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Short-term Water Level Forecast Using ANN Hybrid Gaussian-Nonlinear Autoregressive Neural Network

Wei Ming Wong[1*], Siva Kumar Subramaniam[2], Farah Shahnaz Feroz[3], Lew Ai Fen Rose[4]

[1]Faculty of Electronic and Computer Engineering,
Universiti Teknikal Malaysia Melaka, 76100 Durian Tunggal, Melaka, MALAYSIA

[2]Centre for Telecommunication Research and Innovation, Faculty of Electronic and Computer Engineering,
Universiti Teknikal Malaysia Melaka, 76100 Durian Tunggal, Melaka, MALAYSIA

[3]Pervasive Computing and Educational Technology, Faculty of Electronic and Computer Engineering,
Universiti Teknikal Malaysia Melaka, 76100 Durian Tunggal, Melaka, MALAYSIA

[4]Faculty of Technology Management and Technopreneurship
Universiti Teknikal Malaysia Melaka, 76100 Durian Tunggal, Melaka, MALAYSIA

*Corresponding Author

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Abstract: The aim of this study is to develop the best forecast model using hybrid Gaussian-Nonlinear Autoregressive Neural Network to forecast the water level with multiple hours ahead for Melaka River. The development of flood forecast models is crucial and has led to risk control, policy recommendations, a reduction in human life loss, and a reduction in flood-related property destruction. In this research, Artificial Neural Network (ANN) approach was used to forecast flood by modeling and forecasting water level time series. ANN approach was selected due to its high reputation abilities to learn from the time-series data pattern. A total of 2782 data for the period of one month was used in ANN training, validation, and testing to forecast the flash flood. In this study, Hybrid Gaussian Nonlinear Autoregressive Neural Network (Gaussian-NAR) was used as the ANN approach to forecasting the water level time series. This study's primary focus is to find the most appropriate forecast model to forecast the water level in multiple time steps ahead, which are 1 hour, 3 hours, 5 hours, and 7 hours. The forecast accuracy measures are measured using the Pearson R and R-squared to find the most accurate model for this multiple time-step ahead. The result indicates that with 7 hours forecast ahead, the R squared is 86.7%. The best model in the Gaussian-NAR forecast is a 3-hour water level forecast with the R squared of 99.8 percent and had the best model performance result.

Keywords: Flood, Forecast, ANN, NAR, Gaussian

1. Introduction

Herein many countries worldwide, flood disasters continue to occur. In Melaka, Malaysia, floods are an annual hydrological event due to the unprecedented water discharge volume. River flooding has emerged quite widely in Melaka in recent years, causing massive causalities and property damage. An early warning system will save numerous lives and property by making numerous structural modifications to time and effect. It is possible to achieve an early warning system

*Corresponding author: wongweiming5351@gmail.com

through mathematical modelling developments in the forecast system. In Melaka urban areas, flash floods may occur anytime throughout the year due to infrastructure development. It is crystal clear that a short-term water level forecast is essential and a solution for reducing casualty and property damage. A good water level forecast will allow more time for the people and the response team to prepare and take action before the flood occurs. The short-term water level forecast is crucial to forecast the incoming flash flood.

Various flood forecasting technologies have been developed that contribute to the problem of the flood warning system. Compared to other models, ANN has provided adequate water streamflow modelling and water level. Besides, ANN is a fast and scalable solution that offers promising outcomes [1]. Artificial neural networks (ANN) are used broadly in various research fields in prediction. ANN draws much interest in the application of hydrological forecasting due to its robustness and versatility. Real-time simulation of the dynamic system is ideal for the Artificial Neural Network (ANN). When there is unknown interaction between the input and output of the time series data [2], ANN is a quick and flexible approach that gives promising results event with long duration series of time forecasting. ANN's uniqueness in adaptability and solution for nonlinear time series makes them useful for the forecasting job. ANN also gives satisfying result performance in prediction [3]. ANN can behave and make decisions that mimic the human brain in terms of modelling and simplification. ANN consists of an integrated artificial neuron group, which uses a connectionist computation approach to processing information. ANN consists of multiple layers with many nodes that identify as a neuron. The input interacts with the input layer, and the hidden layer conceals the output by reducing the error when the output layer produces the result.

In a previous study from [4], the authors used the Radial Basis Function Network (RBFN) to achieve the 7-hour water level forecast with the R squared value 82.43 per cent. The short-term water level forecast is about the forecast water level future ahead and the forecast model's performance. According to [4], only the 7-hour maximum lead time can adjust, and the performance is not more than 80 per cent. It is also crucial to design the forecast system with lead time and error correction as the design criteria to ensure the forecast is successful and decide the overall model design [4]. In the study of this paper [5], the author uses the NNARX method in the research and achieves the 7-hour water level forecast. In this paper study [6], the author uses this ANN model approach of NAR for the sea-level prediction in Tanjung Emas Harbour in Semarang. The prediction results produce an r-value of 0.9567 for prediction, and the author proves that the NAR model has good accuracy compared to the tidal harmonic analysis method. [7] proposed an approach using the NAR for the short-term level forecast. The author also compares these two ANN models: the NAR model and the Feed Forward Back Propagation (FFBP) neural networks. The result from the paper showed that the NAR model performs adequately compared to the FFBP model. Conceptually similar work had been pursued by [8] in which the author used the NAR model for the COVID-19 prediction in India. In this study, the author used NAR prediction to forecast the number of COVID-19 cases for the next 50 days. A study conducted by [7] used the NAR method for crop evapotranspiration prediction at Kanchipuram, India. This prediction will allow the reliable project planning and operation of the irrigation system in that particular area. Various authors applied the NAR method to forecast the river's water level or other activities indirectly or directly related to the river [7]. To get a more accurate forecast in time series data, various researchers come out with the hybrid ANN method or combinational of various ANN techniques to increase the forecast accuracy.

The most recent work by [9] used the NAR and extended Kalman Filter combinational to forecast the daily price of steel over 790 days of period. In the study, the author compares the hybrid method with other non-hybrid methods, and it shows that the hybrid method produces better forecast performance compared to others. Conceptually similar work has also been carried out by [10]. The author uses hybrid ANN to predict bacterial contamination. In this study, the author uses the hybrid method of wavelet and Nonlinear Autoregressive Neural Network (WA-NAR) to predict the Escherichia coli (E. coli) concentrations at four Lake Michigan beach sites. In the study, the author also compares the WA-NAR method with the nonlinear input-output network (NIO), nonlinear autoregressive network with exogenous inputs (NARX) method, and NAR network. The result shows that the WA-NAR had good accuracy and performance compare to other models [10].

The purpose of this study is to develop a hybrid Gaussian-NAR ANN model that can produce quality short-term water level forecasts in Pengkalan Rama Jetty, Melaka, by using only water level data. This study explores the optimal number of hidden neurons and delay in the Gaussian-NAR structure for the water level forecast. Expressly, this study set up to develop water level-level short-term forecast in 1 hour, 3 hours, 5 hours, and 7 hours in the future. In the study, to understand the Gaussian-NAR model's ability, the prediction performance was evaluated to find and understand the NAR model performance.

2. Data Preparation

Melaka is located in the Southern Region of Peninsular Malaysia and next to the strait of Melaka. Melaka has population of 870,000 and divided into 3 main districts which is Melaka Tengah, Jasin and Alor Gajah [11]. Melaka is among the state in Malaysia where floods occur annually. The flood occurs not only limited to the seasonal flood but also flash flood. Melaka chosen as the research place was motivated by the various flood cases in Melaka, and Melaka was one of the high-risk flood-prone areas. In Melaka, the estimated flood-prone area is 80.9 square kilometres. Based on the National Register of River Basins study carried out in 2002, the annual average flood damage for the State of Melaka estimated at RM 2.3 million with 18,000 people affected [12]. Given Melaka's topography shown in Fig. 1, Melaka occurred to flood more frequently due to the global mean sea-level rise and frequent high rainfall [13].

Fig. 1 - Location of Melaka in Peninsular Malaysia map

There are two main rivers in Melaka which is Sungai Melaka and Sungai Kesang. Sungai Kesang located at the border of Melaka and Johor, while Sungai Melaka located in the Melaka and it is one of the main river in Melaka. Sungai Melaka is important because along Sungai Melaka, there are industrial, residential and tourism.

In this study, the real-time water level data provided by the Internet of Things (IoT) Flood Observation System (IFOS) developed at the Pengkalan Rama Jetty, Melaka. Fig. 2 showing the location of the IFOS at the Pengkalan Rama Jetty. The location's coordinate stated 2° 12'30.3 "N 102° 15'02.8 "E. Pengkalan Rama Jetty chosen as the location for research due to its geological layout the Sungai Melaka and urban area. Data were taken from 1 July 2020 at 12.00 am until 30 July 2020 at 11.00 pm with 15 minutes intervals for this study. Similar work has also been pursued by [4] and [14], which use 15 minutes of data for their study in water level forecast. There is a total of 2782 data obtained during this period.

Fig. 2 - IFOS location

Internet of Things (IoT) Flood Observation System (IFOS) was designed and developed to functions as the flood warning system and the water level monitoring system.

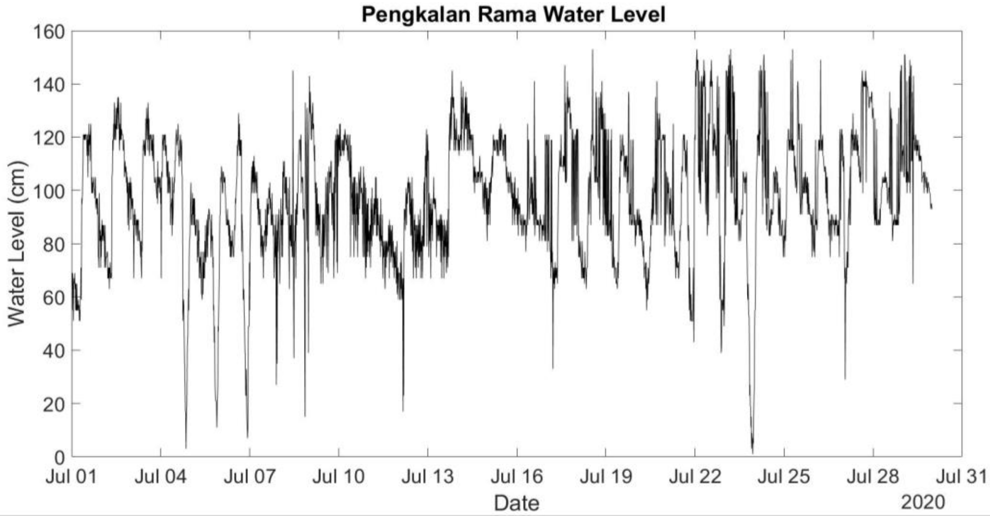

Fig. 3 - Water level data from IFOS

The raw data from the IFOS was obtained from the IFOS cloud and plotted as the time-series data, as shown in Fig. 3. After that, the raw data obtained from the IFOS undergoes the data pre-processing to remove the outlier and generate a cleaned time series data. Then the data was processed using the Gaussian smoothing method to smooth the data before applying with the ANN. Time series data is any data that is sequentially observed over time [15]. Time series forecasting aims to forecast future values based on current and historical data, or stated mathematically [7]. It can observe in Eq. (1), where ŷ was the predicted value of a time series y.

$$\hat{y}(t+\Delta t) = f(y(t-1), y(t-2), y(t-3), \dots) \tag{1}$$

Forecasting time series aims to find the function f(y) to forecast time series values impartial and consistent. In this study, Nonlinear Autoregressive (NAR) Neural Network used as the time series forecast tool. Fig. 4 shows the methodology application of ANN for forecasting the water level in Pengkalan Rama Jetty. The process starts from collect the water level data from the Pengkalan Rama Jetty. Then the data is processed through a data pre-processing process, and the clean data is processed and analysed using ANN for the forecasting process.

2.1 Data Preprocessing

The water level data obtained from the IFOS consist of lot of noise due to various factors that affect the water level sensor. One of the main problems that cause the noise is from the water wave itself. The IFOS locate near the jetty, and the boat passes by from time to time. This situation may cause a sudden change in the water level due to the water wave itself. When time-series data is contaminated with outliers, data analysis results are irrelevant, as outliers can result in model misspecification, skewed parameter estimation, and inaccurate analysis results [16].

2.2 Outlier Detection

Outliers are data that deviate significantly from the rest of the data because a different mechanism generated them. Outliers, in other words, are data that show contradictory behaviour as compared to the rest of the data collection. Outliers may cause several causes, including sensor errors, data logger errors, network compatibility problems, or physical conditions like a water wave [17].

Hydrologic systems such as Water level monitoring systems with outliers are invariably complex dynamical systems. The current state and potential evolution of such dynamical systems determine by a plethora of properties and interactions involving many highly variable physical elements. Since some relationships can only establish through analyses, such dynamical systems' representation in their corresponding models is complex [18].According to the author [19], the outlier is an observation that deviates so much from other observations that it raises suspicions that a different instrument made it. In these ways, the term entrusted a decision on what consider as irregularity for analysts (or a consensus process). Regular observations must be clarified before irregular observations can identify [20].

An outlier can classify into two types which are outliers on the x-axis and outliers on the y-axis. Outliers in the y-axis, on the other hand, are more significant in time series analysis and can be divided into three categories: random, non-random, and gross errors. Consequently, recognising and handling outliers is crucial for time series analysis before identifying trends in them [21].

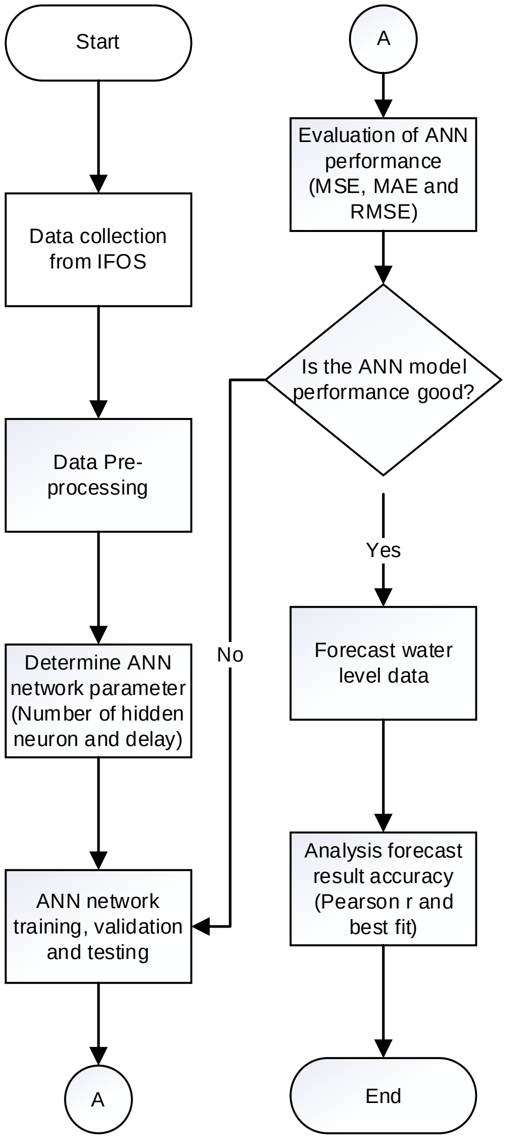

Fig. 4 - Methodology application of ANN for forecasting

2.3 Improved Data Smoothing with Gaussian Smoothing

For several years, the Gaussian filter widely uses in image processing and computer vision, and it has become a de-facto standard for these applications [22]. In this study, the gaussian smoothing method use to smoothing the time series data to be analysed. Conceptually similar work has also been carried out by [23] that use the Gaussian smoothing method to reduce the noise in the time-series data.

In this paper, a Gaussian filter is applied to pre-filtered data sets with MA to achieve adequate variability reductions. The fact that the data dominated by relatively low frequencies of variance, which could be isolated from the higher frequency noise, was critical to the technique's success. When it comes to identifying signatures, the GS is highly accurate. A GS has the form of a Gaussian distribution, as expressed by Eq. (2).

$$G(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right) \tag{2}$$

where μ is the mean value, and σ is the standard deviation that functions to control the window size. The moving averaging filter will substitute each data point with the average of its neighbours. This situation means that all local data contribute equally to the average, while distant data have no bearing. Each data point can be replaced by a weighted average of its neighbours when using a Gaussian filter. As a result, the closest data have a more significant impact on the average, while the farthest data have a minor impact. When the Gaussian uses data smoothing, it is typically set to 0 since we want each data to impact the current, smoothed value. This parameter will allow us to monitor how smooth the final curve is, precisely the size of the smoothing window we use for averaging. The larger it is, the smoother the impact would be. However, the value of σ should be held within a reasonable range. A value that is too small will result in an undesirable smoothing effect, while a value that is too high will result in the loss of essential information [24].

2.4 Nonlinear Autoregressive Neural Networks (NAR)

Nonlinear Autoregressive Neural Networks (NAR) is a part of the Artificial Neural Network model frequently used for time series forecasts from historical data to forecast future values. The NAR's core importance is that it has a straightforward algorithm and can train nonlinear input-output models [25]. Time series forecast aims to find a function f(y) that forecast unbiased and consistent time series values [7].

The NAR algorithm operates by constructing a data-training network. In the developed network, the data will be ongoing the training process. The model's performance is the output of the training data. For the forecast process, this model will be used to forecast future data.

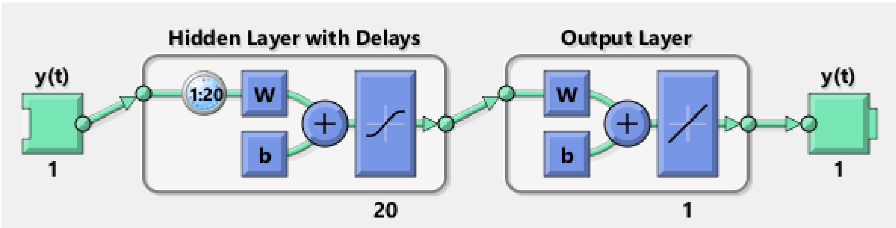

Fig. 5 - NAR open-loop network architecture

Fig. 5 shows a schematic diagram of NAR's algorithm. The input layer containing y(t) displays a single-variable time series in this case. It has 20 input delays and shown by the notation 1:20. The NAR network contains one output time series and one hidden layer neuron with sigmoid activation functions [6]. The water level data use as the NAR's input variables in this analysis. Water level data will be stored after the network is generated and trained in an open loop. The neural network will turn into a closed-loop for water level data forecast after completing the training phase [26].

$$y(t) = f\big(y(t-1), \dots \dots y(t-d)\big) \tag{3}$$

NAR networks are a particular type of ANNs that uses a time series of data to forecast future values. As shown in Eq. (3), the forecast value y in time step t calculate using d past values (also called "delays") of y. The first nonlinear neural model consists of a multilayer feedforward neural network approximating the function f in Eq. (1) [27].

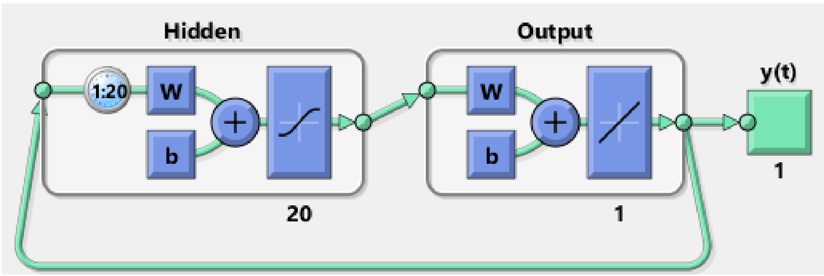

Fig. 6 - NAR close-loop network architecture

The NAR network in Fig. 6 showed that a close-loop in the NAR network converts the output into the input for a multi-step ahead forecast. In the Fig. 6 observation, the NAR closed-loop network architecture and NAR open-loop network architecture are almost the same. The only difference is the NAR close-loop network architecture's input, which reuses the output into the input for multi-step ahead forecast. For the NAR network to achieve a multiple-step ahead forecast, the NAR neural network must be in the recurrent form because the forecast output must feed into the following forecast input. Suppose the aim is to forecast h sampling times in the future. In that case, the network's input layer form by a group of h neurons that memorise previous network outputs. The remaining neurons in the input layer receive the original or measured time-series data [28]. Thus, the forecast model outputs along the interval [t +1, t + h + 1] given by the following equations:

$$y(t+1) = f\big(y(t), \dots \dots y(t-d)\big) \tag{4}$$

$$y(t+2) = f\big(y(t+1), y(t) \ \dots\dots y(t-d)\big) \tag{5}$$

$$y(t+h+1) = f\big(y(t+h), y(t+1), y(t) \ \dots\dots y(t-d+h)\big) \tag{6}$$

In NAR, there are three processes which are training, validation, and testing. The network's training data used to train in the training process, and the network is changed depending on the error. The validation process use data to find the generalisation. When the generalisation was not improving, the validation process will stop the training. At last, is the testing process which used the data for the testing purpose and had no effect on the training [2]

In the NAR training, Levenberg-Marquardt (LM) training architecture was used to train the data. LM is a training optimisation in the backpropagation algorithm. It is the fastest method of backpropagation training. A wide variety of problems outperforms simple gradient descent and other conjugate gradient methods [29]. Short-term water level forecast using neural networks. LM is used to minimise network performance by adjusting the bias and weight of the network. The study from [2], [7], [4] also using the same training architecture for their research in the water level forecast.

2.5 Water Level Time Series Forecast

For NAR to forecast the water level time series, the NAR network was trained, validated, and tested using MATLAB as the tool for analysis. There is integrated support for the NAR network in MATLAB software to be trained and only for the open-loop system to forecast one step. In the multi-step ahead forecast situation, it requires to use a closed-loop network to forecast it. The closed-loop network is different from the open-loop network. It needs some modification in the code by manually updating the one-step-ahead forecast code with a new code line. The latest update will enable the code to run the closed-loop network to perform a multi-step ahead forecast.

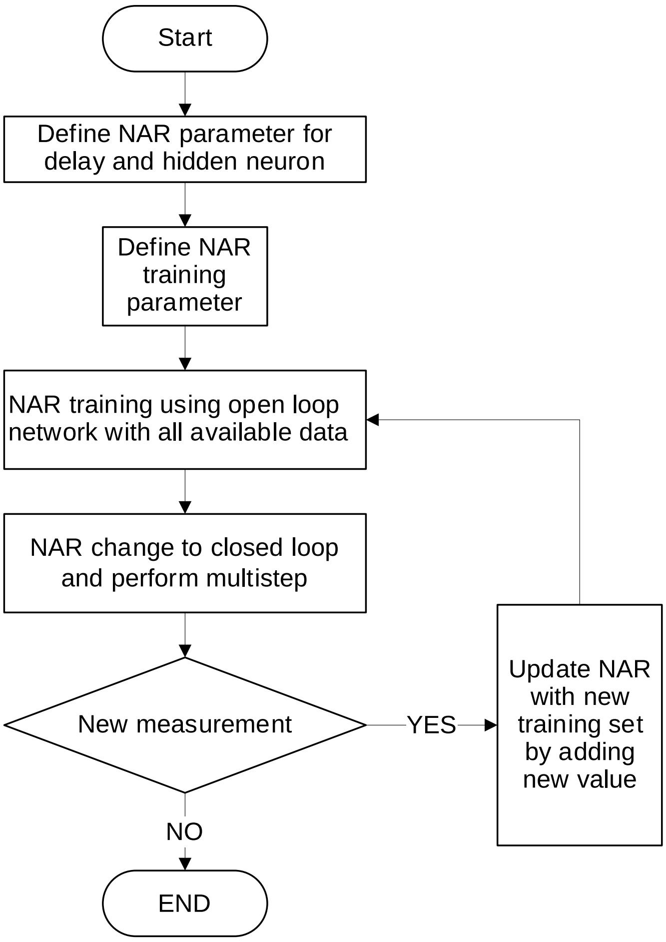

Fig. 7 - Flow chart of NAR training for multi-step ahead forecast

NAR trained using the open-loop network using all the available data. The network was modified to close loop network, and at last multi-step, ahead of water level forecast is executed. The NAR process flow shown in Fig. 8 describes the NAR training method for multi-step ahead forecast. The advantage of using the NAR network training method is that the feedforward network's input is accurate. The network has a sole feedforward architecture and can thus use for training a more effective algorithm.

For identifying the best NAR network structure, 49 NAR network models have developed for 1 hour ahead, 3 hours ahead, 5 hours ahead, and 7 hours ahead water level forecast. Every model equips with a different structure combination number of neurons and the number of delays. The purpose of these various combinations is to investigate each parameter's influence on the forecast result. The best combination of the NAR network structure will use for the Pengkalan Rama Jetty water level forecast. There are 70% data use for training in the ANN model, 15% for data validation, and 15% for data testing. Levenberg-Marquardt backpropagation algorithm used for the ANN training.This method's fundamental aim is to investigate high and weak points in forecasting NAR networks using the available data. Furthermore, short-term modelling carried out with abrupt shifts in water level periods, various data changes, and trend changes.

2.6 Forecast Performance Parameter

Eq. (7), Eq. (9), and Eq. (10) are mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) use to evaluate the forecast accuracy [30]. Concurrent work [31] has used a similar approach using MSE to find the best model for the water demand forecasting for multi-step ahead forecast. Eq. (8) showed the RMSE equation which is used to measure the residual spread. These three parameters used to identify the best NAR network model used in the short-term water level forecast.

Eq. (11) showed the equation for the Pearson correlation coefficient, R. This equation is used to analyse the scatter data points to fit in the line (Goodness of fit). The evaluation of the regression value of the actual water level and forecast water level data perform to analyse both the data's correlation and performance. These evaluations calculated in R squared according to this Eq. (12).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(E_i - R_i)^2 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(E_i - R_i)^2} \tag{8}$$

where E_i = Actual data, R_i = Forecast data, and N = Total number of data.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|E_i - R_i| \tag{9}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_i - R_i}{E_i}\right| \tag{10}$$

$$R = \frac{\sum(\chi_i - \bar{\chi})(y_i - \bar{y})}{\sqrt{\sum(\chi_i - \bar{\chi})^2 \sum(y_i - \bar{y})^2}} \tag{11}$$

$$R\ squared = r^2\ x\ 100 \tag{12}$$

where r = correlation coefficient, χ_i = Values of the x-variable in a sample, $\bar{\chi}$ = mean of the values of the x-variable, y_i = values of the y-variable in a sample, and $\bar{y}$ = mean of the values of the y-variable.

3. Result

Table 1 shows the different hidden neurons and delays and produces the distinct value of MSE, MAE, and RMSE. The lowest value of MSE, MAE, and RMSE showed that the model could have a good forecast with minimum errors. Evaluating the optimal number of hidden neurons and delay starts from obtaining the optimal number of hidden neurons. Once obtained the optimal number of the hidden neuron, the process continues with finding the optimal delay of the ANN. The evaluation of optimal results done by analysing the result of the forecast performance parameter.

In the 1 hour ahead water level forecast, the best number of the hidden neuron was 30 hidden neurons with five delays. During the 3 hours, 5 hours, and 7 hours forecast, the best-hidden neuron was 20 hidden neurons with 20 delays. The training performance is shown in Fig. 8 and Fig. 9 for the 1 hour, 3 hours, 5 hours, and 7 hours forecast indicate that the performance results are promising. The best water level forecast was 5 hours ahead water level forecast among all the water level forecast. It had the lowest MSE, MAE, and RMSE.

Table 1 - ANN forecast performance parameter

Hour Forecast	ANN Structure		Forecast Performance Parameter		
	Hidden Neuron	Delay	MSE	MAE	RMSE
1	10	10	1.1356	1.0655	1.0656
1	15	10	1.5051	1.2256	1.2268
1	20	10	1.5700	1.0267	1.0281
1	25	10	1.1858	1.0887	1.0889
1	30	10	0.9990	0.9972	0.9995
1	35	10	1.4874	1.2184	1.2196
1	40	10	1.5472	1.2428	1.2439
1	50	10	1.2349	1.1104	1.1113
1	30	5	0.8354	0.9042	0.914
1	30	20	2.1534	1.4557	1.4674
1	30	30	0.9128	0.9518	0.9554
1	30	40	1.0515	1.0242	1.0254
1	30	50	1.2996	1.1356	1.1400
3	10	10	1.2123	1.0978	1.1010
3	15	10	2.4089	1.5208	1.5521
3	20	10	0.6400	0.7737	0.8000
3	25	10	0.9742	0.9838	0.9870
3	30	10	0.8036	0.8898	0.8964
3	40	10	1.8908	1.3672	1.3751
3	50	10	1.0120	1.0557	1.0583
3	20	5	0.6397	0.7879	0.7998
3	20	20	0.5162	0.6827	0.7185
3	20	30	2.8533	1.6200	1.6892
3	20	40	4.4963	1.9600	2.1205
3	20	50	4.5747	1.9900	2.1389
5	10	10	3.7544	1.7068	1.9376
5	15	10	7.7738	2.4488	2.7882
5	20	10	1.5021	1.0687	1.2256
5	25	10	2.6304	1.4365	1.6218
5	30	10	4.4810	1.7037	2.1168
5	40	10	4.4514	1.9342	2.1980
5	50	10	3.6625	1.6641	1.9138
5	20	5	2.4535	1.3115	1.5664
5	20	20	1.5022	1.0300	1.2257
5	20	30	10.492	2.7940	3.2392
5	20	40	24.181	4.0044	4.9174
5	20	50	22.339	3.9064	4.7264
7	10	10	6.9107	2.2985	2.6288
7	15	10	15.194	3.3984	3.898
7	20	10	3.2514	1.5300	1.8032
7	25	10	5.6315	2.0454	2.3731
7	30	10	13.556	2.9243	3.6819
7	40	10	6.7877	2.3713	2.6053
7	50	10	8.3185	2.4521	2.8842
7	20	5	6.3377	2.0678	2.5175

7	20	20	3.6700	1.5768	1.9157
7	20	30	20.052	3.8722	4.4779
7	20	40	60.035	6.3446	7.7482
7	20	50	54.771	6.1088	7.4007

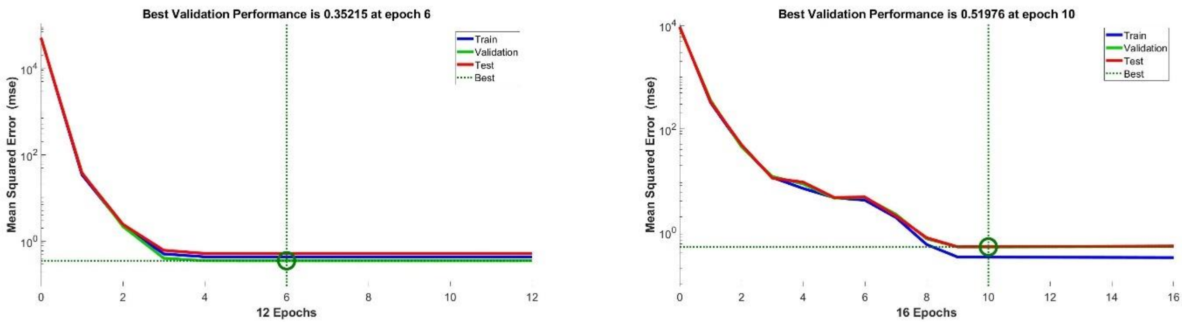

Fig. 8 - Gaussian-NAR network training for 1-hour and 3-hour forecast

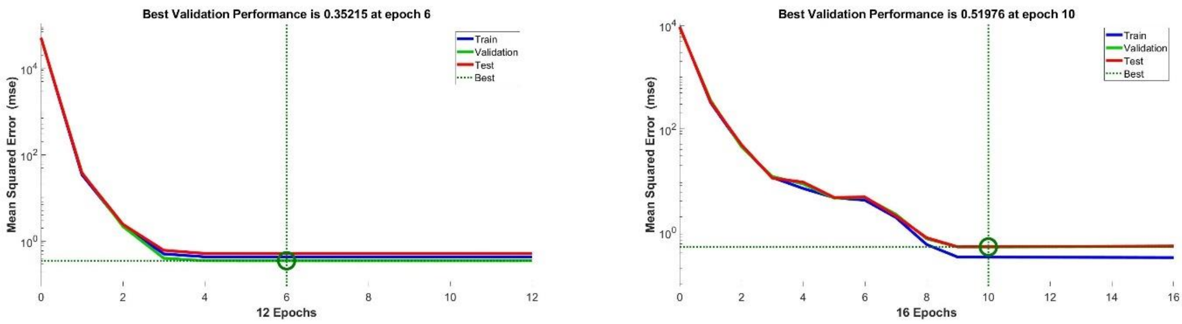

Fig. 9 - Gaussian-NAR network training for 5-hour and 7-hour forecast

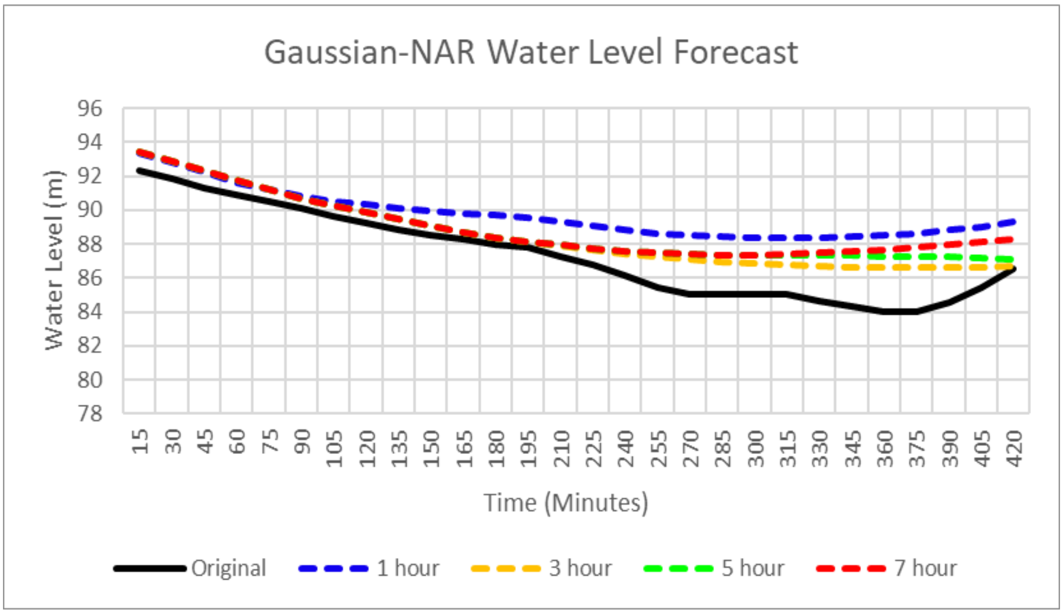

Fig. 10 - Gaussian-NAR water level forecast

Based on the forecast performance parameter, the ANN model with good performance applied in the Gaussian-NAR network structure. After the training parameter set, the forecast result plotted, shown in Fig. 10. Fig. 10 showed the comparison between the actual water level data and the forecast result for 1 hour, 3 hours, 5 hours, and 7 hours water level forecast.

3.1 ANN Performance Result

The calculation of RMSE is to compute the error between the actual water level data and forecasted water level data. Additionally, the Pearson R and coefficient of determination R squared used to ensure the success targets met. The closest Pearson R value approach to the value of 1 indicates that the model has the best value. The actual water level data and forecast water level data were charted on the graph to compare the performance of each model.

Based on Table 2 observation, 3 hours ahead water level forecast is the best in conjugate with the R squared of 99.8 per cent. Table 2 also showed that the NAR model could forecast the water level until 7 hours ahead forecast with the high accuracy of R squared of 86.7 per cent. In Table 3, the result indicates that the multi-step ahead forecast's best performance is 3 hours ahead with RMSE, MSE, and MAPE's best value.

Table 2 - ANN accuracy evaluation

No Hour forecast	R	R squared
1	0.998493	99.69888
3	0.999039	99.80789
5	0.963542	92.84133
7	0.931505	86.77024

Table 3 - ANN forecast Performance

No Hour forecast	RMSE	MSE	MAE	MAPE
1	2.68153	7.190601	2.355906	2.643778
3	1.393095	1.940714	1.191548	1.355796
5	1.719157	2.955502	1.427552	1.620232
7	1.915715	3.669963	1.576785	1.785951

4. Conclusion

The paper addresses the importance of short term water level forecast in the Melaka River. Short term flood forecast is crucial to forecast the occurrence of the flash flood. Hybrid Gaussian-NAR introduced as the water level forecast system in this paper. The hybrid Gaussian-NAR model was selected based on the RMSE, MSE, MAPE, and MAE result. The optimised model with lower RMSE, MSE, MAPE and MAE selected as the best forecast model. The data measured with the Pearson R and R squared to verify the accuracy and correlation between the predicted data from the forecast and actual time series data. The Gaussian-NAR network with the best Pearson R and R squared in the obtained result is a 3-hour level water level forecast with the R squared of 99.8 per cent and 0.999 of R.

This study showed that the Gaussian-NAR network could forecast 7 hours water level with the R squared 86.77 per cent and 0.9315 of R. Overall, the Gaussian-NAR technique produces good results with high accuracy of more than 80% of R-squared. The best model suit for the forecast system in Pengkalan Rama Jetty is the 3-hour water level, forecast model. The Gaussian-NAR technique also showed a good result with 7 hours ahead of water level forecast with high accuracy.

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