

A Promising Wavelet Decomposition –NNARX Model to Predict Flood: Application to Kelantan River Flood

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Abstract – Flood is a major disaster that happens around the world. It has caused many casualties and massive destruction of property. Estimating the chance of a flood occurring depends on several factors, such as rainfall, the structure and the flow rate of the river. This research used the neural network autoregressive exogenous input (NNARX) model to predict floods. One of the research challenges was to develop accurate models and improve the forecasting model. This research aimed to improve the performance of the neural network model for flood prediction. A new technique was proposed for modelling nonlinear data of flood forecasting using the wavelet decomposition-NNARX approach. This paper discusses the process of identifying the parameters involved to make a forecast as the rainfall value requires the flow rate of the river and its water level. The original data were processed by wavelet decomposition and filtered to generate a new set of data for the NNARX prediction model where the process can be compared. This research compared the performance of the wavelet and the non-wavelet NNARX model. Experimental results showed that the proposed approach had better performance testing results in relation to its counterpart in terms of hourly forecast, with the mean square error (MSE) of $2.0491e-4$ m² compared to $6.1642e-4$ m², respectively. The proposed approach was also studied for long-term forecast up to 5 years, where the obtained MSE was higher, i.e., 0.0016 m².

Keywords – backpropagation neural network (BPNN); nonlinear autoregressive neural network with exogenous inputs (NNARX); flood prediction model; wavelet decomposition.

1. INTRODUCTION

A country's progress and development may cause it to become exposed to a natural disaster. Although common, a flood can still be disastrous to a point where it can cause massive destruction of public facilities and residential homes, and even casualties. Flooding can tremendously affect the economy of a country,

especially when the government has to spend its budget on repairing and rebuilding rather than developing the affected area. Kelantan, a state on the east coast of Malaysia, is often affected by the northeast monsoon. This monsoon wind carries rain from the Southeast Asia region from November to March, and has affected

the country on an annual basis. Monsoons have contributed to approximately 86% of the annual rainfall in the east coast areas of Malaysia [1].

The Kelantan River is 248 km long and it is considered as the main water resource for the state. This river originates from two major tributaries, namely, the Galas River from the west and the Lebir River from the south [2]. As tributaries, they both can affect the water level of the Kelantan River. To determine the occurrence of flood, many factors have to be considered, such as rainfall, the water flow rate, and the water level. These factors are related to each other, for example, heavy rainfall upstream can cause a rise in the water level downstream. Forecasting techniques have been developed and improved by numerous researchers, with numerous methods being explored and studied. In addition to linear models, autoregressive integrated moving average (ARIMA), fuzzy logic, and a support vector machine (SVM) are among the methods that have been compared in order to be implemented in the field of hydrology research. The motivation to use AI as a forecasting medium has been present among hydrologists in the last two decades due to its progress and capabilities [3].

ARIMA models are a generalisation of the autoregressive moving average or ARMA models that can estimate future values using their inertia. Wind speed forecasting models have also implemented ARIMA and ANN models. This research has focused on short-term forecasting that applied wind speed records for each month separately. The results showed that ANN can achieve better forecasts than the ARIMA model in terms of the hourly forecast, where it can achieve a 4% difference in the mean absolute percentage error [4]. The comparative results referring to the autoregressive artificial neural network, ARMA, and ARIMA, and based on monthly forecasting of the Dez reservoir have been discussed. According to the performance index of the RMSE and mean bias error results, the neural network was chosen as the best model, with the RMSE value of 0.6380 in forecasting compared to ARIMA and ARMA, with RMSE values of 0.7148 and 0.7981, respectively [5].

Fuzzy logic is one of the artificial intelligence methods applied in the field of hydrology. Researchers prefer fuzzy logic as it is a simple yet flexible approach. Fuzzy logic was also compared with the radial basis function ANN in fault detection. Both Mamdani and Takagi-Sugeno techniques were deployed to fuzzy logic. The output of the research was a system that is able to detect and locate different faults. This system also includes a faulty photovoltaic (PV) module. Both the ANN and the fuzzy logic system produced high levels of detection accuracy. The overall maximum detection was achieved by the ANN, with the overall detection accuracy of 92.1% [6]. The prediction capabilities of the neural network and fuzzy logic techniques have also been tested and studied in landslide susceptibility mapping. A comparative analysis was based on a geographic information system (GIS) environment. The re-

sults of the analysis showed that the prediction by the ANN was 4% better than predictions obtained by the fuzzy logic model [7].

A support vector machine is undoubtedly a powerful tool for forecasting a natural phenomenon. In some studies, the SVM is also found to be superior compared to the neural network. A comparative study of river flow forecasting in the semiarid mountain region showed that the SVM has a 5% lower value of the root mean square error (RMSE) when compared to the ANN and the adaptive network-based fuzzy inference system (ANFIS) model [8]. However, other studies have shown the opposite. For example, an energy consumption forecasting research based on five different intelligent systems showed that the ANN performed better than the SVM [9]. Their research comprised multiple regression (MR), genetic programming, the ANN, deep neural network (DNN), and the SVM. These models were developed on the basis of the following five parameters: solar radiation, temperature, wind speed, humidity, and weekday index. The results showed that the ANN performed better than the SVM. Another study indicated that the ANN can correctly identify up to 50% of learning disabilities, which was better compared to current diagnosis predictors [10].

A neural network has become a known tool used in prediction methods. A multilayer feedforward neural network can lead to better fits by increasing the size of the neural network. However, multilayer feedforward is inferior when compared to a dynamic neural network, e.g., a recurrent neural network [11]. The training algorithm is an important element in the neural network as numerous training algorithms can be applied, such as gradient descent, conjugate gradient, and Levenberg-Marquardt (LM). Better performance and improved accuracy will be ensured by choosing a suitable algorithm. Thus, different types of algorithms should be studied to determine the one assumed to produce the best river forecast possible. The Levenberg-Marquardt training functions have been compared to gradient descent with momentum in lithium-ion battery state of charge estimation. The results showed that the performance of each neural network trained with different functions differs in terms of accuracy and training speed. Thus, it was concluded that the LM algorithm had achieved the best performance [12]. Bhavna Sharma and Venugopalan have also concluded that Levenberg-Marquardt is one of the best performers for training functions [13]. The performance in a feedforward neural network for a brain hematoma classification was compared. Matlab examples for a comparative study [14] of training functions showed that the LM training function performed the best in a function approximation problem. Bayesian regularization (BR) is also among the most commonly used training functions. Numerous studies have compared its capabilities with the LM training function. Both training functions have been applied in various research fields. Thus, identifying and studying the dif-

ferences might help give a better model outcome. One comparative study of the BR training function and the LM training function was conducted in long-term chaotic financial forecasting [15]. This financial forecasting used a parallel-NNARX model trained by BR and LM training functions. The forecast results were based on the mean absolute percentage error (MAPE). The BR training function outperformed LM, resilient backpropagation (RP), and one-step-secant (OSS) training functions. However, another study based on global navigation satellite system (GNSS)-based weather forecasting using NNARX has shown that LM showed better results compared to the BR training function [16]. The authors stated that choosing a suitable training function is important for rainfall prediction. The correlation percentage obtained for LM was higher than the BR percentage, and LM was the most accurate model among various forms of ANNs used.

The literature review has shown that a backpropagation neural network (BPNN) is also an exceptionally great neural network for making predictions. A BPNN is commonly implemented in different types of research related to ANNs. Several studies on the BPNN were conducted in the field of hydrology and one of them was a case study on the lower Chao Phraya River Basin [17]. This study showed that the prediction model composed of the water level, the water flow rate, rainfall, and the height of the basin as the input factor, showed high accuracy in water level prediction. This research compared three different gauging stations and the overall root mean square errors (RMSE) for three different cases have shown high accuracy. The backpropagation technique was also applied in the northern region of Thailand, with the water flow rate and rainfall as the input [18]. That research proposed that a time-lagged backpropagation neural network model with gamma memory would be more accurate compared to its backpropagation counterparts. The RMSE value obtained by the time-lagged model was 0.0962, while backpropagation achieved 0.2085 during testing. Another study applied a decision group backpropagation network or DGBPNN as the model proposed for avoiding prediction risks that are inherent in deterministic backpropagation. The model can provide flexibility for a deterministic BPNN to cope with rainfall-runoff and improve its adaptability. Although a BPNN is still viable to be applied in streamflow forecasting, this model needs to be improved to achieve better accuracy [19].

NNARX is a recent method in the field of flood forecasting, which has been proven to yield excellent results. It became well known in time series forecasting, mainly when handling environmental data, such as solar and wind. Thus, this current study intended to understand its capabilities and limitations when dealing with environmental data. In a sunspot forecasting study, the results were focused more on prediction system accuracy. The NNARX neural network was proven to give greater accuracy compared to backpropagation

and autoregressive integrated moving average (ARIMA) methods [20]. A comparison between seasonal autoregressive integrated moving average (SARIMA), NNARX, and BPNN models in forecasting network traffic showed different outcomes [21]. The SARIMA method obtained an accurate result, with the mean square error (MSE) of 0.064, but the BPNN and NNARX models are more accurate. The MSE values for NNARX and BPNN demonstrated that NNARX has better performance and has successfully supported time series datasets, with the MSE of 0.006717, while the MSE for the BPNN was 0.009424. The NNARX model was also implemented in another river forecasting study in Malaysia, and based on their results, the implementation was successful. Based on flood water level prediction for the Pahang River Basin using NNARX [22], the model was able to validate and test a 3-hour prediction time, with a 0.1087 RMSE. NNARX was also applied in flood prediction in Kedah, another state in Malaysia. The flood water level data are highly nonlinear and the neural network is an effective technique that could be used. Based on four inputs, the model predicted the outcome of downstream flood locations, with the MSE of 0.0067 [23]. NNARX was tested on the Kelantan River and its performance was evaluated based on the MSE. The model with the best performance has seven neurons with five delays, with the MSE value of 1.41319, which was acceptable in water level prediction [24]. Overall, NNARX is a suitable predictor that can be further studied.

In recent years, several methods, such as ANFIS and a genetic algorithm-neural network have been combined to cope with non-linearity and data extremity problems. Thus, researchers have been trying to develop a hybrid model that can minimize these errors, and combining these methods with the wavelet decomposition technique is one of them. This technique was implemented in a study on Thailand tourism forecast. This study used hybrid wavelet decomposition and the NNARX neural network to predict tourist arrivals to the country. Nonlinearity of tourism can seriously affect forecast computation. Based on the results, it was concluded that NNARX alone can perform better than the BPNN, the recurrent neural network (RNN), and the general regression neural network (GRNN), with 26% accuracy improvement. Meanwhile, the system was improved by 63% when discrete wavelet decomposition was added to the NNARX model [25]. Research into hybrid intelligence in short-term load forecasting has also proven that a combination of wavelet and neural networks can affect forecast outcomes [26]. The results of non-wavelet and wavelet-based forecasting models are compared in that paper. A wavelet neural network (WNN) has the lowest MAPE value compared to other non-wavelet counterparts. The data were smoothed by removing high-frequency components. The analysis results showed improvements in the performance and less training time. The wavelet-based method achieved a lower percentage, except during spring, which was 0.015 higher than during other seasons. Apart from the

combination with ANN models, some studies implemented wavelet decomposition with the SVM. This approach was used for optimal wavelet packet decomposition combined with the SVM to predict variable bit rate video traffic [27]. The results showed that the proposed model can predict hundreds of consecutive video frame values and it has increased the prediction precision when compared to the SVM alone. The result also showed that the algorithm has increased the prediction precision when compared to the traditional method. This concept of combining different methods has been applied in hydrology studies. One of them was river stage forecasting by using wavelet packet decomposition, with the ANN and ANFIS. Both methods were compared to their counterparts of the normal ANN and ANFIS. Both methods outperformed the traditional methods. These results indicated that these combinations can be used as an effective tool for river forecasting, whereby the MSE for the wavelet-ANN and the wavelet-ANFIS was 0.0036 and 0.0002, respectively [28].

In this current research, the focus was on NNARX as a predictor. Based on the previously discussed literature findings, NNARX would be able to outperform other methods in time series forecasting. NNARX performances were also found to differ in each research on river flood prediction in Malaysia. Shakila et al. used the NNARX model to predict flood at the Kelantan River and achieved the MSE of 1.4139 [24]. Meanwhile, Ruslan achieved the MSE of 0.00004489 by using NNARX on the Muda River in Kedah [23]. Different values obtained by these studies, other than locations, could be due to a data sample. NNARX in Kelantan used an hourly interval for two years of data collected from 2013 to 2014. Meanwhile, NNARX in Kedah used a 10-minute interval for 3 days. Hence, this current research aimed to uncover the capabilities and limitations of NNARX and determine whether it can be improved by adding wavelets.

2. METHODOLOGY

In flood prediction, the parameters that need to be considered are the rainfall value from the surrounding area, the river flow rate upstream, and the water level of the targeted downstream river. Flood factors and patterns have been studied, as well as neural networks and wavelets. The prediction models used were the backpropagation neural network and the nonlinear autoregressive exogenous input neural network. Wavelet decomposition was added to NNARX to improve the result of the model. Neural network software for flood prediction was developed by using MATLAB. Figure 1 shows the proposed block diagram, starting from the input data to the result.



Figure 1: Block diagram of the model

2.1. INPUT IDENTIFICATION AND DATA SELECTION

Data were obtained from the Department of Irrigation and Drainage Malaysia (DID). This department is responsible for monitoring and measuring input parameters from rivers for the entire country. The data obtained covered the period from 2009 to 2015 in the form of hourly intervals. The study focused on the data collected in a two-month period, i.e., from 1.00 am on 1/11/2013 to 12.00 am on 31/12/2013. To better understand the prediction model, a fuzzy logic-based real-time flood forecasting system for the Narmada River in central India was studied. The input used to forecast the event was hourly rainfall and discharge data (flow rate) [31]. The model in this research was focused on five different inputs and one output. The first three inputs came from three river water discharges located at the Lebir River, the Galas River, and the Sokor River. Meanwhile, the other two inputs were the rainfall values for Kuala Nal Plantation and Kenneth Plantation. The output of this system was the downstream water level of the Kelantan River. Briefly, this system is supposed to predict the outcome of the Kelantan River by analysing the input behaviour of rainfall and water discharges upstream. The selection of the inputs was based on their relations and connections to the Kelantan River [2].

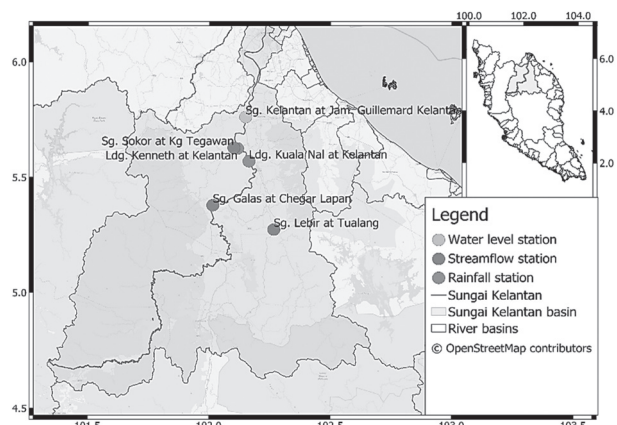


Figure 2: The area of study

Figure 2 shows the map of the Kelantan River, as this model was focused on single-point prediction of the river at the Guillemard Bridge water level station. The water level station is the first station along the Kelantan River flowing downstream. The Galas and Lebir rivers are both upstream and play a significant role in the occurrence of flood since any changes there can affect the outcome downstream. The Galas River and the Lebir River merge in Kuala Krai and flow into the Kelantan River. Input from Sokor River, and rainfall inputs from Ladang Kenneth and Ladang Kuala Nal were additional inputs to improve system accuracy. The Kelantan River is located in Tanah Merah, and its normal depth is 10 m. The alert level is estimated at 12 m and the danger level is at 16 m, as shown in Figure 3.

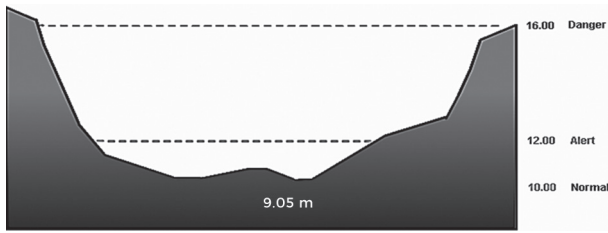


Figure 3: Water level condition [4]

According to the data obtained from the DID, under normal water level circumstances, the rainfall value is usually low or there is no rainfall at all. The flow rate was within 27.0–200.0 m³/s for Lebir, 93.5–400.0 m³/s for the Galas River, and 4.3–12.0 m³/s for the Sokor River. These data were collected for the months March–September, when rain was infrequent due to the west coast monsoon. However, in this period, increased rainfall was recorded in the major part of the west coast of Malaysia [1]. The alert level usually occurs during the northeast monsoon season, i.e., from October to March on the east coast of Malaysia. The alert level of the Kelantan River ranges from 12 m to 16 m. The danger level of the Kelantan River can exceed 16 m. The discharge value is extremely high as this value can reach up to 2,200 m³/s for the Lebir River, 2,556 m³/s for the Galas River, and 354.42 m³/s for the Sokor River, which usually takes place during the northeast monsoon season. The danger level is not usually reached every year, but it did occur in 2014, 2007, and 2004. For Kelantan, flooding is common only during the northeast monsoon season, while the water level is normal for the rest of the year.

The range of data could also play a vital role in the neural network. A small data set could give lower performance compared to a larger data set. In this study, data selection was focused on November and December during the northeast monsoon season. From January to October, the water level is not heavily affected by the monsoon; hence, there is no record from the DID. The 2013 data were selected because they showed one-year data before the massive flood of 2014. This collection was chosen to better understand flood patterns in Kelantan. An article in the local newspaper [32] identified excessive deforestation as the reason behind the massive flood in 2014. This was an external factor that could not be taken into account in this research. The 2013 data helped this research to investigate whether the prediction model can be improved before the event. The proposed model was not tested using other years because they did not exhibit a distinct difference in flood patterns like the 2013 data. The data set consisted of 1,469 items, starting from 1.00 am on 1/11/2013 until 12.00 am on 31/12/2013. The collected data were divided into two parts, namely 70% of data were allocated to training and 30% to testing.

2.2. NEURAL NETWORK MODEL

In a neural network model, the input layer is a layer that communicates with the external environment that will present a pattern to the network itself. The output layer will present a pattern to the external environ-

ment. The number of output neurons should be directly related to the type of work the neural network is to perform. The hidden layer is the collection of neurons that has an activation function. The MATLAB neural network was used to predict the water level of the river.

2.2.1. BACKPROPAGATION NEURAL NETWORK

The BPNN can be divided into two phases, i.e., propagated and weight update. The first process was conducted by forwarding propagation of the input from the input layer to the output layer through the hidden layer. Propagation generates deltas, where the difference between the targeted and the actual output can be seen. The second part of the process was weight update, where the output delta and input activation were multiplied to find the gradient of the weight. In this research, the BPNN model acted as a reference for the selection of training functions and the number of hidden neurons. As for the training function, the Levenberg-Marquardt algorithm is commonly used in neural networks. The literature review has highlighted that Levenberg-Marquardt is undoubtedly superior compared to other algorithms. However, researchers have recently applied Bayesian regularization as the training function. Some research results showed improvements when using Bayesian, while others did not. Thus, this research used the BPNN as a reference model in selecting the training function before proceeding with a comparative study with NNARX. In terms of selecting a hidden number of neurons, no specific method is available for determining a suitable number of hidden neurons. A review article on selecting hidden nodes [33] and a technique proposed by [34] were used to calculate the specific number [34]. Based upon these two papers, this research hypothetically assumed that the number of best hidden neurons range between 6 and 10.

2.2.2. NEURAL NETWORK AUTOREGRESSIVE WITH EXOGENOUS INPUT (NNARX)

Derived from the autoregressive model with exogenous input (ARX), NNARX is a recurrent neural network. It uses a feedback loop that adds to the feedforward neural network architecture. The predicted quantity is regressed on past values of the output parameter and exogenous input parameters. This network consists of two layers of the feedforward network. The activation function is a sigmoid function in the hidden layer and a linear function in the output layer.

NNARX can be expressed as follows:

$$Y_{(n+1)} = f \left[y_{(n)}, \dots, y_{(n-d_y+1)}, u_{(n)}, \dots, u_{(n-d_u+1)} \right] \quad (1)$$

where:

u : data set to predict,

n : past values predicted by the model,

- d_y : input orders,
- d_u : output orders,
- y : exogenous variable,
- $y_{(n)}$ and $u_{(n)}$: external output and input of the network at time n , and
- f : nonlinear function.

Figure 4 shows the NNARX model structure applied in this research. NNARX is characterized by a delay structure, where it creates embedded memory within the network itself and it is an important part of NNARX. The concept of delays refers to how many time-steps in the past have been incorporated into the model. The regressed data act as new input signals for the model by knowing its previous output. Table 1 explains NNARX structure parameters developed in this research.

Table 1: NNARX structure parameters

Network Configuration	[5,11,1] 'Tansig','Purelin'
Learning rate	0.1
Learning algorithm	Bayesian regularization backpropagation
No. of epochs	10000
Training pattern	1029
Testing pattern	440
No. of variables	5

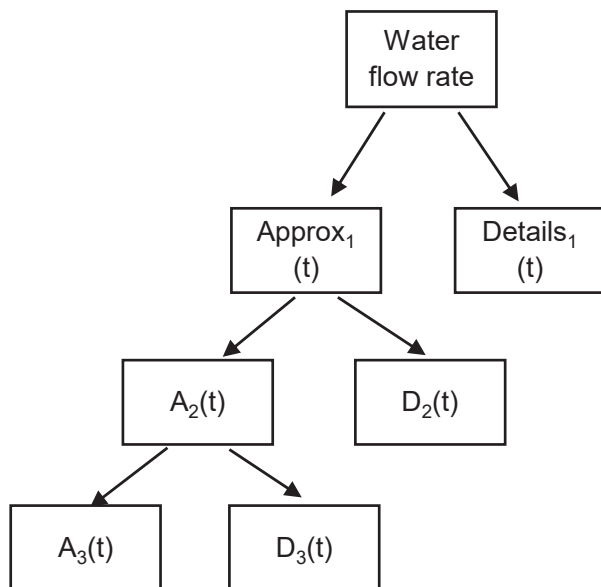


Figure 5: Wavelet decomposition

2.2.3. WAVELET-NNARX MODEL

As shown in Figure 5, this research was focused on the wavelet decomposition data. The selected data were decomposed or filtered through a wavelet system before going through the neural network model.

A large body of research has tried this approach in different fields. The flow of research is as shown in Figure 6 using the top-down design flow for the proposed model. Flood factors and patterns were analysed, followed by neural networks and wavelets. Each of the input data was processed through wavelet decomposition. Thus, every data from the same level of data decomposition was selected and fed as a new input for the neural network. This process differs from the normal process, where the neural network uses the original data. The new data that went through wavelet decomposition acted as the new data for the model. The data from wavelet decomposition has a smooth-like pattern as more data were filtered out.

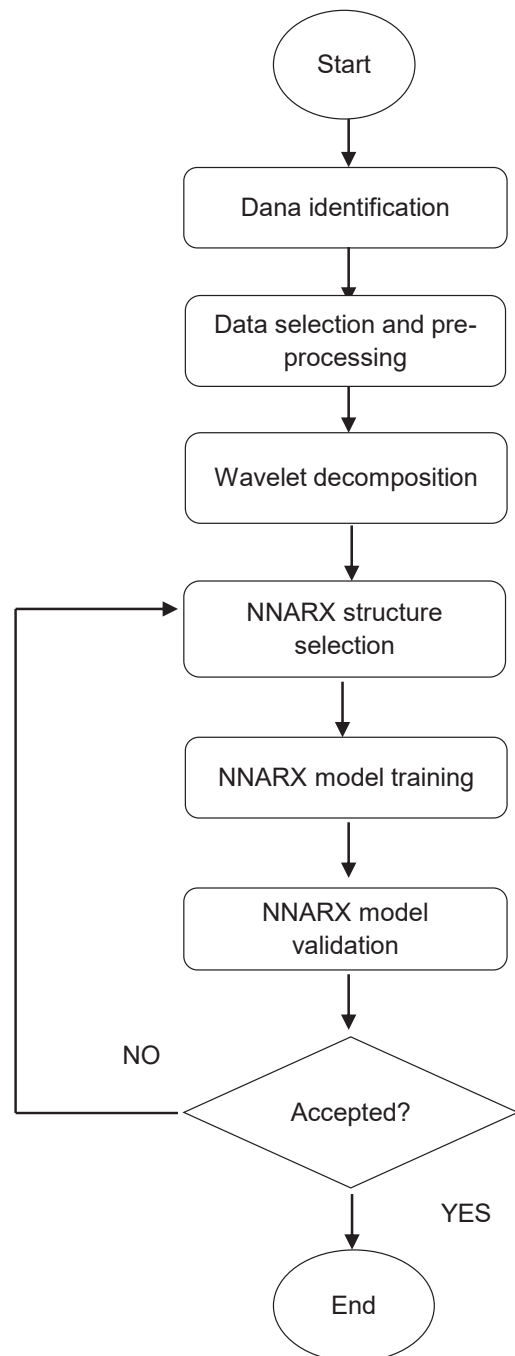


Figure 6: Flowchart of the proposed model

Table 2: Original data used in the normal neural network

Data	1 st hour	2 nd hour	3 rd hour	4 th hour	5 th hour	6 th hour	7 th hour	8 th hour	9 th hour	10 th hour
Galas	646.9	671.7	696.7	719.5	738.9	753.7	763	770.3	775.5	777.5
Lebir	255.1	250.7	242.5	242.5	240.6	239.4	237.5	236.3	235	233.1
Sokor	17.08	17.47	18.52	19.81	21.38	23.25	25.02	26.09	26.8	27.26
Kuala Nal	5.9	1.3	2.7	1.1	1.7	0.3	0.4	0.4	1.1	0.1
Kenneth	4.2	3.3	3.4	1.3	0.7	0.4	0.2	0.2	0.7	0.4

Table 3: Data generated from the 1st level wavelet decomposition

Data	1 st hour	2 nd hour	3 rd hour	4 th hour	5 th hour	6 th hour	7 th hour	8 th hour	9 th hour	10 th hour
Galas	659.3	659.3	708.1	708.1	746.3	746.3	766.6	766.6	776.5	776.5
Lebir	252.9	252.9	244.4	244.4	240.0	240.0	236.9	236.9	234.0	234.0
Sokor	17.2	17.2	19.1	19.1	22.3	22.3	25.5	25.5	27.0	27.0
Kuala Nal	3.6	3.6	1.9	1.9	1.0	1.0	0.4	0.4	0.6	0.6
Kenneth	3.7	3.7	2.3	2.3	0.5	0.5	0.2	0.2	0.5	0.5

When the data have been decomposed via a wavelet, the new filtered data were fed into the NNARX model as the new input replacing the original data. The Haar transform generated approximation and details. The approximation can be calculated as shown in equation (2):

$$\mathbf{a}^1 = \left(\frac{x_1 + x_2}{\sqrt{2}}, \frac{x_3 + x_4}{\sqrt{2}}, \dots, \frac{x_{N-1} + x_N}{\sqrt{2}} \right) \quad (2)$$

The details are as given in equation (3):

$$\mathbf{d}^1 = \left(\frac{x_1 - x_2}{\sqrt{2}}, \frac{x_3 - x_4}{\sqrt{2}}, \dots, \frac{x_{N-1} - x_N}{\sqrt{2}} \right) \quad (3)$$

Wavelet decomposition is based on the level; thus, as the level increases, more data are filtered out. Level 2 Haar transform decomposition can be defined as follows:

$$\mathbf{f} \xrightarrow{H_2} (\mathbf{a}^2, \mathbf{d}^2, \mathbf{d}^1) \quad (4)$$

Table 2 gives the original data used for the normal neural network process in NNARX and the BPNN. The original data went through the normal prediction process, where all five data sets consisted of the Galas, Lebir, and Sokor river flow rates, with Ladang Kuala Nal and Kenneth rainfall data. Table 3 presents data generated from wavelet decomposition. Only approximation was used for new data as the details were removed. The value obtained from the wavelet was calculated by using the previous equation (2).

3. RESULTS & DISCUSSION

The performance index of the model was based on the mean square error (MSE) value. The BPNN model was used as the reference to identify suitable training functions and hidden neurons. NNARX was tested with different values of delays to determine the impact of

their increase on the outcome. The two neural network models were compared and the best model was combined with wavelet decomposition, in which NNARX performed better than the BPNN. A combined model was developed based on hourly predictions on both NNARX and the BPNN.

3.1. COMPARISON OF NNARX AND THE BPNN

Table 4 shows different MSE values obtained by the two methods. In terms of MSE values for training and testing, there is an apparent gap between these methods. The NNARX method has outperformed the BPNN in water level prediction referring to the Kelantan River.

Table 4: Performance difference between the BPNN and NNARX

Model	MSE (m2)	
	Training	Testing
BPNN	5.7863e-2	1.57354e-1
NNARX	7.4827e-5	6.1642e-4

Figure 7 shows the regression of the BPNN model. Regression analysis is a set of statistical processes for estimating the relationships between variables.

The regression was divided into three parts; i.e., training, testing, and the overall value. Regression specification performance was based on the result closer to the value of 1, i.e., the closer the result to 0, the better. The regression value achieved for training was 0.99055, the value for testing was 0.98008, and the overall regression value was 0.98863. Some of the obtained data were far from the fit line. Figure 8 shows regression analysis for the NNARX model. The graph shows that the NNARX model was able to achieve higher MSE values compared to the BPNN model. The data that reached the fit line were also greater than the data obtained by the BPNN. The data achieved for training and testing were 0.99999 and 0.99991, respectively, while 0.99998 was the overall value. These results showed that NNARX is

superior to the BPNN model. The NNARX model was then combined with wavelet decomposition to further study the impact of the proposed model.

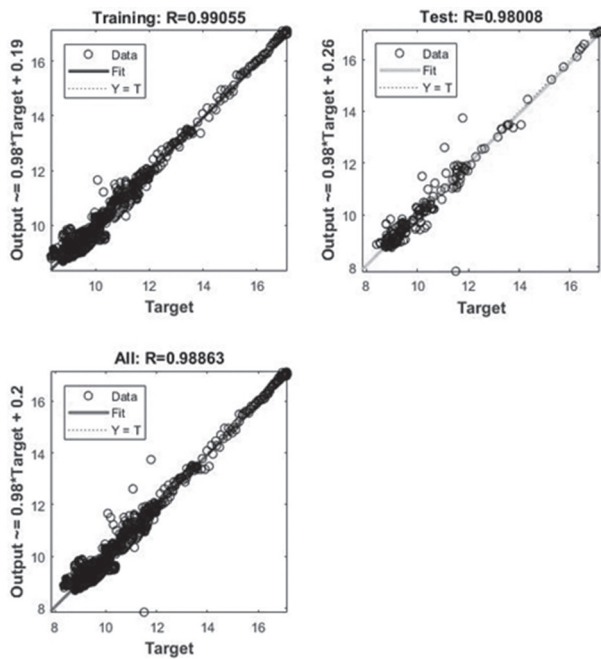


Figure 7: Regression analysis of the BPNN model

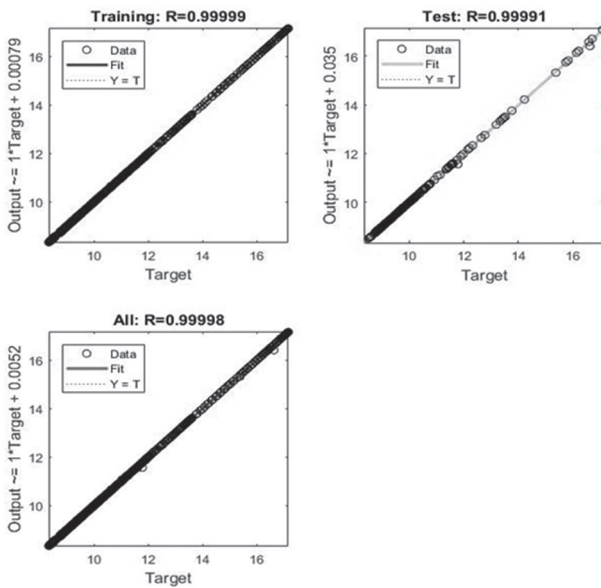


Figure 8: Regression analysis of the NNARX model

3.2. WAVELET DECOMPOSITION

Wavelet decomposition was divided into approximation and details data, and the higher the level, the more the data were decomposed. Table 5 shows the relationships between the data and the wavelet level. In the early level ranging between 1 and 4, the decomposition effect was positive, which showed that more unnecessary data were filtered out. It can be observed that the best performance was achieved at the 4-level

decomposition. However, when the model exceeded level 4, the MSE values began to increase, indicating that more data had to be filtered out. This condition turned the data into a smooth-like pattern, which caused the model to predict the original data.

Table 5: Wavelet level decomposition

Wavelet level of decomposition	MSE (m ²)
1	2.2662e ⁻³
2	5.1456e ⁻⁴
3	8.12061e ⁻⁴
4	1.6002e ⁻⁴
5	3.2630e ⁻⁴
6	5.8825e ⁻⁴
7	4.2471e ⁻³
8	2.2206e ⁻²
9	3.6245e ⁻²
10	4.8555e ⁻²

Figure 9 shows a regression graph of the proposed model. The training regression value was 0.99997, which was slightly lower than the normal value of the NNARX model, i.e., by 0.00002. Meanwhile, for the test, the model improved by 0.00007 compared to the normal NNARX model. Overall, the regression value obtained by the proposed model was slightly lower, i.e., by 0.00001. This difference is quite small to even be compared, but by adding wavelet decomposition, it was possible to improve testing of the model.

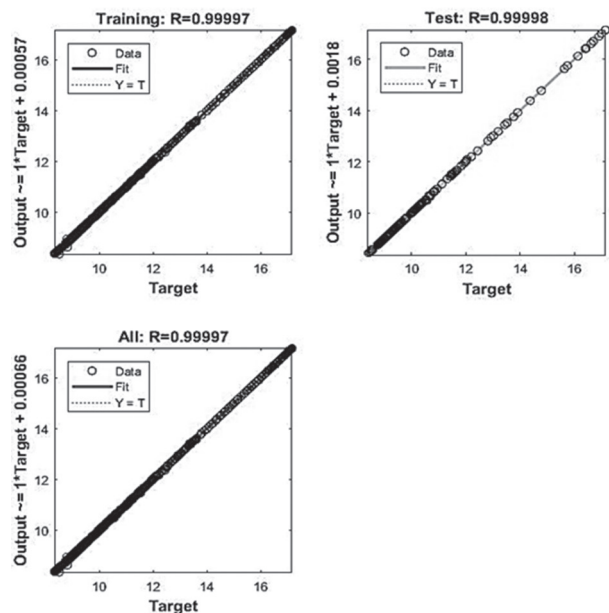


Figure 9: Regression analysis of wavelet decomposition - NNARX

3.4. COMPARISON OF NORMAL AND WAVELET-ADDED MODELS

Table 6 shows a comparison of the model with the wavelet added and the BPNN and NNARX models. In

addition to regression analysis, the MSE values were also taken into consideration. The NNARX model showed great performance during training. However, its performance was decreased during testing. This observation shows that normal NNARX performed well, but improvement was necessary, especially during the testing period. A combined model was also implemented into the BPNN. As such, it became a wavelet decomposition-BPNN model. The reason for conducting this test was to determine whether the addition of wavelet decomposition will affect other neural network techniques. The outcome of the combined model proved to be positive. Both MSE values for NNARX and the BPNN increased in training and testing. Meanwhile, regression analysis showed that the proposed model improved by 0.00402 when it was combined with wavelet decomposition.

Table 6: Comparison of models with wavelet addition.

Model	MSE (m ²)		Regression (R)
	Training	Testing	
Wavelet-NNARX (proposed)	1.7859e ⁻⁴	2.0491e ⁻⁴	0.99997
Normal NNARX	7.4827e ⁻⁵	6.1642e ⁻⁴	0.99998
Wavelet BPNN	3.7768.e ⁻²	6.8299e ⁻²	0.99265
Normal BPNN	5.7863e ⁻²	1.5735e ⁻¹	0.98863

4. CONCLUSION

In conclusion, the aim of this research was to compare the river flood water level prediction system in Kelantan by using the neural network autoregressive with exogenous input and neural network backpropagation. A combination of wavelet decomposition and the NNARX neural network improved system accuracy. The proposed neural network system was able to analyse the flood pattern of the Kelantan River and develop a water level prediction model of the river based on the data input obtained. In this study, MATLAB software was used to develop a neural network water level prediction system. The best neural network was selected based on its performance by using the lowest means square error (MSE) and regression values. A large difference in NNARX and BPNN MSE values has shown that NNARX has outperformed the BPNN. To access the abilities of wavelet decomposition, it was combined with NNARX. Although the difference was indistinctive, the MSE testing phase was improved by the proposed model. In comparison, the normal model showed better performance in the training phase, but was lagging behind in the testing phase. Meanwhile, the training and testing performance

of the proposed model showed only a slight difference. Wavelet decomposition was combined not only with NNARX, but also with the BPNN. The forecast of the wavelet decomposition-BPNN model was improved compared to the normal BPNN forecast. Thus, future work is recommended to improve a wavelet decomposition and neural network combination to achieve better accuracy. This system can also be developed to test the input of a real-time system, where rainfall and the flow rate are measured in real-time and tested in the neural network system. Despite a large number of Malaysian researchers trying to discover a method to develop better forecasting models, there is still room for improvement in future studies.

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