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Prediction of Future Streamflow for Kurau River Basin using Artificial Neural Network (ANN)

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Abstract: The reservoir are used for many purposes, among them are to provide reliable water supply, hydropower and flood mitigation. Due to climate change, the reservoirs are impacted by the increase in global surface temperature. This situation will then lead to the need for an assessment of regional climate change impacts. The objectives of this study are to develop the hydrological model for the Kurau River Basin which is the main water resource for the Kerian Irrigation scheme and the Bukit Merah reservior, to assess climate change impact on river runoff using artificial neural network (ANN) and to predict the future streamflow using Artificial Neural Network (ANN) from Statistical Downscaling Model (SDSM) output. The data for this research included the data for the past and present data from 2010 until 2020 and the future data prediction from 2020 until 2050 as the output data.

Keywords: Future Streamflow, Kurau River Basin , ANN

1. Introduction

The term "streamflow" refers to the amount of water flowing in a river. The everyday forecasting of streamflow is essential to ensure the efficient operation of the water resources management to support the decision making by the water managers and reservoir that strive for balancing a range of competing objectives [1]. The changes in streamflow resulted from the hydrological processes reflect the combined effect of climate, vegetation, and soil. These changes of climate combined with human activities such as land reclamation and soil and water conservation engineering have led to massive changes in hydrological process in many basins globally which cause a series of water resource problems in some regions such as the Johor River basin and Bernam River Basin in Malaysia. To understand the effect of climate change on streamflow, hundreds of studies have been conducted to examine the response of hydrological processes to global climate change [2]

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The particular problems in forecast streamflow are uncertainty and imprecision as per the expert systems due to this many researchers have been directed towards this area. Many problems in the streamflow prediction domain need to be represented at varying degrees of diagnosis to be solved, thus the classification is very important in computer-aided streamflow diagnosis as consequently, accuracy and precision result is very essential in classifiers used for future streamflow prediction [3].The high percentage of the false-negative forecast will increase the risk of the real and serious problematic streamflow of the reservoirs. If full attention needed is not received, a high false alarm rate would cause unwarranted worries, increase the cost, and also the load on water management resources.

1.1 Study Area

Bukit Merah Reservoir is also known as BMR is located in the northern state of Perak in Peninsular Malaysia which in Kerian, Perak. It is the oldest man-made lake in Malaysia which is between the latitude of 100° 39′ 14.7″ E and longitude of 5° 01′ 06.8″ N [4]. The capacity of the reservoir is equal to 74.98 Mm^3 within the reservoir area of 41.0 km^2 while the catchment area is 480.0 km^2 [5]. It was built in 1902 for the Kerian Irrigation Scheme to provide the irrigation water for double cropping to 24000 ha of paddy land in the district of Kerian Domestic and industrial water supply of populace in the Kerian and Larut Matang district [6]. Besides, Bukit Merah Reservoir also supports the ecotourism planning through the lakefront resort and water park (Bukit Merah Laketown Resort), also as a tool to control the flood and drought.

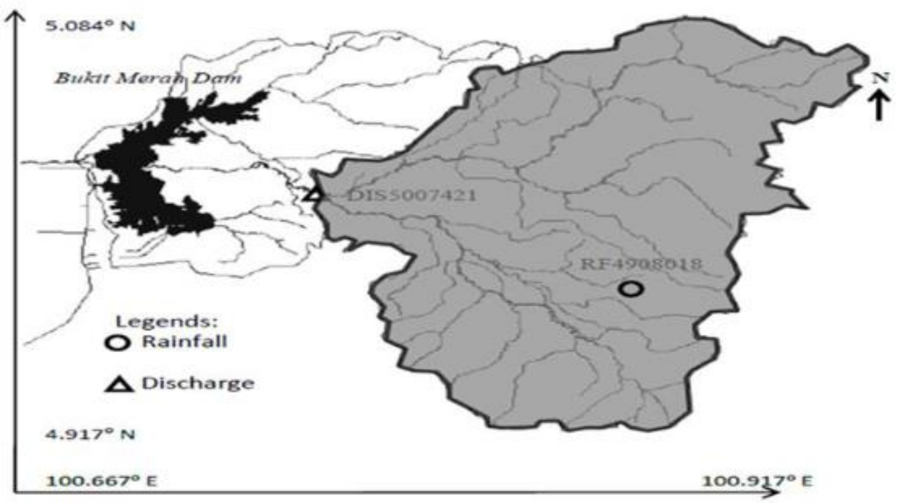

Figure 1: Location of rainfall and discharge station in Kurau River Catchment

Kurau River is located in the northern area of Peninsular Malaysia in the state of Perak and the dam acts as the main water resource for the Kerian Irrigation scheme and the Bukit Merah reservoir, it also provides a domestic water supply for Kerian District and Larut Matang District which located in the same state [7]. Due to the impact of climate change, causing the problem for Kerian Irrigation Scheme in maintaining the water supply for irrigation, and water demand for paddy irrigation needs a flexible water supply due to spatial and temporal variations. To overcome this problem, it is essential to estimate the future irrigation requirement by applying the formulated integrated model before any adaptive policy-making in scheduling and planning the system can be done

2. Materials and Methods

2.1 Artificial Neural Network (ANN)

ANN is made up of input layer, hidden layer and output layer where each layer consists of a number of neurons and weighting functions. The artificial neurons are organized in layers with one or more intermediate hidden layers put in middle of the input layer and output layer, and send their signals "forward". Each layer has a number of neurons that are connected with other neurons in the adjacent layers through unidirectional connection. The information will flow only in one direction during the training process which is from the input layer to the output layer within the hidden layer [3]. ANN has synapses which is a group of nodes that connected with the inputs, outputs, or another neurons. The inputs are composed of weather variables such as temperature, humidity, rainfall, actual load, previous load and wind speed. ANN can performs a variety of tasks which includes prediction or function approximation, clustering, pattern classification and forecasting, but its performance is affected by how the setup of the neural network structure is conducted and how the data is prepared.

2.2 Data collection

Brief descriptions of the data used in the ANN rainfall runoff Model

i. Temperature data

The antecedent mean daily temperature and mean temperature of the current day obtained from year 2010 to 2020 Malaysian Meteorological Department. While the predicted future temperature data for year 2020 to 2050 from the calibrating the statistical downscaling model.

ii. Rainfall data

Rainfall data from year 2010 to 2020 were collected from Malaysia Department of Drainange and Irrigation (DID). The selected rainfall station is the Pondoland Farm in Pondok Tanjung as the station located near to the inlet of Bukit Merah Reservoir. The predicted future data for year 2020 to 2050 has been obtained from the SDSM output.

iii. Streamflow

The streamflow station in Pondok Tanjung is selected since it is near to the inlet of Bukit Merah Reservoir. All the data will be studied and predicted in an interval of time. The data for the past and present data from 2010 until 2020 and the future data prediction from 2020 until 2050.

2.3 Development of an ANN-Based Rainfall Runoff Forecasting Model

The development of an ANN model includes three stages: (1) setting up a two layers feed-forward neural network and determining the connection weights and the activation function, (2) selecting an algorithm (Back-Propagation Learning Algorithm was applied in research) that provides the best fit to the data to train the ANN model, and (3) identifying the optimal number of neurons in the hidden layer by using a trial and error procedure by varying the number of hidden neurons from 2 to 25. The transfer function used in the hidden layer is tan-sigmoid (tansig) and the outer layer has the linear transfer function (purelin). The neurons in each layer are connected to the neurons in the subsequent layer by a weight, adjusted during training. Furthermore, minimum root mean square error is also used to identify the optimal network architecture.

The selection of appropriate input parameters is a very important aspect of ANN modelling because it provides the basic information about the system being modelled. Statistical procedures were suggested for appropriate input vectors for a model. At present, the phase space reconstruction method and partial autocorrelation function method are generally considered as the two target optimum methods to be commonly used to determine the number of antecedents of parameters in ANN model, and , respectively. The performances of the models developed in this study were assessed using standard statistical performance evaluation criteria, including the coefficient of correlation (R), root mean squared error (RMSE), mean absolute error (MAE), relative root mean squared error (RRMSE),. ANN analyses were performed using MATLAB Neural Network Toolbox.

2.4 Data Analysis

All data types (including the monthly average precipitation, monthly average temperature, and monthly average runoff data) used to predict the runoff cover 30 years, which can be regarded as sets of data. All data were divided into two parts as training and testing periods. Only nine (9) of the antecedent rainfall and temperature were used due to limited input data. The inputs represent the antecedent total daily rainfall and antecedent mean daily temperature (T) as followed, *{P(t), P(t-1), P(t-2), P(t-3), P(t-4), P(t-5), P(t-6), P(t-7), P(t-8), P(t-9),* and *T(t) , T(t-1), T(t-2), T(t-3),T(t-4), T(t-5), T(t-6), T(t-7), T(t-8), T(t-9)}*Q(t) *ƒ*{I}.

3. Results and Discussion

3.1 Results

Table 1: Optimum configuration for the calibration of the ANN model

Catchment Basin	5007421 (Pondok Tanjung Station)
Training Algorithm	TRAINSCG
No of neurons	125
Different learning training	0.8

Table 1 demonstrates When simulating streamflow, Table 1 shows the output of the ANN model during model creation. Performance is tested by comparing the statistical characteristics of the observed and simulated daily and monthly results. With the R coefficients and RMSE varying between 0.87–0.94 m ^{3}/s and 2.28–6.860 m^3/s, respectively, the calibration output shows a satisfactory result. Meanwhile for validation and testing periods, that the performances of the ANN model reduced slightly compared to the performances of the model during the calibration period with R coefficients and RMSE ranging between 0.64-0.87 m^3/s and 1.05-13.67 m^3/s, respectively. As in the model development, the calibration of the ANN model does not consider the hydrological process, so the output of ANN can be based on input–output patterns recognized through learning (calibration). In this study, the temperature series (including the antecedent temperature) is a dominant input in this model. This situation leads to the increase in the rate of daily runoff series and future annual runoff, due to the influence of higher increase in future temperature series.

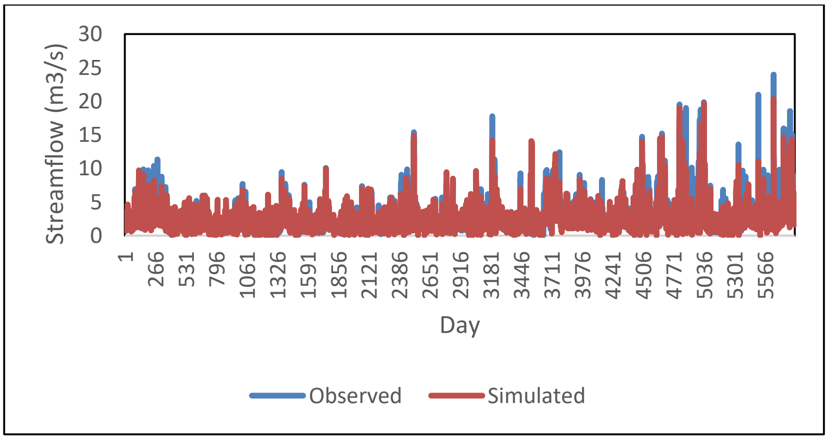

Figure 2: Daily observed and ANN-simulated mean streamflow during calibrating period

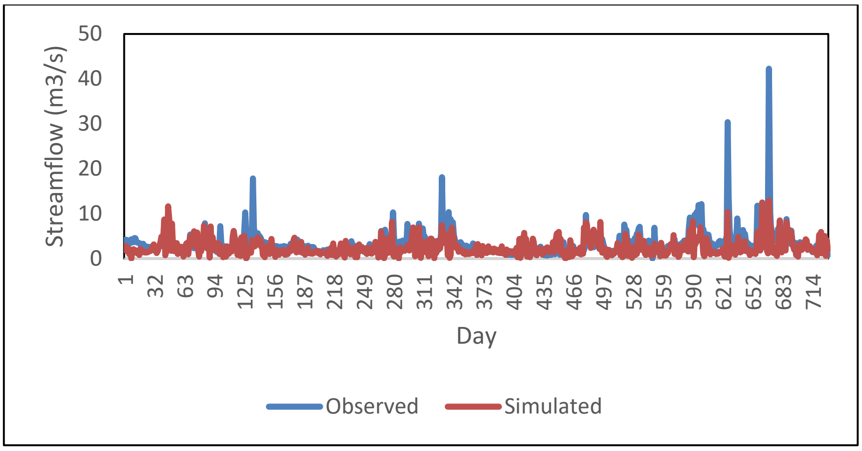

Figure 3: Daily observed and ANN-simulated mean streamflow during validating period

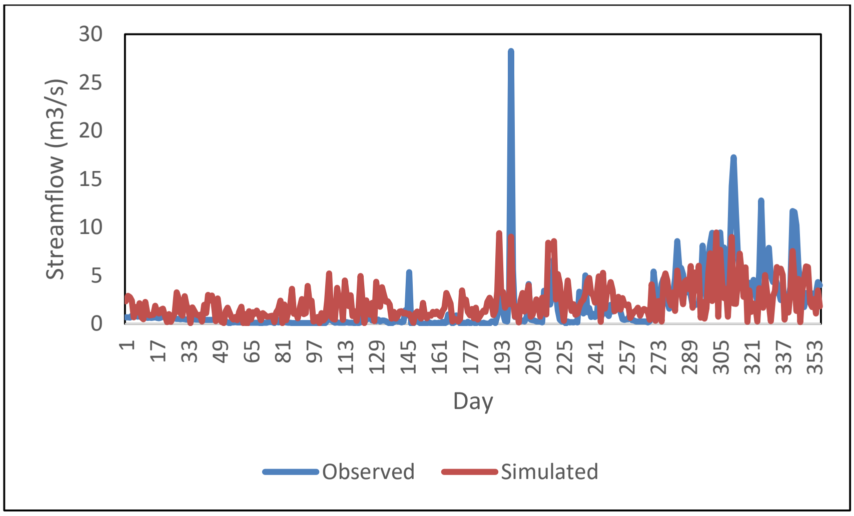

Figure 4: Daily observed and ANN-simulated mean streamflow during testing period

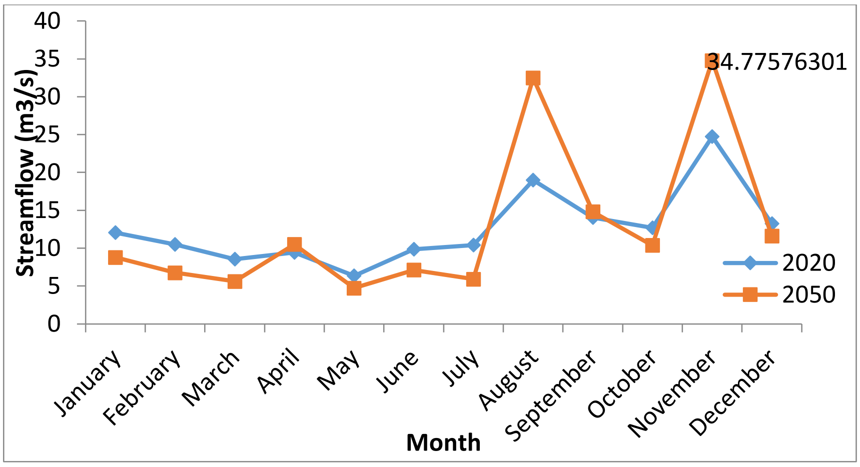

Figure 5: Future streamflow at Pondok Tanjung station simulated by ANN model

The downscaled baseline and future rainfall and temperature obtained from SDSM are entered into the ANN model to simulate the baseline and future streamflow. Figure 5 shows the comparison between simulated future streamflow for year 2020 and year 2050 from ANN model. From the result shown in it revealed that the trend for month increases with the change in mean flow. The highest increment of streamflow occurs in November, which provides additional 24.74 m^3/s, and 34.78 m^3/s for the 2020s, and 2050s respectively. April, March, August and November exhibit higher increase in mean flow, meanwhile March and May contribute the least of mean flow prediction. Hence, in general, this study indicates that the Pondok Tanjung Station will face an increase of streamflow in the future especially for the month of August and November as shown in Figure 5.

4. Conclusion

In simulating and predicting runoff variations to address data limitations, parameter uncertainty, and the daunting task of numerical hydrological model applicability, the ANN technology and prediction method is useful and valid. In this analysis, the three input variables' (runoff, precipitation, and temperature) ANN model produces a high-accuracy performance and has a significantly superior real-time prediction capability in the simulation and forecasting of the runoff dynamics compared to two ANN models were developed for prediction of the runoff in the

The ANN technology and prediction approach is useful and valid in simulating and forecasting runoff variations to overcome data limitations, parameter uncertainty, and the formidable challenge of numerical hydrological model applicability. For prediction of the runoff in the TRHR, two ANN models were developed in this study. If field observations of the runoff are available, the ANN model with three input variables should be developed and applied in permafrost regions. The three input variables' ANN model has a significantly superior real-time prediction capability and produces a high-accuracy performance in the simulation and forecasting of the runoff dynamics. When no field observations of the runoff are available, the ANN model developed using only two input variables of accessible climate data (precipitation and air temperature) also has a good accuracy for simulation and prediction of the variations in runoff. Although the results presented here are promising and these data-driven models can be successfully applied to determine river flow with three ANN forecasting models of input parameters, extreme flood flow is underestimated by these models. Further research is required in the future to improve the accuracy of predictions, especially for flood flows, by combining or improving model parameters. The flow generated by ANN model is reliable and the model successfully simulated a similar pattern to the historical values. The study has found that the climate change would give an impact to the hydrological properties (rainfall, temperature, and streamflow) on the Kerian agricultural watershed.

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