Reservoir water level forecasting using normalization and multiple regression

Siti Rafidah M-Dawam[1], Ku Ruhana Ku-Mahamud[2]
[1]Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Kedah, Malaysia
[2]School of Computing, College of Arts and Sciences, Universiti Utara Malaysia, Sintok, Kedah, Malaysia

Article Info

Article history:

Received Oct 6, 2018
Revised Nov 19, 2018
Accepted Dec 27, 2018

Keywords:

Forecasting model
Reservoir modelling
Reservoir water release
Sliding window
Temporal data mining

ABSTRACT

Many non-parametric techniques such as Neural Network (NN) are used to forecast current reservoir water level (RWLt). However, modelling using these techniques can be established without knowledge of the mathematical relationship between the inputs and the corresponding outputs. Another important issue to be considered which is related to forecasting is the preprocessing stage where most non-parametric techniques normalize data into discretized data. Data normalization can influence the the results of forecasting. This paper presents reservoir water level (RWL) forecasting using normalization and multiple regression. In this study, continuous data of rainfall (RF) and changes of reservoir water level (WC) are normalized using two different normalization methods, Min-Max and Z-Score techniques. Its comparative studies and forecasting process are carried out using multiple regression. Three input scenarios for multiple regression were designed which comprise of temporal patterns of WC and RF, in which the sliding window technique has been applied. The experimental results showed that the best input scenario for forecasting the RWLt employs both the RF and the WC, in which the best predictors are three day's delay of WC and two days' delay of RF. The findings also suggested that the performance of the RWL forecasting model using multiple regression was dependent on the normalization methods.

Corresponding Author:

Siti Rafidah M-Dawam,
Faculty of Computer and Mathematical Sciences,
Universiti Teknologi MARA Kedah,
P.O. Box 187, 08400 Merbok, Kedah, Malaysia.
Email: srafidah192@kedah.uitm.edu.my

1. INTRODUCTION

Forecasting RWL is crucial for reservoir's operator in making decision on the reservoir water release (RWR) of a particular reservoir. It is a challenging and complex task, especially during flood and drought occurances due to unpredictable inflow such as RF [1]. Thus, a few researches have focused on non-structural approaches predicting reservoir inflows [2]. However, during flood or drought, the decision on RWR is not only based on the availability of water inflows, but also on the previous release, demands, time, etc. Besides daily RF, several researches also considered changes in the RWL (WC) as an input in the multipurpose reservoir forecasting model [2]. RF (hydrological data) and reservoir WC are found to be correlated in the flood prediction model [3].

Many literature conducted on the RWR operation have utilized RF data and RWL as inputs [4], and have applied different methods and techniques of Artificial Intelligence and machine learning[5–8]. Only a small number of researches conducted on RWR decisions highlighted on the time delay between the RF and the increase of RWL.

In [9] discretized data are normalized using Min-Max technique. In this study, the results showed eight days' time lag relating to upstream RF and RWL with an ANN model of 24-15-3. Later, the model recommended five days' time lag with 8-23-2 ANN model with a 0.007085% error. Type 2 SVM regression has been used by [2] to forecast the daily RWL of the Klang reservoir, Malaysia. The study employed Z-Score technique for data normalization and found out that the best input variables are combination of both RF and RWL, which were used to determine the best time lag which are two days of RF and with 1.64% error. Autoregressive Integrated Moving Average (ARIMA) model was developed in [4] for predicting the Kainji Dam, Nigeria daily water levels using a ten-year record. The study resulted in a model with a relative error of 0.039% had the best prediction. In [10] ANN with feedforward back propagation was concluded as the suitable predictor for real-time water level forecasting of the Sukhi Reservoir, India. The inputs are the daily data of inflow, RWL, and RWR where the best time lag is ten days with a 0.82% error. NN was also employed in [11] to predict RWL and concluded a 5-25-1 NN model as the best architecture. The study found out that five days' observations of RWL are significant for the RWR decision with a 0.038756% error. A NN architecture of 4-17-1 in forecasting the change of RWL stage was proposed in [3]. The input patterns were the changes and stages of RWL instead of the real value of RWL. The research showed that the changes in the stages of RWL were influenced by the two days of delay. However, modelling using NN techniques can be established without knowledge of the mathematical relationship between the inputs and the corresponding outputs. Whereas multiple regression is used to explore the relationship between one continuous dependent variable (DV) and a number of independent variables (IVs) or predictors (usually continuous). It can determine how well a set of variables is able to predict a particular outcome [12–18]. This study applied multiple regression in order to identify which IVs (slices of RWL and RF) can best be the input predictors to predict DV (RWL_t).

Another important issue to be considered which is related to forecasting is during the preprocessing phase where most non-parametric techniques normalize data into discretized data. Data normalization can influence the results of forecasting. Normalization can be performed at the level of the input features or at the level of the kernel [19]. In many applications, the available features are continuous values, where each feature is measured in a different scale and has a different range of possible values. In such cases, it is often beneficial to scale all features to a common range by standardizing the data. Previous studies mentioned above, have not reported any comparative study done on the normalization method used in their research. In [19–22], normalization process has increased the classification accuracy while in certain datasets, normalization may not demonstrate significant advantages [23] .

In RWL forecasting, the data is in the form of temporal sequences, where time (month, day or hours) is critical [24]. The changes in the patterns of the data can influence certain decision-making. The Temporal Data Mining (TDM) technique is required to uncover the values of the attributes involved from temporal sequences representing temporal information related to certain decisions by the algorithm formulation. The significant time delay between the cause of event and the actual event needs to be captured accurately. Several studies reported on the use of temporal data in forecasting [3], [11], [25–33].

This paper presents reservoir water level (RWL) forecasting using normalization and multiple regression. In this study, continuous data of RF and changes of reservoir water level (WC) are normalized using two different normalization methods, Min-Max and Z-Score techniques. Its comparative studies and forecasting process are carried out using multiple regression. Three input scenarios for multiple regression were designed which comprise of temporal patterns of WC and RF. The sliding window technique has been used to capture the delay in temporal data. The experimental results showed that the best input scenario for forecasting the RWL_t employs both the RF and the WC, in which the best predictors are three day's delay of WC and two days' delay of RF. The findings also suggested that the performance of the RWL forecasting model using multiple regression was dependent on the normalization methods. Root Mean Square (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) have been used as the parameters to measure the forecast results based on the actual data analysis.

2. RESEARCH METHOD

Figure 1 depicts the approach that has been used in conducting the research. The reservoir data which consist of RF and RWL from 1997 until 2006, have been collected from the Department of Irrigation and Drainage (DID), which is in charge of monitoring and managing the Timah Tasoh reservoir. This reservoir is one of the largest multipurpose reservoirs situated in the northern Peninsular of Malaysia.The data consists of operational and hydrological data. The operational data has the daily RWLs measured in metre (m) unit while the hydrological data has the daily RF readings measured in milimetre (mm), recorded from five gauging stations.

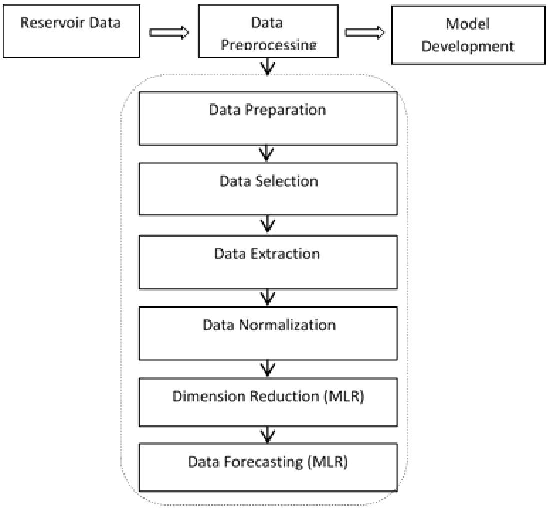

Figure 1. The process flow for RWL forecasting

In the data preparation stage, the attributes are described and records with missing values were interpolated. This study used the RWL as the output whiles the changes of the reservoir water level (WC) and RF were used as the input. These WC will be calculated using equation [3](1):

$$WC_t = RWL_t - RWL_{t-1} \quad (1)$$

where WC_t is the change of RWL at current time *t*, RWL_t is the RWL at current time *t* and RWL_{t-1} is the RWL at one previous day *t-1*. The RF data are averaged by the number of stations that have RF based on [30] (2):

$$Average\_RF = \frac{total\_rain}{number\_of\_stations\_with\_rain} \quad (2)$$

Next, the change-point detection technique is applied, where records which consist of gate opening decision only are extracted [34] while records with gate closing decision were removed. A total of 501 records were detected from ten years of reservoir operation (1997–2006).

The RF and WC data used in this study is temporal data with the time delayed event. The changes in RWL are the impact of several sequences events of RF. In order to capture the temporal information of WC and RF, sliding window technique is applied [34]. Figure 2 shows the pseudo-code for the sliding window where *n* is the size of the window. In this study, *n* is taken as the value of seven to investigate on the effect of seven previous event on current RWL [35] as showed in Table 1 and Table 2.

```
for time t to end of file
        read data at time t
        get data at (t-1)…(t-n)
        add into window slices set
next
```

Figure 2. Steps for Sliding Window

Table 1. Sliced Reservoir WC

Date	RWLt	WCt-1	WCt-2	WCt-3	WCt-4	WCt-5	WCt-6	WCt-7
12-Feb-97	29.275	0.020	0.035	0.055	0.035	0.025	0.150	0.005
13-Feb-97	29.335	0.060	0.020	0.035	0.055	0.035	0.025	0.150
14-Feb-97	29.335	0.000	0.060	0.020	0.035	0.055	0.035	0.025
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	

Table 2. Sliced RF

Date	Average_RF	RFt-1	RFt-2	RFt-3	RFt-4	RFt-5	RFt-6	RFt-7
12-Feb-97	20.250	7.330	5.380	13.00	0.000	46.250	24.500	10.000
13-Feb-97	13.875	20.250	7.330	5.380	13.000	0.000	46.250	24.500
14-Feb-97	8.250	13.880	20.250	7.330	5.380	13.000	0.000	46.250
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	

In the next stage, the reservoir WC and RF are normalized, where the attribute data is scaled so as to fall within a small specified range. In a real application, because of the differences in the range of attributes' values, one attribute might overpower the other. Normalization prevents the outweighing attributes with a large range. The goal is to equalize the size or magnitude and the variability of these attributes. There are many types of data normalization, however only two techniques are used to make a comparison in this study; Z-Score and Min-Max Normalization.

In Z-Score normalization, the values for the attributes of reservoir WC and RF are normalized based on the mean and standard deviation. The equation for such transformation is given as follows (3):

$$Z_{new} = \frac{Z - \overline{Z}}{SD} \tag{3}$$

where $\overline{Z}$ is the mean of attribute and *SD* is the standard deviation of the attribute. This method of normalization is useful if the actual minimum and maximum values of the attributes are unknown. The advantage of this statistical norm is that it reduces the effects of outliers in the data. Table 3 and Table 4 showed the normalized WC and RF using Z-Score technique.

Table 3. Z-Score of Reservoir WC

Date	zRWLt	zWCt-1	zWCt-2	zWCt-3	zWCt-4	zWCt-5	zWCt-6	zWCt-7
12-Feb-97	0.694	0.266	0.292	0.393	0.148	0.017	1.310	-0.204
13-Feb-97	0.908	0.627	0.156	0.207	0.337	0.116	0.003	1.349
14-Feb-97	0.908	0.086	0.519	0.067	0.148	0.314	0.108	0.010
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	

Table 4. Z-Score of RF

Date	zRFt	zRFt-1	zRFt-2	zRFt-3	zRFt-4	zRFt-5	zRFt-6	zRFt-7
12-Feb-97	0.433	-0.463	-0.617	-0.192	-1.039	1.938	0.556	-0.351
13-Feb-97	0.022	0.298	-0.503	-0.642	-0.191	-1.038	1.979	0.605
14-Feb-97	-0.340	-0.077	0.254	-0.527	-0.688	-0.201	-1.045	2.049
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	

The second technique is Min-Max Normalization. This method rescales the attributes or outputs from one range of values to a new range of values. The attributes are rescaled to lie within a range of 0 to 1 or from -1 to 1. The rescaling is accomplished by using the following equation (4):

$$M_{new} = \frac{M - M_{\min}}{M_{\max} - M_{\min}} \tag{4}$$

where *M* is the actual value of an attribute. This method has the advantage of preserving exactly all relationships in the data. Table 5 and Table 6 showed the normalized WC and RF using Min-Max technique.

Table 5. Min-Max of Reservoir WC

Date	mRWLt	mWCt-1	mWCt-2	mWCt-3	mWCt-4	mWCt-5	mWCt-6	mWCt-7
12-Feb-97	0.5838	0.2735	0.2863	0.3034	0.2947	0.2863	0.3918	0.2694
13-Feb-97	0.6185	0.3076	0.2735	0.2863	0.3116	0.2947	0.2863	0.3918
14-Feb-97	0.6185	0.2564	0.3076	0.2735	0.2947	0.3116	0.2947	0.2863
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	

Table 6. Min-Max of RF

Date	mRFt	mRFt-1	mRFt-2	mRFt-3	mRFt-4	mRFt-5	mRFt-6	mRFt-7
12-Feb-97	0.1387	0.0502	0.0368	0.0890	0.0000	0.3846	0.2037	0.0831
13-Feb-97	0.0950	0.1387	0.0502	0.0368	0.1081	0.0000	0.3846	0.2037
14-Feb-97	0.0565	0.0951	0.1387	0.0502	0.0447	0.1081	0.0000	0.3846
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	

Multiple regression is used to explore the relationship between one continuous dependent variable (DV) and a number of independent variables (IVs) or predictors (usually continuous). It can determine how well a set of variables is able to predict a particular outcome. The regression equation (5) takes the following form:

$$Y` = A + B_1X_1 + B_2X_2 + ... + B_nX_n \tag{5}$$

where $Y`$ is the predicted value on the DV, A is the intercept, the *Xs* represent the various IVs, and the *Bs* are the coefficients assigned to each of the IVs during regression.

The ouput for this study is the RWL_t and the inputs are reservoir WC and RF. This study designed three different input scenarios for multiple regression in order to identify which input scenarios (IVs) can best be the input predictors to forecast RWL_t (DV). The first scenario considers the daily RF between time (*t-1*) and (*t-7*) as the sole input, while the second scenario considers both the RF (at *t-1 – t-7*) dan reservoir WC (at *t-1 – t-7*) as inputs. The third scenario uses the reservoir WC only between time (*t-1*) and (*t-7*) as inputs. Equations (6), (7) and (8) represent the first, second and third scenarios, respectively.

$$RWL_t = f RF(t-i) \quad i = \{-1, -2, -3, -4, -5, -6, -7\} \tag{6}$$

$$RWL_t = f\,(RF(t-i), WC(t-j)) \; i = \{-1, -2, -3, -4, -5, -6, -7\} \quad j = \{-1, -2, -3, -4, -5, -6, -7\} \tag{7}$$

$$RWL_t = f WC(t-i) \quad i = \{-1, -2, -3, -4, -5, -6, -7\} \tag{8}$$

3. RESULTS AND ANALYSIS

In this section, the results of the study are discussed based on inputs scenario and data normalization technique.The best input scenario is determined before proceeding further into the forecasting calculation. Based on statistical test in Table 7, the forecasted values obtained by employing second input scenario achieve the best results from other two scenarios. The scenario employs more input data, thus providing a better forecasting estimation. It has greater R^2 which is 0.319 as compared to the first and second scenario which has R^2 values equal to 0.193 and 0.279 respectively. The second input scenario also has smaller standard error of estimate (SEE) for both normalization methods. The SEE for Min-Max Technique is 0.13588, and SEE for Z-Score technique is 0.833856. Therefore, this second input scenario will be used as the best inputs for further data runs.

Table 7. Statistical Test for Three Input Scenarios

Input Scenario	R	R^2	SEE (Min-Max Technique)	SEE (Z-Score Technique)
First	0.440	0.193	0.14673	0.90548
Second	0.565	**0.319**	**0.13588**	**0.83856**
Third	0.528	0.279	0.13872	0.85607

The sliding window technique has been successfully applied on RWL data to extract and segment the temporal data and preserved the delay. The study used multiple regression to find out that the best time lag for forecasting RWL_t is three days' delay of reservoir WC and two days of RF. Based on this finding, two set of regression model for RWL_t are developed in order to investigate which normalization techniques produces less error. The first regression model used the Min-Max while the second model used Z-Score normalization technique as shown in equation (9) and (10):

$$RWL_t = (0.175) + (0.375)mWC_{t-2} + (0.228)mWC_{t-3} + (0.358)mWC_{t-4} + (0.172)mRF_{t-1} + (0.183)mRF_{t-2} \tag{9}$$

$$RWL_t = (0.00) + (0.218)zWC_{t-2} + (0.129)zWC_{t-3} + (0.197)zWC_{t-4} + (0.123)zRF_{t-1} + (0.132)zRF_{t-2} \tag{10}$$

Two sets of data based on two different data normalization were tested using the two regression model developed. Four statistical formula are selected to evaluate the forecasting efficiency in this study, namely Root Mean Square (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and the Correlation Coefficient (R). The comparison of statistical evaluation on two normalization techniques is shown in Table 8. The results showed that the obtained values of RMSE, MAPE and MAE by using Min-Max technique are 0.14125, 0.24191 and 0.11122 respectively. While using the Z-Score technique the results are 0.87165, 6.90884 and 0.68677 respectively. All the RMSE, MAE and MAPE values obtained using Min-Max data normalization are closer to 0 than using Z-Score technique, indicating that the Min-Max techniques is better than Z-Score. However, the Z-Score technique provides slightly greater correlation coefficient values (R = 0.48858), than the Min-Max technique (R = 0.48856). In overall, forecasting using Min-Max data normalization techniques yield less error than using the Z-Score technique. The predicted output using Min-Max normalization is more reliable than that of the Z-Score normalization technique.

Table 8. Comparison of Statistical Evaluation for Normalization Technique

Normalization Technique	RMSE	MAPE	MAE	R
Min-Max	0.14125	0.24191	0.11122	0.48856
Z-Score	0.87165	6.90884	0.68677	0.48858

4. CONCLUSION

This paper has presented reservoir water level (RWL) forecasting using normalization and multiple regression. The research on the comparison of input scenario for multiple regression concludes that the best input scenario for multiple regression is the second input scenario which consists of combination data of RF and WC.

The sliding window technique has been successfully applied on RWL data to extract and segment the temporal data and preserved the delay. The study used multiple regression to find out that the best time lag for forecasting RWL_t is three days' delay of reservoir WC and two days of RF.

The comparative studies on the two different normalization methods of the Timah Tasoh reservoir data using multiple regression showed that data normalized using Min-Max technique can enhance the reliability of the forecasting model for RWL_t. Forecasting using Min-Max techniques yield less error than using the Z-Score technique and the predicted output is more reliable. The experimental results showed that the prediction of the RWL_t using MLR was dependent on the normalization methods used.

In the future, other input variables such as sediment, volume of water release and spatial effect can be explored to improve the forecasting model of RWL_t. The comparison of other various statistical normalization methods such as median, sigmoid and statistical column normalization can also be measured.

ACKNOWLEDGEMENTS

The authors wish to thank the Ministry of Higher Education Malaysia for funding this study under the Long Term Research Grant Scheme (LRGS/b-u/2012/UUM/Teknologi Komunikasi dan Informasi), and the Department of Irrigation and Drainage Malaysia for supplying hydrology and reservoir operational data.

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