1), u(k), \ldots, u(k-q+1)) \quad (9)$$

in which $\{u\}$ is the input sequence, F is a non-linear function of its arguments, and $\{\hat{w}\}$ is the predicted output sequence. NARX has two architectures available for a NARX network. These are serial-parallel (SP) and parallel (P) architectures. The predicted outputs before NARX in Equation (1) are utilized as inputs to estimate the output in the following sample. If these are substituted with the actual values for the output from the system, greater estimation accuracy can be achieved. In this case, Equation (9) would be:

$$\hat{w}(k+1) = F(w(k), \ldots, w(k-q+1), u(k), \ldots, u(k-q+1)) \quad (10)$$

In Eq. (10), the serial-parallel architecture is presented. The structure of the SP model is a fully feed-forward architecture and therefore has the benefit of static back-propagation being available for training (Xie et al. 2009). Moreover, it will provide better results using a more accurate input.

Performance Metric

Within the scope of the study, Kling-Gupta efficiency (KGE) and mean bias error (MBE) statistical metrics used in the literature were employed to asses the success of the SL estimation model. Mathematical equations of these indicators are presented as follows:

$$\text{MBE} = \frac{1}{N}\sum_{i=1}^{n}(p_i - o_i) \quad (11)$$

A new criterion named KGE was introduced by Gupta et al. (2009: 377). The NSE decomposition inspired the KG efficiency.

$$KG = 1 - ED \quad (12)$$

in which ED is the Euclidean distance of *(α, β, r)* to (1,1,1), and is calculated as below:

$$ED = \sqrt{(\alpha - 1)^2 + (\beta - 1)^2 + (r - 1)^2} \quad (13)$$

in which $\beta = m_y/m_{\tilde{y}}$ the dimensionless measure of bias *(β∈R)*. The KGE could have values between minus infinity and unity, in which unity means an excellent match to the measured data similar to R^2 and NSE. Gupta et al. (2009: 377) presented the benefits of KG efficiency compared to the commonly applied NSE. This has encouraged the wide use of KGE in field of hydrology to evaluate the quality of the agreement between relevant observations, $\tilde{y}$ and model simulations, y. There is a potentially relevant concern with the implement of KGE is that the three variables of Equation (13), *α, β* and *r*, are the product-moment ratios, which exhibit very large bias for skewed data such as daily flow data (Lamontagne et al., 2020: 56). The issue remains even for long time series of streams and must be prevented. Lamontagne et al. (2020: 56) provide an improvement estimator of NSE and KGE.

RESULTS

This study used NARX, ENN, and CFNN algorithms to estimate the Ceyhan River's suspended sediment load. The correlation matrix was used as a feature selection approach to identify model input and target variables (Figure 2). Accordingly, the variables with the highest correlation with the output variable, the amount of sediment (Qs(t)) values, were presented as inputs to the model. According to the analysis, the highest positive correlation between Qs(t) values and stream flows Q(t) is 0.63. Accordingly, the structure of the established model is presented in the following function:

F(Q(t)) =Qs(t)

Here, Qs(t) values are obtained by presenting the Q(t) values as input to the machine learning values.

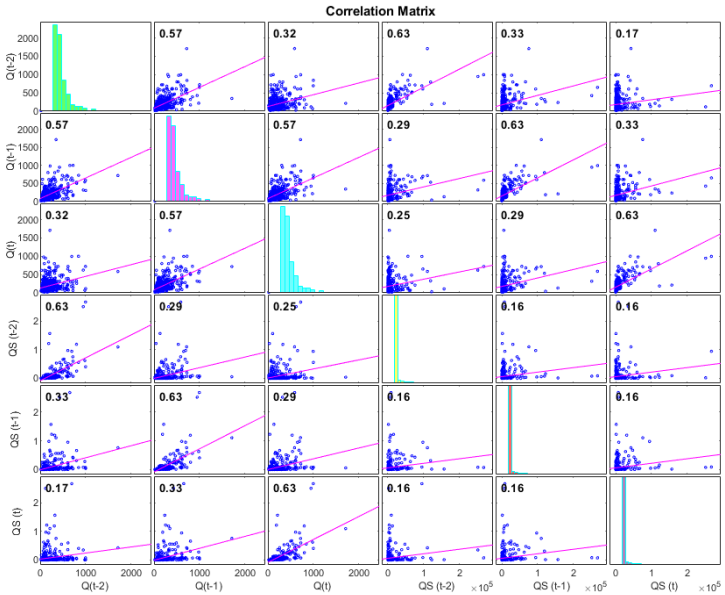


Figure 2: Correlation Matrix of Model Variables

The same parameters were used in all installed models. These parameters are presented in Table 2. Momentum gradient descent is an optimization technique used in the training process to adjust the weights and biases of a neural network using historical gradients. Levenberg-Marquardt (LM) is an optimization technique, while backprop is the recursive application of the chain rule for derivatives. When this technique is far from a local minimum, it ignores the curvature of the loss and is an optimization technique used to minimize the network's prediction error.

Table 2: Model parameters ın training phrase

Parameters	
Training function:	Levenberg-Marquardt backpropagation
Adaptation learning function:	Gradient descent with momentum weight and bias learning function
Number of layer;	2
Number of neurons;	10
Transfer Function;	PURELIN
Epoch;	1000
Goal:	0
Min. Gradyan:	10^{-7}
Max. fail:	6

Results of NARX Prediction

NARX-based AI model was established for SL estimation in this study. Figure 3 shows the structure of the NARX model. Accordingly, there is 1 input variable and 1 output variable. Input variables are monthly flow values, while output variables are monthly sediment values. The structure of the NARX model consists of Input delay vector: [0, 1], Output delay vector: [1, 2]. In addition, there are 10 neurons in the hidden layer.

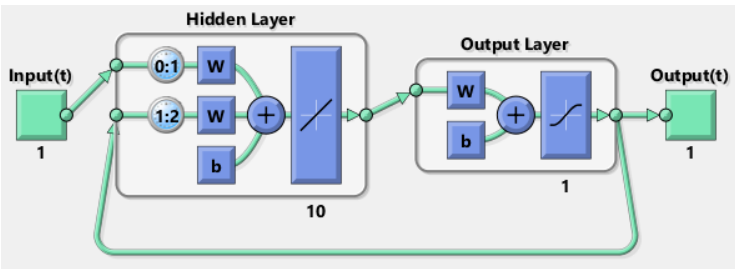


Figure 3: Structure of The NARX Model

Figure 4 shows the variation of MSE values in the setup of the NARX model. The interpretation of the model's training, testing, and validity errors is examined here. Accordingly, the model training was completed when the validity error increased. Thus, optimum results were tried to be achieved.

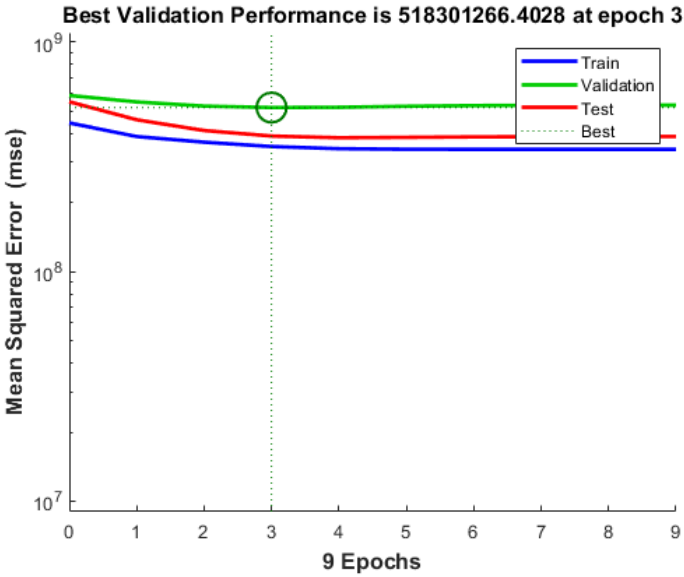


Figure 4: Error Evolution of The NARX Model

In Figure 5, you can see the system's training status, which is depicted through the gradient, mutation and validation control graphs of the established NARX model. The gradient becomes increasingly smaller as the training reaches its minimum performance point. The training process will come to a halt if the magnitude of the gradient is lower than 0.000001. The number of validation checks is identified by the number of successive epochs in which the validation performance does not decrease. When this number is 9, the training ends. In addition, the learning rate (mutation) versus the number of iterations and the validity graph are presented. Accordingly, it was observed that the network error decreased as the training progressed.

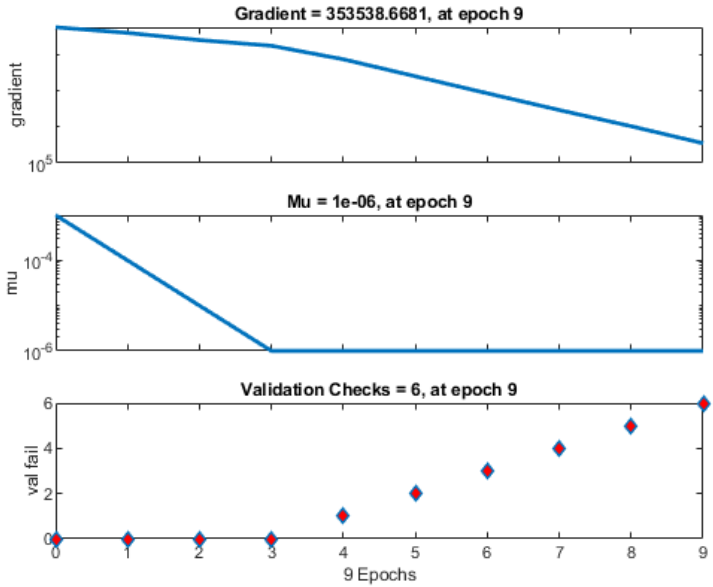


Figure 5: Training state of the NARX algorithm

Results of ENN Prediction

Figure 6 indicates the structure of the ENN model. Accordingly, there is 1 input, hidden and output layer. Input variables are monthly flow values, while output variables are monthly sediment values.. In addition, there are 10 neurons in the hidden layer.

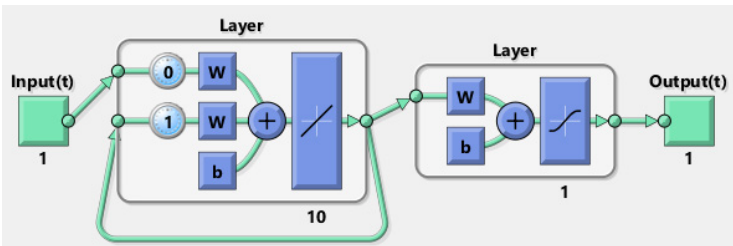


Figure 6: Structure of the ENN model

Figure 7 illustrates the changes in MSE values within the ENN model setup. This analysis examines the model's training, testing, and validation error variation. The increase in the validity error determined the completion of model training. The objective was to reach the optimal outcome.

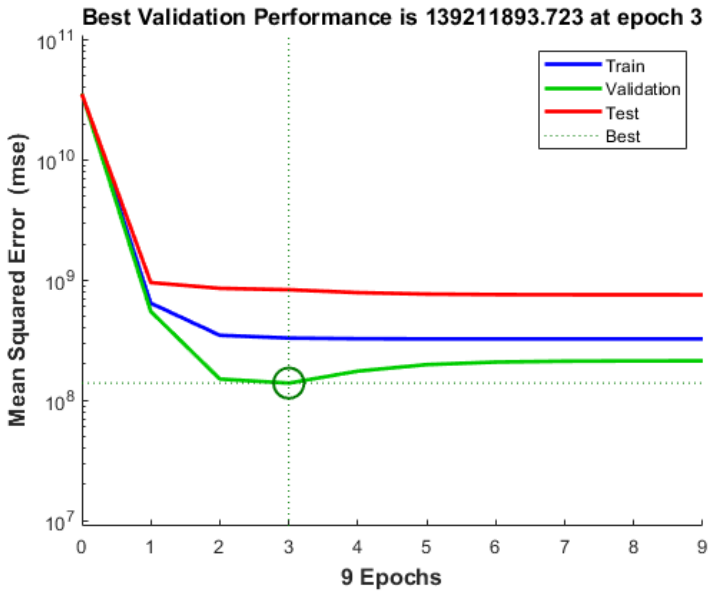


Figure 7: Error Evolution of The ENN Model

The training status of the system is depicted in Figure 8, which displays the established ENN model's gradient, mutation, and validation control graphs. As training approaches the minimum point of performance, the gradient diminishes significantly. The training process will terminate when the gradient's magnitude decreases to less than 0.000001. The count of validation checks pertains to the number of successive iterations in which the validation performance does not decrease.

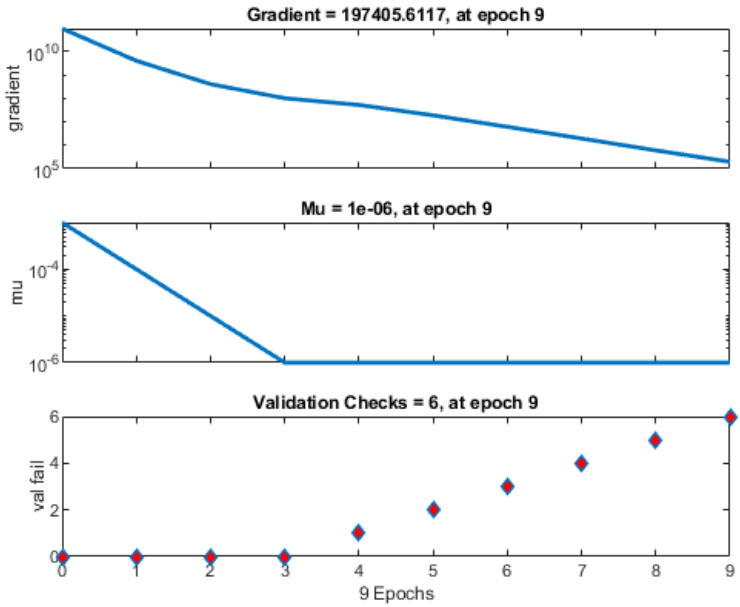


Figure 8: Training State of The ENN Algorithm

Results of CFNN Prediction

The CFNN model structure is illustrated in Figure 9. It can be inferred that the NN architecture consists of only one input, hidden, and output layer. The input variables are monthly flow values, whereas the output variables comprise monthly sediment values. Moreover, the hidden layer contains 10 neurons.

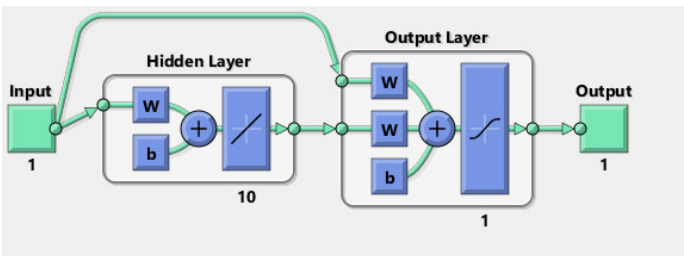


Figure 9: Structure of the CFNN Model

Figure 10 shows a visual representation of how the error changes within the setup of the CFNN model. This analysis examines the fluctuations in the model's training, testing, and validation errors. Once the validity error increased, it was identified as the point of completion for the model training.

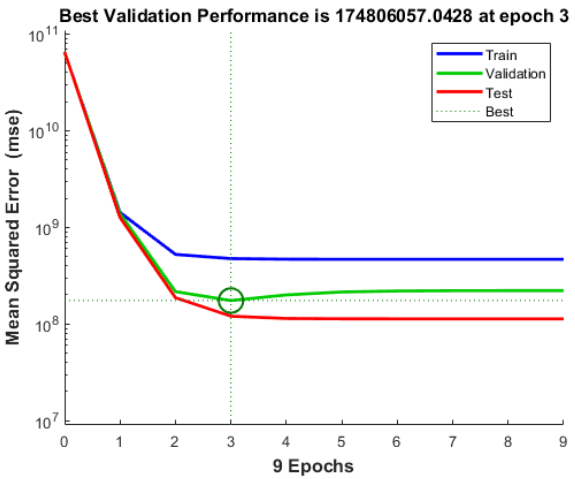


Figure 10: Error Evolution of The CFNN Model

The gradient, mutation, and validation control graphs of the established CFNN model are shown in Figure 11, which depicts the training status of the system. As the training approaches the minimum performance point, the gradient experiences a significant decrease. The validation checks count is the number of successive iterations with no decrease in performance.

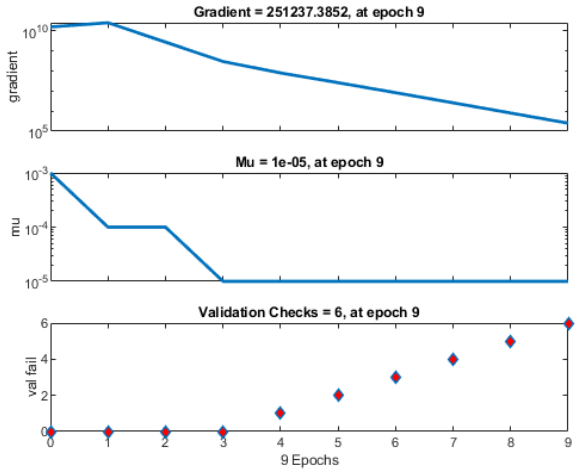
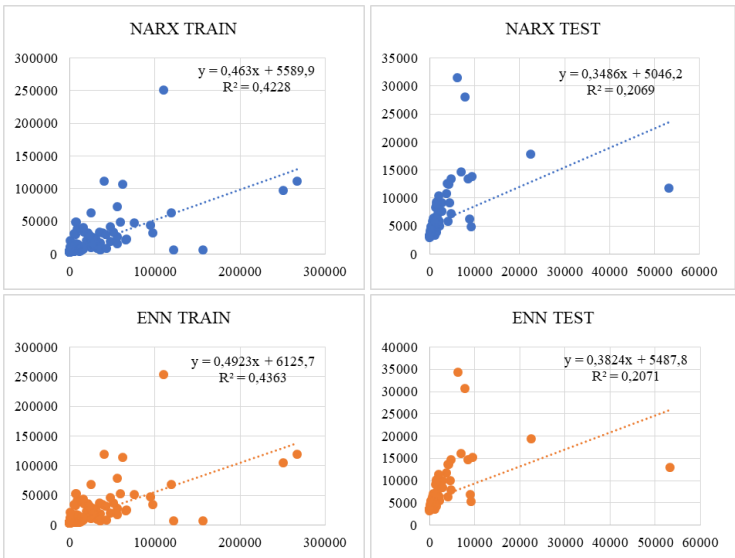


Figure 11: Training State of The CFNN Algorithm



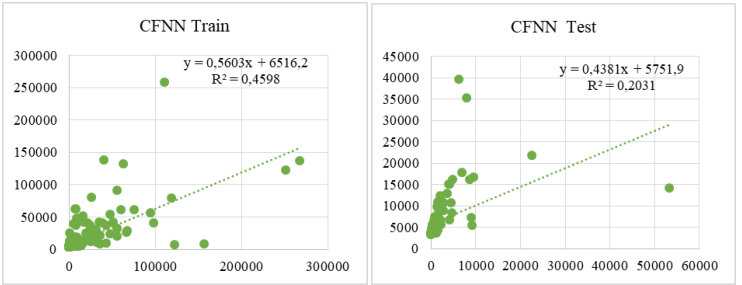


Figure 12: Scatter Diagrams of the Established Models

The scatter diagrams of all the established models show the relationship between the estimated and actual sediment loads in Figure 12. Accordingly, all models' training and test performances are close. However, the CFNN algorithm in the training phase and the ENN algorithm in the testing phase seems to be very successful in the others. A more detailed performance evaluation is required to assess model performance precisely. In Table 3, error evaluation was made according to the KGE and MBE criteria. According to these criteria, the NARX model with the KGI values closest to 1 and the MBE values closest to 0 was selected as the best model.

Table 3: Comparison of sediment estimation results according to statistical metrics

	Train	**Test**
NARX*		
KGI	**0.536**	**-0.971**
MBE	**885**	**3747**
ENN		
KGI	0.534	-1.209
MBE	1678	4256
CFNN		
KGI	0.524	-1.387
MBE	2664	4631

Note: *shows the best model

DISCUSSION

The ST phenomenon at the basin scale is marked by high dynamism and dependence on many combinatorial variables, rendering its prediction a formidable undertaking. Without a doubt, several process-based models have emerged as valuable tools for estimating SL (Ezzaouini et al., 2022: 14). Within the scope of the study, the performances of various ML algorithms for SL estimation were compared. Ezzaouini et al. (2022: 14) applied RF, AdaBoost, SVR, k-NN, and ANN models to predict daily SL in semi-arid region. The precision of the models was evaluated using various statistics metrics and the best-performing models were identified. As a result of the analysis, NARX hydro-climatic input variable and ANN methods produced satisfactory outputs in the range of NSE 0.47 and 0.80 in SS estimation. Singh and Chakrapani (2015: 187) estimated the SS at the Bhagirathi River by presenting the sediment concentration inputs of discharge, precipitation and temperature to the ANN and NARX model. Established models produced satisfactory outputs from the SS estimation. In the study of Alarcon (2021:13), the NARX model was used to model the daily SL values at the outlet of the Francia Creek basin (Valparaiso, Chile). As a result of the analysis, the proposed model produced satisfactory outputs with (R^2 = 0.73, NS = 0.71) values. The outputs of the presented study overlap with previous studies in that ANN and autoregressive-based models produce successful outputs in SL estimation.

CONCLUSION

The estimation of the SL in the Ceyhan River was conducted in the current study using NARX, ENN, and CFNN algorithms. The model setup involved the use of a correlation matrix to select features that were deemed critical. After analyzing the correlation item, it was concluded that the variable with the

strongest correlation to sediment estimation was the flow data. The constructed models were evaluated using various KGE, MBE, R^2 criteria and scattering diagrams. As a result of the analysis, the NARX algorithm showed slightly superior results compared to other models. The outputs of the study are of vital importance in the planning of the dam reservoir, in the planning of water resources and in the planning of hydroelectric power generation, water quality and irrigation systems.

For future studies, evaluating the effect of various meteorological variables on sediment prediction and strengthening AI techniques by using state-of-the-art optimized nature-based algorithms and signal processing processes is recommended.

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