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Flood Prediction Modeling Using Hybrid BPN-EKF And Hybrid ENN-EKF: A Comparative Study

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ABSTRACT

Recently, artificial neural networks have been successfully applied to various hydrologic problems. This paper proposed flood water level modeling using the Hybrid of Back Propagation Neural Network with Extended Kalman Filter and the Hybrid of Elman Neural Network with Extended Kalman Filter that using the water level data from Sungai Kelang which is located at Jambatan Petaling, Kuala Lumpur. The models were developed by processing offline data over time using neural network architecture. The methodologies and techniques of the two models were presented in this paper and comparison of the long term runoff time prediction results between them were also conducted. The prediction results using both hybrid models showed satisfactory and reliable performances for flood water level prediction.

***Keywords*—**Back Propagation Neural Network (BPN); Extended Kalman Filter (EKF); Elman Neural Network (ENN);

I. INTRODUCTION

Flood water level prediction system is very important to densely populated areas that located at downstream of rivers. Without a doubt, flood flows at downstream areas are strongly influenced by upstream water level condition. Thus, flood water level prediction system is very important to help the resident of downstream areas to evacuate prior to flood occurrence. Flood modeling using the artificial neural network (ANN) is best suited for the above mentioned problems. 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 in modeling extremely complex physical systems. For this reason, ANN has been successfully applied to various problems 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, 7] , mean sea-level height estimation [8], flood water level prediction [9] and lots more.

Most ANN models used in water resources field were multi-layer feed-forward neural networks trained using the BPN algorithm. Dawson et al. [10] applied BPN model to predict flood events and providing flood index (the median of the annual maximum series) for 850 catchments across UK. When compared with multiple regression models, BPN provides improved flooding estimation that can be used by engineers and hydrologists. Simulation of water levels at different section of a river using physical flood models is quite cumbersome because it requires many types of data such as hydrologic time series, river geometry and etc. Therefore ANN technique was used as an effective alternative in hydrologic simulation studies. Simulation results using feed-forward neural network architecture with Levenberg Marquardt BPN training algorithm were compared with MIKE 11 hydrodynamic models to predict river stage for the periods of June until September 2006 [11]. The results obtained from the BPN model were found to be much better than that of the MIKE 11 results as indicated by the values of the goodness fit indices used in the paper.

Most references in flood forecasting [12-14] emphasize on how to obtain a deterministic BPN model to achieve an accurate model. Aspects such as structural modification, the determination of the type and number of input variables or hidden variables and the learning data length are very critical factor in determining an accurate BPN model. When applying a deterministic BPN model, the input and output relationship also should be systematic because the learning process of BPN algorithm is a supervised learning. Supervised learning means the model adjust the parameters (weights and biases) according to the "generalized delta rule" to minimize the error between the targets output and the estimated outputs of the BPN model [15-17]. The parameters adjustment stop when the learning criteria are fulfilled and then the optimal value of the parameters are adopted prior designing a deterministic BPN model.

Nevertheless, the application of Elman neural network (ENN) in water resources field is quite new among researchers. It can be seen from the small numbers of literatures and work done on

ENN model for hydrologic applications. In [18] Wu proposed ENN structure to be applied to groundwater level prediction of Naoli River basin. It can be seen that the model has high prediction accuracy and faster convergence time with regards to prediction result. Comparative study on Jordan and Elman neural network model for short term flood forecasting was done by Deshmukh et al. [19]. Both models were developed for rainfall modeling at the upstream area of Wardha River in India. The prediction results using Jordan neural network showed good performance in the three hours ahead of time prediction. They also found out that the Jordan neural network model was more robust than Elman neural network model and can be used as an alternative tool for short term flood flow prediction.
With the advantages of BPN and ENN mentioned above in water resources applications, this paper proposes Hybrid BPN-EKF model and Hybrid ENN-EKF model for flood water level prediction. The state-parameter estimation using standard Kalman Filter algorithm was introduced [20] and later state augmentation technique [21]. However, both techniques were limited to linear dynamics system. Since many problems are nonlinear cases, the modified Kalman Filter was introduced. The most straight forward extension of standard Kalman Filter is Extended Kalman Filter (EKF). EKF has been implemented as a state observer for induction motor drives in various configurations [22-24].
For nonlinear dynamic system, Extended Kalman filter is the best predictor and it is used to track maneuvering targets [25]. These maneuvering targets do not have straight motion and constant velocity, thus causing the process equation to be nonlinear. Same goes to flood water level because its fluctuations are highly nonlinear. Therefore, Extended Kalman Filter is used in this paper.

This paper was organized in the following manner: Section II describes the methodology; Section III is on results and discussion; and finally, Section IV is on conclusions.

II. METHODOLOGY

2.1 Back Propagation Neural Network (BPN)

The BPN model is an extensively used neural network that comprises of many processing units/nodes or widely known as neurons. In general, BPN model consists of three layers structure of neurons as shown in Figure 1. The input layer receives input signals from the external worlds. The hidden layer represents the relationship between input and output layer and finally, the output layer releases the output signals to the external world. It includes training and validation process. The aim of the model training is to perform input and output mapping based on the determined BPN model structure to obtain the optimal weight of neurons in the hidden layer. In addition, there are factors that leads to the optimal weight which are the size of the training data and how it represents the environment of interest, the structure of the BPN model and the physical complexity of which the model is applied [26]. Despite the three factors mentioned above, optimal BPN model structure could be obtained by trial and error method [27].

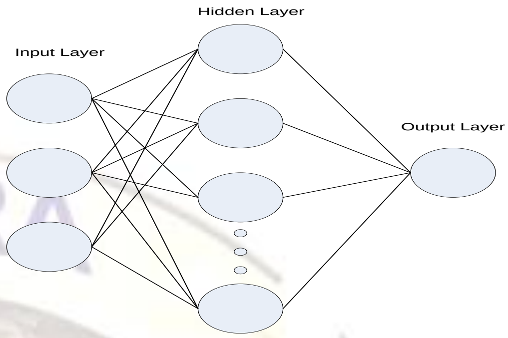

Figure 1. Typical ANN model structure

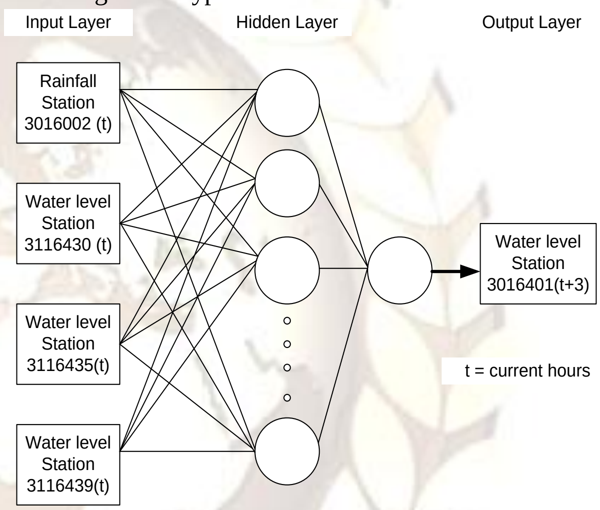

Figure 2. BPN model for flood water level prediction

The BPN model used in this paper is given in Figure 2. The input layer consists of rainfall at flood location and water level at three upstream rivers. The target output layer is the flood location at the downstream river.

2.2 Elman Neural Network (ENN)

The Elman Neural Network (ENN) model structure was first proposed by Elman J.L. in 1990 [28, 29]. ENN has been developed for nonlinear modeling and transfer function cases such as nonlinear stable adaptive control [30], solar activity forecasting [31] and much more. The ENN is one type of recurrent network. The details of ENN can be referred in [32]. The block diagram of ENN structure is shown in Figure 3.

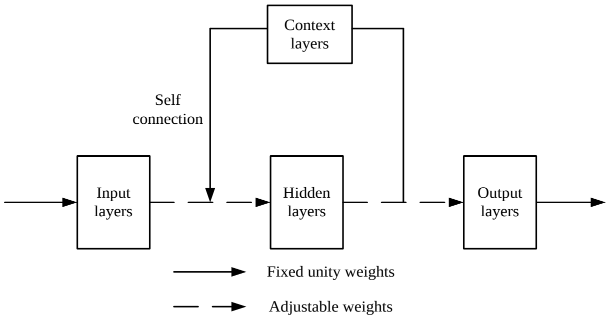

Figure 3. Block diagram of Elman Neural Network

ENN structure has one additional layers compared to BPN model structure which is named as context layers. In ENN structure, the hidden layers are feedback through this context layer. The feedback makes ENN able to learn, recognize and generate temporal patterns as well as spatial pattern. Every hidden layer neuron is connected to only one context layer neuron through a constant weight. Hence, the context layer virtually constitutes a copy of state of the hidden layer one instant before. The number of context layer neurons is consequently the same as the number of hidden layer neurons. Alternatively, every neuron of the output layer can be connected to only one neuron of a second context layer through a constant weight, as well.

2.3 Kalman Filter (KF)

2.3.1 Discrete Kalman Filter

In 1960, Kalman successfully solved filtering problem using state-space approach [33]. The solution is now widely known as Kalman Filter (KF). Two main features in KF: the vector modeling of random processes; and the process noise must be Gaussian [34]. However, the general KF algorithm is limited for linear systems. Therefore, EKF is considered as an extension of KF in solving nonlinear problems. As EKF is the extension of KF, let us discuss the basic theory of KF algorithm first.
KF used feedback control to estimate a process. First, the filter estimates the process state and then obtains the feedback in the form of noisy measurements. Because of that, the equation for the KF falls into two types: time update equations; and measurement update equations. The time update equations are responsible to obtain the priori estimates for the next step by projecting the current state and error covariance estimates, whereas the measurement update equations are responsible for the feedback. Indirectly, the time update equations act as the predictor equations while the measurement update equations act as the corrector equations. The KF estimation algorithm which resembles the predictor-corrector algorithm is shown in Figure 4.

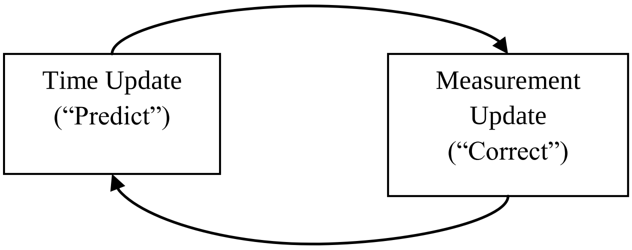

Figure 4. The ongoing discrete Kalman Filter cycle

2.3.2 Extended Kalman Filter (EKF)

It is known that the KF able to estimate the state of a discrete-time controlled process that is governed by a linear stochastic differential equation. When a process to be estimated is nonlinear, KF is not able to do the estimates. Then the KF extension is introduced such that ~~is~~ able to linearize the current mean and covariance. The extension KF is referred to as Extended Kalman Filter (EKF).

The EKF algorithm has two main stages: prediction step; and update (filtering) step. In prediction steps, previous state estimate of the system is being used and in the update step, the predicted state is corrected by using feedback correction step. The feedback correction step contains the weight of the measured and estimated output signals. In EKF, by calculating the stochastic properties of the noise, the initial values of the matrices can be arranged correctly. Furthermore, a critical part of EKF is to apply correct initial values for various covariance matrices. Covariance matrices have an important effects on converge time and filter stability. The computational origin of the EKF is explained in [35].

2.4 Study Area and Data Used in BPN model

The flood location in this study is Sungai Kelang at Jambatan Petaling, Kuala Lumpur. The major contribution of flood water level comes from three upstream rivers, namely Sungai Kelang at Jambatan Sulaiman, Sungai Kelang at Jambatan Tun Perak, and Sungai Gombak at Jalan Parlimen is used in BPN model with additional input of rainfall at the flood location. The water level and rainfall data for training is in meters, starting from 18/11/2010 at 0:10:00 am until 22/11/2010 at 0:10:00 am in 10 minutes time interval. The target flood location data is in 3 hours ahead from the training data, meaning that the data is starting from 18/11/2010 at 3:10:00 am until 22/11/2010 at 3:10:00 am in 10 minutes time interval. For testing, the data range is from 6/3/2011 at 0:10:00 am until 11/3/2011 at 0:10:00 with same time interval. This real-time data is available online from the website www.water.gov.my. The water level data is measured using Supervisory Control and Data Acquisition System (SCADA) by Department of Irrigation and Drainage Malaysia.

Figure 5. Location of Sungai Kelang at Jambatan Petaling basin (http://infobanjir.water.gov.my/ve/vmapkl.cfm)

2.5 Performance Indices

The performance of the hybrid model is calculated using statistical method that is able to compare the result of simulated and actual data. These statistical methods can be expressed as follows:

(i) Akaike's Final Prediction Error(FPE);

$$\text{FPE}=V.\frac{\left(1+d/N\right)}{\left(1-d/N\right)} \qquad (1)$$

where;
V = Loss Function
d = Number of approximated parameter
N = Number of sample

(ii) Loss Function(L);

$$V=\frac{e^2(k)}{N} \qquad (2)$$

where;
$e^2(k)$ = error vector

(iii) Root Mean Square Error(RMSE);

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Q_i-\hat{Q}_i\right)^2} \qquad (3)$$

where;
Q_i = actual data
$\hat{Q}_i$ = simulated/predicted data

III. RESULTS & DISCUSSIONS

3.1 BPN Prediction Results

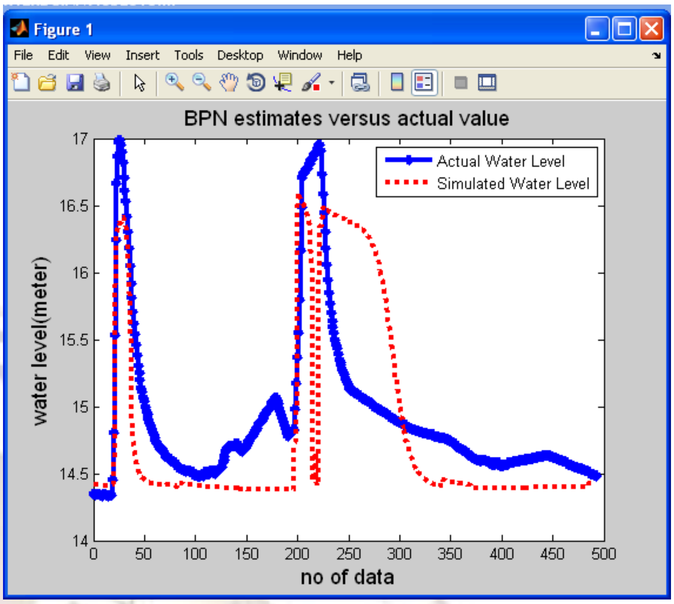

Figure 6. Simulation result of BPN Model

In this study, two types of neural network models were constructed and tested for predicting flood water level at Sungai Kelang that located at Jambatan Petaling, Kuala Lumpur (BPN and ENN). The optimal number of parameters for both models was determined by trial and error method. Various hidden layer neuron number combinations were tested for the BPN model. A feed-forward 4-10-1 neural network was constructed and trained using the Gradient Descent (GD) algorithm with tangent sigmoid as transfer function in the hidden and output layers. The predicted result of the BPN model is given in Figure 6 after 10000 epochs. It can be observed that the BPN model's performance has a good tracking result at the earlier stage of simulation even though it still underestimate the actual water level result. However, towards the end, the BPN model is trying to follow the actual water level to produce good prediction results. This is due to lacking in the number of input parameters in the BPN model.

In this BPN model, only 2 input parameters were considered namely, water level data and rainfall data. This is due to that only both input data were available from the Department of Irrigation and Drainage, Malaysia. Others input parameters such as basin information and physical parameters are difficult to obtain as it involves the confidentiality of data from the respective department involved. Other reason that leads to poor prediction in this BPN model is the effects of nonlinearity of the data itself. In addition, Figure 7 provides the error convergence graph from this BPN model. Even though the error goal is not converged, the result was fairly good because the RMSE is equal to 0.7256m which is still less than 1.

To improve the simulation result from the BPN model, this paper proposed the introduction of EKF at the output of BPN. EKF is an extended version of standard Kalman Filter which undergoes linearization process using first-order Taylor series [36]. EKF works well in nonlinear conditions as it is called a nonlinear state estimator. Figure 8 provides the simulation result of BPN model with EKF. It can be observed that EKF able to track and filter the nonlinearity of the BPN output. The RMSE is decreased to 0.0631m. It can be observed that at early stage, EKF over estimate the actual values and after that EKF able to track the actual values convincingly.

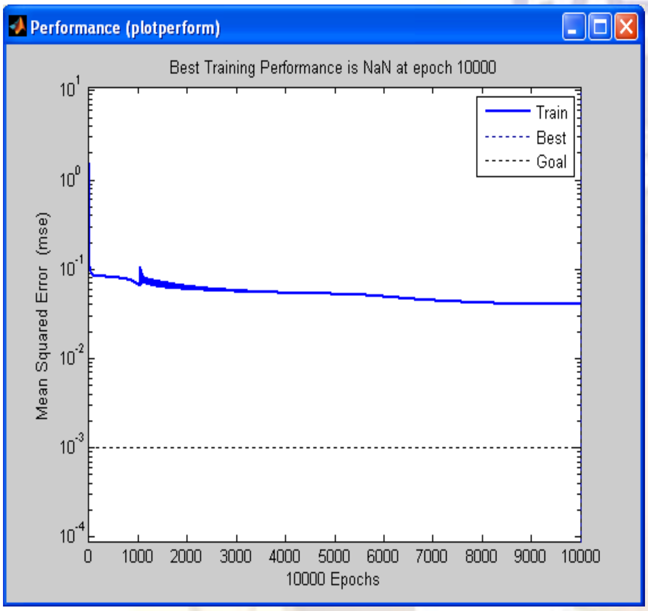

Figure 7. Error convergence result of BPN model

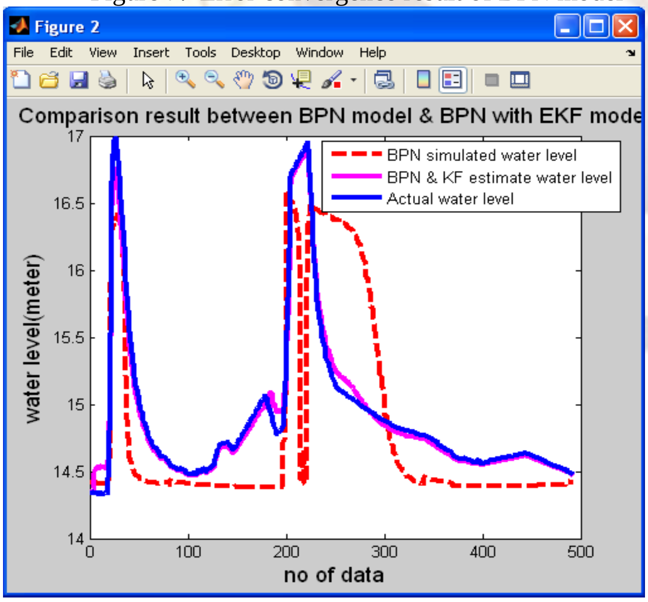

Figure 8. Simulation result of Hybrid BPN and EKF model

3.2 ENN Prediction Results

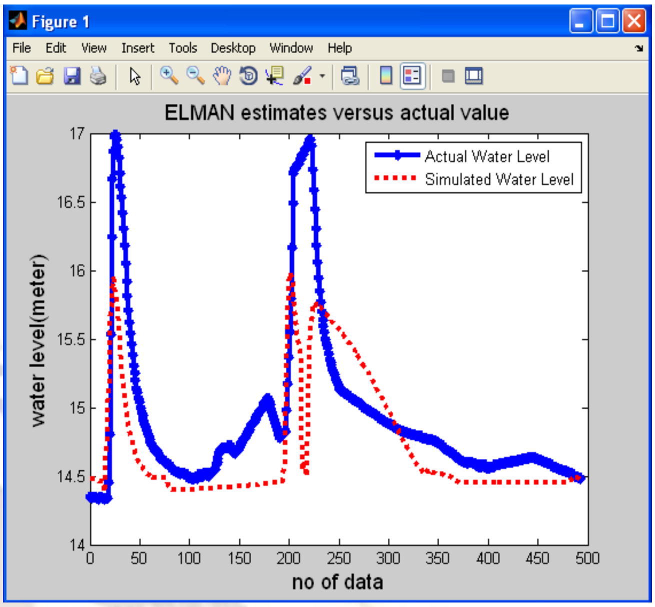

Figure 9. Simulation result of ENN model

Various numbers of hidden layer neuron combinations were tested for the Elman model. The 4-15-1 Elman network was constructed and trained using the gradient descent algorithm with default value of learning rate and momentum constant, 10000 epoch and tangent sigmoid transfer functions in the hidden and output layer. The size of training and validation data was already determined as 493 data points. The prediction results of ENN model produced by GD algorithm are shown in Figure 9. The ENN model shows better result than BPN models in terms of RMSE, whereas BPN model shows better result than ENN in terms of FPE and V. Despite the difference of performance indices value given in Table I, the prediction result of ENN model is nearly the same in trend pattern with BPN model. At the earlier stage of simulation, the ENN model is able to follow the actual water level convincingly but, towards the peak value of flood water level, the model fails to predict the actual data anymore. This is due to the underestimate scatter plot of prediction results that occurred at the peak flood water level stage. Figure 10 displays error convergence results of ENN model with RMSE equal to 0.5738m. Even though the error is not converged, the error measured value still close to zero to justify that the ENN model is an acceptable model in this flood water level prediction.

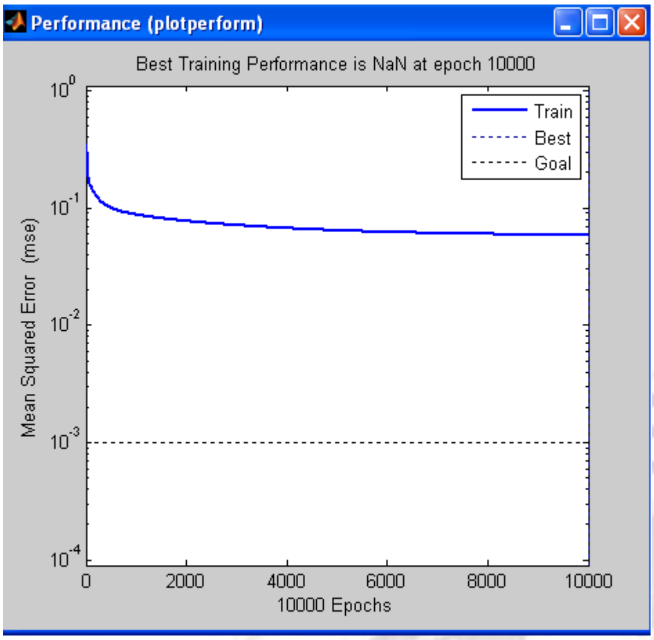

Figure 10. Error convergence result of ENN model

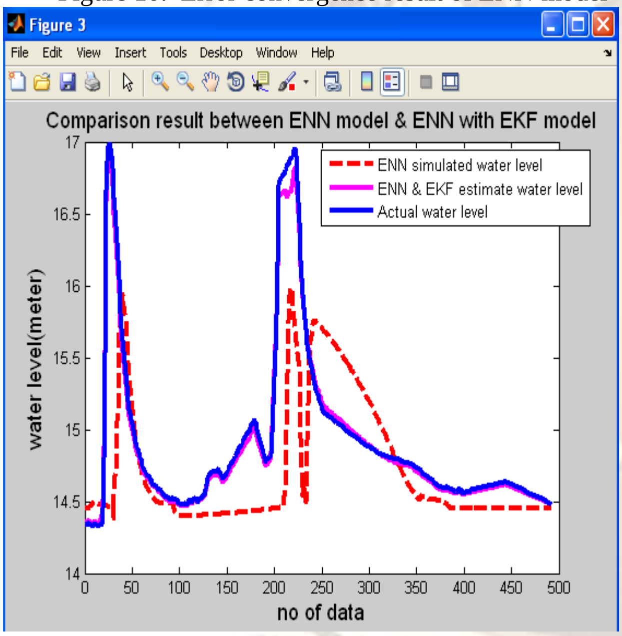

Figure 11. Simulation result of Hybrid ENN and EKF model

By introducing Extended Kalman Filter at the output of the ENN model, the simulation result of the ENN model can be further improved. The nonlinearity output data can be filtered out, thus resulting more smooth result of flood water level prediction as shown in Figure 11. Comparison of measured error values for both hybrid models is given in Table I. It is clearly shown that the RMSE result from BPN model and ENN model show decreasing value whereas for FPE and V is vice versa. Nevertheless, it can be observed that there are significant drops in error from the non-hybrid model and hybrid model for both BPN and ENN model.

TABLE I. PERFORMANCE INDICES RESULT

Performance Indices	BPN Model	BPN & EKF Hybrid Model	ENN Model	ENN &EKF Hybrid Model
Akaike's Final Prediction Error (FPE)	0.1993 m	0.0190 m	0.4085 m	0.0389 m
Loss Function (V)	0.1977 m	0.0188 m	0.4052 m	0.0385 m
Root Mean Square Error (RMSE)	0.7256 m	0.0631 m	0.5738 m	0.0415 m

IV. CONCLUSION

This study describes an approach to predict flood water level from meteorological data sets obtained from the Department of Irrigation and Drainage, Malaysia with two nonlinear modeling techniques integrated with nonlinear estimator. In this study, two relevant variables were used to predict the flood water level namely, water level and rainfall data. The construction of nonlinear modeling structures using the BPN and ENN models with the integration of EKF have been demonstrated. Both models performances were compared in terms of their tracking errors. The performance of Elman model was determined to be better than that of the Back Propagation model in terms of RMSE result only. The resulting errors for BPN model in terms of FPE and V still providing high degree of accuracy compared with ENN model with error less than 1 and merely close to 0. However, both BPN and ENN models shows significant error drops when integrated with EKF. This shows that EKF is the best nonlinear estimator for BPN and ENN model because it able to track the dynamics of the nonlinear system itself. Despite the widespread application of neural network models for nonlinear cases, comparative studies using different models were lacking. Most published research works so far only using a limited number of nonlinear models. Thus, these comparative studies in using different nonlinear models for flood water level prediction would be a valuable source of information to researchers. It is hoping that with further research in the applications of nonlinear neural network models in flood water level prediction would come out with more reliable network structures.

V. ACKNOWLEDGEMENTS

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REFERENCES

[1] Y. Chidthong, H. Tanaka, and S. Supharatid, "Developing a hybrid multi-model for peak flood forecasting," *Hydrological Processes*, vol. 23, pp. 1725-1738, 2009.

[2] M. N. French, W. F. Krajewski, and R. R. Cuykendall, "Rainfall forecasting in space and time using a neural network," *Journal of Hydrology*, vol. 137, pp. 1-31, 1992.

[3] K.-l. Hsu, H. V. Gupta, and S. Sorooshian, "Artificial Neural Network Modeling of the Rainfall-Runoff Process," *Water Resources Research*, vol. 31, pp. 2517-2530, 1995.

[4] H. Cigizoglu, "Application of Generalized Regression Neural Networks to Intermittent Flow Forecasting and Estimation," *Journal of Hydrologic Engineering*, vol. 10, pp. 336-341, 2005.

[5] G. Tayfur, T. Moramarco, and V. P. Singh, "Predicting and forecasting flow discharge at sites receiving significant lateral inflow," *Hydrological Processes*, vol. 21, pp. 1848-1859, 2007.

[6] Y.-T. Chang, L.-C. Chang, and F.-J. Chang, "Intelligent control for modeling of real-time reservoir operation, part II: artificial neural network with operating rule curves," *Hydrological Processes*, vol. 19, pp. 1431-1444, 2005.

[7] S. Jain, A. Das, and D. Srivastava, "Application of ANN for Reservoir Inflow Prediction and Operation," *Journal of Water Resources Planning and Management*, vol. 125, pp. 263-271, 1999.

[8] E. Sertel, H. K. Cigizoglu, and D. U. Sanli, "Estimating Daily Mean Sea Level Heights Using Artificial Neural Networks," *Journal of Coastal Research*, pp. 727-734, 2008/05/01 2008.

[9] R. Adnan, F. A. Ruslan, A. M. Samad, and Z. M. Zain, "Flood water level modelling and prediction using artificial neural network: Case study of Sungai Batu Pahat in Johor," in *Control and System Graduate Research Colloquium (ICSGRC), 2012 IEEE*, 2012, pp. 22-25.

[10] [10] C. W. Dawson, R. J. Abrahart, A. Y. Shamseldin, and R. L. Wilby, "Flood estimation at ungauged sites using artificial neural networks," *Journal of Hydrology*, vol. 319, pp. 391-409, 2006.

[11] R. K. Panda, N. Pramanik, and B. Bala, "Simulation of river stage using artificial neural network and MIKE 11 hydrodynamic model," *Computers & Geosciences*, vol. 36, pp. 735-745, 2010.

[12] G. Corani and G. Guariso, "An application of pruning in the design of neural networks for real time flood forecasting," *Neural Computing & Applications*, vol. 14, pp. 66-77, 2005/03/01 2005.

[13] T. Wardah, S. H. Abu Bakar, A. Bardossy, and M. Maznorizan, "Use of geostationary meteorological satellite images in convective rain estimation for flash-flood forecasting," *Journal of Hydrology*, vol. 356, pp. 283-298, 2008.

[14] E. Toth, A. Brath, and A. Montanari, "Comparison of short-term rainfall prediction models for real-time flood forecasting," *Journal of Hydrology*, vol. 239, pp. 132-147, 2000.

[15] T.-C. Ryan Hsiao, C.-W. Lin, and H. K. Chiang, "Partial least-squares algorithm for weights initialization of backpropagation network," *Neurocomputing*, vol. 50, pp. 237-247, 2003.

[16] C. M. Zealand, D. H. Burn, and S. P. Simonovic, "Short term streamflow forecasting using artificial neural networks," *Journal of Hydrology*, vol. 214, pp. 32-48, 1999.

[17] J. M. Zurada, *Introduction to artificial neural systems* vol. 408: West St. Paul, 1992.

[18] C.-y. Wu, "Research on groundwater Level Prediction of Naoli River Basin based on Elman wavelet neural networks," in *Consumer Electronics, Communications and Networks (CECNet), 2011 International Conference on*, 2011, pp. 2504-2507.

[19] R. P. Deshmukh and A. A. Ghatol, "Comparative study of Jorden and Elman model of neural network for short term flood forecasting," in *Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference on*, 2010, pp. 400-404.

[20] P. O'Connell, "A historical perspective," in *Recent Advances in the Modeling of Hydrologic Systems*, ed: Springer, 1991, pp. 3-30.

[21] R. L. Bras and I. Rodríguez-Iturbe, *Random functions and hydrology*: Courier Dover Publications, 1985.

[22] M. Barut, S. Bogosyan, and M. Gokasan, "Speed-sensorless estimation for induction motors using extended Kalman filters," *Industrial Electronics, IEEE Transactions on*, vol. 54, pp. 272-280, 2007.

[23] N. Salvatore, A. Caponio, F. Neri, S. Stasi, and G. L. Cascella, "Optimization of delayed-state Kalman-filter-based algorithm via differential evolution for sensorless control of induction motors," *Industrial Electronics, IEEE Transactions on*, vol. 57, pp. 385-394, 2010.

[24] Y.-R. Kim, S.-K. Sul, and M.-H. Park, "Speed sensorless vector control of induction motor using extended Kalman filter," *Industry Applications, IEEE Transactions on*, vol. 30, pp. 1225-1233, 1994.

[25] B. Sadeghi and B. Moshiri, "Second-order ekf and unscented kalman filter fusion for tracking maneuvering targets," in *Information Reuse and Integration, 2007. IRI 2007. IEEE International Conference on*, 2007, pp. 514-519.

[26] S. S. Haykin, *Neural networks: a comprehensive foundation*: Prentice Hall Englewood Cliffs, NJ, 2007.

[27] H. R. Maier and G. C. Dandy, "Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications," *Environmental modelling & software*, vol. 15, pp. 101-124, 2000.

[28] J. L. Elman, "Finding structure in time," *Cognitive science*, vol. 14, pp. 179-211, 1990.

[29] H.-t. He and X. Tian, "An improved Elman network and its application in flatness prediction modeling," in *Innovative Computing, Information and Control, 2007. ICICIC'07. Second International Conference on*, 2007, pp. 552-552.

[30] L. Xiang, C. Zengqiang, and Y. Zhuzhi, "Nonlinear stable adaptive control based upon Elman networks," *Applied Mathematics-A Journal of Chinese Universities*, vol. 15, pp. 332-340, 2000.

[31] S. Marra and F. C. Morabito, "A new technique for solar activity forecasting using recurrent elman networks," *International Journal of Computational Intelligence*, vol. 3, pp. 8-13, 2006.

[32] A. Kalinli and S. Sagiroglu, "Short Paper_," *Journal of information science and engineering*, vol. 22, pp. 1555-1568, 2006.

[33] R. A. Best and J. Norton, "A new model and efficient tracker for a target with curvilinear motion," *Aerospace and Electronic Systems, IEEE Transactions on*, vol. 33, pp. 1030-1037, 1997.

[34] R. G. Brown and P. Y. Hwang, *Introduction to random signals and applied Kalman filtering* vol. 1: John Wiley & Sons New York, 1992.

[35] R. Adnan, F. A. Ruslan, A. M. Samad, and Z. M. Zain, "Extended Kalman Filter (EKF) prediction of flood water level," in *Control and System Graduate Research Colloquium (ICSGRC), 2012 IEEE*, 2012, pp. 171-174.

[36] J. Han and M. Feng, "A real-time video surveillance system with human occlusion handling using nonlinear regression," in *Multimedia and Expo, 2008 IEEE International Conference on*, 2008, pp. 305-308.