

Research Article

Using Evolving ANN-Based Algorithm Models for Accurate Meteorological Forecasting Applications in Vietnam

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The reproduction of meteorological tsunamis utilizing physically based hydrodynamic models is complicated in light of the fact that it requires large amounts of information, for example, for modelling the limits of hydrological and water driven time arrangement, stream geometry, and balanced coefficients. Accordingly, an artificial neural network (ANN) strategy utilizing a backpropagation neural network (BPNN) and a radial basis function neural network (RBFNN) is perceived as a viable option for modelling and forecasting the maximum peak and variation with time of meteorological tsunamis in the Mekong estuary in Vietnam. The parameters, including both the nearby climatic weights and the wind field factors, for finding the most extreme meteorological waves, are first examined, through the preparation of evolved neural systems. The time series of meteorological tsunamis were used for training and testing the models, and data for three cyclones were used for model prediction. Given the 22 selected meteorological tidal waves, the exact constants for the Mekong estuary, acquired through relapse investigation, are $A = 9.5 \times 10^{-3}$ and $B = 31 \times 10^{-3}$. Results showed that both the Multilayer Perceptron Network (MLP) and evolved radial basis function (ERBF) methods are capable of predicting the time variation of meteorological tsunamis, and the best topologies of the MLP and ERBF are $I_3H_8O_1$ and $I_3H_{10}O_1$, respectively. The proposed advanced ANN time series model is anything but difficult to use, utilizing display and prediction tools for simulating the time variation of meteorological tsunamis.

1. Introduction

In the last decade, many hybrid artificial intelligence learning techniques have been adapted for environmental issues [1, 2]. Based on successful cases, novel hybrid tools can be adopted for the practical issue of the prediction of tidal waves. A meteorological tsunami is a meteorological tide caused by an unusual increase in the level of ocean water, initiated by the low atmospheric pressures related to a hurricane or typhoon, such as those which regularly strike Vietnam [3]. The height of a meteorological tidal wave at a specific area is obtained by subtracting the anticipated galactic tide from the real recorded ocean level [4]. The danger of flooding in low-lying beach front regions is heightened by the occurrence of higher spring tides alongside genuine meteorological tidal waves.

The least difficult technique for predicting the most extreme meteorological tidal wave is to utilize the exact

equations [4, 5]. For the most part, meteorological waves have been predicted utilizing numerical techniques. For instance, Castelle et al. [6] adapted the limited component technique for this purposed, while Almar et al. [7] applied the limited distinction strategy with nonlinear shallow water conditions to reconstruct meteorological tidal waves. Coupled wave-flood models have been proposed so that mimic beach front flooding arising from meteorological tidal waves and waves is produced by tropical storms. Abrams and Hook [8] built an operational beach front flooding early warning framework that considered both wave setup and meteorological tidal waves, in which the meteorological tidal wave is anticipated by the model. Plant et al. [9] developed coordinated Monte Carlo and hydrodynamic models for assessing extraordinary water levels that happened as an outcome of a meteorological tidal wave.

More recently, the development of innovative neural system methods has been connected to the displaying of nonlinear characteristics. For instance, Yetilmezsoy et al. [10] utilized feedforward back-spread neural systems to predict the flow rate at a waterway mouth and utilized neural systems to fabricate a model for ongoing wave forecasting. The outcomes demonstrate that neural system models perform better than autoregressive models for wave forecasts. Lin et al. [11] utilized a back-engendering neural system for ongoing tide forecasting and utilized the back-proliferation neural system for enhancing the time arrangement of wave information utilizing wave records from neighboring stations. Mabrouk et al. [12] developed a back-proliferation neural system which utilized neural systems, diverse neural system topologies, and transient perception information to anticipate long term ocean levels.

Therefore, we believe that developing tools for the prediction of oceanic systems is important including the preparation of an ocean level time arrangement model utilizing information from past typhoons to predict future storms. The models have only been used to predict the rise in ocean levels during storms, rather than meteorological tidal waves [12]. However, galactic tides need to be considered in combination with meteorological tidal waves in order to build models for the forecasting of increased ocean levels during tempests. At the present time, galactic tides can be precisely anticipated by utilizing examination or numerical strategies [4]. Also, the combination of the most extreme meteorological tidal waves in addition to elevated spring tides should be considered when predicting the risk of beach front flooding. Accordingly, the initial part of this examination is to improve a neural system model for evaluating the most extreme meteorological tidal waves.

Almonacid-Caballer et al. [4] built a back-engendering neural system for anticipating the time variation of meteorological tidal waves. They proposed 18 factors as the sources of information, including the galactic tidal level. They appeared to disregard the meaning of a meteorological tidal wave brought about by unusual meteorological conditions not just reliant upon the galactic tide. Therefore, the second part of this present study is devoted to anticipating the time variation of meteorological tidal waves by utilizing both multilayer recognition and outspread premise work strategies, without requiring many major meteorological variables. The advantages of adopting these particular evaluation criteria for tidal waves are demonstrated but the methodology still needs to be extended to practical issues. Therefore, we examine the presented model which incorporates neural networks and evolved algorithms by examining records including the relationship coefficient and comparison of the root-mean-square error between the observed and predicted results.

2. Evolved Algorithm (EA)

The evolutionary algorithm and artificial neural network (ANN) methods are part of the data preparation framework, which are modelled upon natural processes. The methodology is discussed in detail below.

2.1. Multilayer Perceptron Network (MLP). The MLP is a directed learning procedure with a topology comprising input, hidden neurons, and output. The MLP information is sent from the input layer to the final layer and the feed-forward strategy is formulated as follows:

$$y_j = f(\text{net}_j),$$

$$\text{net}_j = \sum_{i=1}^N W_{ij}X_i - B_j, \quad (1)$$

where the output variable y_j and weight W_{ij} denote the j th and i th neuron, and the input X_i variable, transformation function $f(\text{net}_j)$, threshold B_j , and consolidation function net_j are the simulated biomimetic neuron input signal and a biomimetic nonlinear function, for the j th neuron and the j th neuron, respectively.

A function, normally an S-bend called a sigmoid capacity is incorporated, which builds soundness and can be composed as follows:

$$y_j = f(\text{net}_j) = (1 + e^{-\text{net}_j})^{-1}. \quad (2)$$

The principle strategy in an MLP system network is the spread of the regression to get the last final patterns. The angle drop technique is used in this investigation to determine the weights of the system and to change the weights for limiting mistakes in the yield. The calculation is discussed in detail by Van Gent et al. [13].

2.2. Evolved Radial Basis Function (RBF) Network. The topology of the RBF is fundamentally like that of the MLP; therefore, the most invaluable component of the RBF system is its rapid learning pace, which means it tends to be connected through progressive frameworks. The output and Gaussian function can be formulated as follows:

$$F(x') = \sum_{j=1}^N w_j \varphi_j(x') + B_j, \quad (3)$$

$$\varphi_j(x') = \exp\left(-\frac{\|x' - U_j\|^2}{2\sigma_j^2}\right), \quad (4)$$

where the input vector x' , weight w_j , threshold B_j , basis function φ_j , and output function $F(x')$ are in line with the dimensions of equation (3). The smoothing parameter σ_j controls the radial basis function with the neuron center U_j in the hidden layer.

The computational speed of the Evolved Bat Algorithm (EBA) is quick since its structure is planned with basic and light calculations. Unlike other swarm insight calculation methods, there is just one noteworthy variable which ought to be resolved before utilizing the EBA, i.e., the mechanism for sound waves. The chosen medium decides on the size of progression for the development of the virtual operator in the arrangement space. As a rule, the progression size affects the query item. At the point when the selected estimate is overlarge, virtual operators in the arrangement space

reverberate quickly, starting with one then onto the next significance. It is very possible to pass over the directions where a global ideal exists, without focusing on them. Conversely, when the progression size is excessively small, the virtual operators may be effectively caught in a nearby ideal, as indicated by Tsai et al. [] in the selected medium of air, which is the indigenous habitat of bats. The steps of EBA are as follows. (a) Initialization: the human agent distributes the solution space by randomly assigning coordinates. (b) Move: the human agent generates a random number and checks if it is greater than the fixed pulse emissivity. If the result is positive, the random walk process is used to move the human agent, as defined by

$$\begin{aligned} D &= 0.17 \cdot \Delta T, \\ x_i^t &= x_i^{t-1} + D, \end{aligned} \quad (5)$$

where D denotes the distance; ΔT indicates the time taken between sending the sound wave and receiving the echo; x_i^t indicates the coordinate of the i th artificial agent; and t is the iteration number.

$$x_i^{tR} = \beta \cdot (x_{\text{best}} - x_i^t), \quad \beta \in [0, 1], \quad (6)$$

where β is a random number; x_{best} indicates the coordinate of the nearest solution found so far over all artificial agents; and x_i^{tR} represents the new coordinates of the artificial agent after the operation of the random walk process. (c) Assessment: the suitability of the simulated specialists is determined by the user characterized wellness capacity and refreshed to determine the closest to the best arrangement. (d) End: the ending conditions are checked to decide whether to return to stage 2 or end the program, yielding the closest best arrangement. The wellness capacity utilized in the assessment procedure should be characterized by the user. Briefly, the wellness capacity is a mathematical portrayal of the arrangement space, which the user needs to take care of. The wellness capacity should be modified to manage various issues to reflect the consequences of the arrangements found. Subsequently, we add structure a wellness work in the algorithm for the evolved radial basis function (ERBF).

3. Models for Maximum Meteorological Tsunami

3.1. Data Sources. Information for this investigation was gathered from stations in the Mekong estuary and then utilized for the fabrication of meteorological tidal wave prediction models. Information on meteorological waves and climatic conditions during storms that happened from 1996–2005 was obtained from this station. An aggregated set of 22 storm occasions that affected the Mekong estuary was chosen [14]. Prior to preparing a neural system, pre-processing of data is important to ensure that it conforms to the scope of the process utilized in the system. The standardized formula is

$$x_{\text{inew}} = \left[D_{\min} + \frac{x_{\text{old}} - x_{\min}}{x_{\max} - x_{\min}} (D_{\max} - D_{\min}) \right], \quad (7)$$

where D_{\min} and D_{\max} represent the range to be mapped; x_{\max} and x_{\min} are the maximum and minimum values of all data; and x_{old} and x_{inew} are the values before and after transformation, respectively.

Two agreement indices are used to evaluate the feasibility, root-mean-square errors (RMSE) and correlation coefficients (CC) in which the observation \hat{y}_k , prediction y_k , average \bar{y} , and prediction average \bar{y} consist of n data:

$$\begin{aligned} \text{RMSE} &= \sqrt{\frac{\sum_{k=1}^n (y_k - \hat{y}_k)^2}{n}}, \\ \text{C.C.} &= \frac{\sum_{k=1}^n (y_k - \bar{y})(\hat{y}_k - \bar{y})}{\sqrt{\sum_{k=1}^n (y_k - \bar{y})^2 \sum_{k=1}^n (\hat{y}_k - \bar{y})^2}}. \end{aligned} \quad (8)$$

3.2. Prediction by Empirical Formula. Investigation of meteorological waves at explicit spots becomes increasingly meaningful and necessary. The most extreme meteorological tidal waves in combination with the highest spring tides are examined to predict the danger of coastal immersion. Madsen and Plant [5] suggested that a bigger focal point of low weight would prompt the account to determine an exact equation as far as a solitary parameter and the weight at the focal point of the tempest, to expectation the estimation of the extraordinary meteorological tidal wave. An exact formulation for forecasting the largest meteorological wave:

$$\zeta_{\max} = A \Delta P + B V_{\max}^2 \cos \theta, \quad (9)$$

where the maximum meteorological tsunami is ζ_{\max} ; maximum pressure difference is ΔP ; maximum wind speed is V_{\max} during the cyclone; angle θ ; the tide-gauge station normal line; and A and B are constants determined empirically from the data. In light of the 22 chosen meteorological tidal waves, the exact constants for the Mekong estuary, acquired through relapse investigation, are $A = 9.5 \cdot 10^{-3}$ and $B = 31 \cdot 10^{-3}$.

3.3. Estimations by Evolved Neural Networks. In light of the parameters utilized in three models with various consolidated information, factors for both MLP and EBRF neural systems are explored. In the main model, Model A, as in [5], the most extreme weight contrast is the main variable considered in the estimation of the largest meteorological tidal wave. Another variable, the comparable wind field, is added to produce Model B. Finally, notwithstanding the most extreme weight contrast, the comparison rate is also added to produce Model C. The three models are $\zeta_{\max} = f(\Delta P)$, $\zeta_{\max} = f(\Delta P, U)$, and $\zeta_{\max} = f(\Delta P, U, Q)$, where $U = V_{\max}^2 \cos \theta$ is the wind field factor and Q is the upstream flow rate.

Compared to other major rivers in the world, the Mekong River (Figure 1) is a medium-sized basin unevenly distributed within six Southeast Asian countries. The annual discharge of the river basin is 475 km^3 , which is much higher than that of river basins of the same size. This means that the watershed is much affected by tropical monsoons. In this



FIGURE 1: The Mekong river mainstream gauge stations.

paper, actual assessments will be made on the tidal water level data measured during storms which affected Vietnam from 1996–2005. The topologies of the developed neural systems are exhibited as “ $I_x H_y O_z$ ” with I_1 , I_2 , and I_3 for Models A, B, and C, individually, and the yields of all models are O_1 . The ideal number of neurons is dependent upon the individual complexities case by case and is for the most part obtained by experimentation. According to the table from [15], Table 1 demonstrates the presentation of Models A, B, and C for both the MLP and ERBF neural systems, as well as the exact equation by Almonacid-Caballer et al. [4]. It can be seen that the outcomes from Model B are more exact than those from Model A. From this it can be inferred that, for exact estimation of the meteorological tidal wave, one should not be too reliant on one single weight variable, despite the fact that the wind speed relies upon the weight insufficiency. It can likewise be seen that the presentation of the advanced neural system is a vast improvement over than that of the exact equation, despite the fact that the information factors utilized in Model B are equivalent to those utilized in Almar et al. [7] and Almonacid-Caballer et al. [4]. This result demonstrates that the developed neural systems are appropriate for displaying the nonlinear interrelationships among the physical parameters.

In this examination of the meteorological tidal wave in an estuary, the impact of the upstream flow is additionally researched. As per the estimations from the records in Table 2, the presentation of Model C is on a par with Model B. This shows that the impact of the upstream flow on the

meteorological current in the Mekong estuary is far less than the impact of the wind field or barometric pressure.

Figure 2 shows a comparison of the maximum meteorological tsunamis obtained for the MLP and ERBF evolved neural networks with Model B, as well as with the empirical formula by Almonacid-Caballer et al. [4]. The results for both the MLP and ERBF evolved neural networks (ENN) are precise, especially for the larger meteorological tsunamis; however, the estimations obtained using the empirical formula are mostly lower than the observed values.

4. Prediction Models for Time Series of Meteorological Tsunamis

The ENN for predicting the variation of meteorological tsunamis with time can be developed by inputting the time variations in atmospheric pressure and accompanying wind speed and direction, the major physical parameters used in Model B. In addition, $\zeta(t+1) = f[\Delta P(t+1), U(t+1), \zeta(t)]$ is used as an input variable for the ENN models, which shows that the time series of the meteorological tsunami can be consecutively predicted. This study uses a multilayer, multioutput feedforward ANN model, which is trained using the precomputed storm surge and onshore flooding datasets. We provide a schematic diagram of a multilayer, multioutput ANN model that shows the dependence of ANN on the model parameters, such as the number of neurons, transfer functions, threshold functions (training functions), and input and output data for

TABLE 1: Meteorological tidal waves with different models (RMSE = O₁, C.C. = O₂).

Models		I _x H _y O _z	Agreement indices		Input variables
Empirical formula		—	O ₁	0.267	$\Delta P, U$
Model A	MLP	I ₁ H ₇ O ₁	O ₂	0.565	ΔP
			O ₁	0.156	
Model A	ERBF	I ₁ H ₈ O ₁	O ₁	0.172	ΔP
			O ₂	0.752	
Model B	MLP	I ₂ H ₇ O ₁	O ₁	0.048	$\Delta P, U$
			O ₂	0.983	
Model B	ERBF	I ₂ H ₁₁ O ₁	O ₁	0.094	$\Delta P, U$
			O ₂	0.935	
Model C	MLP	I ₃ H ₆ O ₁	O ₁	0.038	$\Delta P, U, Q$
			O ₂	0.985	
Model C	ERBF	I ₃ H ₁₀ O ₁	O ₁	0.110	$\Delta P, U, Q$
			O ₂	0.906	

TABLE 2: The predictions for meteorological waves.

Cyclone	Methods	RMSE (mg/kg)	Correlation coefficient
A	MLP method	0.074	0.886
A	ERPF method	0.077	0.886
B	MLP method	0.032	0.984
B	ERPF method	0.070	0.881
C	MLP method	0.118	0.924
C	ERPF method	0.090	0.919

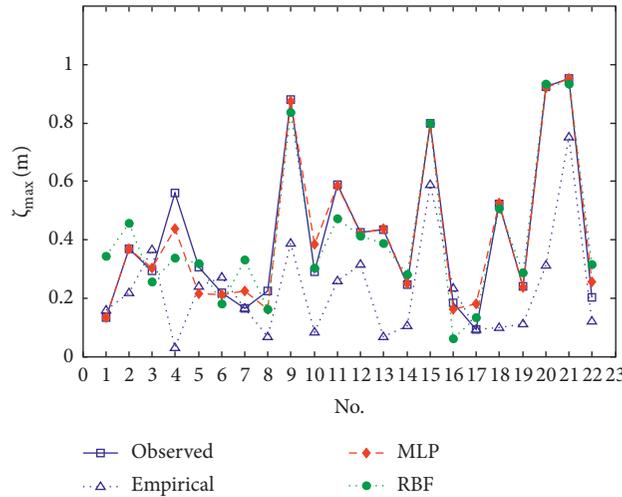


FIGURE 2: Maximum meteorological waves with three approaches.

training. Specifying a smaller number of neurons can hinder the learning process, while specifying a larger number of neurons can lead to overtraining. The combination of transfer function and training function for each layer is also applicable. This first needs to be determined through trial and error, and it can provide confidence in using the optimal amount. For training purposes, more than 100 combinations from cyclone records and common tidal conditions were used as input variables for the ANN model. A similar number of multiple scenarios were also generated for storm surge and crossshore flooding (generated using the above combination of input parameters) for 70 coastal destinations, which is the output of the ANN

model. Tide information from the 3 marked stations is used to train the ANN model because it is the source of real-time tide information that can be used for this analysis. For a further comparison of the powerful tools of training models, please see Ardalani-Farsa and Zolfaghari [16]; Erdil and Arcaklioglu [17]; Menezes and Barreto [18]; Pisoni et al. [19]; Zemouri et al. [20]; Sergeev et al. [21]; and the references therein. In general, the nearby climate weights and breeze field factors are used as inputs to the ANN model, with the output parameters being the storm surge and meteorological waves. A more complete picture of the accuracy of the model can be obtained with the root mean squared relative error (RMSRE), which could also

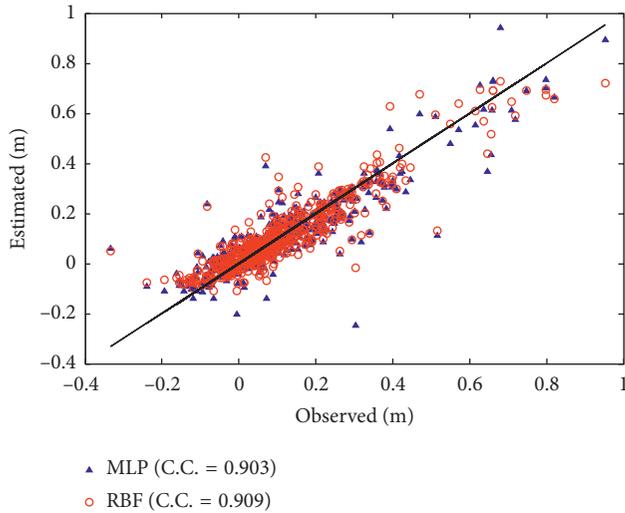


FIGURE 3: Comparison of MLP and ERBF evolved neural networks.

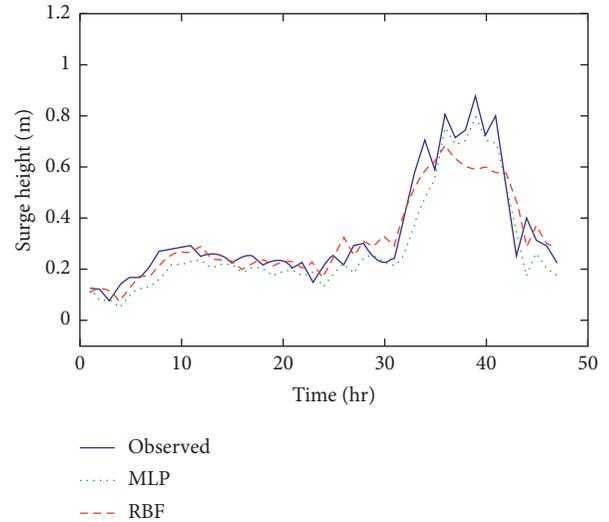


FIGURE 5: Comparison of the MLP and ERBF for cyclone B (Pakse).

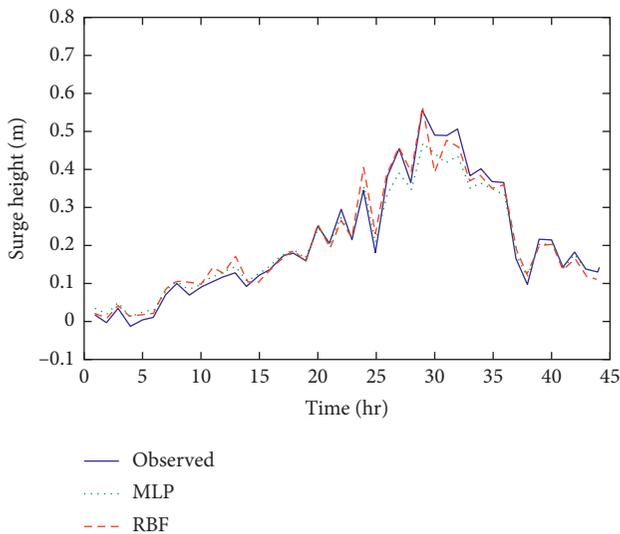


FIGURE 4: Comparison of the MLP and ERBF for cyclone A (Mukdahan).

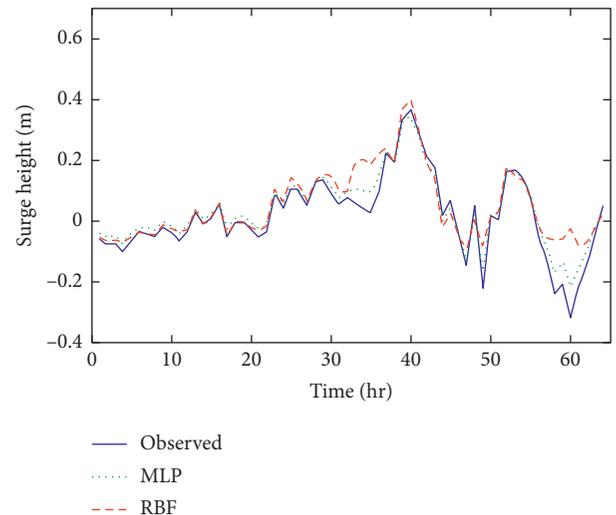


FIGURE 6: Comparison of the MLP and ERBF for Cyclone C (Kratie).

strengthen the reliability of the models. For a more detailed discussion of the operations, refer to Willmott et al. [22–24].

5. Results and Discussion

The time series for meteorological tsunamis for nine cyclone events are selected. The scattering diagram for the correlation coefficients for both MLP and ERBF ENN is depicted in Figure 3. The high correlation and low RMSE obtained indicates that both MLP and ERBF ENNs are capable of predicting the time variation of meteorological tsunamis. The best topologies of the MLP and ERBF are $I_3H_8O_1$ and $I_3H_{10}O_1$, respectively.

Figures 4–6 show the prediction results obtained with the trained ENNs for the time series of meteorological tsunamis caused by Cyclone A, Cyclone B, and Cyclone C, respectively. Two of these can be categorized as severe

cyclones and one is a midstrength cyclone. It can be seen that the meteorological tsunamis could be well prediction by the present ENNs using 3 major physical factors without the 18 input factors presented in Chen et al. [25–27].

The solid line represents the predicted result, and the dashed line represents the observed value. From a comparison of the results shown in the figure, it is found that the predicted trend is quite consistent with the actual observed value. It can also be seen from the distribution in the figure that their correlations are above 0.94, which shows that their prediction effect is quite good. As for the tidal deviation of each forecast case, the solid line in the figure represents the predicted value minus the harmonic analysis of the tide level, and the dashed line represents the measured value minus the harmonic analysis of the tide level. Comparison shows that the phenomenon is lower than the actual value, but the trend of the tide level can still be fully described.

6. Conclusions

Meteorological tidal waves brought about by meteorological elements are more perplexing than flooding related to cosmic tides. They are also difficult to definitely predict utilizing experimental equations. Here, examination is conducted using the innovative MLP and ERBF advanced neural systems to construct models to predict a variety of meteorological torrents dependent on recorded information. First, the ideal developed neural system models were prepared to gauge the most extreme meteorological torrents dependent on the major meteorological elements including the climatic weight distinction, wind speed, and wind direction. Then, the central point with variations with time was connected to construct the prediction models to evaluate the time evolution of meteorological waves. The estimation results for the most extreme meteorological waves demonstrate that both the MLP and ERBF advanced neural system models are exact, especially for the bigger meteorological tidal waves. The time variation of meteorological tidal waves shows that tidal waves at time $t + 1$ can be anticipated well by advanced neural systems depending on 3 noteworthy meteorological variables, including the neighborhood weight, wind speed, and heading time $t + 1$ and the flood tallness at a past time t .

Data Availability

All data analyzed during this study are included in this article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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