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Development of Whale Optimization Neural Network for Daily Water Level Forecasting

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ABSTRACT

Development of water level forecasting model is essential in flood prediction and water resources planning and management. Through accurate water level forecasting models, high efficiency in the usage of water resources as well as minimization of flood damage with proper management of future development can be achieved. Therefore, the objective of this paper was set to develop a novel artificial neural network (ANN) for predicting the water level of Batu Kitang river via the implementation of a metaheuristic algorithm, Whale Optimization Algorithm (WOA). WOA was used to train and optimized the ANN. To compare the reliability of Whale Optimization Neural Network (WONN) in predicting the water level at Batu Kitang river, WONN is compared against a conventional neural network, Levenberg-Marquardt Neural Network (LMNN). The predicted water level showed that WONN outperformed LMNN in various evaluation criterion. However, inaccurate predictions occurred on both WONN and LMNN, which shows that further improvements are required to boost the prediction performance.

Key words: daily water level forecasting, artificial neural network, Levenberg-Marquardt Neural Network, Whale Optimization Neural Network, Kuching.

1. INTRODUCTION

Water level forecasting plays an essential role in water resources planning and management. This is because the predicted water level can be used to facilitate the management of water resources, hence optimizing the use of water. Not only that, the occurrences and potential of flood can be predicted via water level forecasting. Thus, accurate prediction of water level is needed to allow early flood mitigation as well as minimizing the damage and losses of property and lives. Conventional forecasting model often requires complex modelling which often require the knowledge and large amount of data. Complete sets of historical time series data are often required to perform the forecasting studies. However, it is currently unavoidable to have missing data due to human mistakes and malfunctioned equipment for collecting the observations. The discontinuation of historical data hence limiting the efficiency of conventional forecasting model. Thus, there is a need to seek for a better approach to estimate the water level.

To overcome the limitation of conventional forecasting model, artificial neural network (ANN) is more favored due to its flexibility in performing various task. ANNs have been applied by scientists for various prediction modelling which include finance, mathematical, medical, weather forecasting and engineering fields [1]. In hydrological field, ANN models have been applied to forecast precipitation [2-8], water level [1, 9-15] and inflow [16-29]. Jain, et al. [30] had developed error back propagation feed forward neural network for reservoir inflow prediction. The result obtained from error back propagation feed forward neural network is then compared with autoregressive integrated moving average time-series model (ARIMA). Moreover, Xu and Li [31] developed feed-forward neural network that trained with back propagation algorithm for 1 to 7 hours ahead inflow forecasting into a hydropower reservoir. Moreover, there are review papers for the application of ANN models and there are over 210 journal papers have been focused on the prediction of water resource variables in river systems were published from year 1999-2007 [28, 32, 33, 39]. Based on the reviews attempted above, it can be concluded that, it can be concluded that ANN models are efficient tool in different areas of hydrology engineering which include modelling of rainfall-runoff relationship, inflow estimation, runoff analysis in humid forest catchment, setting up stage-discharge relations, ungauged catchment flood prediction, river flow prediction and short-term river flood forecasting.

ANN is much preferred among hydrologist due to its ability to outperformed conventional process-based conceptual physical model. ANN is categorized as data-driven model which does not require large amount of data [13]. Data relevant to physical conditions of the study area can be omitted as ANN can perform the prediction task simply by learning the relationship and pattern between the input and target datasets. However, ANN often suffers from the issues of overfitting and underfitting of training data and traps in local optima, which tend to limit the prediction performances [1].

This study thus, aims to overcome the limitations of ANN by introducing a metaheuristic algorithm to train the ANN for water level prediction. The Whale Optimization algorithm (WOA) is proposed as the solution to train the neural network. As such the objectives of this study is outlined as follow:

1. To develop a novel ANN using WOA – Whale Optimization Neural Network (WONN)
2. To predict the water level of Batu Kitang river using WONN
3. To compare the performance between WOANN and a conventional neural network, Levenberg-Marquardt Neural Network (LMNN)

2. METHODOLOGY

2.1 Artificial Neural Network

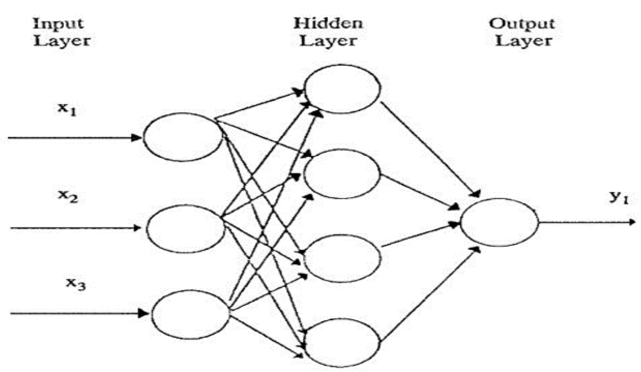

Figure 1: Schematic Diagram of ANN [30]

ANN is a computing system which inspired by the function of the human brain and nervous system. ANN consists of several neurons (circle shape) that are arranged in input layer, output layer and one or more hidden layers as shown in Figure 1. The input neurons receive and process the input signals and send the output to other neurons in the network where this process is continued. This type of network, where the information passes one way through the network, is known as feedforward network [30].

However, one of the challenges when solving optimization problem in ANN is the presence of local solutions. There is only one best return solution, which also known as global optimum, in a single-objective search space. However, many other solutions, in terms of return values, which close to the objective value are shown up in every part of search space. This type of return values closes to the objective value located in particular search space are referred as local solutions. This is because they are locally the best solution in their vicinity but not the best solution globally when consider the entire search space. As a result, the presence of these local solutions leads to the local optima stagnation. In other words, local optima stagnation refers to the situation where an optimization algorithm finds a local solution and mistakenly assumes it as the global optimum. Therefore, using an efficient optimization algorithm can help to resolve the problem of trapping in local optima [34].

In addition, an optimization algorithm, which capable of avoiding local solutions, may not be able to converge effectively towards the global optimum. This issue refers to the convergence speed of an optimization algorithm and this becomes another challenge for algorithms when solving optimization problems. Generally, quick convergence leads to local optima stagnation as local solutions are taken as global optimum quickly whereas the slow convergence happens when there are sudden changes in the solutions due to local optima avoidance. Therefore, these two trade-offs are the main challenges for algorithms when real time problems [34].

2.2 Whale Optimization Algorithm

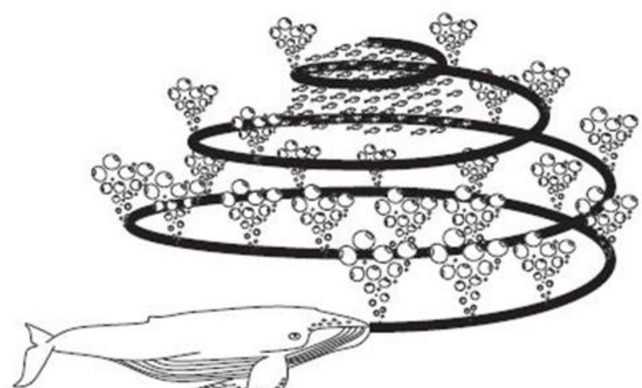

Figure 2: Bubble-net feeding behavior of humpback whales [35]

A new mathematical model, which named Whale Optimization Algorithm (WOA), is introduced from the inspiration of humpback whales [35]. Similar to Particle Swarm Optimization (PSO) algorithm [40], WOA is a novel nature-inspired meta-heuristic optimization algorithm which mimics the social behaviour and hunting behaviour of humpback whales. WOA is chosen in this study due to its population-based meta-heuristic properties which is different than that of swarm intelligence-based algorithm. Their special hunting method called bubble-net feeding method and features of the spiral bubble-net feeding method is mathematically modelled to perform optimization [35]. The optimization process of WOA is inspired by the special hunting method called spiral bubble-net feeding method. The spiral bubble-net feeding method on foraging behavior can only be observed in humpback whale. As illustrated in Figure 2, the foraging is done by creating bubbles in a spiral circle around the prey and swim up towards the surface [35].

WOA is tested with 29 mathematical optimization problems and 6 structural design problems and the results prove that WOA algorithm is very competitive while compared to other meta-heuristic algorithms as well as conventional methods [35]. Hence, WOA is adopted for ANN model development and used to forecast water level for Batu Kitang river.

The overview of flow chart for WOA model development is shown in Figure 3. In order to train feedforward neural network by using WOA, some tweaks will be needed to determine the global optimum, where the weights and biases of the feedforward neural network will be determined with respective to the objective function. Weights and biases are the parameters of neural network, which helps to locate and adjust the relationship between inputs and targets. First, WOA starts to approximate the global optimum by initiating whales' population with random position. After that, whales will start to random search for prey in their own surrounding areas (exploration phase). After whales have found the prey, they will recognize the location and start to encircle them with bubble-net feeding method (exploitation phase). After the whale with best fitness is determined, the best whale position to search for prey will be updated to other whales. Other whales will start to update their position and move towards the position of the whale with best fitness.

The selection of global optimum will be made by evaluating the performance of developed model with respect to the defined objective function. If the output of the developed model is not satisfied, the procedure from initiation of whales' population with random position until performance evaluation will be repeated until the satisfied output is achieved.

2.3 Case Study Area and Datasets

The study areas of this research was set to be at Kuching, Sarawak, Malaysia. The selected study areas are illustrated as in Figure 4. The historical rainfall data (r) and water level data (wl) of Batu Kitang (bk), Taman Siniawan (s) and Kuching International Airport (ka) were collected from Department of Irrigation and Drainage (DID) Sarawak. The collected data was then used to create the input and testing datasets as outlined in Table 1.

2.4 WONN Model Development

The overall process of WONN model development schematic diagram is shown in Figure 5. The first step for the model development is the choice of appropriate model output, such as the variable to be predicted and a set of potential model input variables from the available historical local data. In this study, the inputs of this model was set to be the historical dataset at Batu Kitang, Siniawan and Kuching Airport as well as historical water level data at Siniawan. The output data for this model was set to be the historical water level data at Batu Kitang. These datasets are obtained from DID Sarawak. A total of 27 months of the data were used for the creation of input and testing datasets. The data was arranged into 24 months of training inputs and 3 months of testing inputs for predicting the water level. WONN model was optimized by adjusting number of iterations, search agents and hidden nodes. After every iteration was completed, the performance of model was evaluated by using root mean square error (RMSE), mean absolute error (MAE) and index of agreement (IA). If the result was unsatisfied, adjustment of number of validations, iterations, search agents and hidden notes was carried out again until the result obtained is satisfied.

Once WONN model development is successful, performance of WONN will be compared against LMNN using the performance indicators such RMSE, MAE and IA.

The performance evaluation of WONN and LMNN models such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Index of Agreement (IA) are adopted as statistical indices. Statistical indices can be used to establish the credibility of the trained ANN models [4, 36-38].

RMSE, MAE and IA can be calculated using the following equations:

$$RMSE = \left(\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2\right)^{\frac{1}{2}} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \quad (2)$$

$$IA = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - O_{ave}| + |O_i - O_{ave}|)^2} \quad (3)$$

where n is the number of observations, O_i is the observed value, O_{ave} is the average value of all the observed values, P_i is the predicted value and P_{ave} is the average value of all the predicted values.

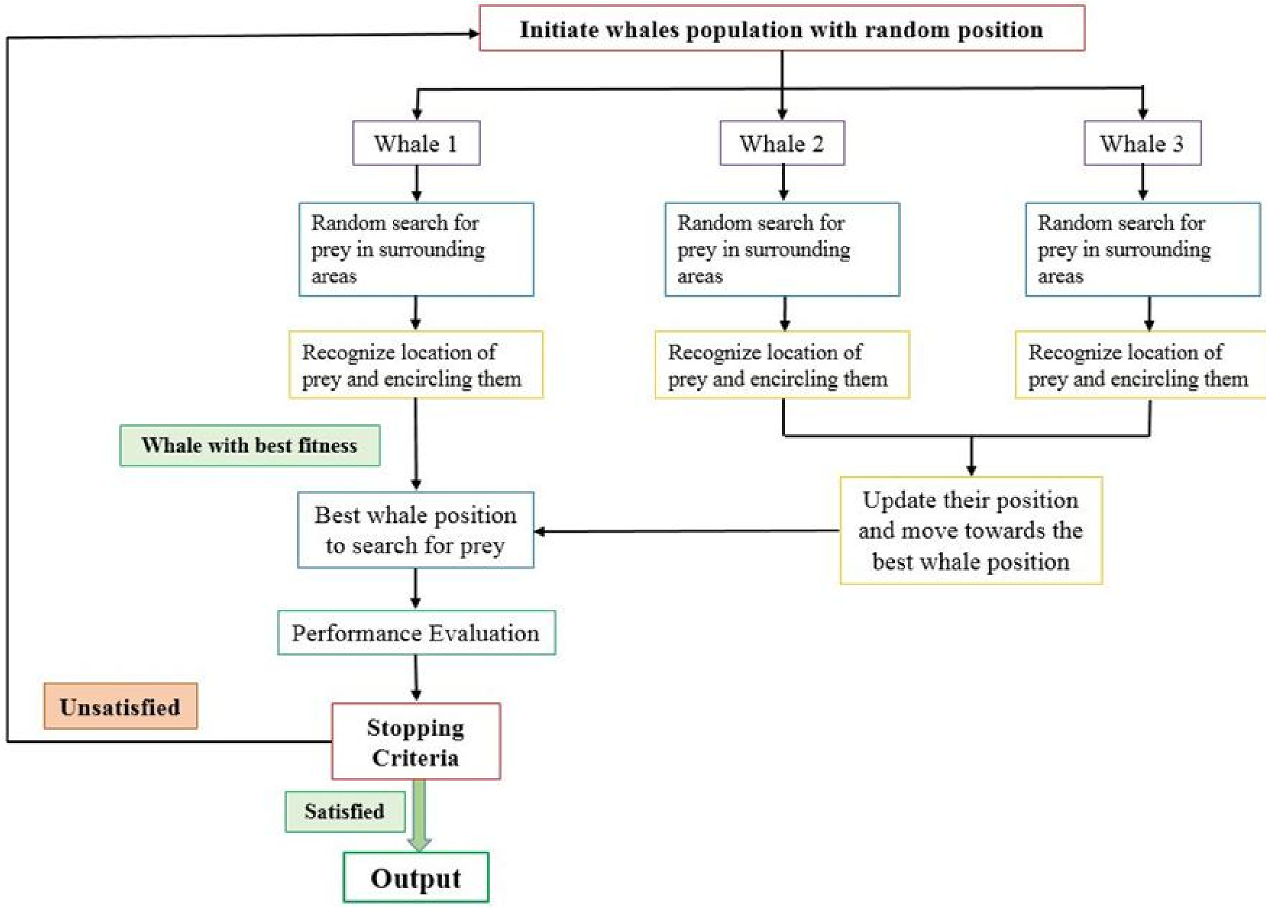

Figure 3: Overview of WOA

Figure 4: Study Area - Batu Kitang at Kuching, Sarawak.

Table 1: Datasets for training and forecasting used for WONN and LMNN model

Dataset	Input Parameters	Date started	Date ended	Rainfall / Water Level (days)	Purpose of dataset
A	r_bk, r_ka, r_s, wl_s, wl_bk	2000-11-01	2000-12-31	61	Training
		2001-01-01	2001-05-31	151	
		2008-01-01	2008-07-31	213	
		2008-10-01	2008-12-31	92	
		2009-01-01	2009-07-31	212	
B	r_bk, r_ka, r_s, wl_s	2009-08-01	2009-10-31	92	Validation/Testing

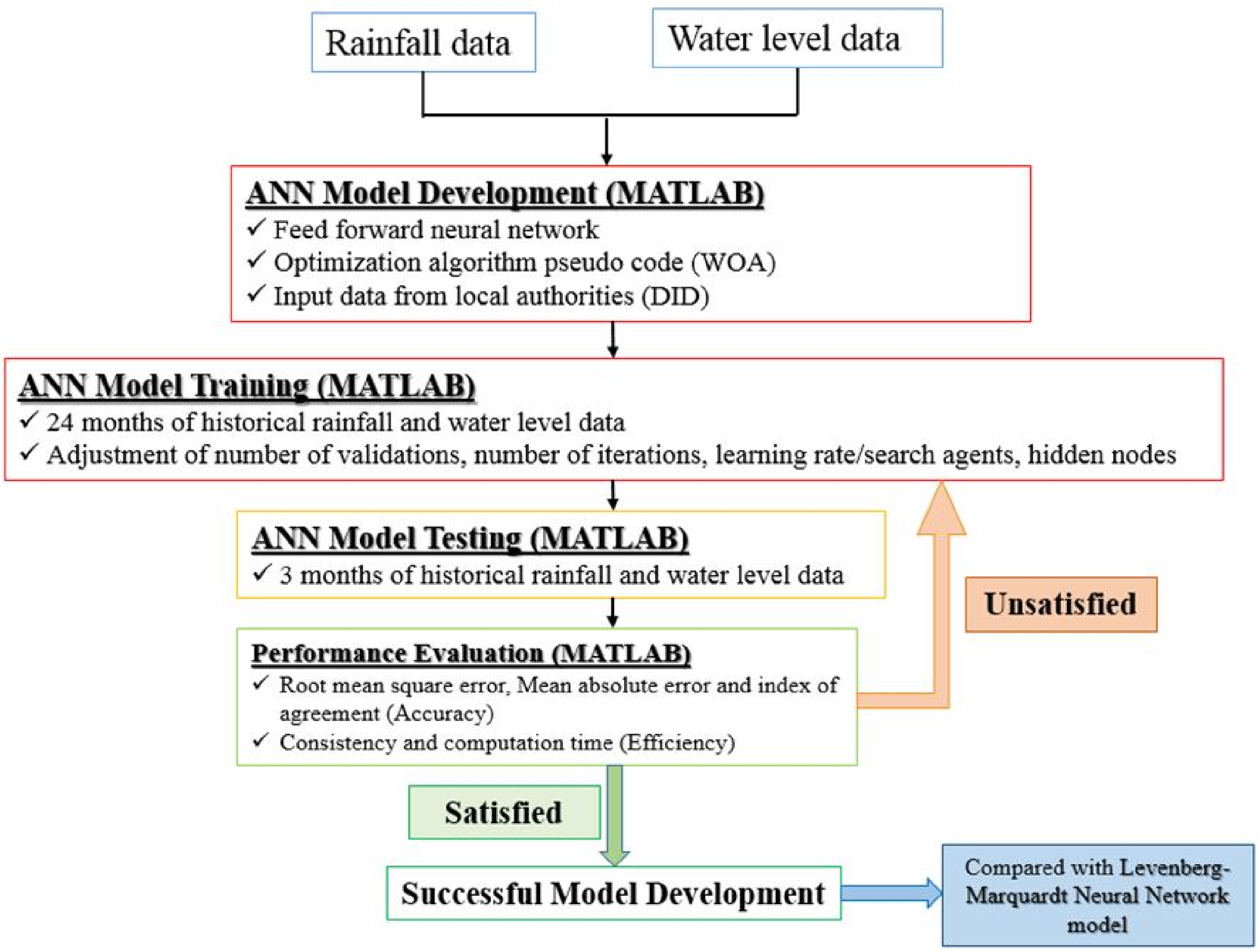

Figure 5: WONN Model Development Schematic Diagram

3. RESULTS AND DISCUSSION

In this study, the performance of LMNN and WONN are evaluated through three performance indicators such as RMSE, MAE and IA. During optimization of LMNN and WONN, all the parameters of ANNs used in this study are tuned based on trial and error method and with respect to the selected evaluation methods. In order to obtain the optimal settings of ANN models, several parameter tests have been carried out for both WONN and LMNN as shown in Table 2 and Table 3, respectively. At each stage of the test, only one of the parameters is manipulated, which the manipulated parameter that results in the best average MAE (closest to 0) will be adopted for the next test with the new manipulated variable. The most optimized parameters with the lowest MAE for WONN and LMNN (as shown in Table 4), are adopted for predicting the water level at Batu Kitang river. It is noticed that the ability of WONN in predicting the water level of Batu Kitang river is confirmed as the performance of WONN is closed to the conventional LMNN. As shown in Table 4, the proposed WONN outperformed the conventional LMNN in terms of RMSE, MAE and IA. Not only that, the illustration in Figure 4 shows that the predicted water level for both LMNN and WONN is similar to one another. But, WONN is more capable in tracing back the graph pattern of original water level plot. Inaccurate predictions are noticed from the plots of WONN and LMNN due to the big gaps observed from the plots in Figure 4. This may be caused by the different type of input data used to train the ANNs where it is obvious that the water level and rainfall data exhibit different graph pattern and range of values. Further normalization, which is the essential process of using ANNs, then further increase the errors and hence resulting in dissimilar output plot when compared to the original water level plot. The evidences imply that future improvement should be made in order to improve the performance of WONN.

4. CONCLUSION

This study proposed a novel metaheuristic optimization algorithm, WOA to train and optimize the parameters of neural network. WONN is proposed in this study to predict the water level of Batu Kitang river. To confirm the robustness and reliability of WONN, the performance of WONN is compared against a conventional neural network, LMNN to predict the water level. Both the parameter of LMNN and WONN were optimized using trial and error method with respect to the selected evaluation method. The performance of WONN in this study is proven to be reliable due to similar performance as exhibited by LMNN and WONN. However, WONN still possesses some drawbacks as LMNN as both of the ANNs failed to trace back the pattern of the original water level plot. Big gaps are also observed between original water level plots with the ANNs' plots hence showing the needs to improve the performance of WONN. Applications of WONN in other hydrological prediction studies such as precipitation and runoff predictions are recommended to be executed to determine the robustness and applicability of WONN in other hydrological domain.

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Table 2: WONN Model Optimization

Parameter test 1 Optimize no. of validation checks		**Parameter test 2** Optimize no. of iterations		**Parameter test 3** Optimize no. of search agents		**Parameter test 4** Optimize no. of hidden nodes	
1000 iterations, 30 search agents, 9 hidden nodes, 20 simulations		25 validation checks, 30 search agents, 9 hidden nodes, 20 simulations		25 validation checks, 1000 iterations, 9 hidden nodes, 20 simulations		25 validation checks, 1000 iterations, 40 search agents, 20 simulations	
Number of Validation checks	Average MAE (m)	Iterations	Average MAE (m)	Search Agents	Average MAE (m)	Hidden nodes	Average MAE (m)
15	0.38823457	500	0.37997837	25	0.37858717	9	0.38513396
20	0.38621544	1000	0.36462206	30	0.39442043	10	0.37427665
25	0.37515126	1500	0.40900624	35	0.38062425	12	0.38390562
30	0.4068478	2000	0.37881761	40	0.37784358	15	0.38825982
50	0.38262873	2500	0.38167381	45	0.38980614	20	0.37991433
100	0.38438274	3000	0.38955654	50	0.390018	50	0.40910797

Table 3: LMNN Model Optimization

Parameter test 1 Optimize no. of iterations		**Parameter test 2** Optimize learning rate		**Parameter test 3** Optimize no. of hidden nodes	
0.6 learning rate, 9 hidden nodes, 20 simulations		3000 iterations, 9 hidden nodes, 20 simulations		3000 iterations, 0.2 learning rate, 20 simulations	
Number of iterations	Average MAE (m)	Learning rate	Average MAE (m)	Hidden nodes	Average MAE (m)
1000	0.38619309	0.2	0.37894331	5	0.38868862
1500	0.39076901	0.4	0.38516032	9	0.40563298
2000	0.38774658	0.6	0.39241669	10	0.39279744
2500	0.38080249	0.8	0.38803267	15	0.4065672
3000	0.37606920	1	0.39817352	20	0.38539583
3500	0.38863487	1.2	0.38559692	25	0.37851808
4000	0.38525009	1.4	0.39807001	30	0.38117966
4500	0.37717725	1.6	0.39290971	40	0.3858129
5000	0.38300184	1.8	0.40067064	50	0.38637487

Table 4: Performance Evaluation of Optimized WONN and LMNN for daily water level forecasting at Batu Kitang

WONN model				**LMNN model**			
25 validation checks, 1000 iterations, 40 search agents, 10 hidden nodes, 20 simulations				3000 iterations, 0.2 learning rate, 25 hidden nodes, 20 simulations			
Test	Average RMSE	Average MAE (m)	Average IA	Test	Average RMSE	Average MAE	Average IA
1	0.429544	0.381764	0.901725	1	0.426958	0.377185	0.901477
2	0.427922	0.376531	0.902344	2	0.436096	0.381634	0.901182
3	0.426471	0.376072	0.903452	3	0.444613	0.389419	0.897701
4	0.418826	0.371045	0.905784	4	0.433796	0.381234	0.901021
5	0.432698	0.380467	0.907501	5	0.469102	0.399941	0.896006

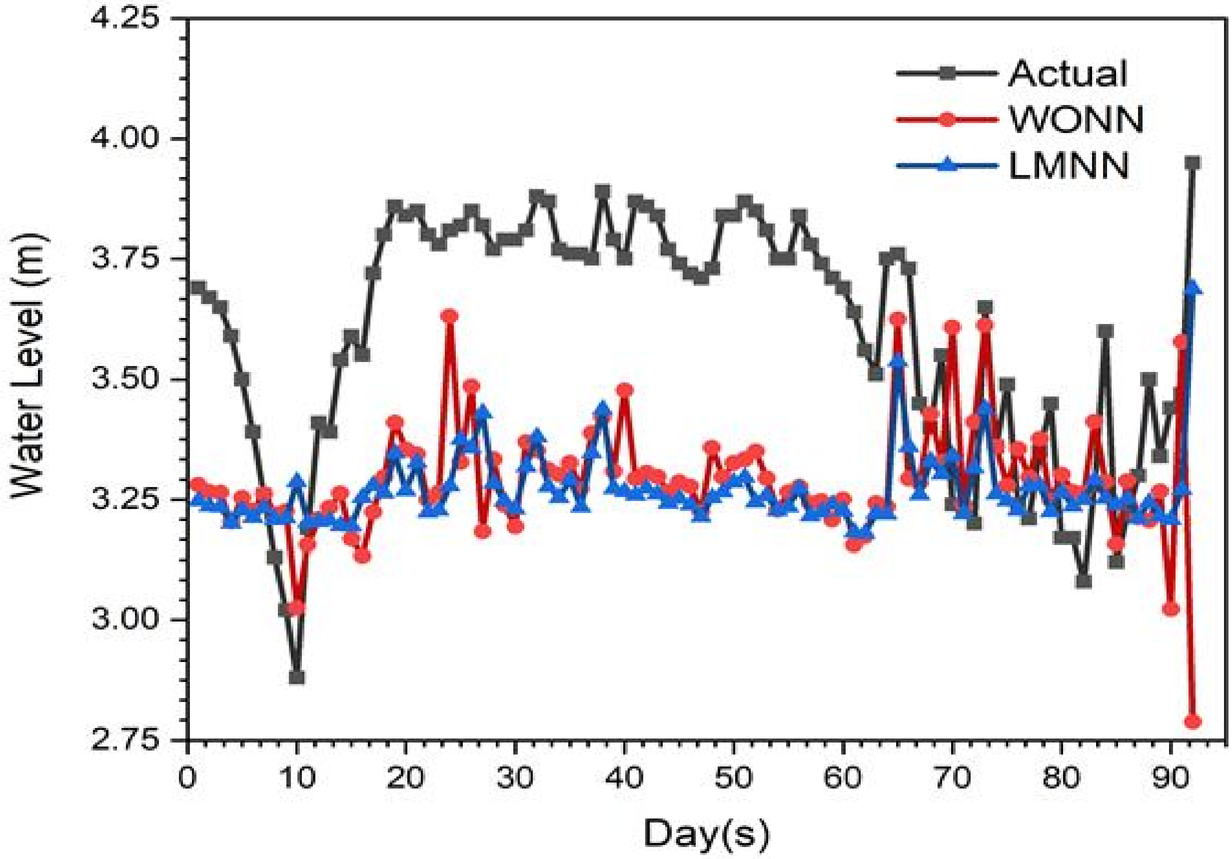

Figure 6: Daily water level forecasting by using WONN and LMNN

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