Hourly Discharge - Rainfall relationship in the Western Ghat catchments

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Abstract -Stream gauging is a very important activity being carried out by agencies involved in water resources department. Stream gauging is a highly involved procedure. Current meter gauging (CMG) is usually done only once in a day and at all other times, only the stage of the river is noted. Stage-discharge curves are then used to compute the corresponding discharge. Usually stage is noted only in the day hours and hence a variation in discharge during the night hours always goes missing. But, measuring rainfall continuously is quite a simple task. Hence, if discharge-rainfall relationships are made available through studies, it would be possible to understand the variations in discharge even during night hours The present study aims to develop such relationships for two very small catchments in Western Ghats of Karnataka India. The study investigates the applicability of various models to suit data and to develop the most reliable model to estimate hourly runoff from hourly rainfall in this catchment. The models investigated include the Multi-Linear Regression, Multi-Layer Perceptron and Cascade Correlation Neural Network. The relationships are developed using all these techniques, the model performances tested and a final model is presented. A generalized equation is developed so that the discharge can be estimated continuously throughout the day in the monsoon season. The multi-linear regression equations developed have been found to be reliable through tests of model performance.

Key Words:Stream gauging, Multi-Linear Regression, Multi-Layer Perceptron, Cascade Correlation Neural Network.

1. INTRODUCTION

Stream gauging is a very important activity being carried out by agencies involved in water resources department. A knowledge about the yield and discharge variations in a river helps design of hydraulic structures and planning development of the available resources. Stream gauging is a highly involved procedure. Current meter gauging (CMG) even in small streams requires a lot of effort and time, and hence cannot be done continuously. CMG is usually done only once in a day and at all other times, only the stage of the river is noted. Stage-discharge curves are then used to compute the corresponding discharge. In India, usually stage is noted at 1-hour intervals only in the day hours and hence a variation in discharge during the night hours always goes missing. On the other hand, measuring rainfall continuously is quite a simple task. Self-recording rain gauges are available in plenty. Hence, if discharge-rainfall relationships are made available through studies, it would be possible to understand the variations in discharge even during night hours and design of projects would be easier. The present study aims to develop such relationships for two very small catchments in Western Ghats of Karnataka India. The WRC of National Institute of Engineering Mysuru Karnataka India has established facilities to monitor continuously the discharge in these streams and SRRG data is also available. The study involves collection of data on hourly basis investigate the applicability of various models to suit this data and to develop the most reliable models to estimate hourly runoff from hourly rainfall in these catchments *(Neil et al., 2009)* The models investigated include the Multi-Linear Regression, Multi-Layer Perceptron and Cascade Correlation Neural Network *(Archana and Rakesh 2012) (ASCE Task Committee 2000)*. The relationships are developed using all these techniques, the model performances tested and a final model is presented. The present work deals with the catchment of Kumaradhara up to Hegademane Bridge (41.9 Km^2) and Hongadahalla up to Mookanmane (40.5 Km^2) in Western Ghats located in Karnataka, India. The details of the study area and the data used in this study are given below.

2. The Study Area and The Data Used

Western Ghats, locally called ‘Sahyadri Ranges’ form an unbroken relief dominating the west coast of Indian peninsula, for almost 1600 km,(Putty and Prasad 2000) extending between north latitudes of 8^o and 21^oas shown in Fig 1. The two catchments are a part of sub-basin of Kumaradhara, a tributary of Netravathi, which drains in to the Indian Ocean, in the state of Karnataka as shown in Fig 2. Index map of Kumaradhara catchment up to Hegademane and Hongadahalla catchment up to Mookanamane are shown in Fig 3 and Fig 4 respectively. Rainfall in this region is heavy during the south-west monsoon, which lasts between June and September. More than 90% of annual rainfall occurs during four monsoon months, with an average of 100-120 rainy days per year. Intensities are moderate and rainfall occurs during most part of the day. Kumaradhara catchment upto Hegademane and Hongadahalla catchment upto Mookanamane has the approximate area of 41.9 Km2 and 40.5 Km2 respectively. The Karnataka Power Corporation Limited (KPCL) has been gauging streamflow at Kumaradhara and Hongadahalla catchments since 2009. NIE-WRC has installed AWLR’s at these catchments. Discharge is measured once in a day and stage readings are taken at regular intervals. But in the case of above mentioned catchments, a continuous data can be obtained from the instruments. The rainfall data at Kudigana in Kumaradhara is monitored by NIE-WRC whereas at Mookanamane in Hongadahalla is monitored by KPCL by installing SRRG are used in the present study.

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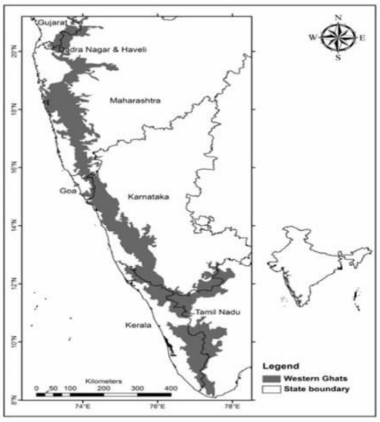

Fig -1: Map of Western Ghats in India

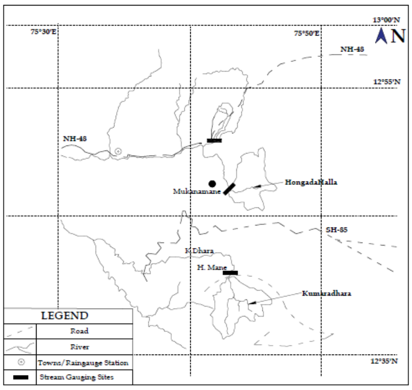

Fig -2: Locations of Kumaradhara and Hongadahalla catchments

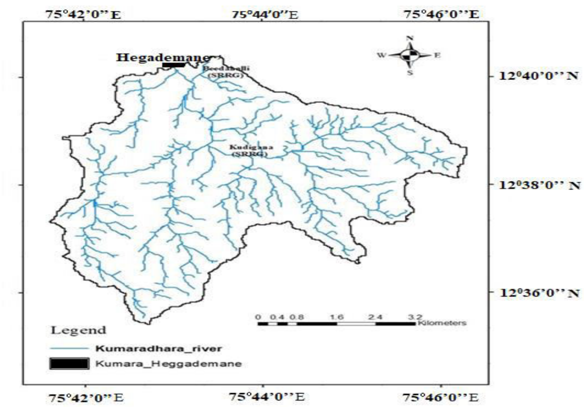

Fig -3: Catchment of Kumaradhara upto Hegademane

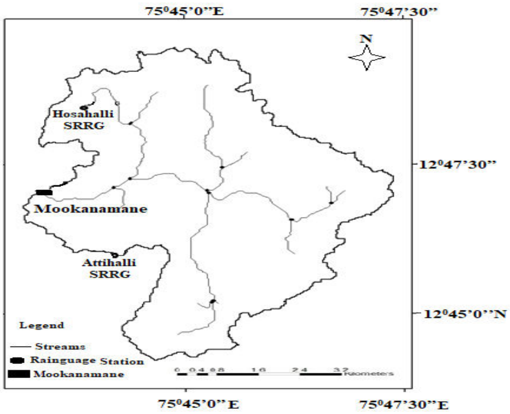

Fig -4: Catchment of Hongadahalla up to Mookanamane

3. Modeling Tools

The present study has been carried out using Multi-Linear Regression, Multi-Layer Perceptron and Cascade Correlation Neural Network. Some details to these models are given below.

3.1 Multi-Linear Regression

When more than one independent variables are present, the relationship used is called a Multi-Linear Regression Equation. The Multi-Linear Regression equation will be of the form $\{Discharge_i = a + b*Rainfall_{i-1} + c*Rainfall_{i-2} + d*Discharge_{i-1}\}$

In the present study the Coefficients of the equation are solved using least square principles (*Putty 2011*). The excel spreadsheet will be used to solve the Multilinear regression equations. The significance of coefficients obtained from the regression results are tested by making use of the Students t-test, Co-efficient of determination (R^2) and co efficient of efficiency (CE).

3.2 Artificial Neural Network

An Artificial Neural Network is a massively parallel distributed information procession system *(Sajikumar and Thandaveswara 1999)*. A neural network consists of a input layer, hidden layer and a output layer. The layers consists of nodes or neurons which is the place where the mathematical operations or functions will be performed. The working of the nodes will be a iterative process. The value which connects the nodes is called the weights. A neural network is characterized by its architecture that represents the pattern of connection between nodes (*Muhammad and Ichiro 2007*), its method of determining the connection weights, and the functions used(*Christian and Dawson 1998*). The two methods Multilayer perceptron and are used in this work. i.e. (i) Multilayer perceptron and (ii) Cascade correlation neural network.

3.2.1 Multi-Layer Perceptron (MLP) 3.2.2 Cascade Correlation Neural Network (CCNN)

MLP consists of input layer, one or more hidden layers and an output layer. The input layer has several nodes which receives input of the data, while output data returns the result back to the input data for rearranging of weights and a final output will be given (*Sridhar et.al 2015)*. CCNN is similar to MLP but, a direct weighted connection will be observed from input layer to output layer (Mahmut and Mustafa 2010). The weights of MLP will be connected in a series pattern connecting layers as shown in fig 5, whereas in CCNN the weights signal will be connected to each and every layer as shown in fig 6. The available data set is generally partitioned into two parts for training and validation. The purpose of training is to determine the set of connection weights that cause the ANN to estimate outputs that are sufficiently close to the target values (observed discharge). This training procedure involves the iterative adjustment and optimization of connection weights and threshold values for each of the nodes. The primary goal of training is to minimize the error function by searching for a set of connection

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strengths and threshold values that cause the ANN to produce outputs that are equal or close to targets. During training, only an input data set is provided to the ANN that automatically adapts its connection weights. Validation of the model is carried out using the supply set of the model.
ANN architectures with three input neuron, one output neuron and six numbers of hidden neurons with Tansig transfer function were adopted for both ANN models in the present study. The output signal from this neuron was the hourly discharge.

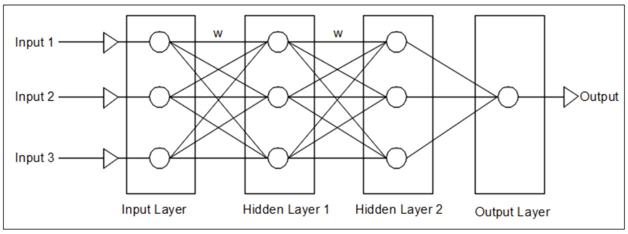

Fig -5: Architecture of Multilayer perceptron

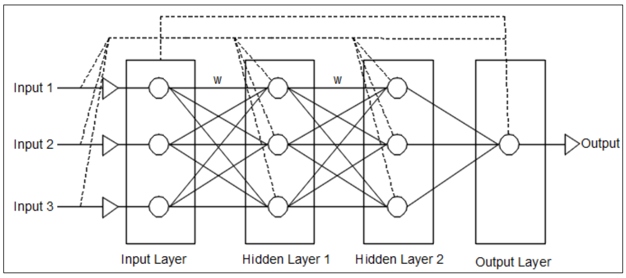

Fig -5: Architecture of Cascade Correlation Neural Network

4. Model Performance Tests

The tests of model performance are based on both graphical and analytical. In graphical tests, the hydrographs plot, and in analytical test the coefficient of Efficiency are used to compare the estimated discharge and observed discharge.
Coefficient of Efficiency (CE) - The coefficient of efficiency is defined as the ratio of variation in the data estimated by the model and those already present in the data.

$$CE= 1- (Q_{Obs} - Q_e^2)/ (Q_{0bs} - Q_{obsm})^2$$

Where, Q_{Obs} = Observed discharge in (m^3/s), Q_e=Estimated discharge in (m^3/s) and Q_{obsm}= mean of observed discharge in (m^3/s).

5. Modeling Hourly Discharge

Based on experience, it is assumed that the hourly discharge in the river depends on the discharge in the preceding hour and the rainfall causing quick flow in the stream. Hence the input data for the models used in the present study are antecedent hour precipitation {P(t-1)……P(t-n)}, antecedent hour discharges {Q(t-1)……Q(t-n)} (*Kuok et al.,*) and the rainfall of the current hour P(t). Some combinations of functions were suitably investigated to determine the output data of hourly stream flow (Qt).

The functions were solved using Multi-Linear Regression analysis. The CE was used to select the best combination. This combination was then tested using the other ANN models. The models were first calibrated by randomly selecting seven days data dated 19, 20 July 2011 and 2, 3,4,5,6 August 2011 for Kumaradhara and 2, 20, 25 July 2012 and 3,4,5,6 August 2012 for Hongadahalla. The CE values were good and found optimal for the model which has antecedent hour rainfall as two and one antecedent discharge. The model hence developed was

$$Q(t) = f\{P(t-1), P(t-2), Q(t-1)\}$$

Where, Q(t) = Current hour discharge, P(t-1) and P(t-2) = Antecedent hour rainfalls and Q(t-1)= Antecedent hour discharge.

6. Results And Discussions

The performance of the three models MLR, MLP and CCNN are mutually compared in order to select the final best model. The comparison of the model is made using the tests and model performance. Results obtained during calibration and validation are presented in the Table 1. During both calibration and validation the MLR model was found working well compared to MLP and CCNN models. Hence, it is concluded that Multi-Linear Regression model is the best suited. Using regression analysis, rainfall - streamflow relationships are then developed for a number of days for which good data could be obtained. The model was calibrated for various days using all hourly observed discharge values and then relationships developed for each day were tested to see the relationships would give better estimates in the absence of data. By observing relationships developed for different days, it was found that they differ from each other very much. Hence, it was decided to develop first a few equations which can simulate hourly streamflow measured suitable for any days. For this purpose Streamflow equations were estimated for the days of the monsoon season are classified as below:

1. Days with high rainfall and high discharge (Rainfall between 80-250 mm and Discharge in the range 30-110 m^3/s)
2. Days with high rainfall and low discharge (RF 75-100 mm and Discharge of 10-25 m3/s)
3. Days with low rainfall and low discharge (Rainfall between 30-50 mm and Discharge in the range 10-25 m^3/s)

For the Kumaradhara catchment the days with high rainfall and high discharge, calibration of the equations, was done using streamflow data of the days dated 4, 5 August 2011, 19, 20, 21, 24 July 2011 and 10, 13 July 2013 are used. During calibration CE value was 0.92. The equation thus obtained is given below:

$$Q(t) = 1.444 +0.261P(t-1) +0 .469P(t-2) +0 .90Q(t-1) \quad \text{…Eqn 1}$$

Where, Q(t) = Current hour discharge, P(t-1) and P(t-2) = Antecedent hour rainfalls and Q(t-1)= Antecedent hour discharge.

The CE value of the Eqn 1 is 0.92. For this equation, t test is significant at 99%. For validation, hydrograph of observed streamflow and estimated streamflow is shown in the Fig 7. The above equation was also found to simulate

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hourly streamflow for the days with high rainfall and low discharge. The days validated are 8, 11 august 2011. Statistical measure, CE used to evaluate the efficiency for the two days are 0.75 and 0.65 respectively. For the days with low rainfall and low discharge, calibration was done using streamflow data of the days dated 24, 25, 26, 27 August 2011, 14, 15, 19 July 2012 and 27 August 2012. The following equation was obtained.

Q(t) = 1.158+ 0.105P(t-1) + 0.366P(t-2) + 0.879Q(t-1) ..Eqn 2

The CE value of the Equation 2 is 0.85. For this equation, t test is significant at 99%. For validation, hydrograph of observed streamflow and estimated streamflow is shown in the Figure 8. During validation of the CE values computed for the various days are given in Table 2

For the Hongadahalla catchment one equation was developed for each case. The equations are:

Q(t) = 1.545+ 0.30P(t-1)+ 0.240P(t-2)+ 0 .873Q(t-1) .....Eqn 3

Q(t) = 0.488 +0 .07P(t-2)+0.107P(t-3)+0.933Q(t-1) .....Eqn 4

Q(t) = 0.850 +0 .164P(t-2)+0.195P(t-3)+0.843Q(t-1).....Eqn 5

For the equations 3,4 and 5 t-test are significant at 99%. For calibration of the Equation 3,4 and 5 the hourly streamflow data of the days dated 6 august 2012, 27 July 2012; 2 July 2012, 2 July 2013 and 20 July 2012, 25 July 2012, 15 June 2013 were used. During calibration, the results of CE values were 0.97, 0.90 and 0.89 respectively. During validation the CE values computed for the various days are given in Table 3. The hydrograph of observed streamflow and estimated streamflow are shown in Fig 9 to Fig11.

The equations which are obtained will be used to calculate the hourly discharge using rainfall data for the various days in the monsoon season. The hourly discharge can be calculated throughout the day without measuring directly from the field.

Table -1: Comparison of CE values between MLR, MLP and CCNN model during calibration and validation.

	Calibration				Validation		
	MLR	MLP	CCNN		MLR	MLP	CCNN
Kumaradhara	0.57	0.53	0.48	13/8/2012	0.45	0.34	-0.04
				18-08-2012	0.53	0.29	0.19
				07-09-2013	0.43	0.19	-0.13
Hongadahalla	0.96	-9.31	-10.60	01-07-2013	0.45	-1541.68	-9884.11
				02-07-2013	0.53	0.29	-9310.05
				10-07-2013	0.43	-6750.81	-9161.77

Table -2: Validation results of various days for Kumaradhara catchment

	High rainfall and high discharge	Low rainfall and low discharge
CE values ranges	No of days	No of days
< 0.1	6	2
0.1-0.4	6	2
0.4-0.6	8	1
0.6-0.8	11	5
0.8-0.95	4	2

Table -3: Validation results of various days for Hongadahalla catchment

High rainfall and high discharge		High rainfall and low discharge		Low rainfall and low discharge	
Date	CE	Date	CE	Date	CE
06-8-2012	0.95	02-7-2012	0.53	20-7-2012	0.60
27-7-2012	0.96	02-7-2013	0.61	25-7-2012	0.81
04-8-2012	0.77	10-7-2013	0.67	15-6-2013	0.54

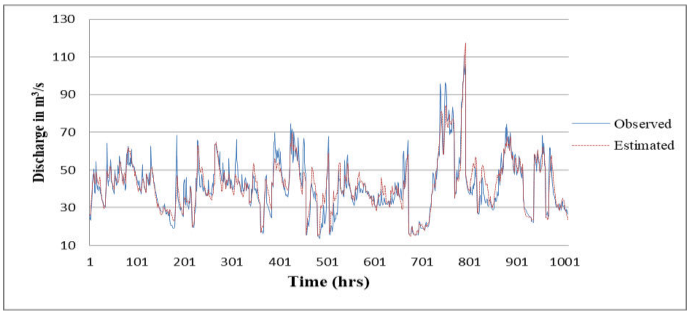

Fig -7: Hydrograph of observed discharge and estimated discharge of days with high rainfall and high discharge of Kumaradhara catchment.

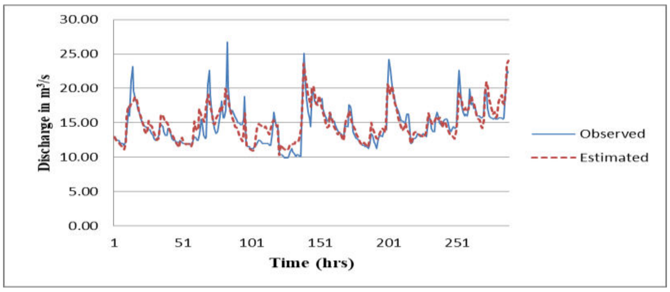

Fig -8: Hydrograph of observed discharge and estimated discharge of days with low rainfall and low discharge of Kumaradhara catchment.

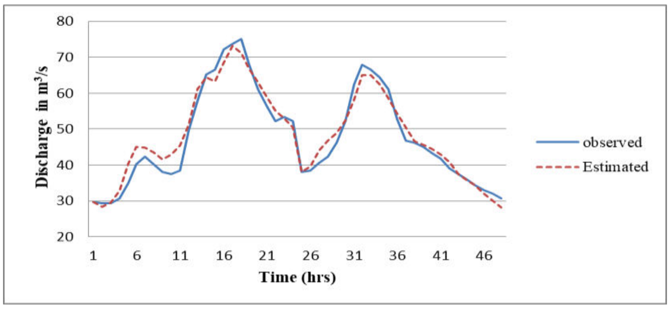

Fig -9: Hydrograph of observed discharge and estimated discharge of days with high rainfall and high discharge of Hongadahalla catchment.

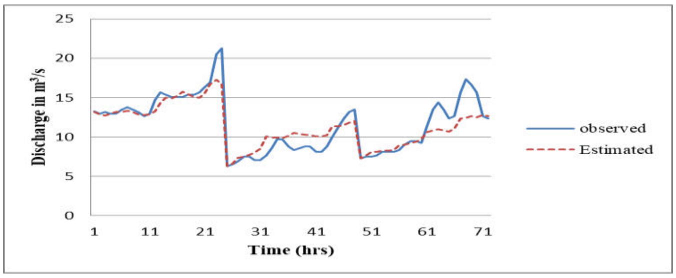

Fig - 10: Hydrograph of observed discharge and estimated discharge of days with high rainfall and low discharge of Hongadahalla catchment.

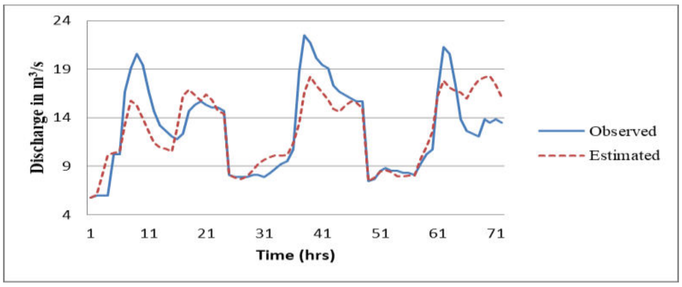

Fig - 11: Hydrograph of observed discharge and estimated discharge of days with low rainfall and low discharge of Hongadahalla catchment.

7. Summary and Conclusion

The purpose of the study was to develop hourly rainfall – discharge relationships, which can simulate the hourly discharge for Kumaradhara and Hongadahalla catchments by using hourly rainfall in the catchment. The applicability of Multi-Linear Regression, Multilayer Perceptron Neural Network and Cascade Correlation Neural Network models were investigated. These models were compared mutually to select the better model. The models were evaluated based on CE. Regression model was found to be the best model based on CE. Using regression model, rainfall-discharge relationships were developed for various days by taking 2 hour antecedent rainfall and one hour antecedent discharge as inputs. Later, generalized equations, suitable for the days in the monsoon were estimated.

7.1 Scope for further studies

The generalized hourly regression equations estimated should be tested for more years of data to achieve more accuracy. Despite the fact that enormous work has been done in Hydrology over the last few decades, the truth remains that deficiencies in the data have rendered research limp and reliance on back box methods of analysis continues unabated. It is probably the lack of quality data which has hampered studies on hourly rainfall-discharge relationships. Hence records obtained by installing the recording gauges at appropriate sites in the experimental watersheds in this region, may probably fill in this gap to a small extent. Also, analysis of these records, if availed, to obtain information is a challenging task. The scope for further research is, obviously, unlimited.

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