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Tidal Level Short-Term Prediction using Back-Propagating Artificial Neural Network (BP-ANN)

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This research paper presents a back-propagating artificial neural network (BPANN) model for short-term prediction of tidal levels in Penang, Malaysia. The model is trained using historical tidal data and meteorological parameters such as tides height within 3 hours, tides coefficient, and tides cycles for four months data were taken from website in May, June, July and August. The study aims to develop an accurate and efficient prediction model to aid in tidal energy management and forecasting for simulating tidal level value that closely matches the actual tide from the input-output relationships in the short-term tidal records through the unknown parameters determine by ANN. The prediction determination used modelling with artificial neural network (ANN) with the back-propagation method. The optimal predictions using ANN were obtained by conducting five input layers, five hidden layers, and one output layer (5-5-1). The results end with mean absolute percentages error (MAPE) for May, June, July and August was 1.76, 0.39, 0.26 and 0.07 respectively. ANN proved very effective in predictions tidal level.

Keywords:

ANN; Tidal level; Forecasting; FFBP; IoT

1. Introduction

Tidal energy is regarded as a renewable energy source since it depends on the tides' innate motion, which is caused by the moon's and the sun's gravitational pull (National Renewable Energy Laboratory) [20]. There are two ways to use tidal energy: tidal range technologies, which use the height difference between high and low tides to produce power, or tidal stream technologies, which use the kinetic energy of ocean currents to spin turbines and produce electricity (European Marine Energy Centre) [7].

Tidal energy is superior to other renewable energy sources in several ways. Tidal energy is predictable and reliable since tides come twice daily and follow a regular pattern, in contrast to solar and wind energy (National Renewable Energy Laboratory) [20]. As a result, it is simpler to add tidal energy to the electrical grid and offer a reliable supply of power.

Moreover, tidal energy has a higher energy density than other renewable energy sources, which allows it to produce more electricity per unit of space (Ocean Energy Europe) [21]. Tidal turbines can

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produce large amounts of electricity when installed in locations with high tidal currents, such as estuaries or constrained channels (European Marine Energy Centre) [7].

Tidal energy is a promising renewable energy source that uses the strength of the tides to produce electricity. Over 800 TWh per year is thought to be the whole theoretical potential for tidal energy on a global scale, which is equal to the yearly electricity consumption of the UK, France, and Canada put together (International Energy Agency) [10]. Only a few tidal power plants are currently in operation, but ongoing research and development activities are anticipated to result in the commercialization of more tidal energy projects in the upcoming years (International Renewable Energy Agency; European Marine Energy Centre) [11]. Nonetheless, it is important to carefully consider and manage any potential environmental effects of tidal energy, such as changes in water flow and noise pollution [16]. Yet, tidal energy offers a substantial chance for nations to diversify their energy mix and lessen their reliance on fossil fuels.

Southeast Asian nation of Malaysia is an archipelago that is bordered by the South China Sea and the Straits of Malacca. The nation boasts a lengthy 4,675 kilometres of coastline, with tide ranges up to 3 metres [19]. The most promising locations for tidal energy production have been found to be the waterways bordering Sabah and Sarawak [23]. Tidal energy still makes up a modest portion of Malaysia's energy mix while having a lot of promise [5]. Tidal energy is one of the potential renewable sources that Malaysia has set as a goal to include in 20% of its energy mix by 2025 [8]. The potential of tidal energy in Malaysia needs to be explored and developed in order to support the nation's energy security and lower its carbon footprint as the need for sustainable energy rises. Additionally, it has a much lower environmental impact than hydroelectric power plants, which trap all living creatures inside the dam, and tidal energy technologies, which disturb fewer birds because of the tidal turbine's submerged position in the sea [8].

Penang Island, which is part of Peninsular Malaysia and is recognised for having a high tidal range, offers a prospective site to produce tidal energy. Tidal energy may produce clean electricity without emitting greenhouse gases and is a renewable and sustainable energy source. The effective and reliable functioning of tidal energy systems is, however, made difficult by the fluctuation of tidal currents and tidal heights. The creation of tidal level short-term prediction models using artificial neural networks is one strategy for solving this problem (ANNs). An example of a machine learning algorithm that can learn from input data and generate predictions is an artificial neural network (ANN).

Many studies, including one in Penang, have investigated the use of ANNs for short-term tidal level prediction. For instance, one study used inputs from meteorological and oceanic data to create a backpropagation ANN model to forecast tidal levels at several places around Penang Island [27]. According to the study, tidal levels may be reliably predicted by the ANN model up to six hours in advance, which could be helpful for tidal energy plants to operate as efficiently as possible and for tidal unpredictability to have a smaller influence. ANN may be used for model comparison and adjustments in accordance with data on wave height, cycle, and ocean current measurements to run a simulation study of the expected port current velocities using the genetic algorithm of ANN, according to a theory described by Hsiao and Hwang [4].

A crucial component of using tidal energy is forecasting tide levels. Tidal power plants can operate more efficiently and effectively if tide levels can be predicted with accuracy [6]. The conventional techniques for predicting tidal levels rely on mathematical models, which can be computationally expensive and call for a large amount of data [22]. Due to their capacity to recognise intricate patterns in historical data, artificial neural networks (ANNs) have become a promising alternative for forecasting tidal levels.

A back-propagating artificial neural network (BPANN) was used in this study to predict short-term tidal levels. Using past tide level data, the BPANN is trained before being applied to forecast future time periods. Backpropagation algorithm-based artificial neural networks, or BPANNs, train the network. An input layer, one or more hidden layers, and an output layer make up the network. Data is ingested by the input layer, processed by the hidden layers, and ultimately produced by the output layer.

For the BPANN to provide the required output, the network's weights must be adjusted during training. The backpropagation algorithm analyses the discrepancy between the desired and actual outputs and modifies the network weights accordingly. Up until the error is reduced, the practise is repeated. To assess the effectiveness of the BPANN, its performance is contrasted with that of conventional prediction techniques. The goal of the study is to show how BPANNs can enhance the precision of tidal level predictions, which could ultimately result in better tidal power plant optimisation [9].

BPANNs have been used in numerous research to forecast tide levels. For instance, a BPANN was utilised in a study by AghaKouchak *et al*., [2] to forecast tide levels in the Persian Gulf. According to the study, the BPANN could correctly forecast tide levels up to 72 hours in advance. A BPANN was employed in a different study by Li *et al.*, [13] to forecast tide levels in the Yangtze River estuary. According to the study, the BPANN could correctly forecast tide levels up to 24 hours in advance.

BPANNs have demonstrated their ability to accurately forecast tide levels over short time scales. In many situations when precise tidal predictions are required, these models can be helpful.

According to research presented by Meena & Agrawal [18], the Feed-Forward Back Propagation (FFBP) network utilizing the Levenberg-Marquardt (LM) algorithm provides good correlations when compared to other algorithms. The results were compared using statistical techniques such as correlation coefficients, RMSE, and Nash-Sutcliff efficiency. The data were related to three unique sites, two on the west coast and one on the east coast of India. It shows how to use an artificial neural network to estimate tides at the base station and at a station that is far away from the main station. It also shows how to utilize this method to quickly generate missing data. The neural network algorithm can produce the optimum weight values and threshold values because of applying the differential evolution algorithm and neural network to the tidal prediction of Qingdao port, improving the capability of the global search according to Qiu *et al.*, [25].

An ANN model for predicting tides using a short-term tidal record was developed and published supported by Lopez *et al.,* [15]. ANN has been used to forecast a rising number of recent natural events. An artificial neural network, or ANN, is a parallel computer system that connects numerous artificial neurons to simulate biological brain networks conducted by Md *et al.,* [17]. Tidal energy uses artificial neural networks (ANNs) to translate data and learn about the interactions between climate and sea level variables. Because neural networks give a non-deterministic mapping between the supplied set of input and output values, the model can predict the tides based on the prior observation by Meena and Agrawal [18].

The output results of a network depend on its many parameters, which are frequently selected through trial and error. The backpropagation network developed by Rumelhart *et al.,* [12] is the most often used self-learning model of ANNs (1986). The backpropagation network, which computes the weight of interconnective neurons using the gradient steepest descent method, may be addressed by merging the hidden layers with the interaction of processing components. During the backpropagation network learning process, the connectivity weights are adjusted using an error convergence method to produce the desired output for a certain input. In the BPN model, errors typically propagate from the output layer to the input layer via the network's hidden layer to produce the intended results.

The efficient operation of tidal power plants depends on the correct forecast of tide levels. The complicated and non-linear correlations between input data and tidal levels cannot be fully captured by conventional techniques for predicting tidal levels, such as harmonic analysis. On the other hand, artificial neural networks (ANNs) have the capacity to learn from previous data and can produce precise predictions as a result of that learning. In this study, we show that the back-propagating artificial neural network (BPANN) may be used to predict short-term tidal levels. These findings demonstrate that the BPANN can provide precise predictions of tide levels, which can aid in tidal power plant operation optimisation. This study emphasises the potential of ANNs for enhancing tide level prediction accuracy and tidal power plant efficiency.

In this paper, some tidal level data collected from the web (Tides4fishing) [24] were used to train the ANN system in MATLAB to predict the tidal level value to be used in the control system for power electronics in the tidal turbine energy technology. It is important to use the ANN system to avoid using complicated calculations and facilitate the user in the power electronic control system.

2. Methodology

2.1 Backpropagation

In this study, ANN was used to determine the prediction of tides levels in Malaysia for a tidal energy harvesting technology by observing through MATLAB with variables data collected from the forecasting website. A backpropagation structure is shown in Figure 1.

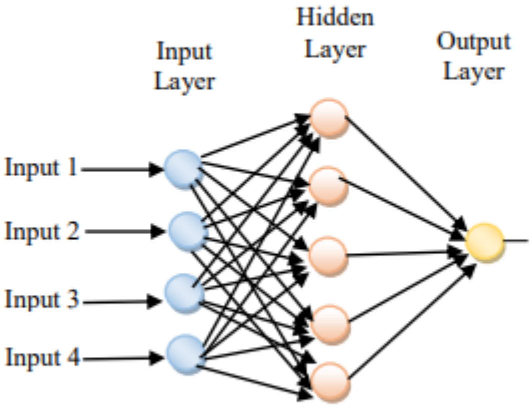


Fig. 1. Structure of Backpropagation in ANN

Backpropagation techniques are popular learning strategies in the ANN community. It has an input layer, one or more hidden layers, and an output layer, which are the three different types of layers. Every node in the input layer is connected to every other node in the hidden layer and vice versa. The input layer represents the unprocessed data delivered to the network, and the values in the output layer remain constant. The input and output layers show the input and output values, respectively. The hidden layer will then receive the data from the input layers at the duplicated nodes. By applying weight values, the output layer will change an output that has been adjusted by the hidden layer using data from the hidden layer [3]

The network's weight, the weight of its connections, and the output are all determined using the gradient descent approach as in Eq. (1). The error function at the output neuron is defined as:

$$E = \frac{1}{2}\sum_{n}\left(T_j - A_j\right)^2 \tag{1}$$

where j is the output neuron and Tj and Aj are the output neuron's respective actual and predicted values.

To train on a chip for a difficult issue, image compression and decompression is utilized. ANN are more effective than more established compression methods like JPEG. The architecture of the 2:2:2:1 neural network was chosen to implement the AND, OR, NAND, NOR, XOR, and XNOR functions of fundamental digital gates. The network contains one output (y) and two inputs (x1 and x2). The neural network design is analysed using MATLAB, and it is discovered that the hyperbolic tangent sigmoid (TANSIG) transfer function provides the best convergence of error during the training to construct digital gates. This algorithm's simplicity and suitability to offer a solution to any complicated patterns make it advantageous to employ. Moreover, depending on the quantity of input-output data included in the layers, this algorithm's execution is quicker and more effective.

2.2 ANN Prediction System in MATLAB

Table 1, Table 2, Table 3 and Table 4 show the data of tidal height, tidal coefficient, and tidal cycle in 5 days every month was taken at 4 different selected times (May, June, July, and August). Each selected time consists of 3 different tidal height values at the previous 3 hours, 2 hours, and 1 hour from the actual time. All data sets were later called in MATLAB to be used in ANN training using (nntraintool). The outcome of the process is the regression curve. The regression curve determined the accuracy of the actual data and the predicted data similarity at a specific time.

Table 1
Height data of each previous hour taken before the time stamp for May

Date	Time	Tidal coefficient	Tidal Cycle	Height (m)		
				P 3hr	P 2hr	P 1hr
May 1st	21:14	87	2	1.25	1.85	2.22
	03:24	85	1	1.50	1.00	0.82
	09:26	85	1	1.70	2.32	2.55
	16:00	82	2	1.49	1.14	0.82
May 2nd	21:43	82	2	1.58	2.08	2.28
	03:49	79	1	1.48	1.10	0.88
	09:49	79	1	1.78	2.30	2.55
	16:27	75	2	1.45	0.98	0.75
May 3rd	22:13	71	1	1.18	1.85	2.00
	04:15	71	1	1.50	1.10	0.85
	10:13	67	2	1.52	2.10	2.42
	16:55	67	2	1.40	1.00	0.80
May 4th	22:43	62	1	1.48	1.85	2.00
	04:40	62	1	1.39	1.00	0.87
	10:37	57	2	1.70	2.10	2.45
	17:24	57	2	1.50	1.14	0.75
May 5th	23:15	52	1	1.30	1.68	1.90
	05:06	52	1	1.68	1.34	1.10
	11:02	47	2	1.70	2.00	2.28
	17:55	47	2	1.32	1.10	0.84

Table 2
Height data of each previous hour taken before the time stamp for June

Date	Time	Tidal coefficient	Tidal Cycle	Height (m)		
				P 3hr	P 2hr	P 1hr
June 1st	22:01	68	1	1.43	1.85	2.00
	03:50	68	1	1.85	1.14	1.08
	09:46	68	1	2.00	2.30	2.46
	16:40	65	2	1.50	0.80	0.63
June 2nd	22:35	62	1	1.14	1.75	1.82
	04:20	62	1	1.08	1.45	1.20
	22:14	59	2	1.88	2.08	2.34
	17:11	59	2	2.30	0.90	0.80
June 3rd	23:11	56	1	2.46	1.70	1.90
	04:52	56	1	1.15	1.45	1.25
	22:43	33	2	0.80	2.20	2.25
	17:44	33	2	0.63	0.90	0.72
June 4th	23:50	50	1	1.30	1.55	1.82
	05:26	50	1	1.75	1.45	1.35
	11:14	47	2	1.82	1.99	2.21
	18:21	47	2	1.66	0.99	0.88
June 5th	00:35	45	1	1.45	1.60	1.70
	05:07	45	1	1.20	1.70	1.46
	11:49	44	2	1.70	2.02	2.10
	19:02	44	2	2.08	1.16	1.02

Table 3
Height data of each previous hour taken before the time stamp for July

Date	Time	Tidal coefficient	Tidal Cycle	Height (m)		
				P 3hr	P 2hr	P 1hr
July 1st	22:32	67	1	1.24	1.72	1.82
	04:13	67	1	1.72	1.45	1.16
	10:02	66	2	1.82	2.25	2.20
	17:01	66	2	1.68	0.90	0.70
July 2nd	23:06	64	1	1.45	1.70	1.90
	04:48	64	1	1.16	1.45	1.25
	10:34	63	2	1.70	2.16	2.39
	17:32	63	2	2.25	0.98	0.76
July 3rd	23:41	61	1	2.20	1.88	2.00
	05:25	61	1	1.30	1.45	1.35
	11:06	59	2	0.90	2.1	2.25
	18:05	59	2	0.70	0.98	0.80
July 4th	00:19	58	1	1.92	1.85	2.00
	06:05	58	1	1.70	1.45	1.40
	11:41	56	2	1.90	2.10	2.15
	18:40	56	2	1.65	0.80	0.78
July 5th	01:01	55	1	1.45	1.88	2.08
	06:52	55	1	1.25	1.48	1.34
	12:21	54	2	1.76	1.14	2.08
	19:19	54	2	2.16	1.14	0.94

Table 4
Height data of each previous hour taken before the time stamp for August

Date	Time	Tidal coefficient	Tidal Cycle	Height (m)		
				P 3hr	P 2hr	P 1hr
August 1st	23:18	74	1	1.16	1.85	1.90
	05:15	74	1	1.85	1.48	1.30
	10:54	72	2	1.90	2.25	2.35
	05:40	72	2	1.88	0.78	0.50
August 2nd	23:49	70	1	1.48	2.05	2.25
	05:50	70	1	1.30	1.30	1.12
	11:27	68	2	1.65	2.08	2.25
	18:10	68	2	2.25	0.90	0.75
August 3rd	00:23	65	1	2.35	1.90	2.28
	06:29	65	1	1.10	1.30	1.12
	12:02	62	2	0.78	1.88	2.18
	18:43	62	2	0.50	0.85	0.78
August 4th	01:01	59	1	1.48	1.88	2.18
	07:15	59	1	2.05	1.47	1.26
	12:43	56	2	2.25	1.88	1.98
	19:21	56	2	1.50	1.10	0.82
August 5th	01:47	53	1	1.30	2.08	2.18
	08:13	53	1	1.12	1.45	1.25
	13:35	51	2	1.65	1.66	1.84
	20:08	51	2	2.08	1.16	1.12

2.3 Statistical Calculations

The degree of discrepancy between the outcomes of demand forecasting and the actual demand is indicated by the accuracy of forecasting results, which is a measure of forecasting error. There is some uncertainty involved in forecasting in any situation. In addition to being a component of the error, the variance in the prediction also reflects the forecasting model's inability to discern between various components of the data series. So, the size of the predicting results variance may be caused by unanticipated factors (outliers). It is impossible to isolate forecasting accuracy metrics from the validation of forecasting methodologies. There are a several metrics to gauge predicting accuracy, but the most popular ones are Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Deviation (MAD). The accuracy of forecasting will be high if the values decrease. The accuracy and precision values in the optimization outcomes are calculated using statistical formulae [1].

2.2.1 Mean absolute percentage error (MAPE)

The percentage value of deviations from the estimation findings is calculated using the Mean Absolute Percentage Error (MAPE) relative determination model. The equations are used in Eq. (2).

$$MAPE = \frac{1}{N}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{2}$$

where: A_t = Actual and F_t = Forecast

2.2.2 Root mean square error (RMSE)

Other calculations which are the square root version of Mean Square Error (MSE) is Root Mean Square Error (RMSE). The equations used can be seen in Eq. (3).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \quad (3)$$

where: A_t = Actual and F_t = Forecast

2.2.3 Mean square error (MSE)

The average square of the difference between the actual value and the estimated value yields the error value known as the mean square error (MSE). The equations used can be seen in Eq. (4).

$$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n} \quad (4)$$

where: A_t = Actual and F_t = Forecast

2.2.4 The mean absolute deviation (MAD)

The mean absolute deviation (MAD), also known as the mean absolute deviation, is the total of the absolute differences between the actual and estimated values divided by the number of observations. The equations used can be seen in Eq. (5).

$$MAD = \frac{\sum_{t=1}^{n}|A_t - F_t|}{n} \quad (5)$$

where: A_t = Actual and F_t = Forecast

3. Results and Discussion

3.1 Result for ANN Prediction System in MATLAB

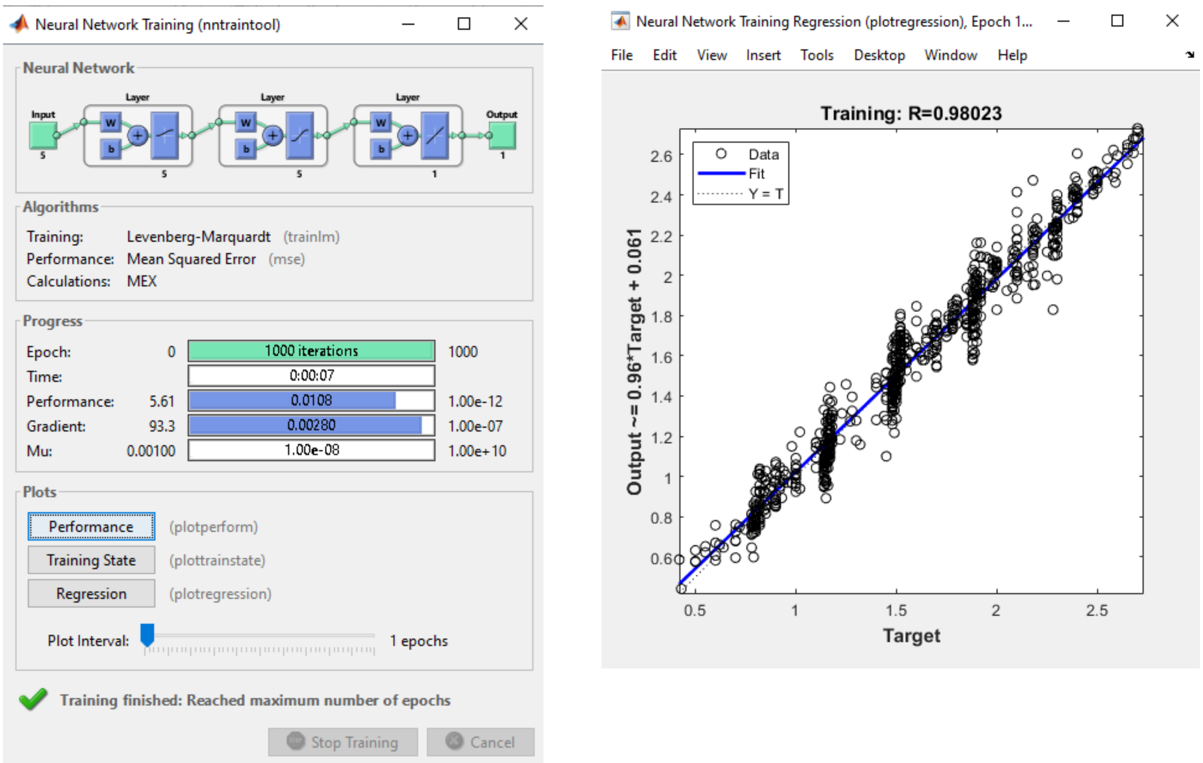
This section discusses the ANN result in MATLAB (nntraintools) for May, June, July, and August 2022 with for initial 5 days every month for 4-time stamps each. In Table 5, the training system is successful as the correlation coefficient, r achieved is greater than 0.9 where correlation coefficient is referred to as product-moment of r. R achieved were above 0.9 which mean more linear relationship between the variables [1]. ANN can be used for any complex power system or any problem that a mathematical equation is unknown as it can go into the training process for the learning and understanding of the relationship between the input and output data. The details share shown in the figures and tables below for several neurons of input layer-hidden layer-output layer is 5-3-1 for May, June, July and August datasets.

Table 5
Coefficient of Determination, R2 for May, June, July and August

Month	Tidal Level		
	R	R^2	
		Training Data	Testing Data
May	0.98	0.96	0.96
June	0.98	0.96	0.96
July	0.98	0.95	0.95
August	0.99	0.97	0.97

3.1.1 May 2022

Figure 2 shows the (a) post-processing of the nntraintool of May 2022 using data collected from (*Tides4fishing*) [24] with a (b) regression data plot.



(a) (b)

Fig. 2. Correlation coefficient value, R of May

The neural network training figure consists of 3 layers which are the input, hidden, and output layers. The hidden layer contained 5 neurons while the output has 1 neuron. The name of the training algorithm is Levenburg-Marquardt (trainlm). Tidal data was trained successfully for 1000 iterations or also called epochs by getting a correlation coefficient value, R of 0.98 which was very close to 1 (stronger correlation of variables) showing that the accuracy is high between trained data and the tested data. The data points lie on the blue line (Fit).

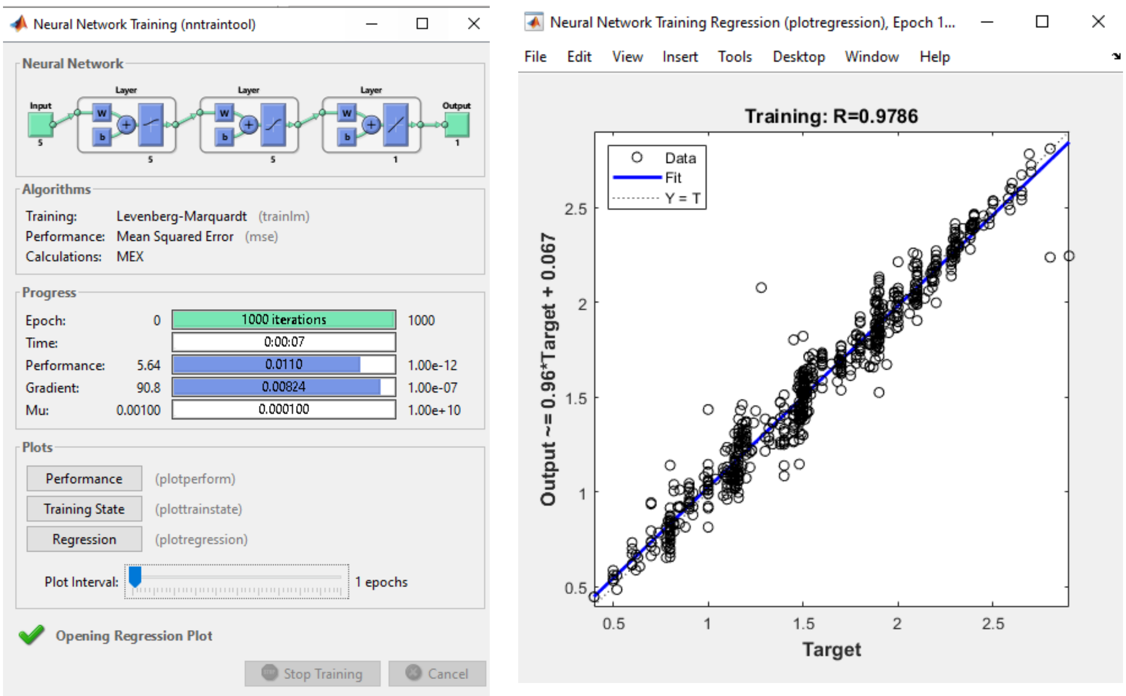
Table 6 shows the comparison between the actual height and ANN-obtained height data according to the selected time in May. The height data obtained is like the actual height. MAPE, MAD, MSE, and RMSE values for May were 1.760, 0.017, 0.002, and 0.041 respectively shown in Table 10.

Table 6
Height result in actual and obtained comparison of May

Date	Current Time	Actual height	ANN obtained height
May 1st	00:14	2.20	2.20
	06:24	0.70	0.72
	12:26	2.60	2.60
	19:00	0.70	0.70
May 2nd	00:43	2.20	2.20
	06:49	0.80	0.80
	12:49	2.60	2.60
	19:27	0.60	0.60
May 3rd	01:13	2.20	2.18
	07:15	0.80	0.80
	13:13	2.50	2.50
	19:55	0.70	0.70
May 4th	01:43	2.10	2.10
	07:40	0.90	0.90
	13:37	2.50	2.49
	20:24	0.70	0.68
May 5th	02:15	2.00	2.00
	08:06	1.10	1.10
	14:02	2.30	2.30
	20:55	0.80	0.80

3.1.2 June 2022

Figure 3 shows the (a) post-processing of the nntraintool of June 2022 using data collected from (tides4fishing.com) with a (b) regression data plot.



(a) (b)

Fig. 3. Correlation coefficient value, R of June

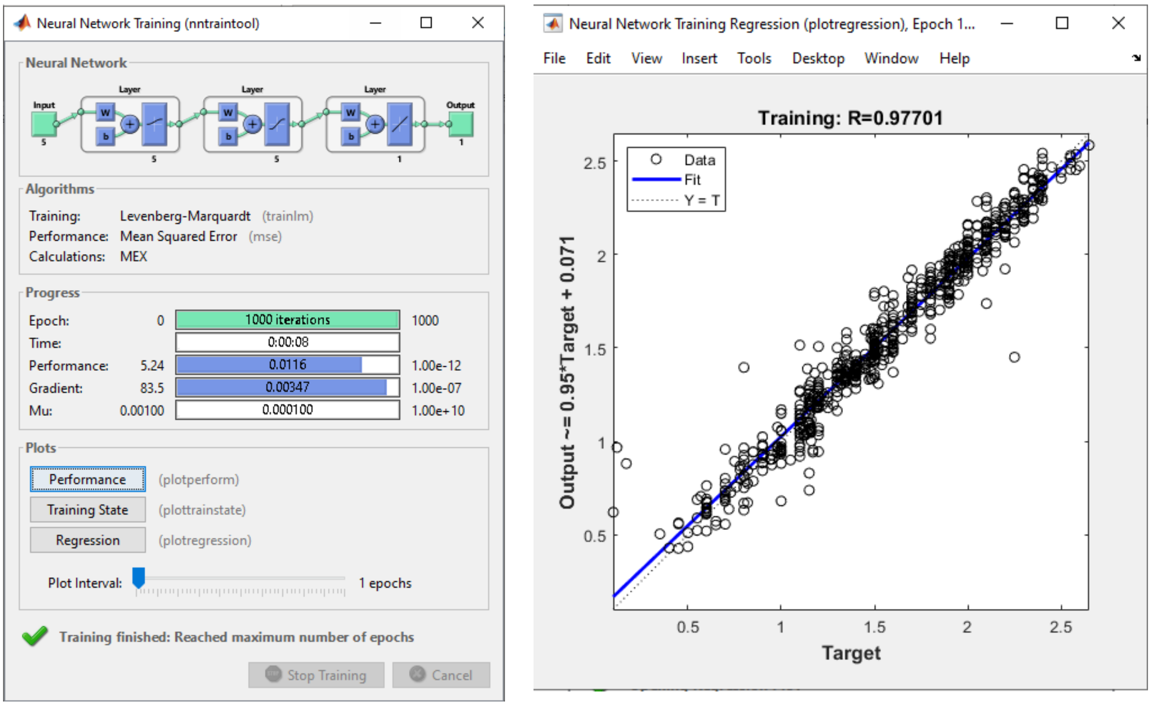
Tidal data was trained successfully for 1000 iterations or also called epochs by getting a correlation coefficient value, r of 0.98 which also very close to 1 (stronger correlation of variables) shows that the accuracy is high between trained data and the tested data. The data points lie on the blue line (Fit). Table 7 shows the comparison between the actual height and ANN-obtained height data according to the selected time in June. The height data obtained is like the actual height. MAPE, MAD, MSE and RMSE values for June were 0.388, 0.006, 0.000 and 0.012 as shown in Table 10.

Table 7
Height result in actual and obtained comparison of June

Date	Current Time	Actual height	ANN obtained height
June 1st	01:01	2.10	2.10
	06:50	1.00	1.00
	12:46	2.50	2.50
	17:40	0.60	0.60
June 2nd	01:35	2.00	2.01
	07:20	1.10	1.10
	13:14	2.40	2.40
	20:11	0.70	0.70
June 3rd	02:11	2.00	2.03
	07:52	1.20	1.20
	13:43	2.30	2.30
	20:44	0.70	0.70
June 4th	02:50	1.90	1.88
	08:36	1.30	1.30
	14:14	2.20	2.18
	21:21	0.80	0.80
June 5th	03:35	1.90	1.87
	09:07	1.40	1.40
	14:49	2.10	2.10
	22:02	0.90	0.88

3.1.3 July 2022

Figure 4 shows the (a) post-processing of the nntraintool of July 2022 using data collected from (tides4fishing.com) with a (b) regression data plot.



(a) (b)

Fig. 4. Correlation coefficient value, R of July

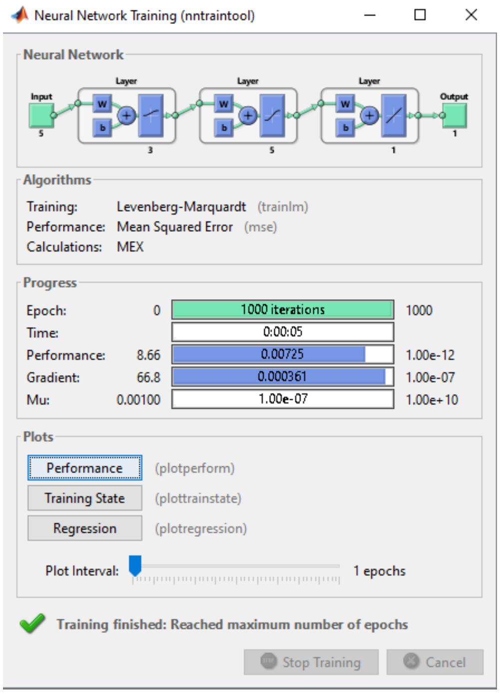
Tidal data was trained successfully for 1000 iterations or also called epochs by getting a correlation coefficient value, r of 0.98 which is likely to produce tested data closely accurate to the actual data. Table 8 shows the comparison between the actual height and ANN-obtained height data according to the selected time in July. The height data obtained is like the actual height. MAPE, MAD, MSE and RMSE values for July were 0.261, 0.004, 0.000, and 0.007 as shown in Table 10.

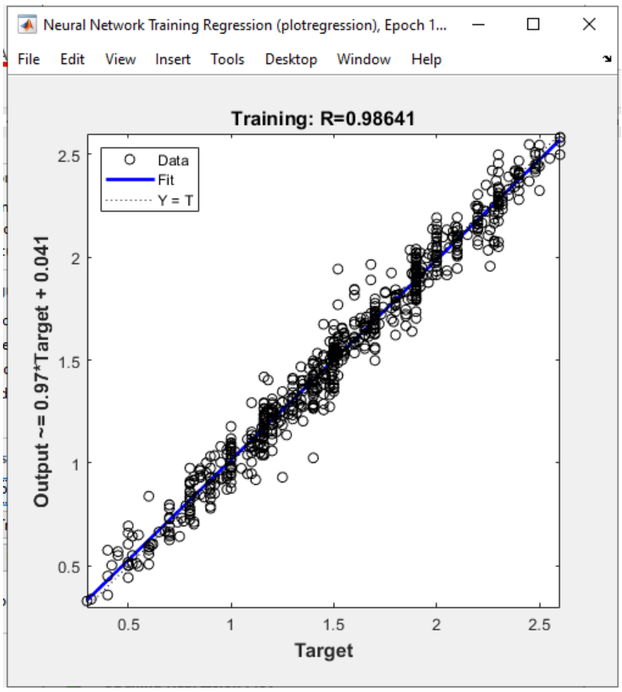
Table 8
Height result in actual and obtained comparison of July

Date	Current Time	Actual height	ANN obtained height
July 1st	01:32	2.0	1.98
	07:13	1.10	1.10
	13:02	2.40	2.38
	20:01	0.60	0.59
July 2nd	02:06	2.10	2.09
	07:48	1.20	1.20
	13:34	2.40	2.40
	20:32	0.60	0.60
July 3rd	02:41	2.10	2.10
	08:25	1.20	1.20
	14:06	2.30	2.30
	21:05	0.70	0.70
July 4th	03:19	2.10	2.10
	09:05	1.30	1.30
	14:41	2.20	2.20
	21:40	0.70	0.70
July 5th	04:01	2.10	2.10
	09:52	1.30	1.30
	15:21	2.10	2.10
	22:19	0.80	0.81

3.1.4 August 2022

Figure 5 shows the (a) post-processing of the nntraintool of August 2022 using data collected from (tides4fishing.com) with a (b) regression data plot.





(a) (b)

Fig. 5. Correlation coefficient value, R of August

Tidal data was trained successfully for 1000 iterations or also called epochs by getting a correlation coefficient, r of 0.99 which was highly close to 1 which is the highest dataset trained.

The comparison between the actual height and ANN-obtained height data in Table 9 according to the selected time in August. The height data obtained is like the actual height. MAPE, MAD, MSE, and RMSE values for August were 0.066, 0.002, 0.000, and 0.005 or as shown in Table 10.

Table 9
Height result in actual and obtained comparison of August

Date	Current Time	Actual height	ANN obtained height
August 1st	02:18	2.20	2.19
	08:15	1.10	1.10
	13:54	2.40	2.40
	20:40	0.50	0.50
August 2nd	02:49	2.30	2.30
	08:50	1.10	1.10
	14:27	2.30	2.30
	21:10	0.60	0.60
August 3rd	03:23	2.30	2.28
	09:29	1.10	1.10
	15:02	2.20	2.20
	21:43	0.70	0.70
August 4th	04:01	2.20	2.20
	10:15	1.20	1.20
	15:43	2.00	2.00
	22:21	0.80	0.80

August 5th	04:47	2.20	2.20
	11:13	1.20	1.20
	16:35	1.90	1.90
	23:08	1.00	1.00

Table 10
Level of Accuracy of statistical dataset for May, June, July, and August

Stats item	The calculation results of tidal level data			
	Month			
	May	June	July	August
MAPE	1.760	0.388	0.261	0.066
MAD	0.017	0.006	0.004	0.002
MSE	0.002	0.000	0.000	0.000
RMSE	0.041	0.012	0.007	0.005

4. Conclusions

In conclusion, the developed system with a back-propagation Neural Network achieved reasonable results for the height tidal level with the average value of correlation coefficient of May, June, July, and August were 0.98 and the average value of accuracy for four months is 96%. The mean percentage error for four months was 1.76, 0.39. 0.26, and 0.066. The system can be used to predict tidal level data at a specific time and get good accuracy without complex mathematical equations. With the proper source of actual data, the developed system will produce better output data in a short time.

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