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WAVELET TRANSFORM AND NEURAL NETWORK MODEL FOR STREAMFLOW FORECASTING

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ABSTRACT

Analysis and fast streamflow forecasting are essential. Reliable predicting for river flow, as per the major source of usable water, which can be a crucial factor in the drought analysis and construction of water-related infrastructures. Data-driven and hybrid methods are increasingly being used to address the nonlinear and variable components of hydraulic processes. In this paper, a streamflow forecasting model is built utilizing Neural Network (NN) and Wavelet Transform (WT) at Western Australia for Ellen Brook River with the application of Railway Parade station. Initially, the sequences of signals are applying to the wavelet to be evaluated at several levels and extract a sequence of different features from the chosen output in the wavelet. Then, the obtained output is presented to the neural network for tuning to get the best intermittent streamflow forecasting. The existing input and structures are designed for streamflow forecasting. The proposed model has a better performance compared to the previous models. The proposed model is beneficial for application of forecasts to examine the relation between the characteristics of river flow, optimal decomposition degree, data duration, and the precise wavelet transform form.
Keywords: *Neural Network (NN), Streamflow forecasting, Wavelet Transform (WT).*

1. INTRODUCTION

Water request is growing because of residents growing and growths in the agricultural and industrial fields. As a source of global change, urbanization and wasteful depletion of groundwater, the availability of surface water is expected to decrease. On the other hand, severe weather conditions in numerous locations around the world result in flooding, droughts, and heatwaves [1].

Environmental disasters (e.g., flood) are destructive and general natural risks cause damage to both property and lifetime in numerous portions of the world every year [2]. based on to the Research Center of Disaster Epidemiology [3] that the greatest reported hazard is floods, amounting to up to 33% of the disasters until the year 2011.

Reliable knowledge of the existing and potential state of water availability is critical to effectively preserving the scarce water supplies and mitigating floods [4]. Precise predicting of river flow, as the major resource of usable water [5], is also a crucial factor in the research of lack and the construction of water-related structures. Several studies have been already conducted to enhance the precision and reliability of river flow forecasts [6]. Scientists are interested in developing and researching different forms of hydrological predicting approaches to accomplish enhanced control for restricted water supplies and decrease the hazard of upcoming flooding [7]. Forecasting is the way to create forward-knowledge projections depends on historical and current data, which is commonly done using pattern investigation [8].

Adaptive-NeuroFuzzy Inference System (ANFIS) is one of the computational intelligence technique base fuzzy-logic approach. Zadeh et al. [9] pioneered the knowledge of fuzzy logic, modelling of fuzzy IA applied in numerous engineering applications since the previous decade, together with some hydrology-related projects. ANFIS, which was originally introduced by Jang [10], which offer the advantages for techniques of Neural Network (NN) and fuzzy reasoning.

The findings reported by the above-mentioned researches propose that ANFIS is a talented technique capable of reaching accurate and rapid forecasts. However, ANFIS has some disadvantages because of the limited configuration for the fuzzy inference systems (FISs). This approach is not model for input-output schemes over- extent training and might also inappropriate to the extreme condition forecasting [11].

Furthermore, several studies offered novel approaches to overcome different drawbacks in wide-ranging applications, such as image classification for underwater cable using deep-convolutional-neural network [12], fault detection and feature extraction by the hybrid model of long short-term memory and stacked autoencoders (SAE) [13], maintenance optimization using the approach of coevolutionary multi-objective particle swarm optimization [14].

The time series for river flow is a very difficult section, which includes a wide variety of frequency components. In the current developments, implementing the wavelet analysis of multi-resolution to the time series of stream flows can improve the accuracy of forecasting. Numerous scholars have designed hybrid models for the previous decade through joining model of forecasting with a wavelet. Approach of wavelet NNs is the general model of hybrid wavelet applied to forecasting of streamflow [15]. The model performance for forecasting river flow was enhanced, where various combinations of input and methods of signal processing were implemented to multi-layer NNs and backpropagation. The Haar Daubechies and Coiflet wavelet analyses have joint the model of backpropagation NN to create hybrid models NN with wavelets.

Only a few studies have investigated the combination of a technique of neuro-fuzzy and wavelet analysis for the purposes of hydrological forecasting. In [16], a novel conjoining approach (neuro-fuzzy-wavelet (NFW)) was proposed to precipitate the forecasting. Their method incorporates two transformation approaches, which are neuro-fuzzy and discrete wavelet. Approximately decomposed sub-series are created by the experiential daily precipitations by means of the discrete wavelet transformation method, and formerly precise sub-series are applied by means of inputs to the models of neuro-fuzzy aimed at predicting everyday precipitation.

In [17], the capability of the neuro-fuzzy and wavelet conjoining method for the forecasting the groundwater depth was examined. Integration of these two techniques, the neuro-fuzzy and the transformation of discrete wavelet, a proposed model is developed and improved using the neuro-fuzzy-wavelet technique. The conjunctive framework has been implemented to various joining of input of the Bondville and Perry wells systematic data of groundwater depth. An advanced streamflow forecasting model is proposed in [18] by applying the ANFIS data pre-processing techniques. For the development the model of hybrid neuro-fuzzy-wavelet (HNFW), Wavelet multiresolution investigation is joined to model of an ANFIS.

Previous studies were utilized by employing altered time lagged and streamflow series as its inputs make them in the same elements, for example, the five days before the current day are as the current inputs. Therefore, these two inputs will be similar in some elements. After the analysis process using a wavelet, the output of the wavelet is directly given to NN. However, in this study, a series of unique features are extract from the wavelet output, and then these features, which are different to each other, will be given to NN. Accordingly, the weighted coefficients could not be trained appropriately, and the wavelet neuro-fuzzy cannot train the membership functions properly.

Numerous researchers put out novel techniques for a multitude of applications [19] applied a hybrid wavelet-artificial neural network (WANN) to forecast Sobradinho Reservoir water flows seven days in advance. This work identified the best mother-wavelet for artificial neural network (ANN) forecasting and compared 1836 simulations with WANN hybrid systems to forecasts without a wavelet transform (WT) [20] created ANFIS precipitation/runoff models. Using WT in combination with the ANFIS model for runoff forecasting shows promising results, especially for monthly forecasts [21] developed a wavelet-based ANFIS model to predict monthly runoff. Comparing observed and forecasted values, they concluded the results require improvement.

In [22] suggested using the WNN for river flow modelling by developing a rainfall-runoff model for India's Malaprabha basin. To forecast the Khorasan Razavi plain's [23] groundwater level between 1992 and 2007, investigated four models: wavelet network and fuzzy system in combination with ANN, FIS, and wavelet neuro network (WNN). The ANN fared better than other models. Ahmed, et al. [24] explains how to forecast stream water levels using climatic mode indices, rainfall, and a monthly component based on periodicity. In order to estimate future streamflow water levels, this novel method discovers a better correlation between stream water level and climate mode indexes.

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In [25] created two hybrid models for monthly streamflow and rainfall forecasts (LSTM). Two streamflow and two rainfall datasets are used to validate the models.

A review of the literature reveals a significant research gap regarding the selection of the suitable hybrid wavelet neuro-fuzzy model. Nonlinear water flow behavior reduces forecast accuracy and sometimes results in forecasting errors. According to researchers, no useful research has been conducted to improve the data reduction technique. This study introduces a novel feature extraction-based method for addressing computational problems. Due to its limited structure, ANFIS has limitations. For defuzzification, rule evolution, and antecedent processing, it employs a based method. Following preprocessing and preparation of input data for the hybrid model, the data will be de-noised before to be utilized as signals.

1.1 Main Research Question:

The main research question are, which model or model combination developed in this study obtains the highest forecast accuracy and which model or model combination is most suitable for forecasting in the Ellen Brook Basin with respect to stream flow?

Sub-research questions are as follows:
- Can the pre-processing in data lead to main method increase the accuracy?
- Can the forecasting accuracy be further improved with hybrid models?

Therefore, the main objectives of this study are:
- To propose an accurate Wavelet Neural model by investigating model performance.
– To improve pre-processing using feature extraction.

Furthermore, this study offered approach of flood-forecasting depends on WT-NN to resolve the flood forecasting precision problem for the Ellen Brook River Railway Parade station, Western Australia.

The organization of the study will be as following: Section 2 elaborate on the proposed methodology. The data set is presented in Section 3. The results of the simulation implemented with the proposed method are illustrated in Section 4. Lastly, Section 5 determines the conclusion of study and future works.

2. PROPOSED METHODOLOGY

2.1. Neural Network

The full communication organization in RBF (radial basis function) can produce the networks with extra expression capability, therefore, the model would be more likely overfitting the data. To solve that problem, NN is used via the structure of sparse connection, as revealed in Figure 2. Nodes Initially are connected at a high layer to nodes at a low layer, that may efficiently decrease the total parameter numbers. Moreover, high layer nodes bear the similar weights. As shown in Figure 2, the identical weight values and arrows are the equivalent colours. This figure presents a represented illustration of feed-forward NN with a three-layer.

Radial basis function (RBF) network is consisting of three layers of feedforward neural network, which are layers of input, hidden, and output. The initial layer matches to the network inputs, the next is the hidden layer, which consists of several RBF nonlinear activation parts, and the latest layer matches to the last network output. The hidden RBF layer is consisted of several neurons with its activation function, which is the Gaussian activator for this study. The number of nodes in each layer is illustrated in figure 1.

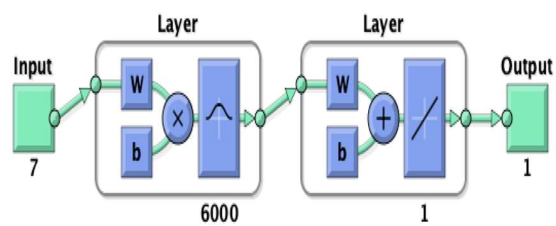

Figure 1. NN architecture.

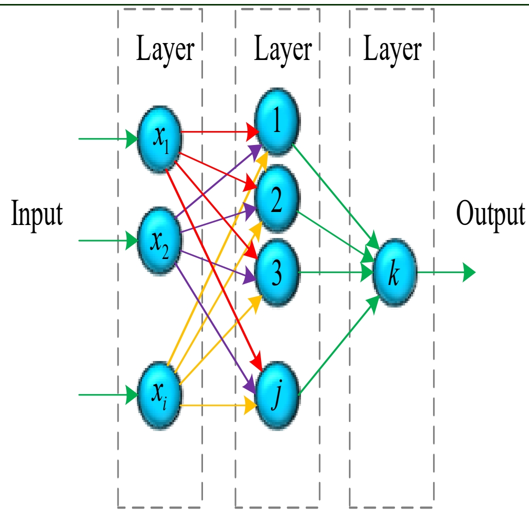

Figure 2. Layers in a neural network [26].

2.2. Wavelet Transfer

Analysis of wavelet is a signal processing method, which is of different awareness to unequal and asymmetric signals [27]. In [28], the authors presented the wavelet analysis knowledge, Wavelets' capability to estimate the transformation details of time-frequency for the continuous signal, which sets it distinct comparing with Fourier transformation. Dissimilar to the Fourier transform of short-term, the analysis of wavelet will repeatedly be varying the lengths of window to test the signal coincidentally in the domains of frequency and time. For wavelet, in fact, is besides named as mother wavelet function (Ψ) and necessity to accomplish definite mathematical necessities. The wavelet can add additional flexibility using scale of squeeze and stretch or through translating as following:

$$\Psi\_(\alpha,\beta)=1/\sqrt{\alpha}\ \Psi((t-\beta)/\alpha) \quad (\alpha>0) \quad (1)$$

where α and β are the parameters of scale and the translation, respectively. The wavelet transforms based on the wavelet function of a discrete-time series, can be constructed as following:

$$W_{\alpha,\beta} = \frac{1}{\sqrt{\alpha}} \sum_{t=1}^{N-1} f(t) \Psi^* \left(\frac{t-\beta}{\alpha}\right) \quad (2)$$

The wavelet coefficients are $W_{\alpha,\beta}$ and the duration of the series of discrete-time is N. The estimation represents the low-frequency signal and portion of high-scale, which denotes the background data for the time series. signal information of high-frequency and low-scale components offer the details of time series knowledge.

2.3. Wavelet Transform and Neural

The offered NN is an organized model with pre-processed input by the decomposition wavelet transform (DWT). This framework linked two main models of wavelet decomposition and NNs. The output of the wavelet model is used as the ANN model input.

Figure 3 displays the diagram of streamflow forecasting by NN and WT. In the first step, 70% of daily streamflow discharge is applied for training, and the remaining for testing benefits [18]. The signal series are offered to the wavelet for analysing at several levels and unique features extract action for the wanted wavelet output. And finally, the obtained output is applied to the NN for tuning and obtaining the best intermittent streamflow forecasting. The output of proposed model is the streamflow time series with benefit time for predicting, which is defined as the forecast horizon.

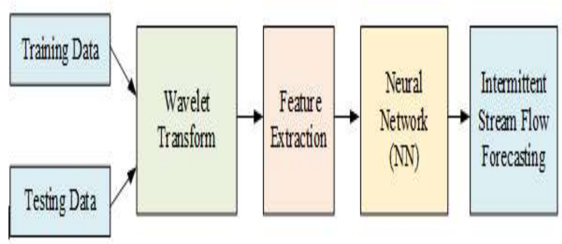

Figure 3. Forecasting of Stream Flow Diagram

3. DATA SET

The data of streamflow collected through the station of Railway Parade at the river of Ellen Brook, which are employed in this research to elaborate on the offered method. The catchment at Ellen Brook is presented in Figure 4, that is sited in western Australia around 20 km from town of Perth. The 720 km is catchment area of Ellen Brook surface water, which are ruled by three governed states. The temperature of the area is a mild typical climate of Mediterranean. In this study, the time series of day-to-day streamflow for 34 years by the length of 12410 from 1977 to 2010 was adapted by permission from [15]. Therefore, 23 years (70%) of the input data were utilized as a training potion and remailing 30% (11 years) as a testing potion. These data were gathered from the Australian Water

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Department. For time series, the initial four steps are chosen as the optimal figure for daily predicting. As deliberated, decomposition of different levels and mother wavelets are picked for improving the hybrid WNN model. The proposed decomposition level for every time series can be 8, respectively. The input of the WNN models could prove to be the features, that extract from wavelet outputs of decomposition. In the initial step, streamflow time series decay through the appointed mother wavelet toward a definite decomposition level.

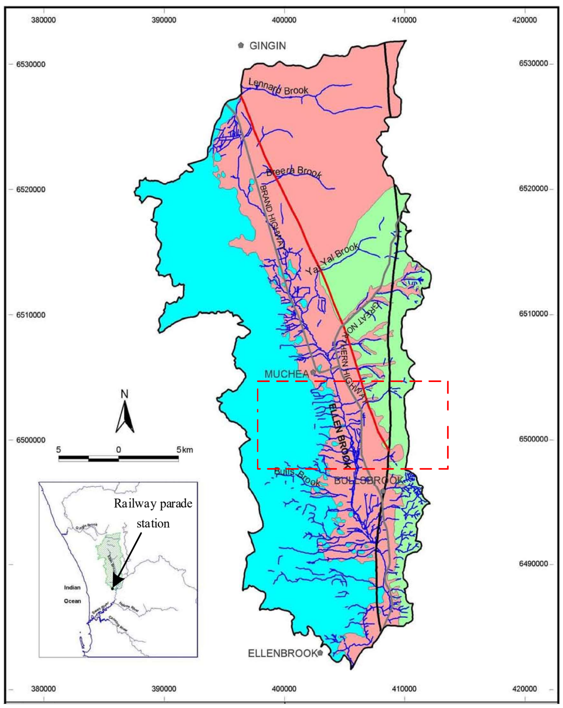


Figure 4. Map for the station of railway parade in Australian Ellen Brook River [18].

4. RESULTS AND DISCUSSIONS

After designing the new models and defining the input selection, the model was employed the forecasting the streamflow of Ellen Brook. The results of the hybrid model were compared with the previous models [18] in terms of daily-term forecasting. Thus, a combination of WT and NN can be employed to better forecast floods. At first, we have 12410 daily data which analysed in 8 levels of decomposition, as expected to increase our data because we have signals in different levels, which will be given to NN and also from each level directly give to NN as input. The size of the input data turns out to be too big that will consume time. Consequently, the 8 levels of wavelet are applied in the proposed model for extracting the unique features, which is seven features. The result proves that the proposed method reduces the number of inputs with growing the processing rapidity. The obtained signal had inputs, as final output, which was given to the RBF and NN to be tuned. Figure 5 shows the observed daily streamflow. The models can be shown to get the best fit in the experiential time series. Likewise, it can be shown in the daily modelling, unlike NN and WT simulations, the precision of the previous model [18] declines.

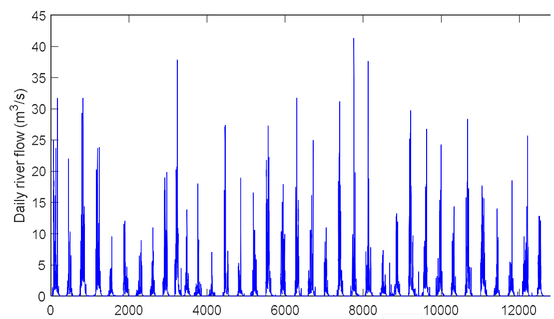


Figure 5. Observed Daily Streamflow

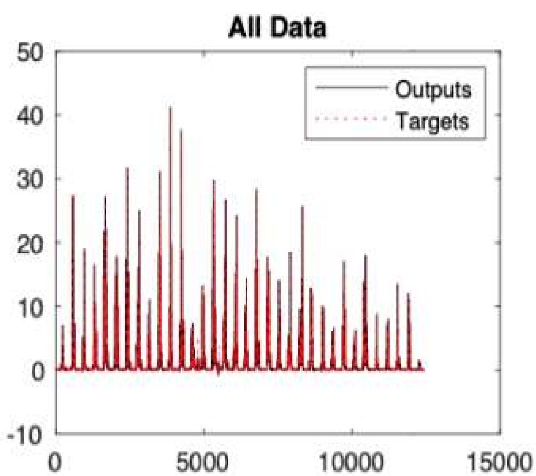
Table 1 shows the similarity between the river flow inspected and predicted using the hybrid proposed model is often stronger compared to the previous model. The Mean Squares Error (MSE), the Nash Sutcliffe-coefficient of Efficiency (NSE), and Root MSE (RMSE) were implemented to estimate the suggested method performance.

It is noticeable from Table1, the proposed model has the best performance in comparison with the earlier model in terms of training. The NSE was enhanced from 0.89 to 0.98, and the RMSE was changed from 0.19 to 0.08 m³/s. The researchers in [18] did not cover the MSE value and wholly figures in NSE and RMSE. Thus, the results validate the advantage of the offered approach.

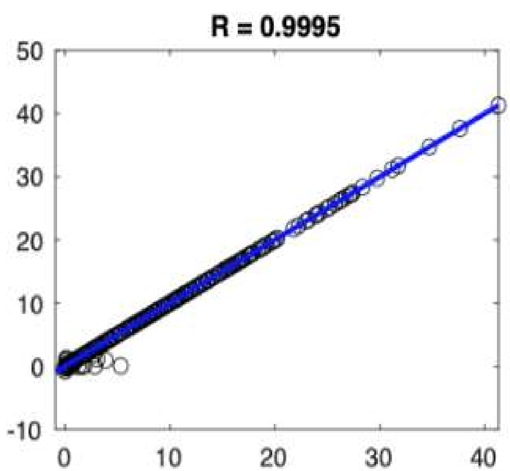
Table 1. Comparison Of The Accuracy Of The Proposed Method With That Of A Previously-Conducted Study At A Daily Level.

	Data	MSE			RMSE (m³/s)			NSE		
Daily		All	Train	Test	All	Train	Test	All	Train	Test
	Proposed	0.005	0.007	0.002	0.077	0.067	0.047	0.982	0.983	0.986
	Ref [18]	-	-	-	-	0.19	0.23	-	0.89	0.83

The scatter schemes of forecasted and detected streamflow through the NN and WT of for all data, training data and testing data are shown in Figures 6-8, respectively. These scatter plots demonstrate the best fit of the model river flow and the consistency of the model suggested in plot R quantity. Input data utilized in two categories for network training and test, which are the essential steps in training and testing the proposed process. Figure 6 (a) shows the total data. The output value is definite, and the similar target value is gotten based to the output. This quantity of the target shows the reached value. In Figure 6 (b), the correlation value (R) is revealed with a significant value of 0.09995. Figure 6 (c) displays the error value, with minor error, and normal parameters in Figure 6 (d). Based on the curve of this figure, no scattering was detected and as well for Figures 7 and 8.



(a)



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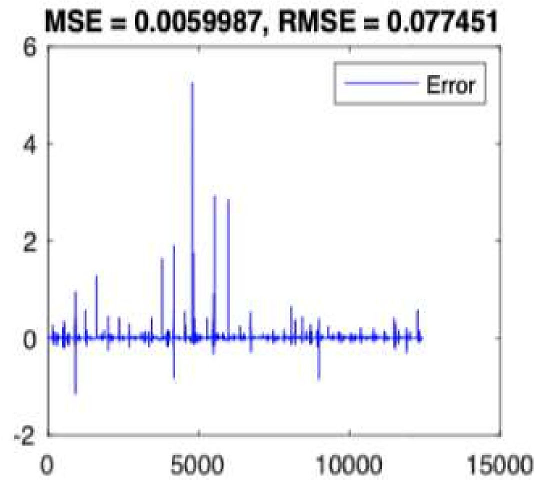

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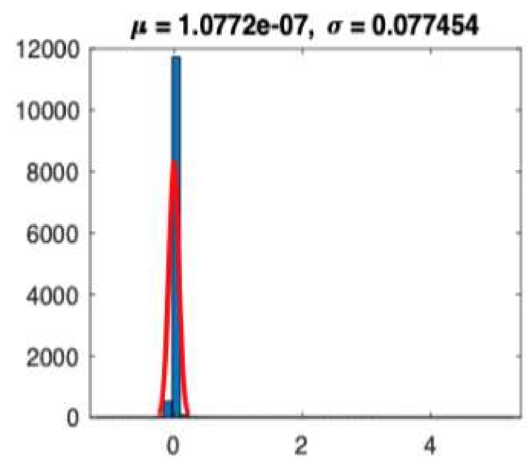
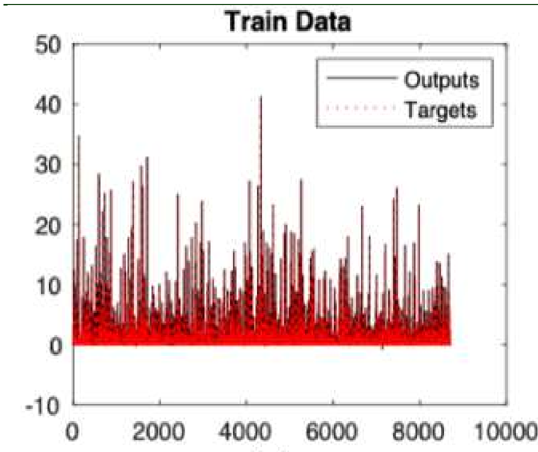
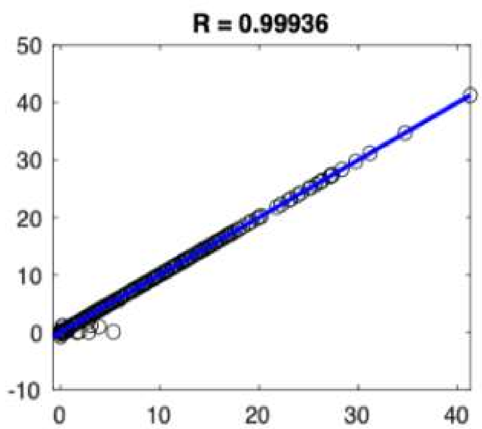


(d)

Figure 6. Scatter Schemes Of The Detected Streamflow For All Data.



(a)



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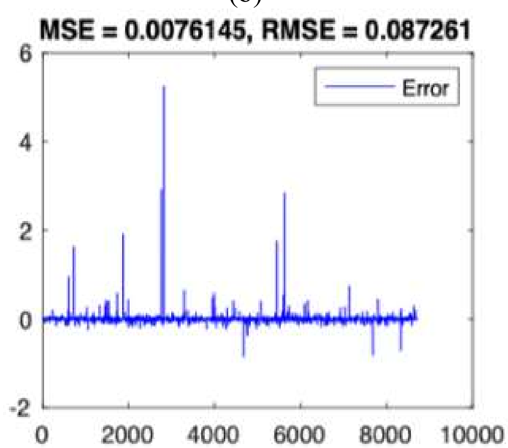

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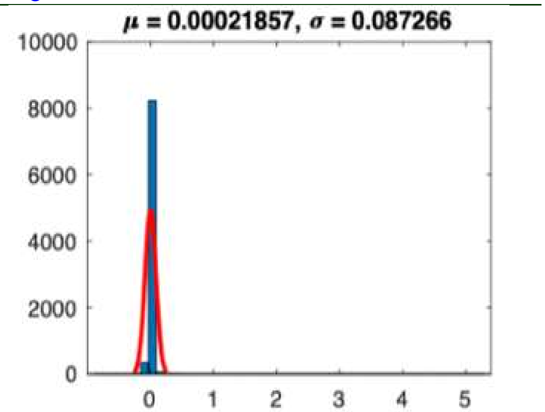
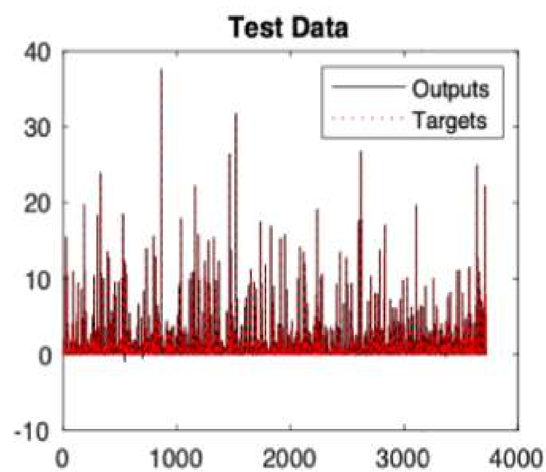
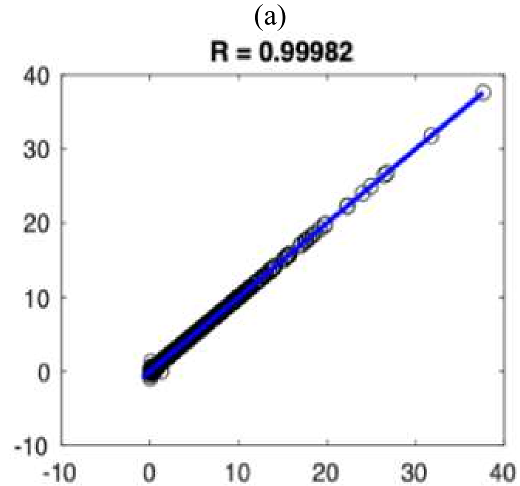


(d)

Figure 7. Scatter schemes of the detected streamflow for the train data.



(a)



(b)

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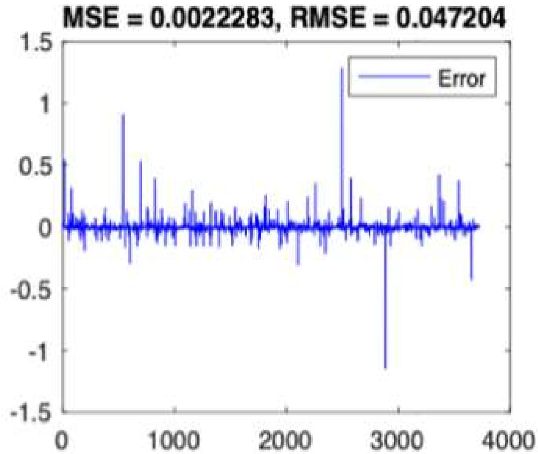

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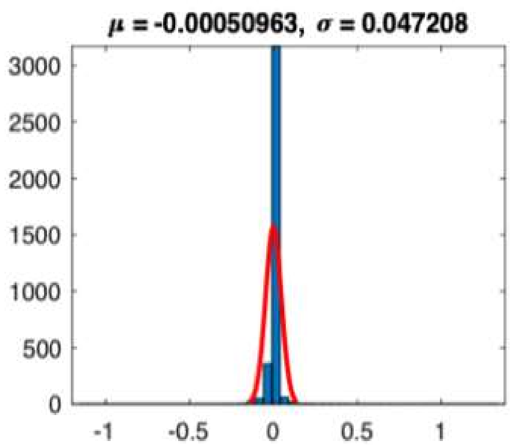

(d)

Figure 8. Scatter Schemes Of The Detected Streamflow For The Test Data.

In brief, this section compares and contrasts the use of the previous model with the new model proposed for forecasting stream flow. Once the model's framework and inputs have been set, the Ellen Brook river flow can be forecasted. First, the hybrid wavelet neuro-fuzzy model [18] is compared to the proposed new model because it has the same input and therefore can be compared to each other's outputs. As can be seen from a side-by-side comparison of the two methods, the new method appears to be better in terms of performance, as well as speed and accuracy. Figures 6, 7 and 8 illustrate the hybrid wavelet neuro-network model daily data, including correlation coefficient, scatter plots, and RMSE which compares the results of this model with the previous method.

The performance of the proposed method was assessed using the mean square error (MSE), root mean square error (RMSE), and Nash-Sutcliffe coefficient of efficiency (NSE). For daily forecasting in [18], the model's NSE increased from 0.89 to 0.98 and its RMSE decreased from 0.19 to 0.08. The output value in our study is provided, and the goal value is computed using the output value. This objective shows a significant enhancement has been attained. Figure 7 (b) provides the correlation with the value R. This amount has increased to 0.099936, which is a considerable increase. According to Table 2, the suggested model performs significantly better during training than the previous model. The root mean square error was modified, and the Nash Sutcliffe coefficient of efficiency was enhanced. The MSE value was not mentioned by the authors in [18], and all data were in NSE. This is an advantage of the suggested approach.

5. CONCLUSION AND FUTURE WORKS

Streamflow forecasting is crucial for simulation analysis and fast forecasting. The reliable predicting of river flow (the major source of accessible water supplies) is similarly the crucial factor in the lack analysis and construction for related groundworks of water. Data-driven and hybrid methods are increasingly being used to address the nonlinear and variable components of hydraulic processes.

In this article, the NN and WT methods were utilized, a streamflow forecasting model was designed for the station of Railway Parade in the Australian Ellen Brook River. Initially, a sequence of signals is introduced to the wavelet for analysing at several levels and extracting unique sequence of features from the wanted wavelet output. And then, the obtained output is offered to the NN for tuning to get the best intermittent streamflow forecasting. It is noticeable that the offered model has the best performance when compared with the previous model in terms of training.

The NSE was enhanced from 0.89 to 0.98, and RMSE was changed from 0.19 to 0.08 m^3/s. Various models with various input selections and assemblies for forecasting the daily streamflow were used. Investigation of the relationships between the characteristics of river flow and the precise wavelet conversion of the NN and shape, data size and optimal degree of decomposition will be a supportive contribution in upcoming forecasting applications. More details to enhance the precision of river flow forecasting must also be explored by adding the expected rainfall input. In enhancing the term of multi-phase ahead reliability and flow forecasts of regular river, this technique may be particularly successful.

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