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An Effective Framework for an Early Flood Prediction with Respect to Water Level using Enhanced ENN

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Abstract: In recent years ANN methodology has been effectively used in flood water level prediction model. Moreover most of the works on flood predictions only concentrated on flood model but no prediction on time was proposed. So flood water level prediction is a fresh avenue to embark on in level to give early predictions which is proposed. This work proposed 4 years a head flood level of water prediction using enhanced ENN model for general rivers which can be in any places. So this approach can be applied on any area with any river for flood level of water. The results of actual Elman Neural Network structure indicate with less accuracy so this work extended with enhanced ENN model was introduced. The ENN performance indicates the results which concluded that enhanced ENN which is versatile than the actual ENN framework with significant improvement from the actual ENN framework which can be observed when the enhanced ENN was started.

Keywords: Flood water level prediction: Artificial Neural Network (ANN), Elman Neural Network (ENN), Enhanced ENN

I. INTRODUCTION

Flood prediction framework is frequently worried about the impacts on thickly populated regions found downstream of the streams. Without uncertainty, flood streams in downstream regions are firmly impacted by upstream conditions. In this way, flood forecast framework is critical to help the inhabitant of the downstream zones to clear preceding flood event.

The Artificial Neural Network (ANN) model is best suited for the above mentioned problem. ANN is widely known as an effective approach for handling large amount of dynamic, nonlinear and noisy data especially in situation where the underlying physical relationships are not fully understood. The ANN model also has various mathematical compositions that capable of modelling extremely complex physical systems. For this reason, it has been successfully applied to variety issues in water resources field whereby most cases deals with nonlinear data. ANN has been applied in rainfall runoff models [1-3], stream flow forecasting [4, 5], reservoir inflow prediction [6], mean sea level height estimation [7] and etc.

Elman Neural Network (ENN) is one type of ANN models. The Elman recursion neural network model was introduced by Elman J. L. in 1990 [8, 9], which later was known as Elman Neural Network. The researches on Elman Neural Network have been developed for nonlinear modeling [10], dynamic system identification [11], load prediction [12] and so on. The advantage of Elman Neural Network compared with other recurrent neural networks was that back propagation algorithm was applied as the training algorithm however it was not possible for other recurrent neural network where the training algorithms were more complex and slower [13]. Despite that, the application of ENN in hydrology field is quite new among researchers. With the advantages of ENN mentioned above, this work proposed a 4 years ahead flood water level prediction using Improved ENN structure. This paper was organized in the following manner: Section II states the related theory, Section III explains the methodology, Section IV is on results and discussion and finally, Section V is on conclusions.

II. RELATED THEORY

Elman Neural Network (ENN) is one kind of recurrent neural networks that has additional recurrent link in hidden layer acting as feedback connections. It is called recurrent link because it feedbacks on itself [14]. This additional recurrent link is also known as context layer. Recurrent neural networks are categorized as one of dynamic systems because its future state and output rely solely on its current state and input [15]. The feedback connections enable

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Elman Neural Network to learn, recognize and then generate spatial and temporal patterns [16]. It also indirectly develops Elman Neural Network that is very sensitive to past input data. This criterion is very important to develop dynamic system model [17]. Another advantage of Elman Neural Network is that back propagation algorithm is applied as training algorithm in this neural network .However, this algorithm is not available for other recurrent neural networks. Therefore complex training algorithm causes slower training process in other recurrent neural networks [18].
From Figure 1, it can be seen that every neuron in hidden layer is connected to each neuron in context layer on one to one basis with fixed weight value of one which is represented by b1 and b2. In other words, the number of neurons in context layer definitely will be the same as the number of neurons in hidden layer. Thus, context layer replicate the hidden layer state one step before as shown in Equation (4) and Equation (5). However, all other connections are in the opposite directions such as connection from input to hidden layer, context to hidden layer and hidden to output layer. All other weights are adjustable. w1, w2, w3 and w4are weight values between input and hidden layer, w5and w6 are weight values between hidden and output layer, while wc1, wc2, wc3 and wc4 are weight values between context and hidden layer. u1(t-1) and u2(t-1) are the network input with one step delay. The nonlinear input-output state space model for Elman Neural Network is represented by Equation (1), Equation (2), Equation (3), Equation (4) and Equation (5).

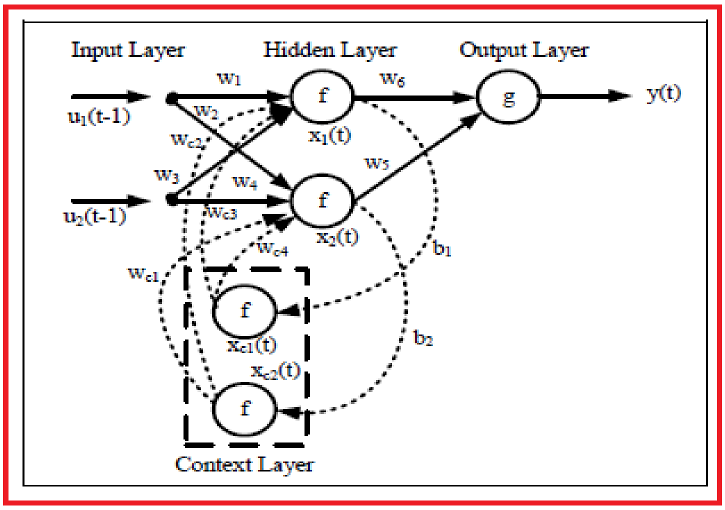

Fig1: ENN model

$$y(t) = g(w_6 x_1(t) + b_1 + w_5 x_2(t) + b_2) \quad (1)$$

$$x_1(t) = f\big(w_{c2}x_{c2}(t) + w_{c3}x_{c1}(t) + w_1 u_1(t-1) + w_3 u_2(t-1)\big) \quad (2)$$

$$x_2(t) = f\big(w_{c1}x_{c2}(t) + w_{c4}x_{c1}(t) + w_2 u_1(t-1) + w_4 u_2(t-1)\big) \quad (3)$$

$$x_{c1}(t) = x_1(t-1) \quad (4)$$

$$x_{c2}(t) = x_2(t-1) \quad (5)$$

u(t-1) is the scalar input, y(t) is the scalar output, x(t) is the values in hidden layer and xc(t) is the feedback values in the context layer. g(.) and f(.) are the respective transfer functions. Normally, f(.) applied hyperbolic tan-sigmoid transfer function while g(.) applied linear transfer function, purelin.

III. METHODOLOGY

A. Data Collection: The river branch analyzed in this paper is Kelang River, located at Petaling Bridge that originated from three upstream rivers which are Kelang River at Sulaiman Bridge, Kelang River at Tun Perak Bridge and Gombak River at Jalan Parlimen as shown in Figure 2. River conditions were measured in terms of water level and rainfall data and this real-time data can be obtained from UCI Machine learning repository.

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B. Data Used: Normally, data for ENN modelling is divided into 3 dataset: training, validation & testing. The training data set was used to train the ENN model whereas the validation data set was used to evaluate the performance of the model. 10 minutes time interval data from the period of 6/2/2010 13:50:00to 7/2/2010 10:30:00 were used for 4 hours prediction time of ENN model training. This data was chosen because flood event was occurring during this period of time and providing reliable water level and rainfall data. Thus, to obtain good ENN model, the validation data also must fulfilled the same criterion. So, the data from 5/2/2010 11:40:00 to 6/2/2010 0:30:00 were used for ENN model validation. After the model has been developed, the testing data were fed into the proposed model to evaluate the performance of the proposed model. The testing data ranges from 19/11/2010 21:00:00 to 21/11/2010 1:00:00.

Fig2: Upstream station for case study

C. Flood Prediction Model: Figure 3 shows the block diagram of 5 hours flood water level prediction model for Kuala Lumpur flood prone area using ENNstructure. Four inputs were fed to the ENNmodel to predict flood water level 4 hours ahead of time. The input water levels were normalized between +1 and -1 before fed into the model to keep the water level within the same range. Later, the water levels were renormalized back to obtain the actual predicted flood water level value at the output. ST1, ST2 and ST3 represent three upstream rivers and δy/δk represents difference of water level at flood location due to rainfall. yˆ represents predicted water level at flood location . Table I displays the optimized parameters for Elman Neural Network model structure based on trial and error method.

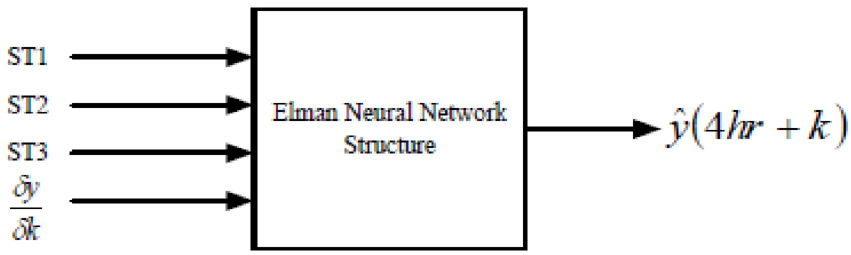

Fig3: Enn stucture for predictions

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TABLE I
ELMAN NEURAL NETWORK STRUCTURE PARAMETERS

Network Configuration	[4,15,1] 'tansig','tansig','tansig'
Learning rate	0.1
Momentum constant	0.9
Training algorithm	Gradient Descent Back Propagation
Training goal	0.0001
No of epochs	35000
Training pattern	493
Testing pattern	493
No of variables	4

D. Improved Flood Prediction Model: Figure 4shows the block diagram of improved 4 hours flood water level prediction model. The predicted flood water level obtained from the original ENN structure was fed into the Correction Filter which acts as model improver to meet the targeted output which is the actual water level at flood location. The predicted water level, y^ obtained from the improved ENN model will then be compared with the actual water level at flood location. Table II displays the optimized parameters for correction filter Elman Neural Network(ENN) model structure based on trial and error method.

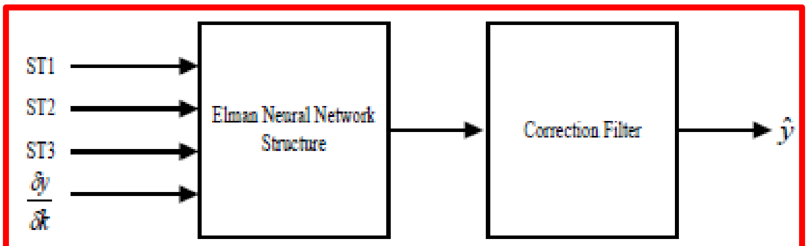

Fig. 4 TheENN with Improved Model Structure

TABLE II
CORRECTION FILTER ELMAN NEURAL NETWORK STRUCTURE PARAMETERS

Network Configuration	[4,10,1] 'tansig','tansig','tansig'
Learning rate	0.2
Momentum constant	0.7
Training algorithm	Gradient Descent Back Propagation
Training goal	0.0001
No of epochs	35000
Training pattern	493
Testing pattern	493
No of variables	4

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IV. RESULTS AND DISCUSSION

Figure 5 shows 4 hours prediction result of ENN modelling using Gradient Descent with Adaptive Learning Rate and Momentum Constant (traingdx) as training algorithm. From Figure 5, it can be observed that the ENN model only able to predict the actual water level graph at early section but cannot predict the actual water level at any other section even at linear section. The poor prediction result by the ENN model resulting low Best Fit value of 12.75% and high RMSE value of 0.5516 meter as given in Table III. Figure 6 shows the flood water level prediction after testing samples were applied to the model obtained from Figure 5. It can be observed that even though ENN model leading the actual water level by 4 hours, the pattern trend between both graphs are not in sequence. Thus, mapping of both graphs for RMSE analysis is not required.

TABLE III PERFORMANCE INDICES RESULT

Performance Indices	ENN Model
Best Fit (%)	12.75
Root Mean Square Error (RMSE)	0.5516 m

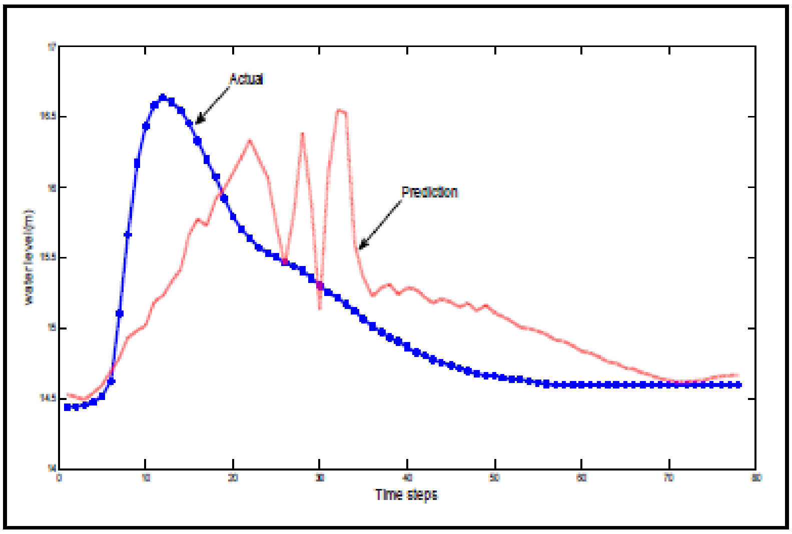

Fig. 5 4 hr Flood Water Level Prediction of ENNModeling Result

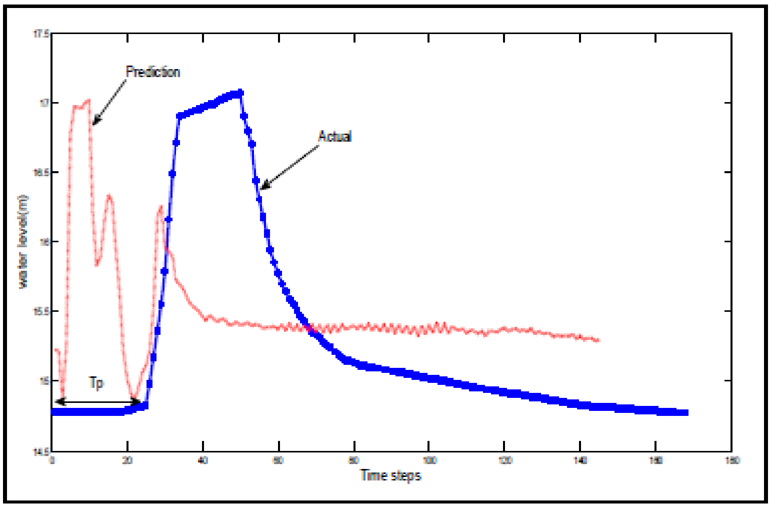

Fig. 6 4 hr Flood Water Level Prediction of ENN Model Test Result

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B. 4 years Improved ENN Prediction Model: Figure 7 shows the modeling result of 4 hours flood water level prediction using Improved ENN model. From Figure 5, the ENN model cannot match with the actual water level at any segment except at early segment. It can be observed from Figure 7 that the ENN model prediction result is drastically improved. The Improved ENN model fits nicely match with the actual water level despite the small prediction error at early and high frequency segment. However, the prediction error is very small and thus, less effect to the overall performance result. The Improved ENN model produces high Best Fit value of 97.15% and low RMSE value of 0.018 meter as given in Table IV.

TABLE IV PERFORMANCE INDICES RESULT

Performance Indices	Improved ENN Model
Best Fit (%)	97.15
Root Mean Square Error (RMSE)	0.018 m

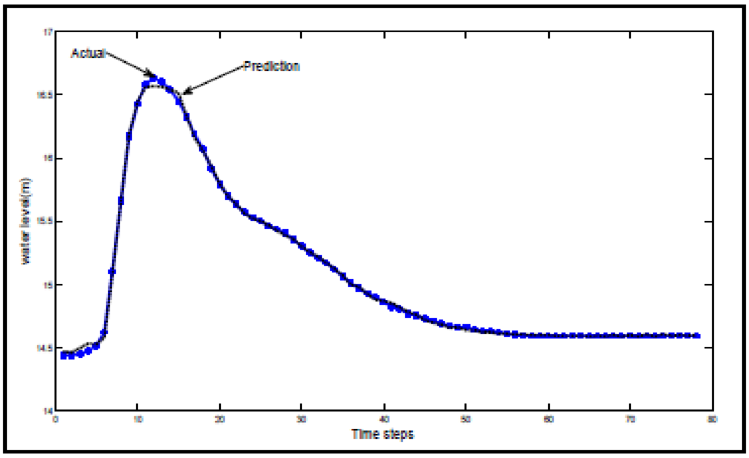
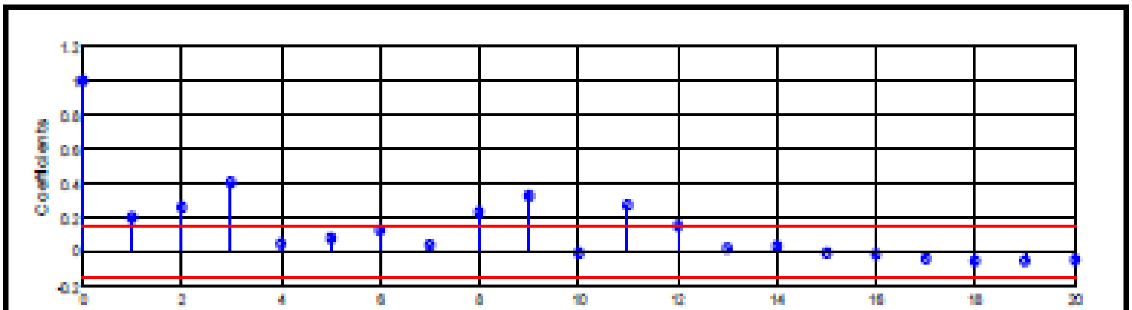


Fig. 7 4 hr Flood Water Level Prediction of Improved ENN Modeling Result

Despite the good prediction result from Figure 7, the autocorrelation and cross-correlation plot shows vice versa. The autocorrelation plot from Figure 8(a) shows several correlated coefficients have been detected outside the 85% Confidence limit specifically at lags 1, 2, 3, 8, 9, 11 and marginally exceed the confidence limit at lag 12. Thus, it can be concluded that the prediction residual failed in whiteness test. Meanwhile, cross-correlation plot in Figure 8(b) shows correlated coefficients have been detected between lags -5 till 13. This happens because the dynamic of the flood water level is not properly modeled due to the small prediction error as can be seen in Figure 7.



a) Autocorrelation Plot

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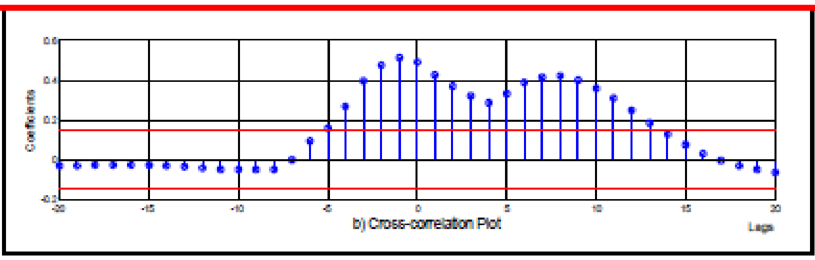

Fig. 8 Autocorrelation and Cross-correlation Plots of 4 hr Improved ENN Prediction Model

Figure 9 shows the prediction result of the Improved ENN model after testing samples were applied to the model obtained in Figure 7. Generally, the Improved ENN model manages to predict the actual water level 4 hours ahead of time with nearly the same pattern trend with the actual water level graph. Thus, mapping of both graphs need to be done for detailed comparison analysis. Figure 10 shows the mapping results of the Improved ENN model with the actual water level. From Figure 6, ENN model cannot even match with the actual water level and hence significant improvement can be seen in Figure 10. The Improved ENN model successfully predicted the actual water level despite only small over predicted and under predicted value of flood water level occurred at the high frequency segment. Therefore, from Figure 11, high errors are observed at that segment with low RMSE value of 0.0237 meter which is reduced from 0.6714 meter for ENN model obtained from Figure 6. Meanwhile, the other segments provide good prediction results with nearly 100% match between the predicted and actual water level.

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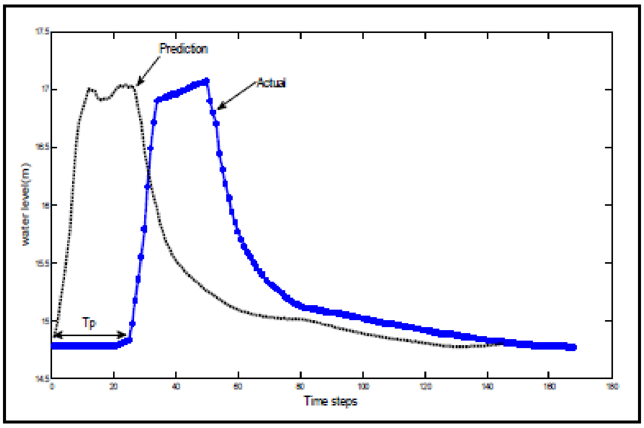

Fig. 9 4 hr Flood Water Level Prediction of Improved ENN Model Test Result

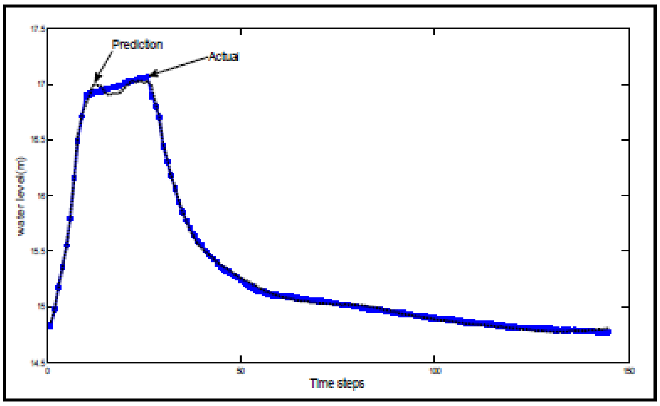

Fig. 10 Mapping of the Predicted and Actual Water Level for RMSE Analysis

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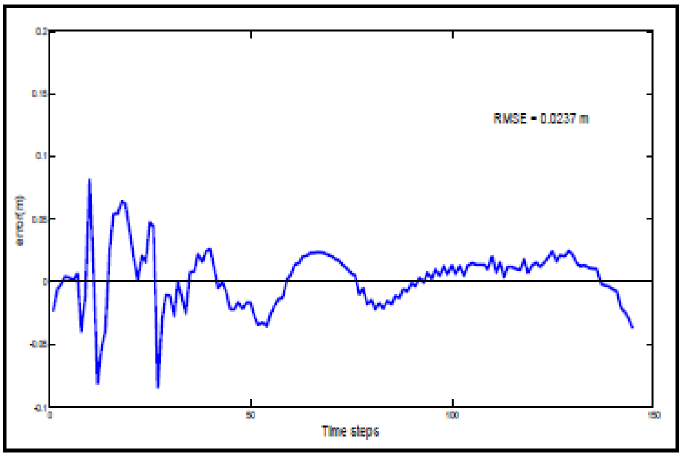

Fig. 11 Error Plot of the Predicted and Actual Water Level

V.CONCLUSION

The 4 hours flood water level prediction model using existing ENN model has been successfully developed and tested for flood prone area in Kuala Lumpur. Significant improvement can be seen using Improved ENN structure from the original ENN structure.

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