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Flow Forecasting For Selangor River Using Artificial Neural Network Models to Improve Reservoir Operation Efficiency

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Abstract

Selangor is an important river basin in adjacent to the city of Kuala Lumpur, the federal capital of Malaysia and it supplies about 70% of the water required for domestic and industrial use for the city. Selangor river basin is presently regulated by two water supply dams, namely the Tinggi dam and the Selangor dam. Water is abstracted at an intake located 21 and 42 km downstream of the Tinggi and Selangor dam respectively. In the wet season, when unregulated flows downstream of the dams are sufficient for abstraction, no releases from the dams are required. However, releases are required in the dry season when flows downstream fall below the normal level. The present practice in dam operation is to use recession analysis in low flow forecasting during prolonged dry periods. Recession constants were derived using stream flow data and future flows were forecasted using the current flow and the recession constants assuming that there is no rain for the coming period where forecasts were made. Decisions were then made for releases from the dams. The disadvantage of recession analysis in forecasting low flow is that the forecast is not accurate if rain falls during the period and over release will occur. This study reports the use of Artificial Neural Network (ANN) models to forecast one and two time steps ahead river flows at the Rantau Panjang gauging station near the water supply intake for different travel times from the dams to the intake point to help in determining the regulating releases from the dams for more efficient reservoir operation. Two different ANN models, the Multi -Layer Perceptron (MLP) and the General Regression Neural Network (GRNN), were developed and their performances were compared. Endogenous and exogenous input variables such as stream flow and rainfall with various lags were used and compared for their ability to make future flow predictions. The input variables required are decided considering statistical properties of the recorded rainfall and flow such as cross-correlation between flow and rainfall, auto and partial autocorrelation of the flows which are best in representing the catchment response. Results show that both methods perform well in terms of R^2 but GRNN models generally give lower RME and MAE values indicating their superiority compared to MLP models.

Keywords: *Flow forecasting ANN GRNN*

1. Introduction

The Selangor basin (see Figure 1) is presently regulated by two upstream dams, namely Tinggi and Selangor. The severe 2014 drought recorded in the Selangor river basin has affected the everyday life of three million people inhabited in the northern area of Selangor and the neighbouring federal capital of Malaysia, the city of Kuala Lumpur, where 70% of the source of water supply comes from Selangor dam and the Tinggi dam.

Of particular importance is the water rationing imposed by the water authority in April 2014 lasting for one month and the shortage of food supply in the dry period. Efficient water management and accurate regulating releases from the dams for downstream uses help in conserving reservoir storage, especially during dry seasons. To achieve this aim,

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flow forecasting is required so that the future flow, based on a certain time interval, estimated using current rainfall and river flow can be known. Over the past decades, mathematical models either of black-box type or physical, have been developed for flow forecasting mainly based on the rainfall- runoff process .Physical based models involved a detailed description of various physical processes controlling the hydrologic behaviour of a basin. Artificial Neural Networks (ANN) are examples of black-box models which do not require knowledge of internal functions to recognize relationships between inputs and outputs. ANN models are suitable for large space search where human expertise is needed. ANN models need less data and are suitable for long term forecasting. The data used for ANN are divided into groups and used for training and testing. The measured training data is used to train the model to represent the relationship and processes within the data set. Once trained, the model is able to generalise relevant output for the set of input data The output is then compared with the measured testing data set. The model is satisfactory if it is similar in performance during the testing and training period.

ANN models have been used to simulate rainfall runoff processes (Kumar *et al.*, 2005, Mutlu *et al.*, 2008, Wu *et al.*, 2005), real time flood forecasting (Sudheer 2000, Thirumalaiah and Deo 2000, Hong and Hong 2016), drought forecasting (Belayneh *et al.*, 2013, Mishra and Desai 2006, Hong and Hong 2016) and reservoir operation study (Khare and Gajbhiye 2013, Cheng *et al.*, 2015). In this study, the MLP and GRNN neural networks were used for flow forecasting for the Selagor river. Flow forecasting helps in deciding reservoir releases and efficient reservoir operation. The objective of this study is to develop and evaluate the ability of the MLP and GRNN models to predict the multiple time ahead flows using the rainfall and gauging records of the Selangor basin to improve reservoir operation efficiency. Various input variables and their impact on the flow prediction abilities of the methods were evaluated.

2. Materials and Methods

2.1. The Study Area

In this study, autographic rainfall and stream flow records of the Selangor river basin were used for flow forecasting. Figure 1 shows a location map of the Selangor basin. Selangor river basin up to the intake point has an area of 1450 km^2 and the maximum length and width of the basin are 48 km and 39 km respectively. About 30% of the basin is steep mountainous country above 600 m, 38% is in hilly country and the remainder undulating low terrain. A large portion (two-thirds) of the basin is under jungle and the remainder under rubber, oil palm, paddy, maize, and vegetable cultivation. In the eastern half fine to coarse granite and other allied rocks are found and sandstone is found in the western half of the basin. Wet seasons occur in April and May in the south west monsoon season and October to December in the north east monsoon season. Dry periods generally dominate in January to March and June to September. Autographic rainfall stations with long term records are shown in Figure 1. Although the basin basically receives higher rainfall than other parts of the world, drought has frequently been recorded as drought occurs when the rainfall amount for a certain period falls below the normal level recorded in the past, for a particular time scale. Floods occur in the monsoon seasons when heavy and prolonged rainfall dominates. The gauging station is located upstream of the water supply intake.

2.2. Rainfall and Stream Flow Data

Automatic recorded rainfall and streamflow data are available for the stations shown in Figure 1 and presented in Table 1.

Table 1. Rainfall and Stream Flow Stations for Selangor Basin

Station name	Station no	Basin size (km²)	Periods of record
Stream flow: Selangor river at Rantau Panjang	3414421	1450	1960-2000
Rainfall:			
Rumah Pam	3314001	-	1960-2000
Ulu Yam	3416001	-	1960-2000
Kuala Kubu Hospital	3516022	-	1960-2000

2.3. Preparation of Input Dataset

To use the rainfall and stream flow data as inputs to forecast the flow at Rantau Panjang, it is necessary to estimate:

(a) the catchment time of concentration ,which is a measure of the catchment response (in terms of flow) to the moisture supply (in terms of rainfall input)
(b) the travel time from Selangor dam and Tinggi dam to Rantau Panjang intake (near the gauging station)
(c) correlation between the catchment rainfall and flow at Rantau Panjang gauging station
(d) autocorrelation and partial autocorrelation of the flow at Rantau Panjang gauging station

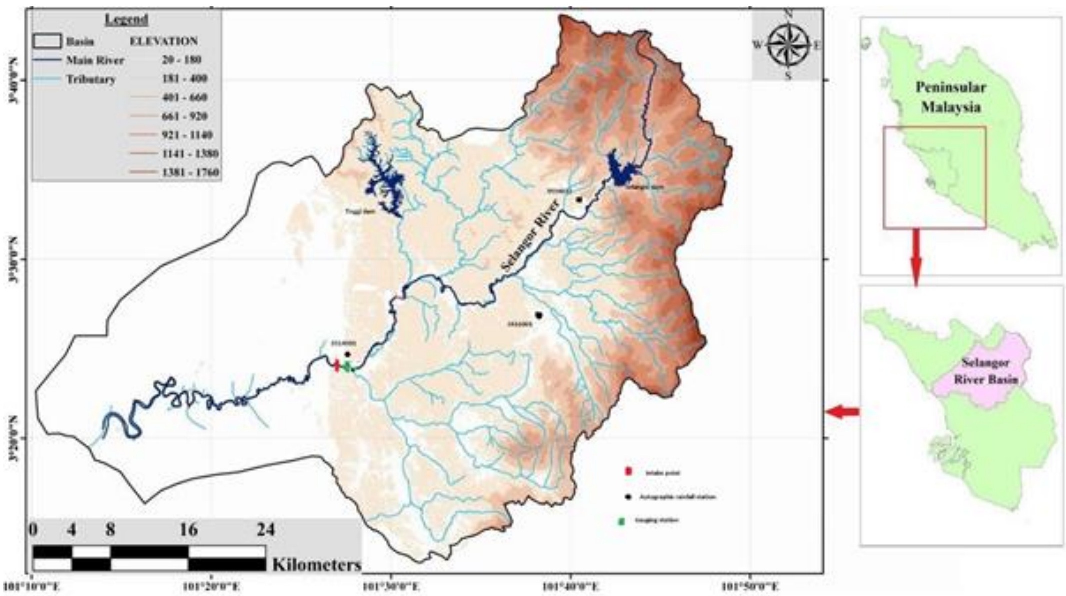

Figure 1. Selangor River Basin

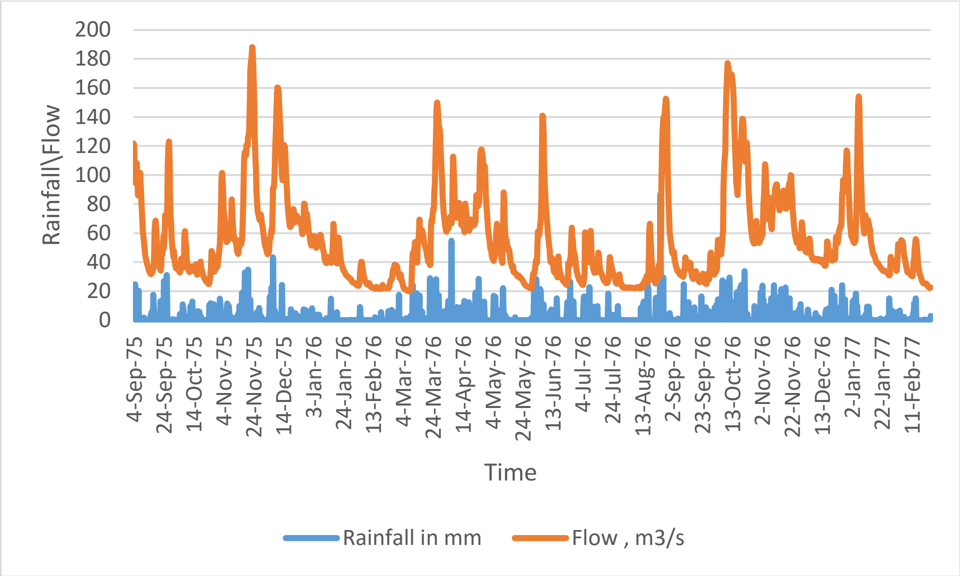

Figure 2. 9 Hour Flow of Selangor at Rantau Panjang September 4 1975 to February 24 1977

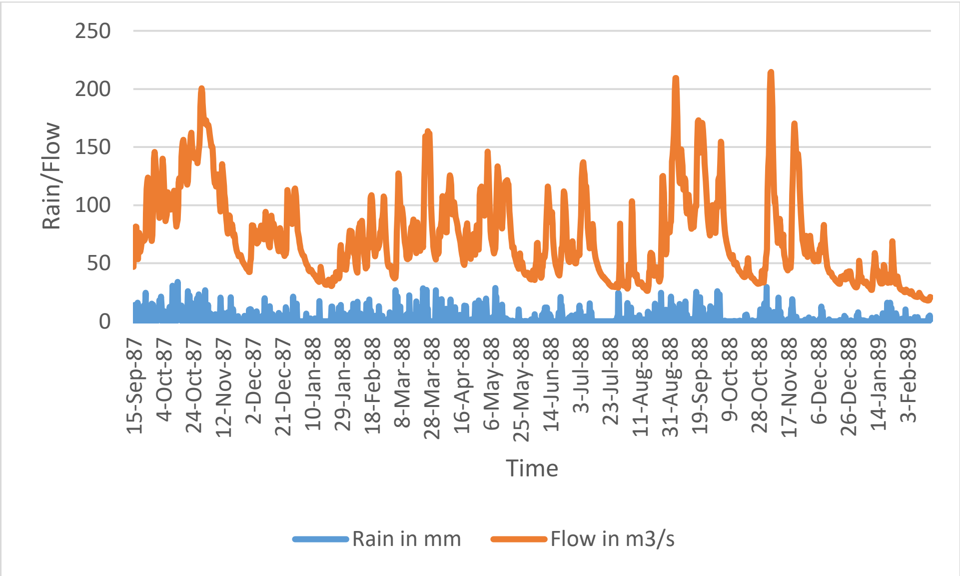

Figure 3. 9 Hour Flow of Selangor at Rantau Panjang September 15 1987 to February 18 1989

The rainfall and stream flow data were carefully examined and it was found that the following three periods are with concurrent rainfall and stream flow records and are used for this study. Average rainfall of the 3 stations were computed to give the catchment rainfall. The average 9 hourly flow and total rainfall for the periods selected are shown in Figure 2 to Figure 4. A time interval of 9 hours was adopted to coincide with the travel time from the Tinggi dam to the intake as discussed in a later section. The catchment time of concentration is required as storm occurring within a duration equal to the time of concentration would exhibit the greatest influence on stream flows. In this study, the time of concentration of the Selangor river at Rantau Panjang gauging station has been estimated using two methods. First, selected stream flow and rainfall events were adopted to estimate the time of concentration using the HEC-HMS model of Hydrologic Engineering Centre (U.S. Army Corps of Engineers, HEC 2014).Simulations were carried out to obtain the optimised parameters and the calibrated results for Selangor river are shown in Figure 5 to Figure 8.The time of concentration obtained from the calibrations are given in Table 2.The average time of concentration is 36.7 hours. An alternative is to use the formula of DID (DID 2010) to find the time of concentration, the formula is:

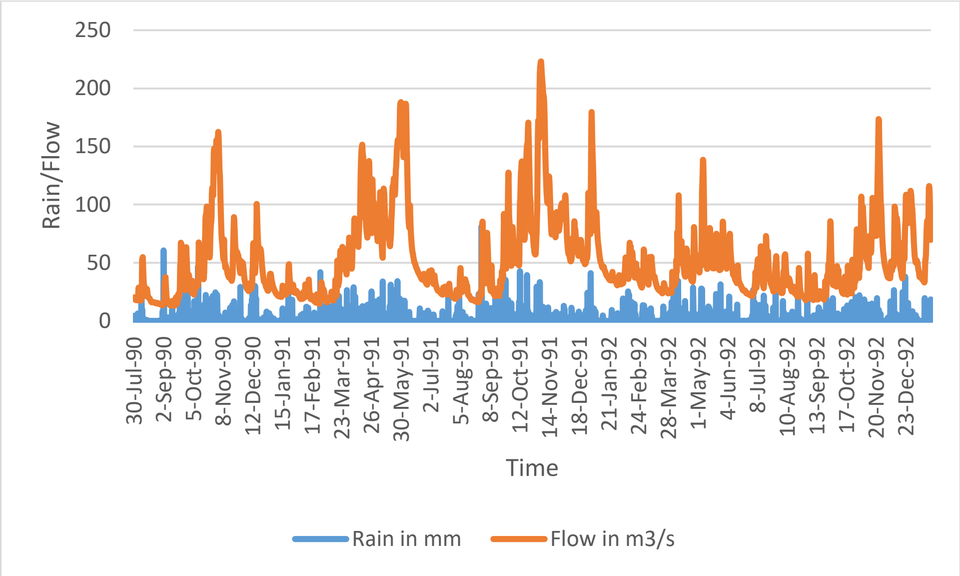

Figure 4. 9 Hour Flow of Selangor at Rantau Panjang July 30 1990 to January 22 1993

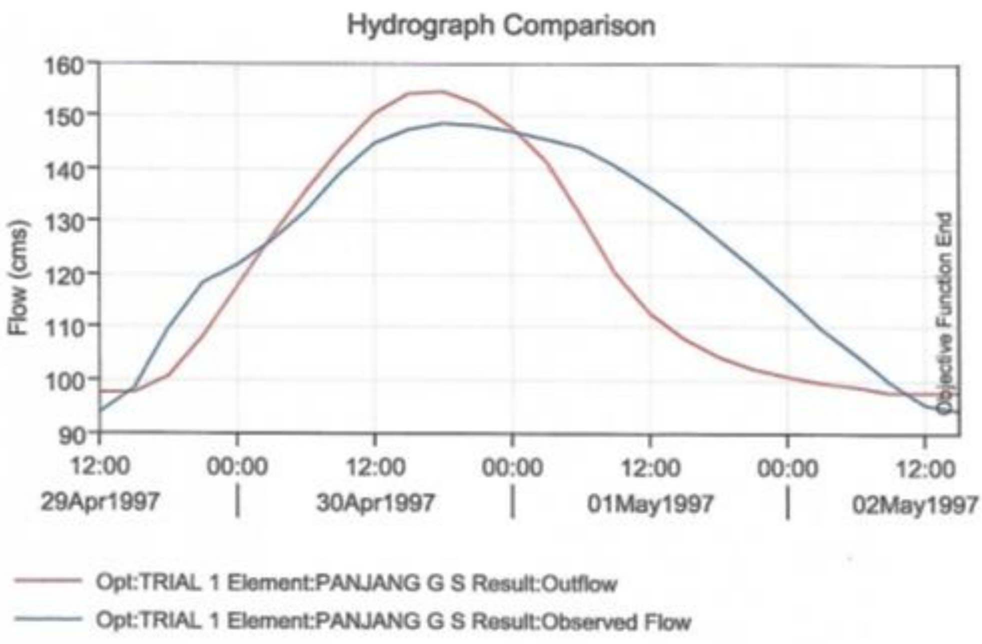

Figure 5. Hydrograph Calibration for the April 1997 Event

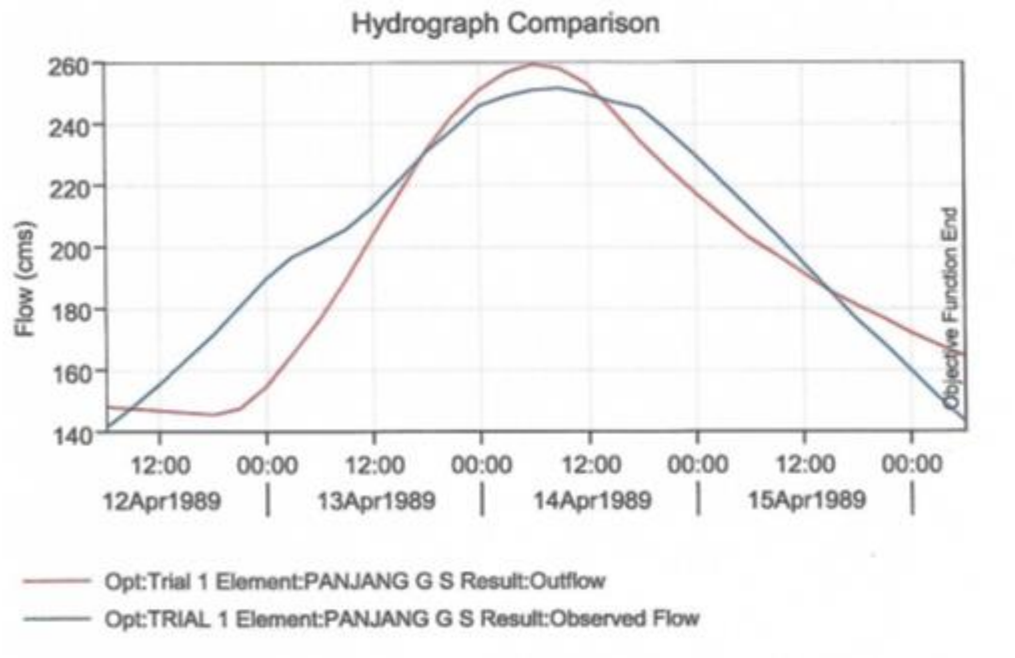

Figure 6. Hydrograph Calibration for the April 1989 Event

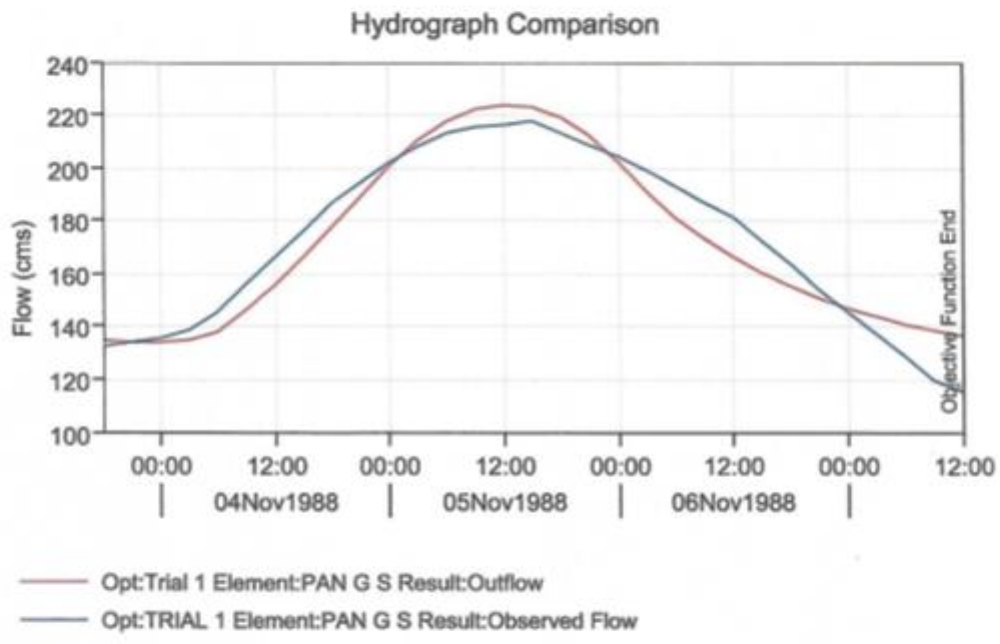

Figure 7. Hydrograph Calibration for the April 1988 Event

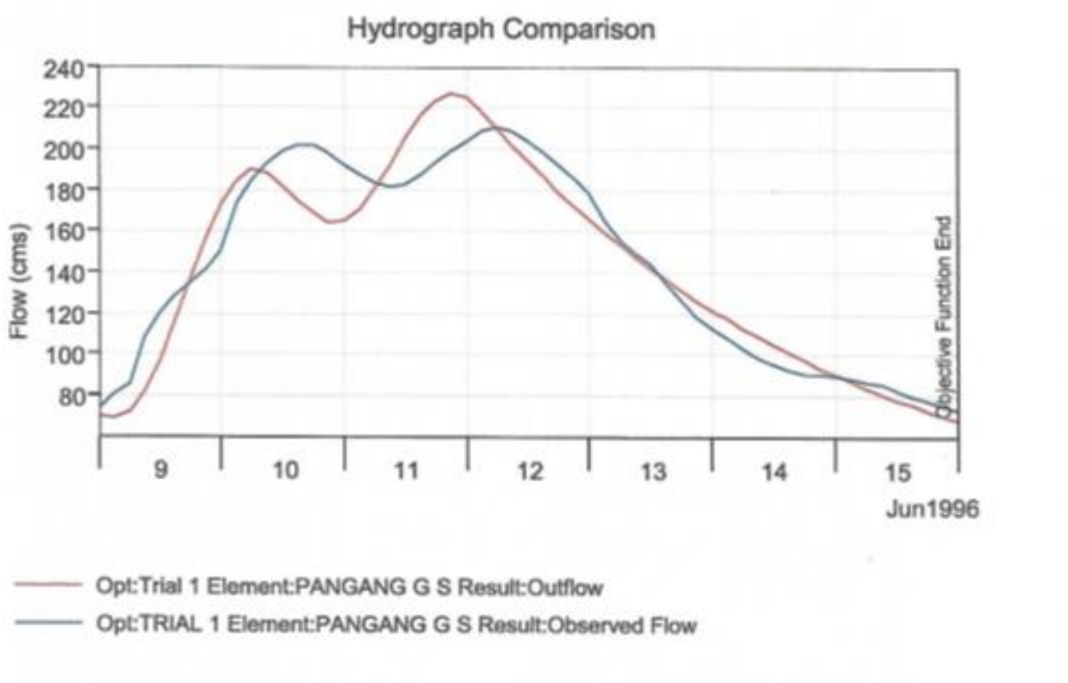

Figure 6. Hydrograph Calibration for the April 1996 Event

Table 2. Time of Concentration Obtained from HEC-HMS Calibrations

Storm event	Tc for Selangor at Rantau Panjang ,hours
April 1989	40.6
April 1997	36.8
November 1988	41.9
June 1996	27.3
Mean	36.7

$$T_c = 2.32A^{-0.1188}L^{0.9573}S^{-0.5074} \quad (1)$$

Where Tc is the time of concentration in hours
A is the catchment area in km²
L is the main stream length in km
and S is the weighted catchment slope in m/km
The Tc obtained using the general formula is 32 hours.

Comparing the travel time to the intake site and the number of events used for calibration, a 32 hours Tc obtained from the DID formula was adopted for this study.

Estimation for the time for water released from the dam to reach the intake is required to decide the number of time steps ahead needed for flow forecast. As no field data are available, it was decided to calculate the travel time using the estimated flow velocity of the natural channel. Channels downstream of the dams are generally flat and the velocity of flowing water at low stage can be around 0.46 m/s (1.5 fps) to 0.76 m/s (2.5 fps). In this study, an average channel flow velocity of 0.65 m/s was adopted and the travel time for water released from the two dams were estimated as shown in Table 3.

Table 3. Estimated Travel Time

Channel reach	Distance km	flow velocity ,m/s	Travel time ,hours
Tinggi dam to intake	21	0.65	9
Selangor dam to intake	42	0.65	18

We adopt a time interval of 9 hours for simulation calculations for the ANN models and flows are forecasted for time steps of 9 and 18 hours ahead for Selangor gauging station at Rantau Panjang to coincide with the travel time of Tinggi dam and Selangor dam to Rantau Panjang intake. This helps the dam operator in making decision on releases from the dams from time to time. To check the influence of catchment rainfall on Rantau Panjang flow, a cross correlation analysis was carried out using flows of Rantau Panjang and catchment rainfall with different lags to decide rainfall and antecedent rainfall to be included in the ANN models. The cross correlation shows the degree of linear relationships between the rainfall and the flow values. The cross correlation results for the 3 selected datasets are shown in Figure 7.

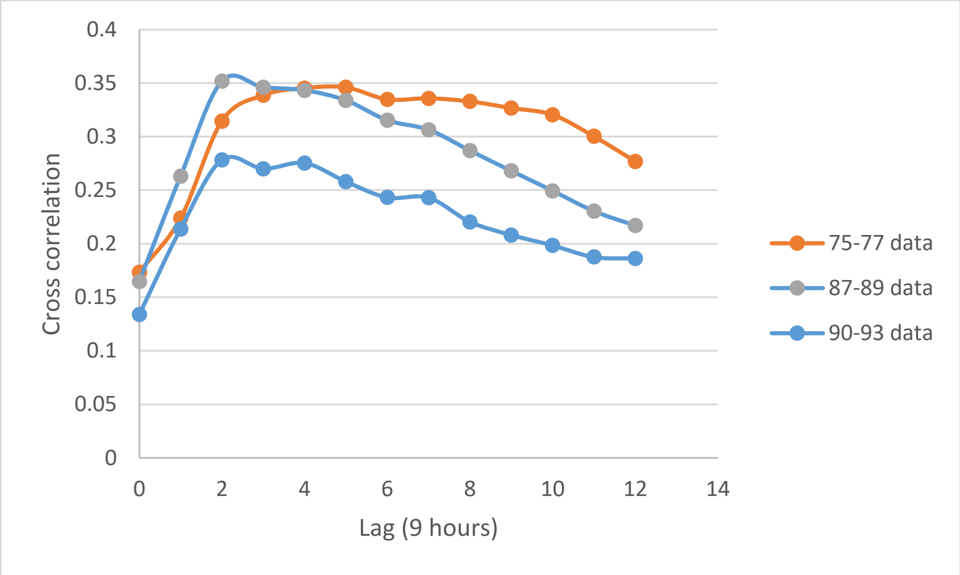

Figure 7. Cross Correlation Plot of 9 Hours Flow Series and Corresponding Rainfall Series for Selangor Basin

The highest correlation and the lag at which the highest correlation occurs are summarised in Table 4.

Table 4. Highest Correlation for Rainfall Flow Relationship for the Selected Datasets

Dataset	Maximum correlation	At rainfall lag
1975-77	0.3460	5
1987-89	0.3517	2
1990-93	0.2782	2

The average lag at which the maximum correlation occurs for the 3 datasets is 3. In this study, antecedent catchment rainfall values up to a lag of 3 were adopted for the ANN model simulations. This corresponds to a rainfall duration of about 36 hours which is close to the catchment time of concentration. The autocorrelation describes the correlation between all the pairs of time series (flow in this study) with a given separation in time or lag. A partial autocorrelation is the autocorrelation of a series with itself under stationary conditions. A partial autocorrelation shows the precise autocorrelation of a series with itself without the confounding effects of intervening lagged autocorrelation. Autocorrelation analysis was carried out for the 3 selected datasets and results were plotted in Figure 8 to Figure 10. The corresponding partial autocorrelation plots are shown in Figure 11 to Figure 13.

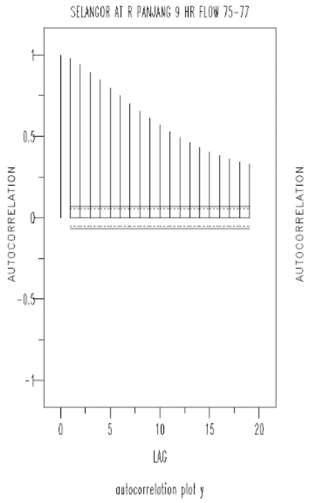

Figure 8. Autocorrelation Plot for 1975-77 Flow Series

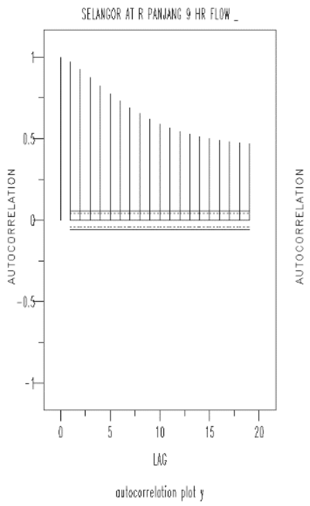

Figure 9. Autocorrelation Plot For 1987-89 Flow Series

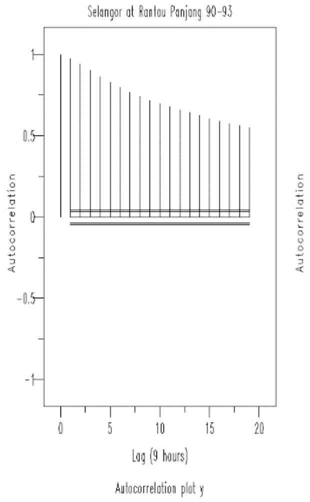

Figure 10. Autocorrelation Plot For 1990-93 Flow Series

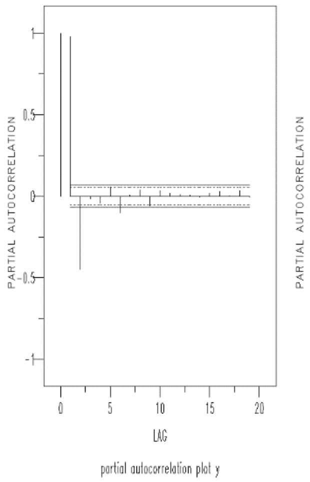

Figure 11. Partial Autocorrelation for 1975-77 Flow Series

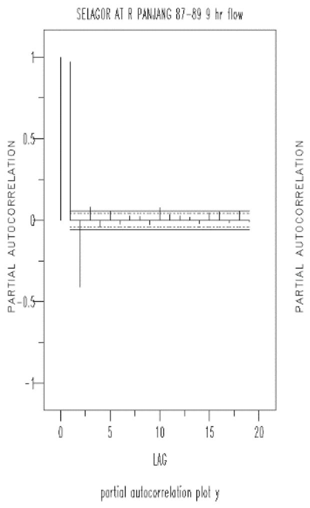

Figure 12. Partial Autocorrelation for 1987-89 Flow Series

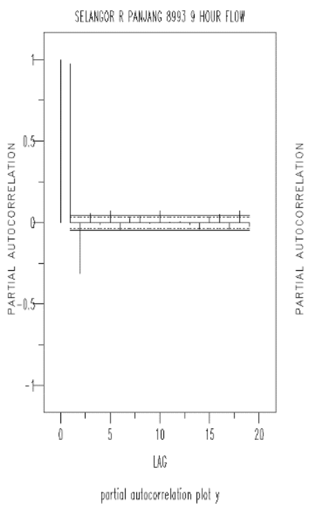

Figure 13. Partial Autocorrelation for 1990-93 Flow Series

From the autocorrelation plots (AP) and partial autocorrelation plots (PAP) it is noted that the PAP for all the 3 series have two significant spikes at lags 1 and 2, meaning all the higher order autoregressive autocorrelations are effectively explained by the lags 1 and 2 autocorrelation. Autocorrelation of the flow series at lag 3 and above are merely due to the propagation of the autocorrelation at lags 1 and 2. Thus the current flow and antecedent flows up to lag 2 at Rantau Panjang are used for ANN simulations. Stream flows at the preceding hours help in providing the base flow information prior to the onset of a storm.

2.4. Methodology

The aim of the current study is to use Multi-Layer Perceptron (MLP) artificial neural network model and the General Regression Neural Network (RGNN) model to forecast flows for Selangor river at Rantau Panjang and evaluate the performance of the two methods. The model constructed which performs best can be adopted to provide real time flow forecasting to improve the efficiency of reservoir operation for the Selangor river regulating system.

2.4.1. The MLP Model

Artificial Neural Networks (ANN) are nonlinear and flexible massively parallel distributed information processing system. For a number of nonlinear processing units, it is possible to train the neural networks to learn from experience and compute the complex functional relationships with accuracy. A number of neural networks has been proposed in the literature but the most commonly method used in hydrology for flow forecasting is the feed forward Multi-Layer Perceptron (MLP) model. As an example, a typical three-layer feed forward MLP model is shown in Figure 14. For most flow forecasting studies based on rainfall runoff data carried out in the past two decades, the three layer MLP model was used with the input nodes consist the lagged rainfall and stream flow values and the output is the forecasted future flow. In the MLP model, hidden nodes are used to process the information transmitted from the input nodes with a particular nonlinear transfer function. For this paper, the model considered is a single output MLP model. The network is processed through training, testing and validation stages in order to forecast the flow using the input rainfall and flow data. Back propagation (BP) algorithm (Rumehaet 1986) is used to correct the weights of the interconnecting neurons. Back propagation (BP) uses the steepest gradient descent method to correct the weight of the interconnecting neurons. BP solves the interconnection of the processing of processing elements by adding hidden layers. For the learning process in the back propagation method, the interconnection weights are adjusted using the error convergence method to obtain a desired output from an input. The BP algorithm propagates the error at the output to the input layer through the hidden nodes to obtain the final output. The gradient technique is used to calculate the weight of the network and adjust the weight of the interconnections to minimize the output error.

The BP method uses the following equation (ASCE Task Committee, 2000) to correct the weighting factor:

$$\Delta w_{ij}(n) = \alpha \Delta w_{ij}(n-1) - \varepsilon\left(\frac{\partial E}{\partial w_{ij}}\right) \tag{2}$$

Where $\Delta w_{ij}(n) and\ \Delta w_{ij}(n-1)$

$are\ weights\ interconnecting\ nodes\ i\ and\ j\ during\ the\ nth\ and\ (n-1)th\ steps$

α is the momentum factor used to speed up training in flat regions of the error surface and helps to prevent oscillations in the weights.

A learning rate ε is used to increase the chance of avoiding the training process being trapped in a local minima instead of a global minima

The number of neurons in the input and output layers are problem dependent and decided by the number of input and output variables in the MLP model. The size of hidden neurons is an important factor in solving the problems using MLP. There are no fixed rules in determining the number of hidden neurons required for the model and trial and error experiments are normally adopted to determine the hidden node that gives the model the best performance. However, empirical relationships between optimum hidden neurons and number of input and output elements were given by some authors *e.g.* Mishra et Al. (2006) used 2n+1 for estimating the number of hidden neurons

Where n is the number of input neurons

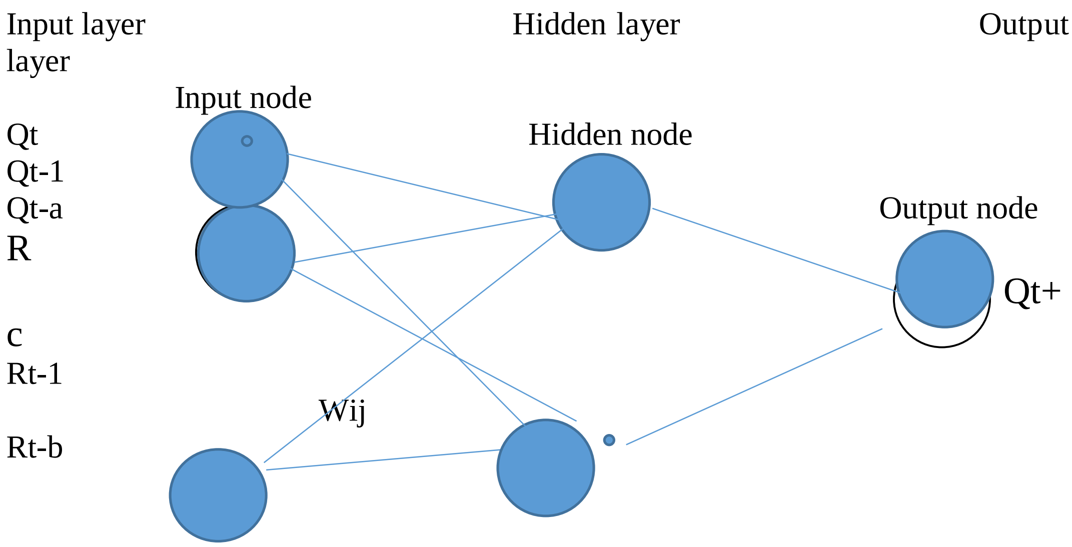

Figure 14. A Three Layer MLP Neural Network Method

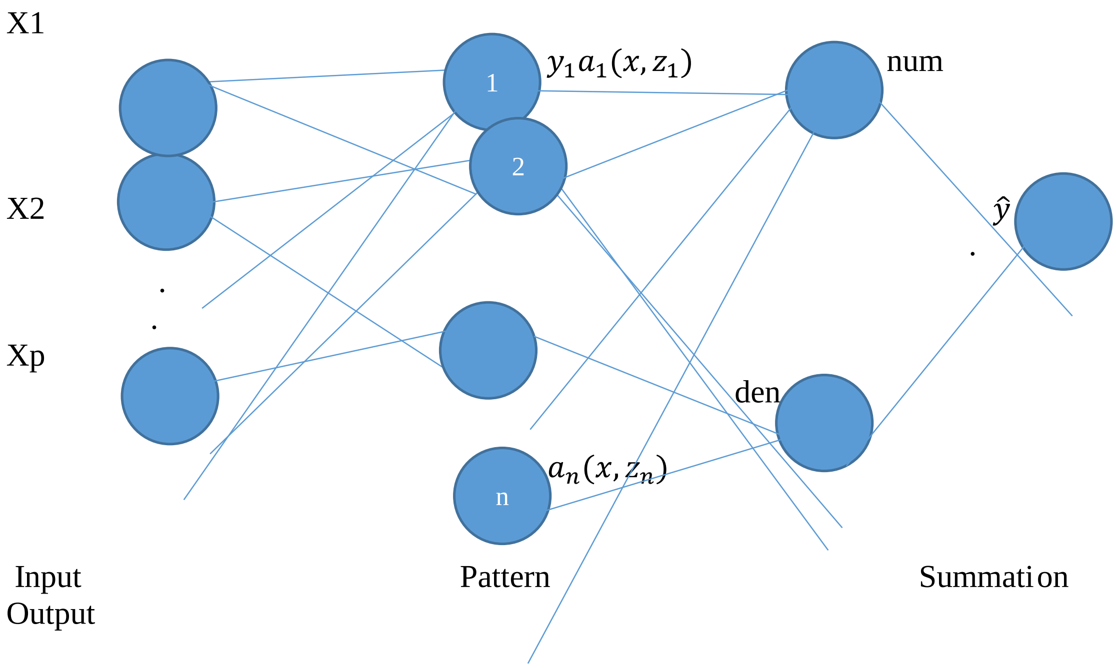

Figure 15. The GRNN Network Architecture

2.4.2. General Regression Neural Network

The GRNN was first introduced by Specht (1991) as a neural network paradigm for kernel regression. GRNN is a probability neural network and it is similar to the radial basis networks (RBN). GRNN is basically a special case of the normalised RBN network. The GRNN adopted for this study is the ANN introduced by Specht (1991) and applied by May *et. al*. (2008) for forecasting water quality in water distribution system.

Figure 15 shows the architecture of the GRNN. The input x is connect to each pattern layer node denoted as j ,for which an activation a(x) is decided based on a kernel function connected on a training input vector Zj. The Eucllidean function distance metric in the Gaussian kernel function determines the activation, and the Gaussian function is used as the activation function in the pattern layer. The activation function is:

$$a_j(x) = exp\frac{-||x-Z_j||^2}{2h^2} \quad (3)$$

Where h is the GRNN bandwidth or smoothing parameter

The two nodes in the summation layer will receive the activation of each pattern layer node and generate weighted sums of the pattern node activations. The connection weights between the num summation nodes and the pattern layer are the values y_i that correspond to each Z_i so that the activation function of the num summation node is :

$$\text{num}=\sum_{j=1}^{n} y_j\, a_j \quad (4)$$

The connection weights between the pattern layer and the den summation node are equal to 1, and the activation of the node is given as:

$$den = \sum_{j=1}^{n} a_j \quad (5)$$

The ratio of the activations of num and den nodes determines the network output in the output layer, and the global transfer function G(x) activated by the GRNN is

$$\text{G(x)}=\frac{\sum_{j=1}^{n} y_j a_j}{\sum_{j=1}^{n} a_j} \quad (6)$$

Which is the kernel estimate for E(y|x), the conditional expectation of y given x

Compared to MLP, GRNN has both advantages and disadvantages. The GRNN used memory (lazy) learning, therefore it has increased memory requirements to store training data and a greater computational requirement. As GRNN has only a parameter, the kernel bandwidth, it is faster to develop the model. Moreover, the network architecture of GRNN is fixed and it avoids to train multiple models to optimize the network architecture (Sepht 1991, May et al. 2008).

2.5. Implementation of ANN Models

The neural network add-in version 1.5 software developed by the University of Adelaide (2014) was used for the computational purposes for 9 hours and 18 hours lead time flow forecasting for Selangor river at Rantau Panjang.

The activation function used is the logical sigmoid function.

For training and validation purposes, data are normalized using the scaling method.

Input variable selection is used to identify the best set of variables to use as inputs for an ANN model. The aim of input selection is to select a set of variables with maximum predictive power, and minimum redundancy. The program provides an implementation of a step-wise selection scheme based on analysis of partial mutual information (PMI). The algorithm iteratively selects variables by first calculating the PMI of each variable, and selecting the one that maximises the PMI.

For the ANN used in this study, input variables are selected using the partial mutual information selection option and data are split randomly with 60% ,20% ,20% for training ,testing and validation purposes using the program.

The data for MLP is trained using learning rate of 0.001 and momentum coefficient of 0.9.

2.6. Performance Criteria

The performances of the MLP and the GRNN network models in predicting the flows are assessed using:

$$R^2 = [\frac{\sum(Q_o-\bar{Q}_o)(Q_p-\bar{Q}_p)}{\sqrt{\sum(Q_o-\bar{Q}_o)^2\sum(Q_p-\bar{Q}_p)^2}}]^2 \quad (7)$$

$$\text{MSE}=\frac{\sum_1^n(Q_p-Q_o)^2}{n} \quad (8)$$

$$\text{MAE}=1/n\sum_{1}^{n}\left|(Q_o)-Q_p\right)| \tag{9}$$

Where Qo and Qp represent the observed and predicted flow
n= total number of observations
MAE is the mean absolute error
MSE is mean square error
R^2 is the coefficient of determination

In this study, the MSE is the primary measure of forecasting error, and it was also used as the training error. The MAE provides a secondary indication of the expected magnitude of the error in terms of the units of the output. The R^2 provides an indication of the similarity between the actual flow residuals and the model forecast.

2.7. ANN Model Architecture

The goal of the ANN is to generalize a relationship in the form

$$Y^m = f(X^n) \tag{10}$$

Where X^n is the n dimensional input vector consisting of variables X_1……..X_i………..X_n ;Y^m is an m-dimensional output vector consisting of the resulting variables Y_1 ….Y_i……Y_m. In this study ,values of X_i are the catchment rainfall and flow at Rantau Panjang with different lags and Y_i is the flow at Rantau Panjang with 9 hours and 18 hours lead time.

The MLP and GRNN models consist of catchment rainfall and flow input data from Selangor basin at 9 hour interval for the 3 selected periods (1975-77, 1987-89 ,1990-93).

Details are shown in Table 5.

Table 5. The MLP and GRNN Model for Selangor River

ANN –MLP and GRNN model	Variable
Input Selangor catchment rainfall Rantau Panjang flow	 Rt ,Rt-dt ,Rt-2dt ,Rt-3dt Qt , Qt-dt , Qt-2dt
Output Rantau Panjang flow	 Qt+dt , Qt+2dt
Computation time step	dt=9 hours

Note : Qt=Rantau Panjang flow at time t
Qt-dt= Rantau Panjang flow at time t-dt
Qt+dt= Rantau Panjang flow at time t+dt
Rt= Catchment rainfall at time t
Rt-1= Catchment rainfall at time t-dt

Determining the number of input variables (flow and rainfall) involved finding the lags of Rantau Panjang flow and Selangor catchment rainfall that have a significant influence on the predicted flow at Rantau Panjang. These influencing values corresponding to different lags are discussed in section 2.3.

After inputs were determined, the MLP and the GRNN models were optimized to obtain the best prediction model. The number of nodes was changed in the hidden layer to determine the optimum number for the MLP model. As the architecture of the GRNN model is fixed, no changes are required.

3. Results and Discussion

Data of current and antecedent Selangor catchment rainfall and flows at Rantau Panjang gauging station as presented in section 2.3 were used as input for the MLP and GRNN models. Output of the models is the flow at Rantau Panjang. The MLP model was simulated by varying the nodes of the hidden layer from 1 to 17 and the GRNN architecture was not changed since its structure is fixed. Using the neural network add-in version 1.5 software to perform the simulation work, results in terms of MSE, MAE and R^2 values were obtained. Table 6 presents the results of the two models.

Table 6. Performance of MLP and GRNN Models Simulating Flows for Selangor River at Rantau Panjang

Performance measure		MSE	MAE	R^2	MLP architecture
Simulation mode , 9 hour lead time ANN model	MLP training	100	11.14	0.984	7-7-1*
	GRNN training	51.6	5.3	0.981	
	MLP testing	164	11.29	0.982	7-7-1
	GRNN testing	93.3	6.4	0.971	
	MLP validation	109	11.2	0.985	7-7-1
	GRNN validation	90	6.6	0.973	
Simulation mode , 18 hour lead time ANN model	MLP training	322	13	0.95	7-7-1
	GRNN training	83	6.3	0.969	
	MLP testing	337	14	0.95	7-7-1
	GRNN testing	143	8.1	0.954	
	MLP validation	317	13.8	0.95	7-7-1
	GRNN validation	141	7.8	0.944	

*Denotes a network with 7 input nodes ,7 hidden nodes and 1 output node

Although MLP models give better R^2 , GRNN models generally perform better in terms of MAE and MSE , it is considered that GRNN models generally perform better than the MLP for data from Selangor basin. Figure 16 shows the observed and predicted flows for Selangor at Rantau Panjang for the GRNN validation simulation. Good agreements between the observed and predicted flows were noted.

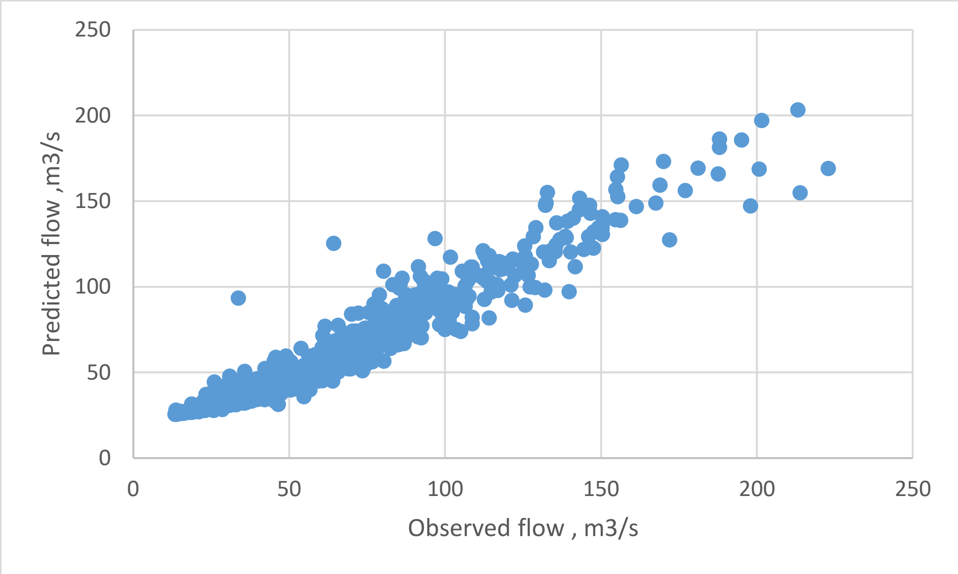

Figure 16. Observed and Predicted Flows, Rantau Panjang (From GRNN Validation Run)

4. Summary and Conclusion

Selangor is an important river basin in adjacent to the city of Kuala Lumpur, the federal capital of Malaysia and it supplies about 70% of the water required for domestic and industrial use for the city. Selangor river basin is presently regulated by two water supply dams, namely the Tinggi dam and the Selangor dam. Water is abstracted at an intake located 21 and 42 km downstream of the Tinggi and Selangor dam respectively. In the wet season, when unregulated flows downstream of the dams are sufficient for abstraction, no releases from the dams are required. However, releases are required in the dry season when flows downstream fall below the normal level. The present practice in dam operation is to use recession analysis in low flow forecasting during prolonged dry periods. Recession constants were derived using stream flow data and future flows were forecasted using the current flow and the recession constants assuming that there is no rain for the coming period where forecasts were made. Decisions were then made for releases from the dams. The disadvantage of recession analysis in forecasting low flow is that the forecast is not accurate if rain falls during the period and over release will occur. This study reports the use of Artificial Neural Network (ANN) models to forecast one and two time steps ahead river flows at the Rantau Panjang gauging station near the water supply intake for different travel times from the dams to the intake point to help in determining the regulating releases from the dams for more efficient reservoir operation. Two different ANN models, the Multi-Layer Perceptron (MLP) and the General Regression Neural Network (GRNN), were developed and their performances were compared. Endogenous and exogenous input variables such as stream flow and rainfall with various lags were used and compared for their ability to make future flow predictions. The input variables required are decided considering statistical properties of the recorded rainfall and flow such as cross-correlation between flow and rainfall, auto and partial autocorrelation of the flows which are best in representing the catchment response. Results show that both methods perform well in terms of R^2 but GRNN models generally give lower RME and MAE values indicating their superiority compared to MLP models.

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