Water Supply

Check for updates

IWA PUBLISHING

© 2023 The Authors

Water Supply Vol 23 No 11, 4403 doi: 10.2166/ws.2023.288

Boosting flood routing prediction performance through a hybrid approach using empirical mode decomposition and neural networks: a case study of the Mera River in Ankara

Okan Mert katipoğlu [a,*,†] and Metin Sarıgöl [b,†]

[a] Faculty of Engineering and Architecture, Department of Civil Engineering, Erzincan Binali Yıldırım University, Erzincan, Türkiye
[b] Design Department, Erzincan Uzumlu Vocational School, Erzincan Binali Yildirim University, Erzincan, Türkiye
*Corresponding author. E-mail: okatipoglu@erzincan.edu.tr
[†]The authors contributed equally to the publication.

OMk, 0000-0001-6421-6087

ABSTRACT

Flood routing is vital in helping to reduce the impact of floods on people and communities by allowing timely and appropriate responses. In this study, the empirical mode decomposition (EMD) signal decomposition technique is combined with cascade forward backpropagation neural network (CFBNN) and feed-forward backpropagation neural network (FFBNN) machine learning (ML) techniques to model 2014 floods in Ankara, Mera River. The data are split in order to avoid the underfitting and overfitting problems of the algorithm. While establishing the algorithm, 70% of the data were divided into training, 15% testing and 15% validation. Graphical indicators and statistical parameters were used for the analysis of model performance. As a result, the EMD signal decomposition technique has been found to improve the performance of ML models. In addition, the EMD-FFBNN hybrid model showed the most accurate estimation results in the flood routing calculation. The study's outputs can assist in designing flood control structures such as levees and dams to help reduce flood risk.

Key words: Ankara, cascade forward backpropagation, empirical mode decomposition, feed-forward backpropagation, flood routing, machine learning

HIGHLIGHTS

- It has been proven that machine learning techniques can be used effectively in flood routing forecasting.
- It can assist in flood management strategies and mitigation in risky areas with flood routing forecasts.
- Signal separation techniques have been shown to increase the success of flood translation estimation.
- The EMD-FFBNN hybrid model showed the most accurate results in flood routing calculation.

1. INTRODUCTION

Natural disasters have threatened humanity for thousands of years and negatively affect life. Flood is one of the most destructive and dangerous disasters which can be effective in large areas. It causes many material and moral damages, such as flooding of houses in the regions where people live, damage to transportation systems, erosion of soils and damage to crops (Bagatur & Onen 2018; Fotovatikhah *et al.* 2018; Node Farahani *et al.* 2018; Akbari *et al.* 2020). For this reason, it is vital to minimize the damage caused by flooding and take preventive measures, especially flood forecasting and flood control (Yuan *et al.* 2020; Pal *et al.* 2022). The flood routing method acquires the downstream flood data and is considered an important method in analyzing nonstructural and structural flood control (Asiaban *et al.* 2015; Barati *et al.* 2018; Norouzi & Bazargan 2020). Flood routing techniques are divided into hydrological and hydraulic methods in most cases. While the momentum and equations continuity is used for the solution of hydraulic methods, these equations are solved by numerical methods because they are challenging to solve. The solution of hydrological methods is based solely on the principles of conservation of mass and is simpler than hydraulic methods. However, although many parameters are needed for the solution of each model, obtaining the data is costly and the analysis takes a long time (Chow *et al.* 1988).

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (http://creativecommons.org/licenses/by/4.0/).

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

Because of the disadvantages of statistical and physical methods, machine learning (ML) algorithms are becoming increasingly common. Their use in many engineering fields is increasing thanks to minimum output and input data, the faster and lower computational cost for prediction models created with ML algorithms (Wu *et al.* 2009; Yaseen *et al.* 2015; Tayfur 2017; Adarsh *et al.* 2018; Mosavi *et al.* 2018; Dazzi *et al.* 2021). ML models are also increasingly used in hydrology due to minimum output and input data, faster speed and lower computational cost. Empirical mode decomposition (EMD) and artificial neural network (ANN) models have widespread and wide usage areas. Razavi & Karamouz (2007) used recurrent neural network (RNN), Time delayed recurrent neural network (TDRNN), multilayer perceptron network (MLP) and time delayed neural network (TDNN) algorithms to apply the flood routing method to river systems. In conclusion, they found that TDNN and TDRNN algorithms gave better prediction results than other models. Ghalkhani *et al.* (2013) used adaptive neuro-fuzzy inference system (ANFIS) and ANN models to forecast the flood routing analysis and found that the flood routing simulation obtained from ANN and ANFIS can be easily used in flood prediction and warning systems. Huang *et al.* (2014) researched support vector machine (SVM), ANN and EMD-SVM models to forecast the monthly streamflow and found that the EMD-SVM algorithm has the best statistics among all the models. Paul & Das (2014) investigated back propagation (BP) and multi linear perceptron (MLP)-based feed-forward (FF) algorithm to forecast the flood water level in a river and determined that the established algorithm successfully predicted the level of flood water in the advance. Elsafi (2014) used the ANN model to forecast the flood level along the River Nile and found that this established model is a reliable tool for detecting flood levels in the River Nile. Latt (2015) applied the feed-forward multilayer detector (FMLP) algorithm for the Muskingum flood routing method for real flood cases and found that the FMLP model performances gave very satisfactory results for all indices. Nikoo *et al.* (2016) researched a social-based feed-forward (FF-SBA) model to solve the flood routing problem. They determined that the results of these models showed greater flexibility and accuracy. Zhao *et al.* (2017) researched the hybrid algorithm EMD-based chaotic least squares support vector machine (EMD-CLSSVM) and CLSSVM to predict the annual streamflow and determined that the hybrid algorithm reduces error results and gives better results than the CLSSVM algorithm. Hassanvand *et al.* (2018) used ANFIS and ANN models for flood routing prediction. ANN model was optimized using imperialist competitive algorithm (ICA) and bat algorithm and the ANFIS model was performed by combining with particle swarm optimization (PSO) and genetic algorithm. As a result of the process, they determined that the ANN-ICA algorithm gave good results compared to other algorithms. Pashazadeh & Javan (2020) researched gene expression programming (GEP) and ANN models to forecast the downstream hydrograph and found that the GEP algorithm gave better results than the other algorithms. Jamei *et al.* (2022) investigated a novel hybrid framework coupling time-varying filter-based EMD (TVF-EMD), long short-term memory (LSTM), classification and regression trees (CART) gradient boosting decision tree (GBDT), cascaded forward neural network (CFBNN) and multivariate adaptive regression spline (MARS) algorithms to predict the long-term multi-step ahead of daily flood water level. At the end of the research, they determined that CART-TVF-EMD-CFBNN algorithm gave the best results for 1- and 7-day horizons among the other models. Tawfik (2023) estimated the maximum flow, upstream and downstream hydrograph values using the ANN algorithm and found that the flood routing values along the river can be easily, quickly and accurately performed using the ANN algorithm. Katipoğlu & Sarıgöl (2023a) compared the performance of the K-Nearest Neighbor (KNN) algorithm with tree-based, kernel-based algorithms for flood routing prediction in Central Anatolia. As a result of the analyses, KNN has produced successful outputs for flood forecasting. Katipoğlu & Sarıgöl (2023b) integrated various artificial intelligence approaches, signal processing techniques and PSO for flood modeling in the Eastern Black Sea Basin in Ordu, Turkey. As a result of the analysis, PSO least squares-SVM technique was the best algorithm. Katipoğlu & Sarıgöl (2023c) investigated the boosted tree (BT) algorithm with EMD, robust EMD (REMD), complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), empirical wavelet transforms (EWT) and variational mode decomposition (VMD) to forecast the daily average streamflow. As a result of the study, they found that the VMD-based BT hybrid algorithm gave the most successful results. Chen *et al.* (2023) used a new algorithm that performs ensemble empirical mode decomposition (EEMD) and stepwise regression to predict the water level of a tidal river and found that the proposed algorithm is simple and highly reliably accurate. Zhou & Kang (2023) researched the support vector regression (SVR), random forest regression (RFR), Gaussian process regression (GPR), multilayer perceptron (MLP), LSTM and gated recurrent unit (GRU) algorithms to predict the flood hydrograph and determined that GRU algorithm gave the most accurate results. Moreover, several studies have been produced on the modeling and environmental impacts of floods and droughts (Faye 2022; Nama *et al.* 2022; Sutopo *et al.* 2022).

As a result of the literature review, it was determined that SVM and ANN models were mainly used in research (Ghalkhani *et al.* 2013; Huang *et al.* 2014; Paul & Das 2014). However, artificial intelligence models are generally used in studies such as

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

flood prediction (level, peak flow, risk, flood management, flood mapping) and research on flood routing prediction models is less numerous and limited to certain algorithms (Yang *et al.* 2019; Munawar *et al.* 2021; Sarıgöl & Katipoğlu 2023). It is thought that the use of signal separation methods in the study will contribute significantly to the literature and contribute to those working in this field. Thus, it investigated how flood routing predictions yielded results by applying signal decomposition techniques to neural networks. On the other hand, flood routing studies with hybrid algorithms have increased considerably in recent years, but it has been observed that they are limited to certain hybrid algorithms (Nikoo *et al.* 2016; Zhao *et al.* 2017; Hassanvand *et al.* 2018). Consequently, it was first researched how flood routing forecasts give results by combining FFBNN and CFBNN algorithms with EMD signal decomposition techniques in the literature.

The most important contribution of this research to the literature is that it shows how signal decomposition techniques combined with neural network algorithms give results in flood routing prediction. In addition, it is to determine the estimation result performances of the models obtained due to the hybridization of FFBNN and CFBNN algorithms with the EMD algorithm. Thus, it is thought that the downstream hydrograph of a future flood can be predicted by entering only the input parameter to the model established without the need for more parameters. It is estimated that the most important gain of the study will be minimizing the loss of life and property as a result of warning the regions where the flood may reach by applying hybrid algorithm models established with signal separation techniques to different regions. Additionally, making the flood analysis processes fast will be very important to save time.

2. MATERIAL AND METHOD

2.1. Study data and area

Discharge observation stations (DOS) are located on the Mera River in Sakarya Basin, and these DOS are shown in Figure 1.

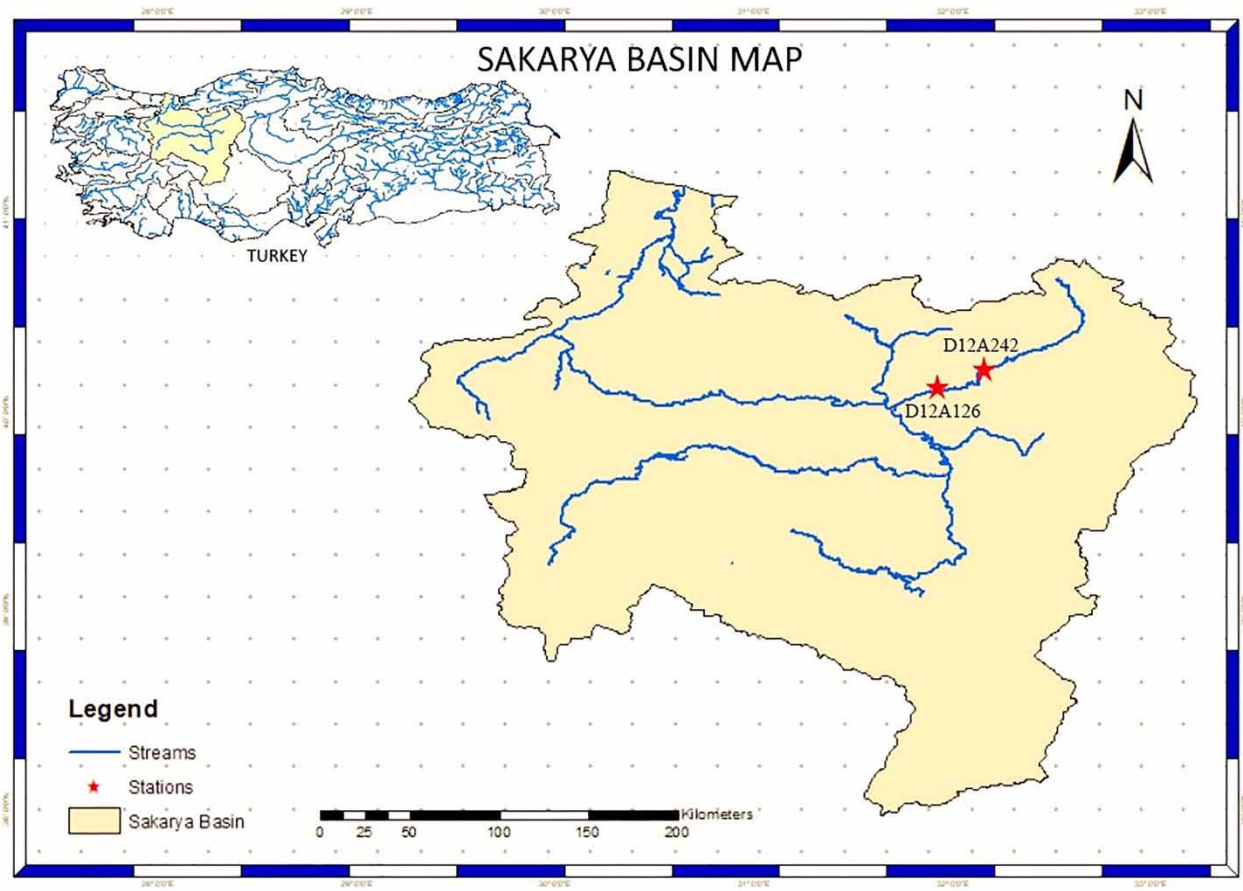


Figure 1 | Location of D12A242 and D12A126 DOS (Sarıgöl & Yesilyurt 2022).

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

Uğurlu (D12A242) is at DOS 32:40:54 East, 40:21:02 North coordinates and 1,015 m altitude, Pazar Yol Ayırımı (D12A126) DOS at an altitude of 965 m and at 32:42:02 East, 40:20:02 North coordinates were used in Ankara. The flood dated 05 May 2014 that occurred in Mera Stream was modeled with the EMD technique combined with FFBNN and CFBNN ML techniques. The input hourly flood values were used as D12A142 station upstream data, and the output hourly flood values were used as D12A126 station downstream data were used. The downstream and upstream flood hydrographs were modeled with the EMD technique, which combined with FFBNN and CFBNN ML techniques. Then it was passed through training and testing stages, and graphical indicators and statistical parameters were used for the analysis of model performance

This research shows input and output DOS data in Table 1. In Figure 2, the hydrographs are plotted.

2.2. ML models

Flood routing prediction algorithms modeled using FFBNN, CFBNN, EMD-FFBNN and EMD-CFBNN algorithms were investigated. While establishing the model, 70% of the data were divided into training, 15% testing and 15% validation.

2.2.1. Artificial neural network

This algorithm is a processor made up of neurons and has the ability to learn and store information throughout the training process. Because it can overcome nonlinear problems, it has wide application in many areas of hydrology, including hydrograph estimation in flood routing. The three-layer network in Figure 3 shows the general structure of the ANN in flood hydrograph forecasting problems. Here, after the input data (x_i) is entered into input layer neurons, it is multiplied by the connection weights (v_{ij}) and transmitted to the neurons in the hidden layer. Next, each neuron collects all weighted information ($x_i v_{ij}$) and sends it to output (z_i) through an activation function. The output information from each inner layer neuron is then multiplied by the corresponding link weight (w_{ij}). Finally, all the resulting signal ($z_i w_{ij}$) is transmitted to the output neuron, which passes an activation function to generate the network output (y_i) (Tayfur *et al.* 2018).

2.2.2. Feed-forward backpropagation neural network

This algorithm consists of output, hidden and input layers and the backpropagation learning method is applied to learn the networks. For the training of the network, calculations are made from the input layer to the output layer and the error values are transmitted to the previous layers. This model usually has a linear neuron output layer and one or more hidden sigmoid neuron layers. Nonlinear multiple neuron layers learn nonlinear and linear relationships between the output and input

Table 1 | Topographic and hydrographic information of the stations used in the study

Province/District name	Station number	Station code	Station name	Basin name	River name	Station elevation (m)	Area (km^2)
Ankara/Kızılcahamam	1	D12A242	Uğurlu	Sakarya	Mera	1015	120.9
	2	D12A126	Pazar Yol Ayırımı	Sakarya	Mera	965	197.2

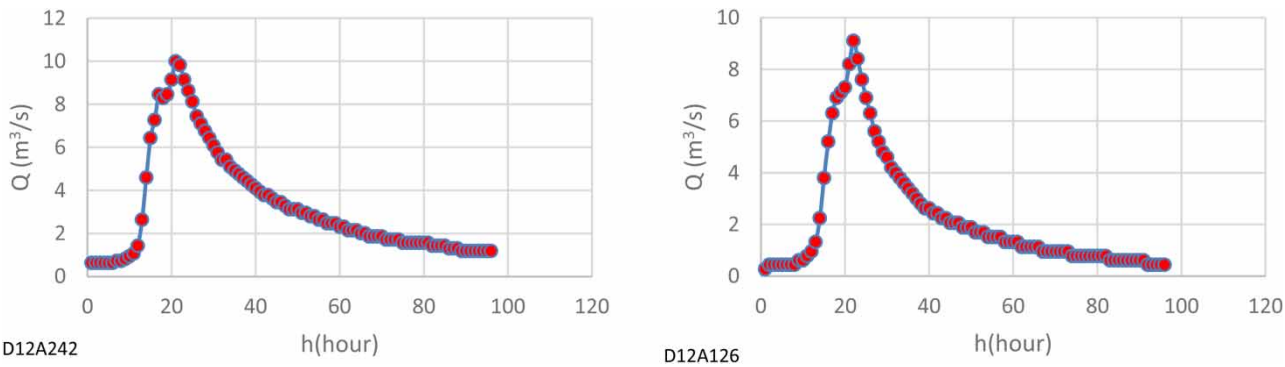


Figure 2 | Hourly flood hydrograph of D12A242 and D12A126 DOS for 2014.

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

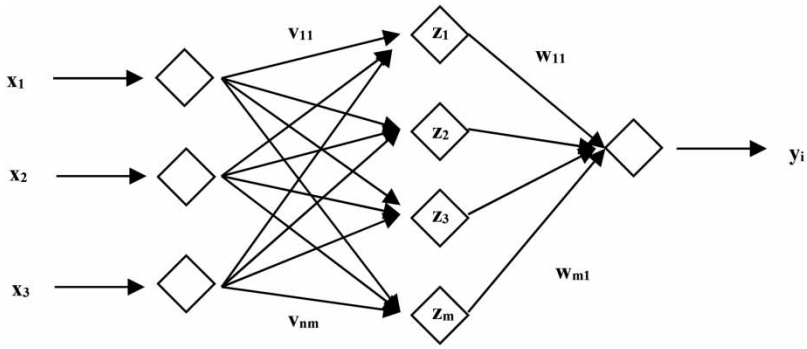


Figure 3 | The schematic structure of the ANN algorithm.

vectors of the network. The linear output layer uses a sigmoid transfer function for values between 0 and 1, allowing it to generate values outside the −1 to +1 (Goyal & Goyal 2011).

2.2.3. Cascade forward backpropagation neural network

This algorithm is similar to FFBNN, but there is a weight link to each layer after the input and to the next layers. This structure includes connections from layer 1 to layer 2, layer 2 to layer 3 and layer 1 to layer 3 for a three-layer network. These connections can increase the speed at which the network learns to associate. Logarithmic sigmoid transfer function, pure linear threshold function and tangent sigmoid transfer function are applied to reach the optimized state (Chayjan 2010).

2.3. Empirical mode decomposition

This algorithm is a model for nonlinear and nonstationary time series analysis. This model decomposes the original signal into different oscillating time scale components: the IMF (intrinsic mode function). It extracts the IMF components from the original signal without the need for any predetermined basis functions for the EMD algorithm. The order of operations for the $x(t)$ $(t = 1, 2, \ldots, n)$ time series of the EMD algorithm is explained below in items;

(1) All local minimums and maximums of the $x(t)$ time series are defined.
(2) Three curve interpolation operators are used to construct the lower envelopes $e_{\text{low}}(t)$ and the upper envelopes $e_{\text{up}}(t)$ of the time series.
(3) The average value of the lower and upper envelopes $(m(t) = [e_{\text{up}}(t) + e_{\text{low}}\ (t)]/2)$ is calculated.
(4) $d(t) = x(t) - m(t)$ value between the mean value $m(t)$ and the time series $x(t)$ is calculated.
(5) $d(t)$ difference value is checked.
(6) Steps (1)–(5) are repeated until $r(t) = x(t) - d(t)$ is a monotonic function or until the excessive number is less than or equal to 1.

Finally, time series $x(t)$ can be represented as the sum of the IMFs $c_i(t)$ and $r(t)$;

$$x_t = \sum_{i=1}^{m} c_i(t) + r(t) \tag{1}$$

In Equation (1), $c_i(t)$ is the ith IMF and $r(t)$ represents the components of decomposed residual (Zhang *et al.* 2018).

2.4. Performance measurement

In this research, statistical analyses were made to determine the accuracy of the ML algorithms. Thus, correlation coefficient (R) performance measures are used. R values close to 1 indicate good forecasting performance. The performance indicator formulas were calculated as follows:

$$R = \frac{\sum_{i=1}^{n} (Q_{oi} - Q_{om})(Q_{pi} - Q_{pm})}{\sqrt{\sum_{i=1}^{n} (Q_{oi} - Q_{om})^2 \sum_{i=1}^{n} (Q_{pi} - Q_{pm})^2}} \tag{2}$$

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

where n is the number of prediction and observation values, Q_{oi} is the observed value, Q_{pi} is the predicted value, Q_{om} is the average of observed value, Q_{pm} is the average of the predicted value (Asuero *et al.* 2006; Başakın *et al.* 2021).

3. RESULTS AND DISCUSSION

This study combines the EMD signal decomposition technique with FFBNN and CFBNN ML algorithms to model the 2014 floods in Ankara, Mera River. In order to mitigate the issues of underfitting and overfitting, the data are divided. During the establishment of the algorithm, the data were partitioned into three subsets; 70% for training, 15% for testing and 15% for validation. The model's performance was analyzed using graphical indicators and statistical parameters. In Figures 4 and 5, the structure of the CFBNN and FFBNN algorithms and the statistical model results of the program are drawn as graphics. The following parameters were used in the setup of the CFBNN and FFBNN models: Training function: Trainlm, Adaption learning function: Learngdm, number of layers: 2, number of neurons: 10, Transfer function: Tansig.

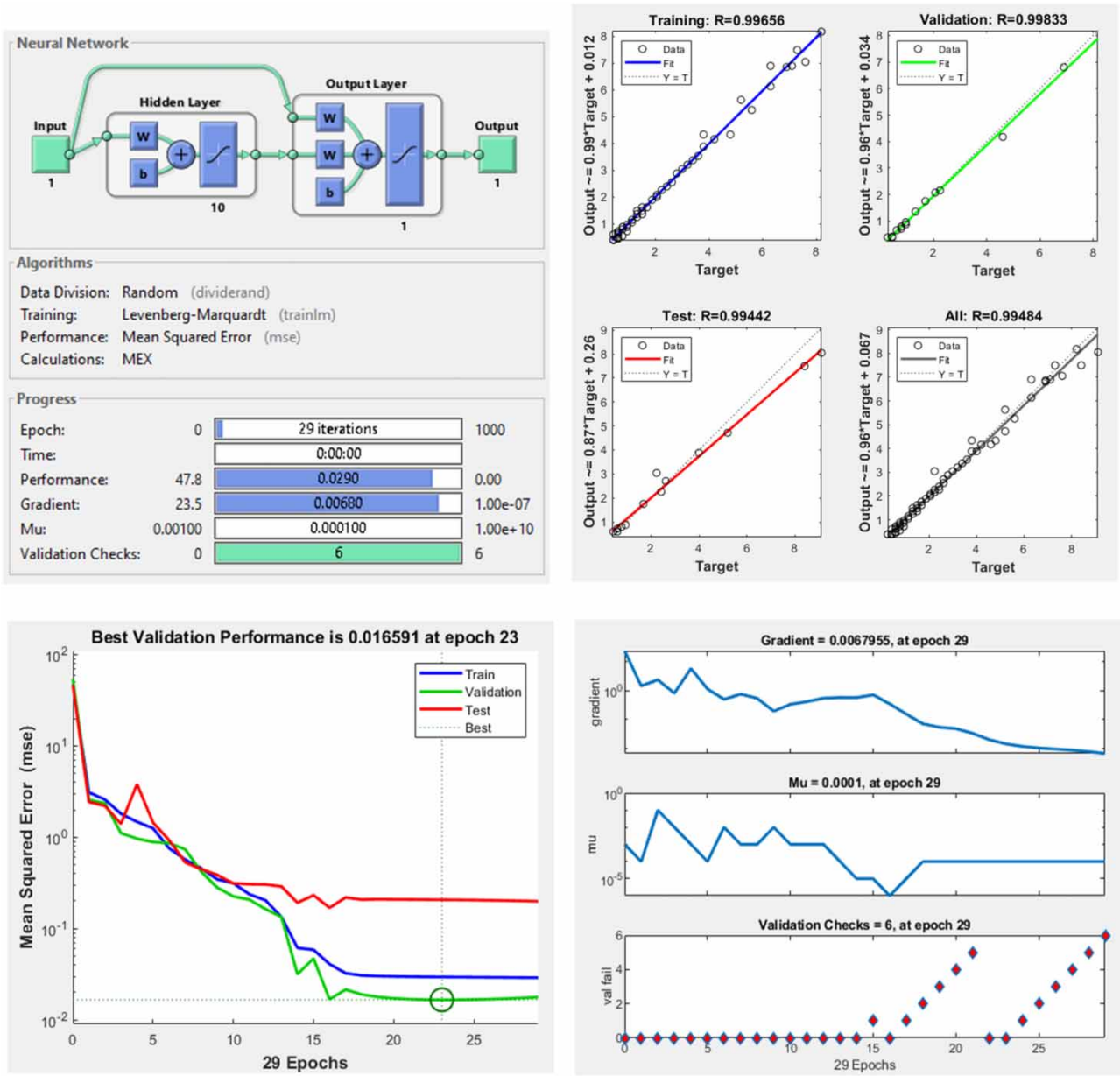


Figure 4 | Structure and result graphs of the CFBNN algorithm.

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

The structure and training parameters of model, regression plots, model performance graphs and error propagation graphs of the established CFBNN model are shown in Figure 4. According to the structure and training parameters of model, the Levenberg–Marquardt algorithm was used in the training of flood data, the data were randomly divided, and the model training was completed by reaching the lowest error values in the 23rd iteration. The scatter diagrams of the model are evaluated, and the scattering of the estimated and real values around the 1:1 line in the training, testing, validation and overall model stages shows that the model's accuracy is high. When the change graph of model errors is examined, it is seen that the validity error increases after the 23rd iteration. In this case, training was stopped and model outputs were produced. Additionally, mu and gradient coefficients and current error changes up to 29th iterations are presented visually.

Figure 5 expresses the structure, training parameters of model, regression plots, model performance graphs and error propagation graphs of the established FFBNN model. Accordingly, the training was terminated when the lowest error values were

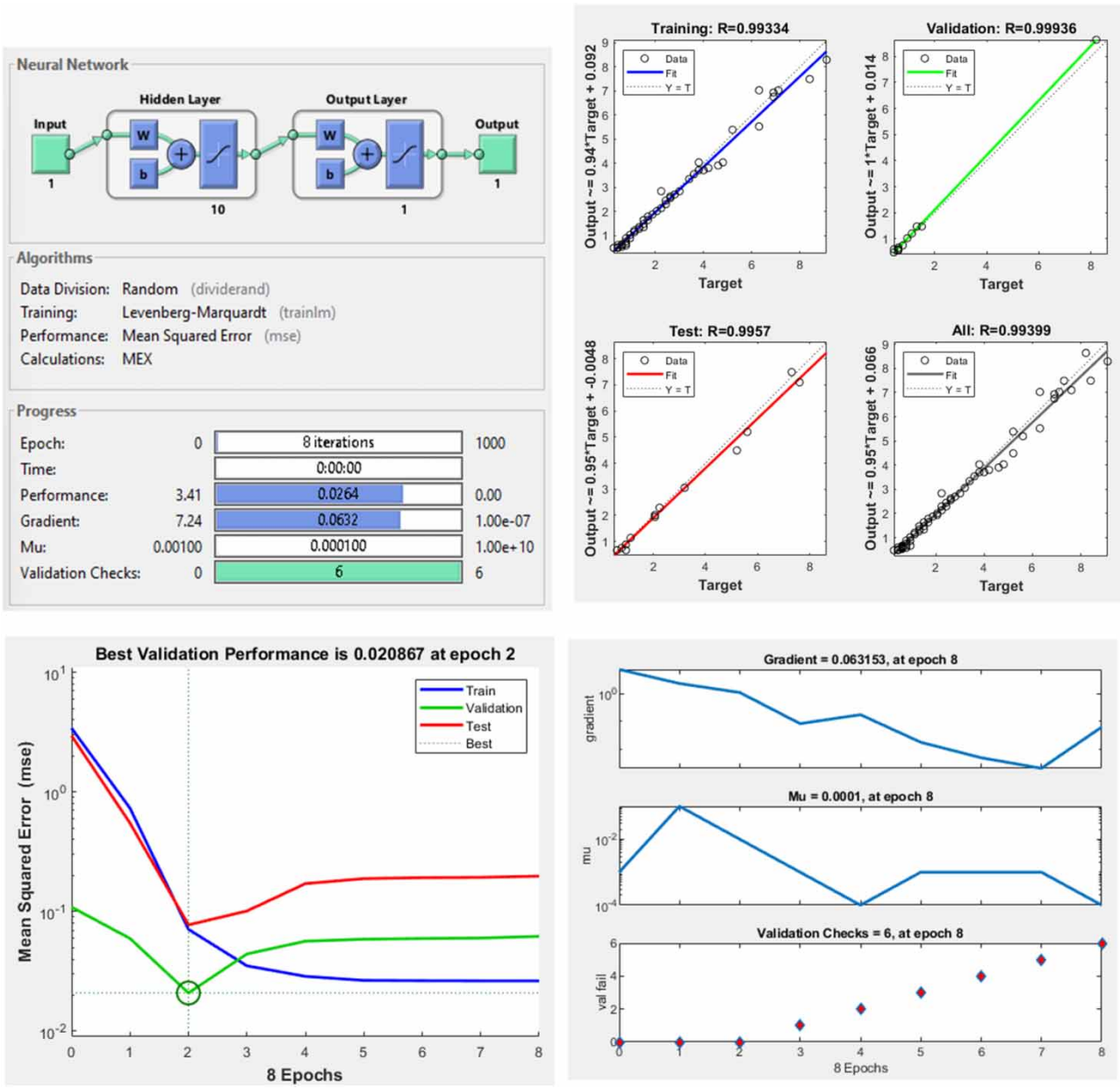


Figure 5 | Structure and result graphs of the FFBNN algorithm.

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

reached in the 62nd iteration. In addition, when the scatter diagrams of the model are examined, the scattering of all graphs around the estimated and actual values 1:1 line shows that the estimation of the model is close to reality. Examining the change graph of the model errors reveals that the validity error rises after the second iteration. In this instance, training was halted, and model outputs were generated. The current error changes up to the eighth iteration as well as the mu and gradient coefficients are also visually displayed.

In the establishment of the hybrid algorithms, the input variables were separated into three IMF and residual by decomposition approaches and applied to the CFBNN and FFBNN models. For example, in Figure 6, the input variable $Q(t)$, which is decomposed into various sub-series with the EMD technique, is shown. The resulting estimation outputs are collected by modeling the sub-signals separately. As a result, hybrid models were obtained. The results of the model were contrasted with different statistical metrics in order to assess the effectiveness of the EMD model for ML. The EMD data parsing procedure offers distinct modeling opportunities that remove data noise. This enables a more thorough association of fundamental information by allowing you to concentrate on particular patterns and variations within the data. These capabilities enable EMD to improve the predictive capability of ML.

In Figures 7 and 8, the structure of the CFBNN and FFBNN algorithms after using signal decomposition techniques and the statistical model results, and program outputs are drawn as graphics. The structure, training parameters, model performance graphs, regression plots and error propagation graphs of the EMD-CFBNN model established are presented in Figure 7. Accordingly, the Levenberg–Marquardt algorithm was used in the training of the flood data, the data were randomly divided and the model training was stopped when the lowest error values were obtained in the sixth iteration. According to scatter diagrams of the model, the distribution of the estimated and real values around the 1:1 line in the training, testing, validation and overall model stages shows that the estimation of the model is at a satisfactory level. Validation error increases after the sixth iteration, as can be seen when the change graph of model errors is looked at. This time, the training process was halted, and model outputs were generated.

The structure, training parameters, model performance graphs, regression plots and error propagation graphs of the established EMD-FFBNN model are shown in Figure 8. Accordingly, the Levenberg–Marquardt algorithm was used in the flood

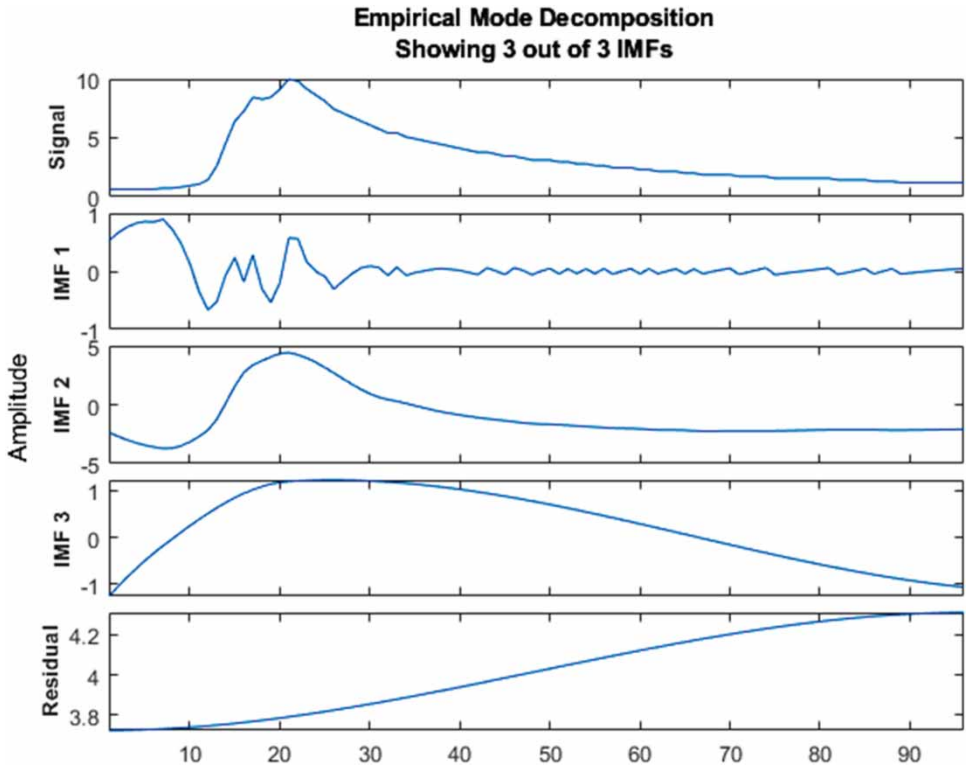


Figure 6 | Subcomponents of the 2014 flood data separated by EMD technique.

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

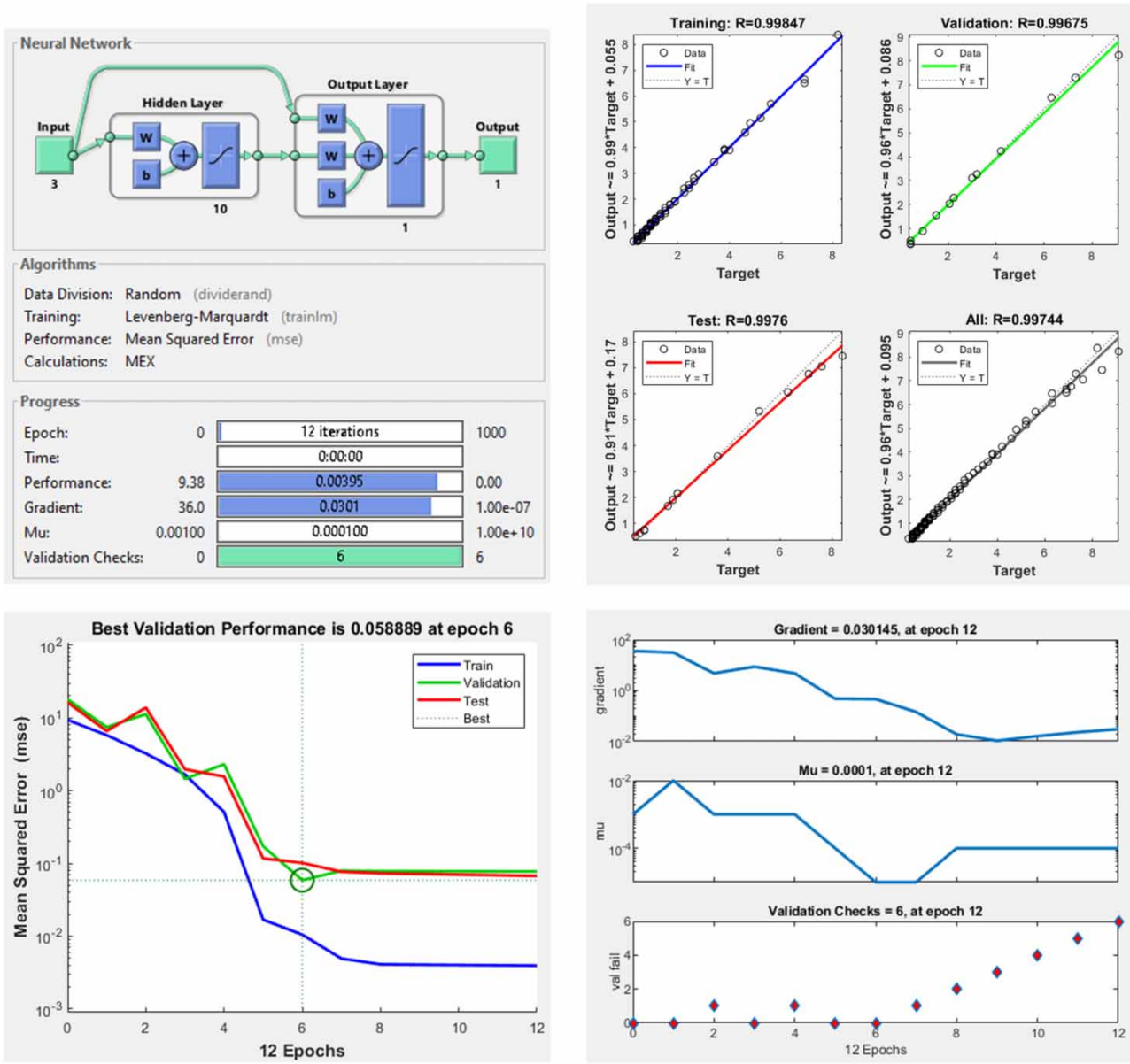


Figure 7 | Structure and result graphs of the EMD-CFBNN algorithm.

data training. The data were randomly divided and the training was completed when the lowest error values were reached in the third iteration. In addition, when the scatter diagrams of the model are examined, the distribution of all graphics around the estimated and actual values 1:1 line shows that the estimation of the model is at a satisfactory level. Examining the change graph of the model errors reveals that the validation error increases after the sixth iteration. In this instance, training was halted, and model outputs were generated.

Table 2 shows the statistical performance criteria of ML algorithms applied for flood routing prediction without applying the signal decomposition technique. *R* statistical training, testing and validation data parameters were used to determine the most successful ML algorithm. According to these parameters, both algorithms show very high prediction success. According to the test and verification results, it is seen that the FFBNN algorithm is slightly superior to the CFBNN algorithm. Moreover, according to these parameters, it is seen that both hybrid algorithms give higher accuracy than the previous nonhybrid algorithms and both test and training results have very high prediction success. According to the test and training results, it was determined that the FFBNN algorithm was slightly superior to the CFBNN algorithm.

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

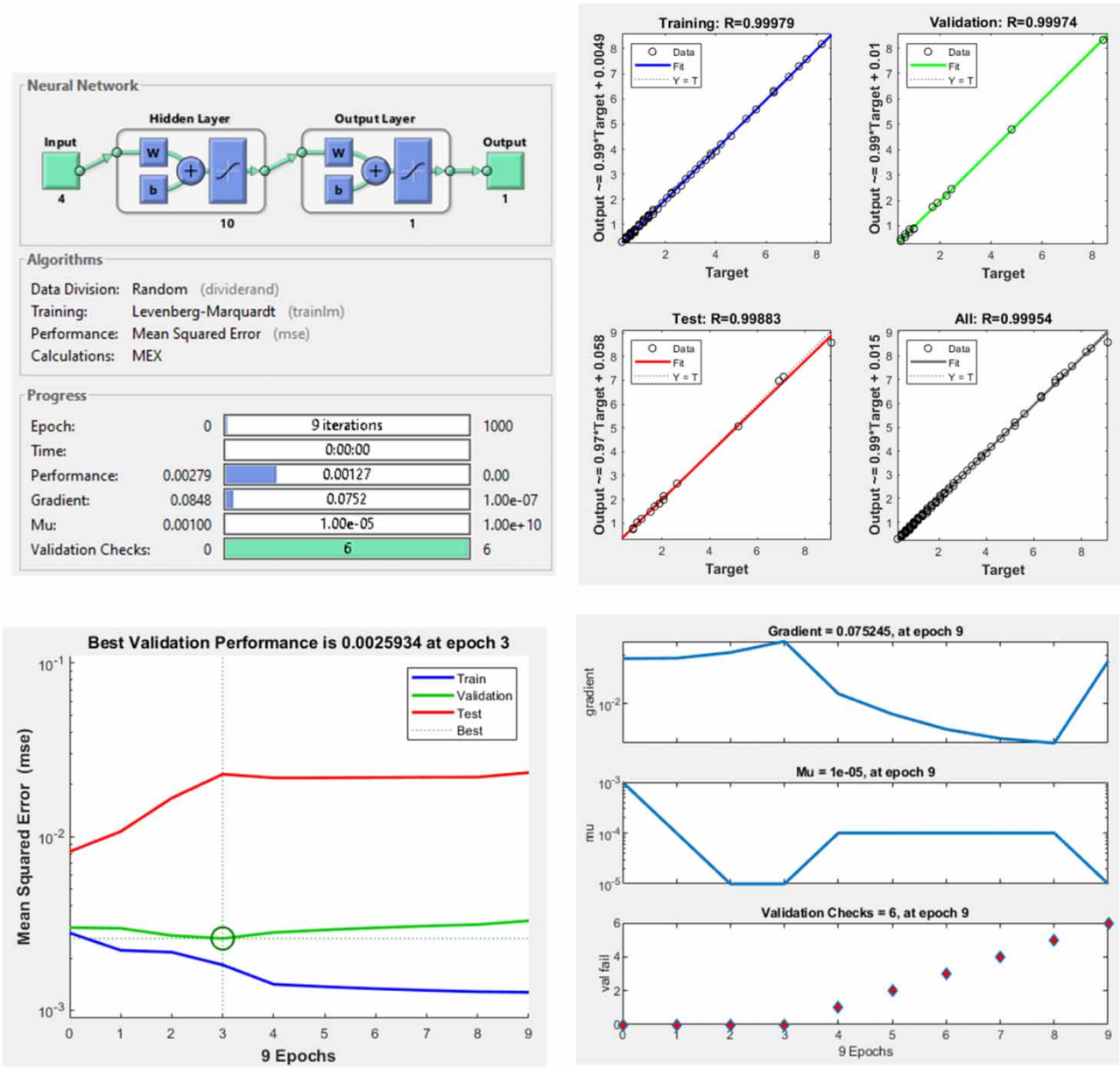


Figure 8 | Structure and result graphs of the EMD-FFBNN algorithm.

Table 2 | ML algorithms used in flood routing

Model No	Model type	Train *R*	Test *R*	Validation *R*
1	CFBNN	0.996	0.994	0.998
2	FFBNN	0.993	0.995	0.999
3	EMD-CFBNN	0.998	0.997	0.996
4	**EMD-FFBNN**	0.999	0.999	0.999

Note: Bold characters indicate the best model.

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

The most crucial aim of this research is to forecast the flood data downstream by artificial intelligence algorithms, which are EMD signal decomposition techniques combined with FFBNN and CFBNN ML hybrid algorithms. For this reason, downstream data as output and upstream data as input are entered into the algorithm established. At the end of the research, it was seen that the model results were used reliably and effectively of flood estimation. Moreover, studies by Katipoğlu & Sarıgöl (2023c), Chen *et al.* (2023), Zhao *et al.* (2017), Nikoo *et al.* (2016), Hassanvand *et al.* (2018) and Huang *et al.* (2014) are compatible with the presented research. Katipoğlu & Sarıgöl (2023c) combined the BT algorithm with REMD, CEEMDAN, EMD, EWT and VMD to forecast the daily average streamflow and found that the hybrid VMD-BT algorithm gave the most successful results. This study overlaps with the use of the signal decomposition technique in Katipoğlu & Sarıgöl (2023c)'s study together with hybrid algorithms in stream flow estimation and obtaining more successful results than other nonhybrid models. Chen *et al.* (2023) used a new algorithm that performs EEMD and stepwise regression to predict the water level of a tidal river and found that the proposed algorithm is simple and highly reliably accurate. Findings from the study by Chen *et al.* (2023) overlap in terms of similar signal decomposition techniques and reliable prediction results. Zhao *et al.* (2017) researched the hybrid algorithm EMD-based chaotic least squares support vector machine (EMD-CLSSVM) and CLSSVM to predict the annual streamflow. They determined that the hybrid algorithm reduces error results and gives better results than the CLSSVM algorithm. This study coincides with the use of algorithms combined with Zhao *et al.* (2017) EMD signal decomposition technique in streamflow forecasting and to obtain more successful results than other nonhybrid models. Nikoo *et al.* (2016) researched a social-based feed-forward (FF-SBA) model to solve the flood routing problem. They determined that the results of these models showed greater flexibility and accuracy. Findings from the study by Nikoo *et al.* (2016) overlap in terms of similar hybrid models used and good and reliable prediction results obtained in this study. Hassanvand *et al.* (2018) used ANFIS and ANN models for flood routing prediction. ANN model was optimized using the ICA and bat algorithm and the ANFIS model was performed by combining with PSO and genetic algorithm. As a result of the process, they determined that the ANN-ICA algorithm gave good results compared to other algorithms. The study's findings overlap with Hassanvand *et al.*'s (2018) hybrid algorithms in producing more effective outcomes than nonhybrid models in flood routing prediction. Huang *et al.* (2014) investigated SVM, ANN and EMD-SVM algorithms to forecast the monthly streamflow and found that the EMD-SVM algorithm has the best statistics among all the models. The result of the research coincides with the study of Huang *et al.* (2014) in that hybrid models obtained by adding signal separation methods to the models give the best results.

4. CONCLUSION

This study combined the FFBNN and CFBNN models with the EMD algorithm to forecast a downstream flood event in Ankara, Mera River and to determine the effect of hybrid models on flood routing calculations. The most important results obtained from the research are listed below:

- The flood routing prediction results of the models created with FFBNN and CFBNN algorithms are quite high.
- The EMD-FFBNN algorithm was determined as the most successful algorithm in the analysis of flood routing.
- Hybrid algorithms created with signal processing techniques showed higher prediction accuracy than nonhybrid ML models.
- The EMD signal processing technique allows adaptive processing and revealing of different frequency components by decomposing flood data into frequency components. Thus, it helped to create a hybrid approach in flood modeling and model the data in detail.
- It has been revealed that successful flood routing results can be obtained by selecting the streamflow values in the upstream region as input and the streamflow values in the downstream region as the target in two DOSs located on a separate stream branch.
- ML techniques can be used as an alternative and powerful tool in the development of flood routing estimation, flood management strategies and mitigation policies.

The results of this research are significant for hydrologists, various government agencies and civil engineers in terms of vital measures that can be taken before a flood may occur in a region.

It has been determined that hybridized artificial intelligence techniques give successful results in flood hydrograph predictions in the downstream region. Furthermore, the findings obtained as a result of the study are compatible with previous studies. It has been concluded that artificial intelligence techniques produce cost-effective and accurate solutions in a

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

short time in modeling complex flood motion. In conclusion, it is predicted that the dissemination of artificial intelligence techniques for developing flood routing estimation algorithms can reduce the loss of life thanks to the measures to be taken before the floods occur.

The study's primary limitations are that it only examines the Mera River in Ankara as a case study and that the time series is only moderately long given the nature of the flood event. Due to the nature of the flood, it is obvious that the hybrid strategy developed as a result of the study will produce positive outcomes in other geographical areas. Future research should test and validate the suggested model in various regions and river regimes. This study proved that flood routing with hybrid EMD-based artificial intelligence techniques had successfully attained a satisfactory level of accuracy.

In future research, flood routing prediction can be combined with gray wolf optimizer, grasshopper optimization algorithm, moth flame optimizer, ant colony optimization, dragonfly algorithm, cheetah optimizer, whale optimization algorithm and various ML algorithms.

ACKNOWLEDGEMENTS

The author thanks the General Directorate for State Hydraulic Works of Turkey for the streamflow data provided, the Editor and the anonymous reviewers for their contributions to the content and development of this paper. This study was presented orally at the INSAC International Researches Congress on Natural and Engineering Sciences (INSAC-IRNES-2023).

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Adarsh, S., John, A. P., Anagha, R. N., Abraham, A., Afiya, M. P., Arathi, K. K. & Azeem, A. 2018 Developing stage–discharge relationships using multivariate empirical mode decomposition-based hybrid modeling. *Applied Water Science* **8**, 1–13.

Akbari, R., Hessami-Kermani, M. R. & Shojaee, S. 2020 Flood routing: Improving outflow using a new nonlinear Muskingum model with four variable parameters coupled with PSO-GA algorithm. *Water Resources Management* **34** (10), 3291–3316.

Asiaban, P., Amiri Tokaldany, E. & Tahmasebi Nasab, M. 2015 Simulation of water surface profile in vertically stratified rockfill dams. *Journal of Water Sciences Research* **7** (2), 25–37.

Asuero, A. G., Sayago, A. & González, A. G. 2006 The correlation coefficient: An overview. *Critical Reviews in Analytical Chemistry* **36** (1), 41–59.

Bagatur, T. & Onen, F. 2018 Development of predictive model for flood routing using genetic expression programming. *Journal of Flood Risk Management* **11**, S444–S454.

Barati, R., Badfar, M., Azizyan, G. & Akbari, G. H. 2018 Discussion of 'Parameter estimation of extended nonlinear Muskingum models with the weed optimization algorithm' by Farzan Hamedi, Omid Bozorg-Haddad, Maryam Pazoki, Hamid-Reza Asgari, Mehran Parsa, and Hugo A. Loáiciga. *Journal of Irrigation and Drainage Engineering* **144**, 7017021.

Başakın, E. E., Ekmekcioğlu, Ö. & Özger, M. 2021 Drought prediction using hybrid soft-computing methods for semi-arid region. *Modeling Earth Systems and Environment* **7** (4), 2363–2371.

Chayjan, R. A. 2010 Modeling of sesame seed dehydration energy requirements by a soft-computing approach. *Australian Journal of Crop Science* **4** (3), 180–184.

Chen, Y. C., Yeh, H. C., Kao, S. P., Wei, C. & Su, P. Y. 2023 Water level forecasting in tidal rivers during typhoon periods through ensemble empirical mode decomposition. *Hydrology* **10** (2), 47.

Chow, V. T., Maidment, D. R. & Mays, L. W. 1988 *Applied Hydrology*. McGraw-Hill, New York.

Dazzi, S., Vacondio, R. & Mignosa, P. 2021 Flood stage forecasting using machine-learning methods: A case study on the Parma River (Italy). *Water* **13** (12), 1612.

Elsafi, S. H. 2014 Artificial neural networks (ANNs) for flood forecasting at Dongola Station in the River Nile, Sudan. *Alexandria Engineering Journal* **53** (3), 655–662.

Faye, C. 2022 Comparative analysis of meteorological drought based on the SPI and SPEI indices. *High Tech and Innovation Journal* **3**, 15–27.

Fotovatikhah, F., Herrera, M., Shamshirband, S., Chau, K. W., Faizollahzadeh Ardabili, S. & Piran, M. J. 2018 Survey of computational intelligence as basis to big flood management: Challenges, research directions and future work. *Engineering Applications of Computational Fluid Mechanics* **12** (1), 411–437.

Ghalkhani, H., Golian, S., Saghafian, B., Farokhnia, A. & Shamseldin, A. 2013 Application of surrogate artificial intelligent models for real-time flood routing. *Water and Environment Journal* **27** (4), 535–548.

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest

Goyal, S. & Goyal, G. K. 2011 Cascade and feed-forward backpropagation artificial neural networks models for prediction of sensory quality of instant coffee flavoured sterilized drink. *Canadian Journal on Artificial Intelligence, Machine Learning and Pattern Recognition* **2** (6), 78–82.

Hassanvand, M. R., Karami, H. & Mousavi, S. F. 2018 Investigation of neural network and fuzzy inference neural network and their optimization using meta-algorithms in river flood routing. *Natural Hazards* **94**, 1057–1080.

Huang, S., Chang, J., Huang, Q. & Chen, Y. 2014 Monthly streamflow prediction using modified EMD-based support vector machine. *Journal of Hydrology* **511**, 764–775.

Jamei, M., Ali, M., Malik, A., Prasad, R., Abdulla, S. & Yaseen, Z. M. 2022 Forecasting daily flood water level using hybrid advanced machine learning based time-varying filtered empirical mode decomposition approach. *Water Resources Management* **36** (12), 4637–4676.

Katipoğlu, O. M. & Sarıgöl, M. 2023a Prediction of flood routing results in the Central Anatolian region of Türkiye with various machine learning models. *Stochastic Environmental Research and Risk Assessment* **37**, 1–20.

Katipoğlu, O. M. & Sarıgöl, M. 2023b Coupling machine learning with signal process techniques and particle swarm optimization for forecasting flood routing calculations in the Eastern Black Sea Basin, Türkiye. *Environmental Science and Pollution Research* **30**, 1–18.

Katipoğlu, O. M. & Sarıgöl, M. 2023c Application of boosted tree algorithm with new data preprocessing techniques in the forecasting one day ahead streamflow values in the Tigris basin, Türkiye. *Journal of Hydro-Environment Research* **50**, 13–25.

Latt, Z. Z. 2015 Application of feed-forward artificial neural network in Muskingum flood routing: A black-box forecasting approach for a natural river system. *Water Resources Management* **29**, 4995–5014.

Mosavi, A., Ozturk, P. & Chau, K. W. 2018 Flood prediction using machine learning models: Literature review. *Water* **10** (11), 1536.

Munawar, H. S., Hammad, A. W. & Waller, S. T. 2021 A review on flood management technologies related to image processing and machine learning. *Automation in Construction* **132**, 103916.

Nama, A. H., Abbas, A. S. & Maatooq, J. S. 2022 Field and satellite images-based investigation of rivers morphological aspects. *Civil Engineering Journal* **8** (7), 1339–1357.

Nikoo, M., Ramezani, F., Hadzima-Nyarko, M., Nyarko, E. K. & Nikoo, M. 2016 Flood-routing modeling with neural network optimized by social-based algorithm. *Natural Hazards* **82**, 1–24.

Node Farahani, N., Farzin, S. & Karami, H. 2018 Flood routing by kidney algorithm and Muskingum model. *Natural Hazards* 1–19.

Norouzi, H. & Bazargan, J. 2020 Flood routing by linear Muskingum method using two basic floods data using particle swarm optimization (PSO) algorithm. *Water Supply* **20** (5), 1897–1908.

Pal, S. C., Chowdhuri, I., Das, B., Chakrabortty, R., Roy, P., Saha, A. & Shit, M. 2022 Threats of climate change and land use patterns enhance the susceptibility of future floods in India. *Journal of Environmental Management* **305**, 114317.

Pashazadeh, A. & Javan, M. 2020 Comparison of the gene expression programming, artificial neural network (ANN), and equivalent Muskingum inflow models in the flood routing of multiple branched rivers. *Theoretical and Applied Climatology* **139**, 1349–1362.

Paul, A. & Das, P. 2014 Flood prediction model using artificial neural network. *International Journal of Computer Applications Technology and Research* **3** (7), 473–478.

Razavi, S. & Karamouz, M. 2007 Adaptive neural networks for flood routing in river systems. *Water International* **32** (3), 360–375.

Sarıgöl, M. & Katipoğlu, O. M. 2023 Estimation of hourly flood hydrograph from daily flows using machine learning techniques in the Büyük Menderes River. *Natural Hazards* 1–17.

Sarigöl, M. & Yesilyurt, S. N. 2022 Flood routing calculation with ANN, SVM, GPR, and RTE methods. *Polish Journal Of Environmental Studies* **31** (6), 1–8.

Sutopo, Y., Utomo, K. S. & Tinov, N. 2022 The effects of spillway width on outflow discharge and flow elevation for the Probable Maximum Flood (PMF). *Civil Engineering Journal* **8** (4), 723–733.

Tawfik, A. M. 2023 River flood routing using artificial neural networks. *Ain Shams Engineering Journal* **14** (3), 101904.

Tayfur, G. 2017 Modern optimization methods in water resources planning, engineering and management. *Water Resources Management* **31** (10), 3205–3233.

Tayfur, G., Singh, V. P., Moramarco, T. & Barbetta, S. 2018 Flood hydrograph prediction using machine learning methods. *Water* **10** (8), 968.

Wu, C. L., Chau, K. W. & Li, Y. S. 2009 Methods to improve neural network performance in daily flows prediction. *Journal of Hydrology* **372** (1–4), 80–93.

Yang, T., Sun, F., Gentine, P., Liu, W., Wang, H., Yin, J., Du, M. & Liu, C. 2019 Evaluation and machine learning improvement of global hydrological model-based flood simulations. *Environmental Research Letters* **14** (11), 114027.

Yaseen, M., El-Shafie, A., Jaafar, O., Afan, H. A. & Sayl, K. N. 2015 Artificial intelligence-based models for streamflow forecasting: 2000–2015. *Journal of Hydrology* **530**, 829–844.

Yuan, X., Zhang, X. & Tian, F. 2020 Research and application of an intelligent networking model for flood forecasting in the arid mountainous basins. *Journal of Flood Risk Management* **13**, e12638.

Zhang, X., Zhang, Q., Zhang, G., Nie, Z. & Gui, Z. 2018 A hybrid model for annual runoff time series forecasting using Elman neural network with ensemble empirical mode decomposition. *Water* **10** (4), 416.

Zhao, X., Chen, X., Xu, Y., Xi, D., Zhang, Y. & Zheng, X. 2017 An EMD-based chaotic least squares support vector machine hybrid model for annual runoff forecasting. *Water* **9** (3), 153.

Zhou, L. & Kang, L. 2023 A comparative analysis of multiple machine learning methods for flood routing in the Yangtze River. *Water* **15** (8), 1556.

First received 14 March 2023; accepted in revised form 15 October 2023. Available online 31 October 2023

Downloaded from http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2023.288/1333464/ws2023288.pdf
by guest