Flood Forecasting via Time Lag Forward Network; Kelantan, Malaysia

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Abstract. Forecasting water level is one of the critical issues in Malaysia for Kelantan region. Based on the flood events in 2014, this study investigates the hourly-forecasting of water level in one station namely Kg Jenob in Kelantan. For this issue, Time Lag Forward Network (TLFN) is evaluated for forecasting the water level as dynamic model. Heuristic method in stepwise forward methodology is performed. Rainfall and water level are the input and output of the modelling respectively. For selected flood period 15/12/2014 to 30/12/2014, 8 scenarios are developed to obtain a minimum error in water level forecasting. By monitoring the error, it will show that the optimum configuration of network has 2 processors in hidden layer and 7 lags have enough contribution on the result of hourly forecasting. Transfer functions in hidden and output layers are is Tangent hyperbolic and bias. Observed and simulated data are compared with usual error criteria called Mean Square Error (MSE) and Root Mean Square Error (RMSE) which obtained 0.005 and 0.07 respectively. In conclusion, this study will be as a baseline for Kelantan to show that TLFN has promising result to forecast the flood events.

1. Introduction

Time Lag Forward Networks (TLFN) are an alternative model in hydrological prediction [1]. TLFN is classified as data driven models with short memory structures. TLFN includes local recurrent connections and they include memory layer, limit to the given data as input which they are pre-processor. TLFN is dynamic network which means that the information is based on time instead a static pattern. Therefore, TLFN can be used for prediction and forecast of time series data. For temporal prediction, TLFN is a suitable model and is under evaluations for optimization and application in different fields [1]. One of the applications of this data driven technique can be for temporal problems such as time series forecasting, system identification and temporal pattern recognition[2]. The main advantage of TLFN is the smaller network size required to learn temporal problems. Moreover, the another advantage of TLFN is their low sensitivity to noise. In this study, TLFN is investigated for hourly forecasting the water level in Malaysia, Kelantan region which is potential for flood events as Kelantan has involved with a huge flood in 2014 [3].Therefore, forecasting the fluctuation of water level is the objective of this study upon the development of different scenarios to reach optimum results.

2. Methodology

For Kelantan watershed, data are collected for Kg Jenob station in both rainfall (mm) and water level (m). The data that has been obtained in hourly time scale from 15/12/2014 to 30/12/2014 has covered the two weeks rainfall and water level in Kg Jenob station as a flood event in 2014. Figure 1 shows trend visualization rainfall and water level in Kg Jenob station. The highest rainfall has occurred in 20/12/2014 at 11:00 which is 35.6 mm. Also, the maximum recorded water level has been observed on 17/12/2014 at 8:00 which is 2.49 m. Figure 1 shows presentation of rainfall versus water level in Kg Jenob station. Rainfall has a firm fluctuation approximately. It might be a reason that water level has smooth trend. However, highest rainfall events have own impact slightly to increase the water level in upcoming water levels events.

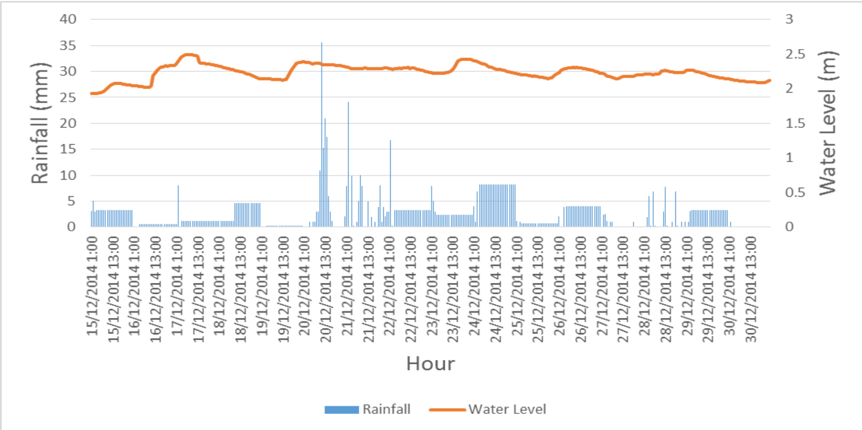

Figure 1. Presentation of rainfall versus water level at Kg Jenob station, Malaysia

The development of TLFN includes a systematic steps which are choosing of data set for learning, cross validation and test, determination of the input and output variables including scaling; choosing of the network topology and specification the required number of cells for hidden layer; training and monitoring the cross validation and testing of TLFN to find optimum results. Configuration of TLFN model for Kg Jenob station includes three layers, which are: input, hidden and output layer. The number of cells for input layer is related to the input data vector, and the cell for output layer is related to the output vector. Normally, application of one hidden layer is enough for rainfall-runoff modelling by ANNs. One of the common and broadly-used methods is the heuristic approach to find optimum configuration of ANNs. Stepwise heuristic approach keep the non-linear relationship of hydrologic phenomena and monitoring the increasing inputs help to recognition of number of lags. In this study rainfall as main element to produce the flow has been considered as input of model. It should be investigated optimum maximum lags, which is also called memory length since this will increase the memory length besides considering the complexity of the neural network by the application of a number of inputs variables (e.g. attributed lags and different variables). For Kg Jenob, 8 scenarios have been developed in step wise method. In this methodology, next hour water level is forecasted as an objective. For instance, scenario 1 is to forecast the water level at 15/12/2014 2:00, which water level derived from rainfall 15/12/2014 1:00. Consequently, scenario 8 is related with forecasting the water level at 15/12/2014 9:00, which derived from rainfalls in previous hours between 15/12/2014 1:00 to 15/12/2014 8:00 in Kg Jenob station. Table 1 illustrates developed scenarios for Kg Jenob station based on water level (Q) and rainfall (PCP).

Table 1. Developed scenarios in Kg Jenob by TLFN

Scenario	Variables
1	Q_2 =f{ PCP_1}
2	Q_3 =f{ PCP_1, PCP_2}
3	Q_4 =f{ PCP_1, PCP_2, PCP_3}

4	Q_5 =f{ $PCP_{1, ...,}$ PCP_4}
5	Q_6 =f{ $PCP_{1,......,}$$PCP_5$}
6	Q_7 =f{ $PCP_{1, ...,}$ PCP_6}
7	Q_8 =f{ $PCP_{1,}$ …..,PCP_7}
8	Q_9 =f{ $PCP_{1, ...,}$$PCP_8$}

3. Result

Configuration of TLFN for Kg Jenob station includes three layers as input, hidden and output layer. The optimum TLFN network has one hidden layer and 2 neurons or process elements in hidden layer. Tangent hyperbolic and bias have been used as transfer functions in hidden and output layers respectively. Training algorithm is used back propagation with momentum term for whole network. Figure 2 shows the observed Mean Square Error (MSE) and Root Mean Square error (RMSE) for monitoring the accuracy of developed models. TLFN has been improved from scenario 1 to scenario 7 based on error optimization generally. The main reason can be related with sufficient input data to improve the pattern recognition of input data which related with output. In this study, further scenarios have not any significant improvement on result and scenario 8 has gained higher error in comparison with scenario 7 and it has been chosen the stop level. Therefore, scenario 7 has been introduced as optimum scenario. Indeed, further lags on rainfall and development of TLFN leads in a complex network which is usually considered as a disadvantage.

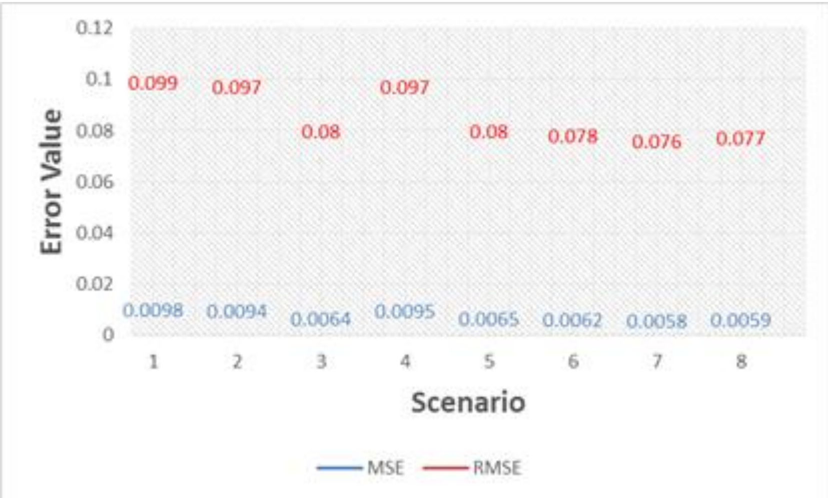

Figure 2. Error visualization of TLFN on water level forecasting in Kg Jenob

Figure 3 illustrates optimum simulation of water level for Kg Jenob station. However, the trend has under and over estimations for water level events. The minimum and maximum recorded water levels are 1.99 and 2.48 which are forecasted 2.1 and 2.37 respectively. Table 2 includes basic statistical analysis for observed and forecasted water level. Generally, discrepancies of the indices are based on over and under estimation of observed and forecasted values. For Kg Jenob station, mean, median, minimum and maximum values and standard deviation have a promising value, which are close to observed data. Although, mean, median and standard deviation have slightly underestimation.

Table 2. Basic Statistical analysis for observed and forecasted water level in Kg Jenob station

Index	Mean	Median	Min	Max	Standard deviation

Observed Water Level	2.24	2.24	2	2.4	0.1
Forecasted Water Level	2.22	2.23	2	2.3	0.07

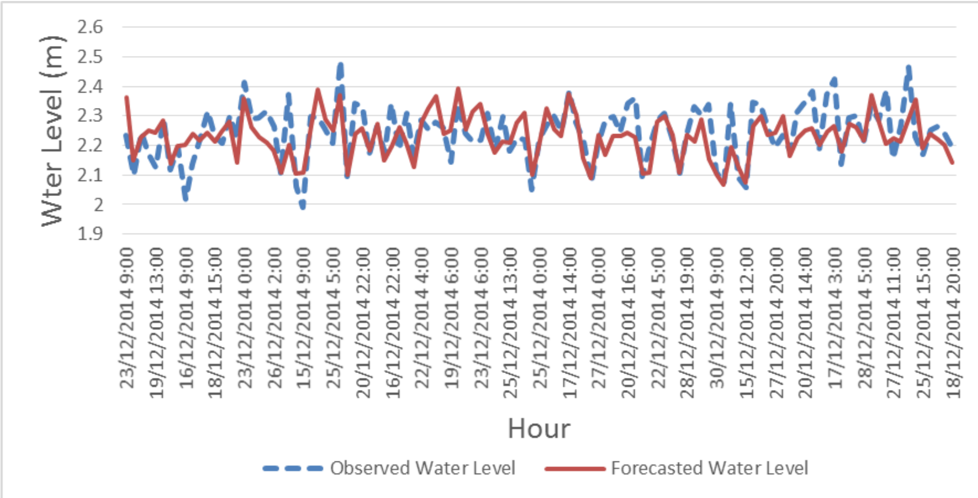

Figure 3. Trend presentation of scenario 7 as optimum forecasting of water level in Kg Jenob station

4. Conclusion

For this study, Time-Lagged Feed Forward network (TLFN) has been used for water level forecasting in kg Jenob station in Kelantan region for a flood period in 2014. For development of model is used available data as rainfall (mm) and water level (m). Development of TLFN is involved with definition of input data and related lags which is lead to 8 scenarios. Optimum TLFN is involved with one hidden layer including 2 neurons for processing. Tangent hyperbolic and bias have been used as transfer function in hidden and output layers respectively. Training algorithm is used back propagation with momentum term. Result shows that the model has progressive respond to use more lags for rainfall as inputs and using the rainfall lags bring a better memory for pattern recognition of water level in Kg Jenob station. However, using more rainfall after scenario 7 shows that there is not any significant improvement for forecasted values. It can be concluded that optimum hourly water level modeling for Kg Jenob is derived from 7 hours rainfall lags, in other word, next hour water level has high relationship with 7 hours previous rainfall. Both statistical and graphical analysis admit that TLFN can be an alternative technique in Kelantan for further evaluations in regard with forecasting the flood and water level which are beneficial as subsidiary tools for a hydrologist.

References

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