

River water level forecasting for flood warning system using deep learning long short-term memory network

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Abstract. Flood is considered chaotic, complex, volatile, and dynamics. Undoubtedly, its prediction is one of the most challenging tasks in time-series forecasting. Long short-term memory (LSTM) networks are a state of the art technique for time-series sequence learning. They are less commonly applied to the hydrological engineering area, especially for river water level time-series data for flood warning and forecasting systems. Yet it is inherently suitable for this subject. This paper examines an LSTM network for forecasting the river water level in Klang river basin, Malaysia. The river water level contains of single time series observed data, with time steps corresponding to hourly data and values corresponding to the water level or stage level in meters. In this study, prediction responses for river water level data using a trained recurrent neural network and update the network state function is applied. The result verified that the LSTM network with specified training set options is a promising alternative technique to the solution of flood modelling and forecasting problems. The performance indicates with the root mean square error, RMSE 0.20593 and coefficient of determination value, R^2 0.844 are closely accurate when updating the network state compared with the observed values.

1. Introduction

Urban floods are considered one of the wide-scale devastating natural disasters affected globally, and improved flood forecasting model is essential for better flood warning and management system. It has become an issue of great importance recently due to extensive damage to human life, properties, and lead to large socioeconomic problems caused by floods. Flood forecasting system plays a crucial role in planning and regulating the disaster risk reduction and management (DRRM). The Sendai frameworks 2015-2030, highlighted ‘investing in disaster risk reduction for resilience’ and ‘enhancing disaster risk preparedness for effective response’ are respectively for priority number three and four regarding the DRRM [1].

Research on flood forecasting models has a long tradition in the hydrological engineering area. However, the determination of improved flood modelling and forecasting is technically challenging.



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As reported in numerous published studies, river water level forecasting for flood management is difficult task and highly dynamic to model. Recently, researchers have shown an increased interest in river flood prediction and modelling, namely, data-driven methods. The types of models use the generalized relationship between input and output variable datasets without requiring the physical mechanism behind the process of the model. In which, the model is constructed based on historical data

Neural network models, especially as data-driven approaches, are developed through training the network to demonstrate the relationships and processes that are inherent within the data. Research on flood water level forecasting has been successfully taken by the authors [2, 3]. The works are growing advance in exploring more suitable flood forecasting model. Reviewing some published research works, by using the Artificial Neural Networks (ANNs) model, Elsafi [4] has demonstrated real-time flood forecasting in the case of River Nile at Dongola Station. Reference in [5] explored the applicability of a deep learning approach for predicting hourly air temperature using real sensor data of the Northwestern Nevada region. The results indicate that stacked denoising auto-encoder (SDAE) as deep learning approach performs better rather than standard neural networks model. Moreover, as a part of machine learning methods, ANNs is the most popular Artificial Intelligent (AI)-based technique in flood forecasting [6].

The continued advancement of AI methods in recent years has seen a growing trend towards deep learning techniques and their application in time-series prediction. Deep learning is being studied in many types of problems such as image processing, speech recognition, and natural language processing. In the field of forecasting, a recent experiment has been reported the successful use of deep learning in various fields, respectively for power load and probability density forecasting [7], traffic flow forecasting [8], and rainfall forecasting [9]. As it developed that deep learning can be quite promising reported better results than the traditional ANN model [10]. Research on the subject in deep learning has the most significant current discussion are advancing computer vision utilizing convolutional neural networks (CNN) and modelling time-series or type of sequential data through recurrent neural network (RNN) [11].

It was until the late 1990s that more advanced RNN architectures have been developed and one of the successful networks is the long short-term memory (LSTM) [11, 12]. Although studies have recognized LSTM in solving time-series prediction [13], to date, few published research works have explored the use of LSTM as deep learning approach in hydrological engineering problems, especially for flood forecasting. Thus, it is a chance to employs the LSTM network to predict river water levels for flood forecasting and warning system. The specific objective of this study is to build real-time data-driven models that enable to simulate and forecast river water levels from historical data using the LSTM network. The long short-term memory network is a type of recurrent neural network used in deep learning due to large architecture can be successfully trained.

2. Methodology

The usefulness of the approached method will be evaluated using a case study for the Klang River, Kuala Lumpur, Malaysia. The Klang River was chosen as a flood forecasting point based on the department of irrigation water level at Sulaiman Bridge. The total catchment area up to the station is approximately 466 km² [14]. 19008 hourly time-series observations dataset provided by the department of irrigation and drainage (DID) system Malaysia recorded in November 2011-December 2013, was used as historical input data to the LSTM network. The main feature of the LSTM network is the hidden layer called memory cells. LSTM networks consist of an input layer, one or more memory cells, and an output layer. The number of neurons in the input layer is equal to the number of explicative variables [11, 12]. Each of the memory cells has three gates maintaining and adjusting its cell state S_t : a forget gate (f_t), an input gate (i_t), and output gate (O_t). Figure 1 shows the LSTM architecture memory cell.

The state of the layer consists of the hidden state (also known as the output state) and the cell state. The hidden state at time step t contains the output of the LSTM layer for this step. The cell state

contains information learned from the previous time steps. At each time step, the layer adds information to or remove information from the cell state. The layer controls these updates using gates. At every time-step t , each of the three gates is presented with the input x_t (one element of the input sequence) as well as the output h_{t-1} of the memory cells at the previous time-step $t - 1$. According to the references [11], [12] and [15], hereby, the gates serve as filters, each having different purposes:

- The forget gate determines what information is removed from the cell state
- The input gate specifies what information is applied to the cell state
- The output gate specifies what information from the cell state is used,

and the sequential update formulas are can be referred to as reference [11]. The specified topology of the proposed LSTM networks is according to `predictAndUpdateState` provided by Matlab toolbox function can be seen in Table 1, to predict time steps one at a time and update the network state at each prediction.

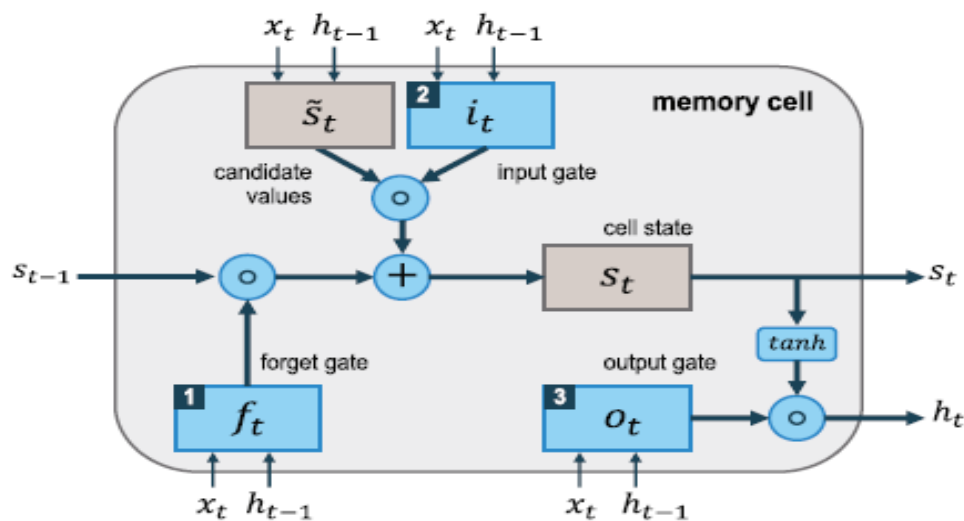


Figure 1. The LSTM network architecture memory cell [15]

Table 1. Parameters setting used in LSTM network

Variables	Value
Number of features and response	1
Time step	1
LSTM layer hidden units	200
Network type	Fully connected
Training dataset	80%
Validation test	20%
Training epochs	300
Gradient Threshold	1
Initial learn rate	0.005
Learn rate drop period	125
Learn rate drop factor	0.2
State and Gate activation function	tanh and sigmoid

In order to demonstrate the efficiency of the LSTM network model, in this study, performance is assessed by using the root mean square error, $RMSE$. It is formulated in Equation (1). While R^2 in Equation (2) is the coefficient of determination, value describes the proportion of the variance in the observed dataset that can be explained by the model.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n |y - y'|^2} \quad (1)$$

$$R^2 = \frac{\sum_{i=1}^n (y' - \bar{y})^2}{\sum_{i=1}^n (y - \bar{y})^2} \quad (2)$$

Where n is the number of data points, y' represents the forecasted value of river water level, y is the observed river water level at the time i , and \bar{y} is the average value of the actual or observed records. In this study, Matlab and its environment were used to be the platform for programming and simulation tool in establishing the developed model.

3. Result and discussions

The simulated model was done using `trainNetwork` Matlab function to train an LSTM network for deep learning. For a better fit and to prevent the training from diverging, standardized the training data is applied to have zero mean and unit of variance. The standardized data obtained from the difference between training data and the mean of training data divided by the standard deviation value of training data. At prediction time, the standardized test data using the same parameters as the training data. The standardized water level data can be illustrated in Figure 2. In this study, the network state was initialized at first using 80% training data that is 15207 of the 19008 input data set. Then simulated the next prediction of 20% or 3801 validation test data using the last time step of the training response. Continued by looping over the remaining predictions and input the previous prediction to the LSTM network.

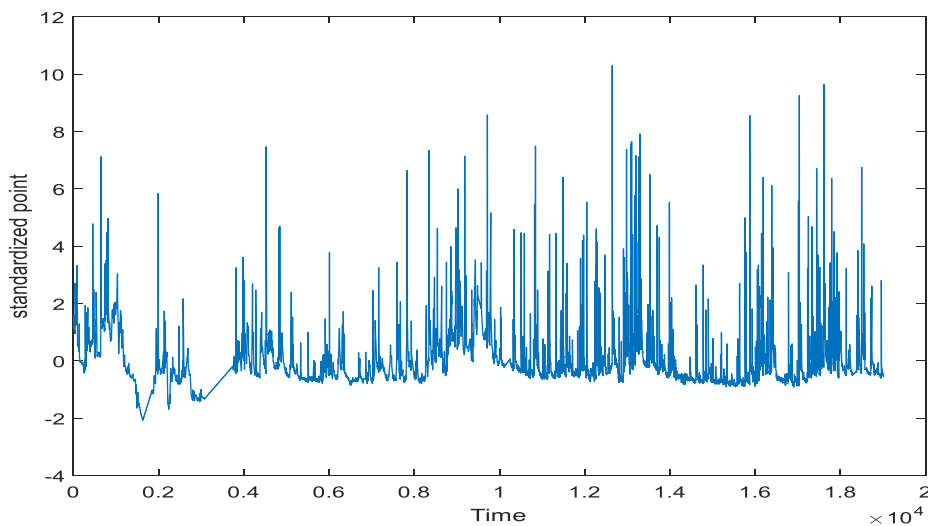


Figure 2. Hourly River Klang water level after data standardized

The experiment result of 3801 validation data sets can be referred to in Figure 3 with the red line distribution values. Quantitatively, with forecasted and observed values booths are unstandardized to their original scale. From Figure 3, it showed that the forecasted red line distribution value quite follows the validated pattern from the actual value after it's unstandardized. The result was shown in the original stage river water level. The result shown in Figure 4 seems that the LSTM network provides a considerable accurate in terms of error criteria. Although LSTM has difficulties in explaining the detailed peak values, the network is adequate to follow the dominant trends. The LSTM

network generally reflected observed river water level. The RMSE and the coefficient of determination, R^2 were calculated to evaluate model performance. These two evaluated performances were calculated from the unstandardized prediction results. The results showed that the RMSE and R^2 in Figure 5 were respectively of 0.20593 and 0.844, which showed quit precision.

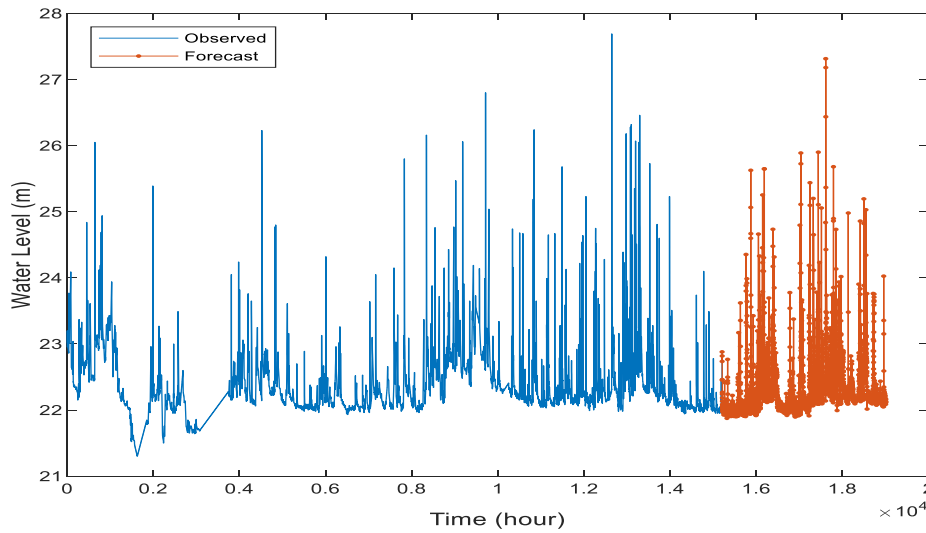


Figure 3. Hourly River Klang water level forecasting and observed data after unstandardized

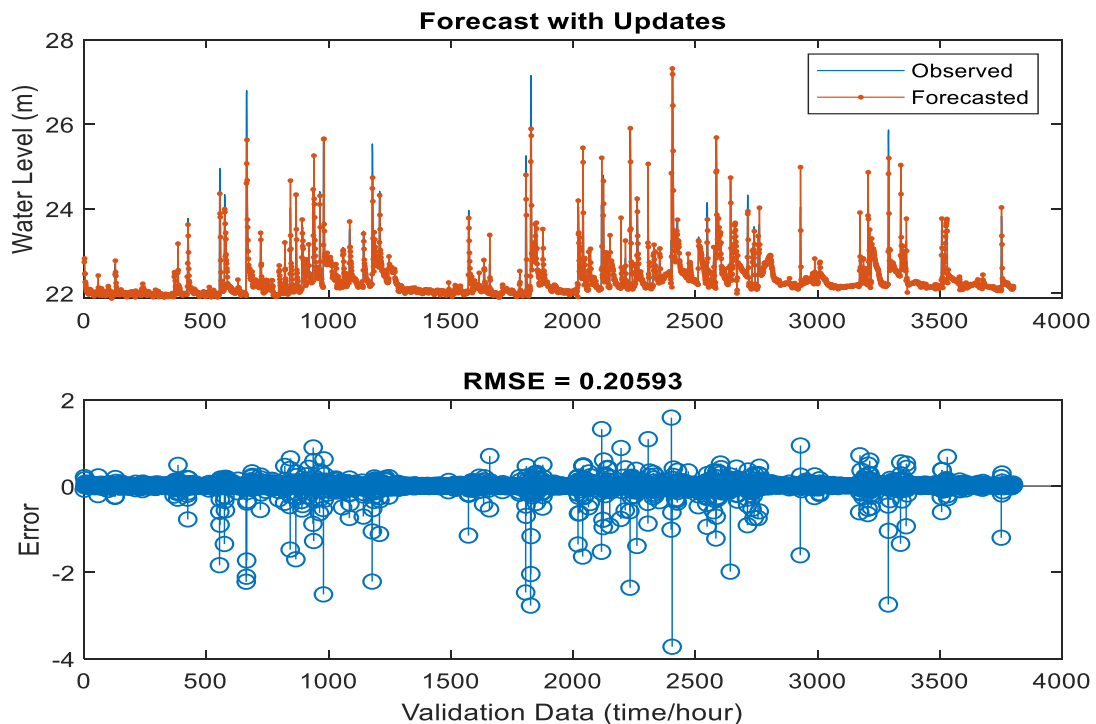


Figure 4. Hourly forecasting based on test data and error distribution

After the quantitative analysis of LSTM models, the observed and simulated water level distribution value also scattered. The LSTM model has a high value showing that the model could well represent the relationship between observed and simulated performance. From Figure 5, the data is scattered relatively closer to the LSTM model. It is clearly shown that LSTM model is good correlation with the observed water level data.

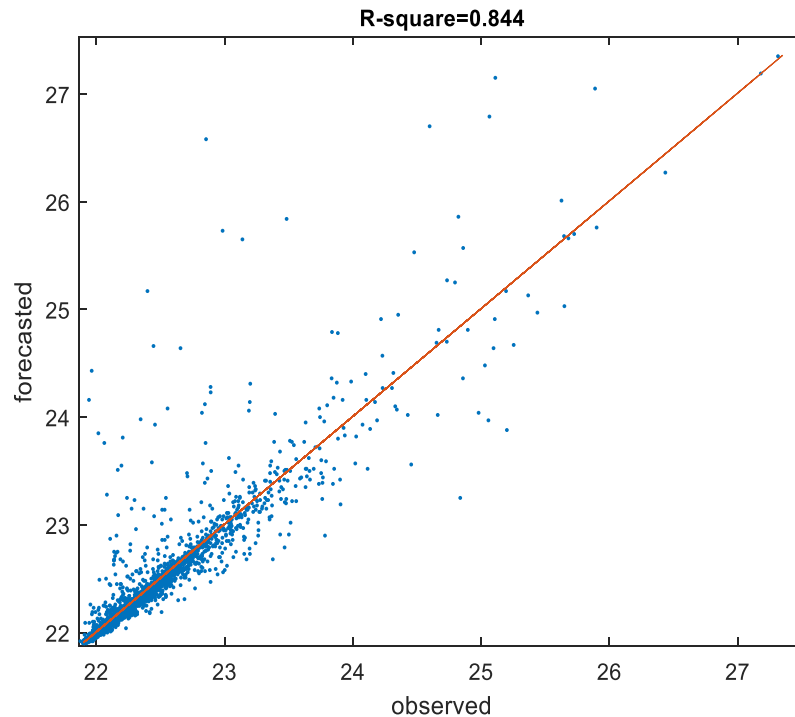


Figure 5. Scatter-plot distribution of the observed and forecasted data

In connection with disaster risk management and flood warning system, according to DID [16, 17] for river level data-above mean sea level, it can be classified as three main categories including “alert level”, “warning level”, and “danger level”. The alert level for Klang River, in Sulaiman Bridge is 27.00 meters, while for warning level is 28.25 meters, and the danger level is 29.50 meters. From the inside of forecasted data, the maximum value is about 27.314 meters compared to the maximum actual value is 27.35 which was categorized as “alert level” at that time. It indicates when the river water level more than the maximum observed value, can be assumed flood will occur in that particular area since it could be reached at a danger level.

4. Conclusions

This paper set out to develop a simulated model for river water levels using the LSTM network. The study has examined the concept of RNN as a deep learning LSTM cell. The LSTM model not only takes full advantage of the current data characteristics but also uses its gate structure to decide whether to remember or forget the previous feature. With the progress of AI techniques, the deep learning method of long short-term memory network model could be better used in the hydrological engineering problems, due to the LSTM is very effective in modelling large time-series data. In this paper, the input data set was considered from one downstream to forecast the river water level of the next hours for flood warning system. The result verified that the LSTM network with specified training set options is a promising alternative technique to the solution of flood modeling and forecasting problems. The performance indicates with the root mean square error, RMSE 0.20593 and R^2 value 0.844 are closely accurate when updating the network state compared with the observed value.

For further research study, employing more input variables including weather forecast, rainfall data, and streamflow data can be addressed in order to get the relationship impact of the improved flood forecasting performance. Furthermore, the enhancement of machine learning algorithm in advance AI-based methods will be more challenging to develop robustness of the flood forecasting system.

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Research materials

The research data material can be accessed through <https://osf.io/gh5es/> it contains water level of Klang River at Sulaiman Bridge, Kuala Lumpur, Malaysia, in meters stage.

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