IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)
e-ISSN: 2278-1684,p-ISSN: 2320-334X, Volume 13, Issue 4 Ver. II (Jul. - Aug. 2016), PP 50-56
www.iosrjournals.org

A Comparison Study on Artificial Neural Network and Sediment Rating Curve Modeling for Suspended Sediment Estimation (Case Study: Lokapavani River Basin)

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Abstract: *Erosion and sediment transport phenomenon in the rivers is one of the most complicated and crucial subjects in river engineering. These phenomena have significant influences on bed and bank scouring, water quality, and considerable damages to water-related structures and projects. Hence, accurate prediction and estimation of river sediment has an essential role in water resource management, planning as well as design and construction of hydraulic structures. In this study it has been attempted to evaluate the artificial neural networks efficiency in estimation of suspended sediment. The suspended sediment has been estimated at Lokapavani river basin using multilayer perceptron neural network and then, the results have been compared to those of sediment rating curve model. Finally, the limitation and strength of both models have been analyzed. Based on obtained results, artificial neural network has offered acceptable suspended sediment estimation in comparison with the sediment rating curve model. The* R^2 *value resulted from artificial neural network and sediment rating curve models is 0.88 and 0.846 respectively. Though, it must be noted that artificial neural network is not capable of estimating the peak values with significant accuracy which can be mentioned as a weakness of this model.*
Keywords: *Suspended sediment, Artificial neural network, Sediment rating curve*

I. Introduction

Erosion and sedimentation as an aggravated process lead to the loss of fertile agricultural soil and also cause irreparable damage to water development projects such as accumulation of sediment behind dams and reduction in the volume of them, demolition of structures, damage to beaches and ports, reducing the capacity of irrigation canals and increasing the maintenance costs of them. On the other hand, the sediment transport affects the water quality indices in terms of drinking and agricultural consumption. Therefore, the sediment estimation is essentially required in soil conservation projects, design and implementation of water structures, watershed management and utilization of water resources [1]. In this context, the mathematical models and empirical formulas have been applied, although in many cases it is not possible to use some of these mathematical models and empirical formulas due to the complexity and a large number of input parameters necessities. Also, due to the limitations represented by some models such as regression models, in recent years another category of nonlinear models as artificial intelligence models such as neural networks –which are based on learning process through measured and observed data –have been used in various fields related to hydrology and hydraulics such as sediment prediction and estimation [14]. Artificial Neural Networks (ANNs) as a member of artificial intelligence has been still using in modeling and predicting the precipitation, water flow and sediment; and they have often represented acceptable results. Artificial neural networks inspired by the human brain and the pursuit of knowledge hidden in the data, access the relationship between the data and these networks are also capable of generalizing in cases where the model is not encountered. In this method, models get trained using a series of data and the network weights are determined by the results obtained from the data [2]. Optimizing these weights causes the model to learn the process and provides the possibility of the model extension to the new conditions. As mentioned earlier, artificial neural networks have been employed in various fields of science related to water and suspended sediment.

Ardiclioglo et al. (2007) had used the artificial neural network in order to suspended sediment estimation. For this purpose, they have applied two different algorithms of neural network and then a comparison had been done between the results of artificial neural network and those of Multi Linear Regression (MLR). They claimed that the Feed-forward neural network has represented better results than MLR model [3]. Firat and Gunger (2009) studied on prediction of scour depth around bridge piers using regression neural networks and feed-forward neural networks [5]. Hamidi and Kayaalp (2008) estimated the amount of suspended sediment in Tigris River using artificial neural networks [7]. Zhu et al. (2007) had modeled the suspended sediment flux of Longchuanjiang River in the upper Yangtze catchment using artificial neural network. for this purpose, at the first, four climate factors including average monthly temperature, rainfall, evaporation and humidity have been considered as input data. After an initial survey, they had found that rainfall and temperature have the most effect in this case. A comparison had been done between the results obtained from the neural network modeling and those of multi linear regression modeling. It was concluded that neural network results were more accurate than the results of multi linear regression [15]. Karami et al. (2006) had employed neural networks to predict the water quality of Karoon River located at Iran. MLP structure has been used in this research. The results indicated that MLP networks are capable of water quality prediction with a very high accuracy [8]. A study was done on sediment transport estimation in Tamr hydrometery station at Gorganrood River (Iran) using artificial neural networks by Mosaedi et al. (2006). MLP neural network was selected for this study. The other method to estimate the sediment transport at the same area was sediment rating curve modeling. However, the MLP model had presented more accurate results in comparison with sediment rating curve model [11]. Abbasi and Kashefipoor (2006) were applied the neural networks for suspended sediment estimation at Ahwaz station located in Iran. They had used some parameters including water discharge and rainfall for simulation. They concluded that neural networks have presented precise results compared to USBR method [1]. Naeini et al. (2008) had examined the sensitivity analysis of the artificial neural networks activation function in suspended sediment prediction. The feed-forward neural network with back propagation algorithm was taken for this study. The data collected from Mississippi River and Colorado River had been used to train and to test the neural network. The input data consisted of water discharge, the average diameter of the particles (d_{50}) and the slope of the river bed. The sensitivity analysis was done and they concluded that water discharge has the most effect on the amount of the suspended sediment. They had also noticed the efficiency and ability of the artificial neural networks in suspended sediment estimation [12]. Melesse et al. (2011) investigated on suspended sediment load prediction of river systems using artificial neural network approach. For this purpose, MLP neural network was selected to predict the suspended sediment load in Mississippi River, Missouri River and Rio Grande River located at USA. The daily and weekly rainfall, water discharge of considered day and a day before, and also sediment discharge of a day before had been imported into the network as input data to predict the suspended sediment. The result of neural network was compared with those of multi linear regression and ARIMA model. The result of daily prediction was better than the result of weekly prediction. And the output was most accurate in comparison with the output of other models used for the prediction [9].

This paper tries to evaluate the efficiency of Artificial Neural Network (ANN) method to estimate the suspended sediment at Lokapavani river basin. For this purpose, the Multilayer Perceptron (MLP) neural network has been selected. In this regard, the results obtained from artificial neural network have been compared with those of Sediment Rating Curve (SRC) model.

It must be noted that although, many researches have been done on suspended sediment estimation using artificial neural networks across the world during recent years, but it is obvious that the efficiency of these neural networks in different places and locations will vary based on the number, the volume and the type of available data. Therefore, a reliable judgment and evaluation can be done about their efficiency once enough research has been carried out using different type of neural networks and also various types of data. The main difference between this study and former studies is the regional climatic conditions as well as the type of data used as input data into the neural network. Hence, water discharge, rainfall data (daily and also accumulative) were applied as input data.

II. Artificial Neural Network

Artificial neural network is one of the varieties of artificial intelligence which generally acts like the human brain. In fact, an artificial neural network is an idea to process the information which is inspired by bio-nervous system; such as the brain, processes the information. The system is composed of a large number of processing elements called neurons. These neurons operate consonantly together to solve a problem. Neurons learn the process using observed data as specimen. In other words, observed data processing helps the neurons to transmit the knowledge and the relationship hidden among the data through the network structure. Actually, the artificial neural network is a mathematical model capable of modeling and generating the mathematical non-linear relationships in order to interpolating. Artificial neural networks are generally trained by a limited series of real data. If the parameters affecting the phenomenon under study are properly selected and imported into the network, then it could be expected to obtain a reasonable and logical output from the network. The artificial neural network is composed of the following sections:

- Input layer: The nodes in this layer are called input units, which encodes the instance present to the network for processing. For example each input unit may be designated by an attribute value possessed by the instance.
- Hidden layer: A layer in which the processing is done. The nodes in this layer are called hidden units, which are not directly observable and hence hidden. They provide the non-linearities for the network. A

network may have one or more hidden layer. The number of layers and nodes per layer is often obtained by network designer through trial and error process.

- Output layer: The nodes in this layer are called output nodes, which encode possible concepts or values to be assigned to the instance under consideration; for example each output unit presents a class of objects.

III. Study Area

The Lokapavani River is another tributary of the Cauvery River. It is a perennial river and is about 150 feet wide and 52 kilometers in length. Lokapavani River takes its birth at Honakere in Nagamangala taluk and takes a southerly course flowing through Nagamangala, Pandavapura and Srirangapatna taluk and joins Cauvery at Sangama near Srirangapatna. Two dams have been constructed across this river, one near Uyyanahalli of Nagamangala taluk and the other at Bolenahalli of Melkote hobli. The Lokapavani river basin area is 477.38 km^2. The Lokapavani river basin is located between North latitude 12° 30' to 12° 45' and East longitudes 76° 25' to 76° 50'. It is also placed at the center part of Cauvery river basin in Karnataka state. The Location of Lokapavani river basin over India and Karnataka state is illustrated in figure 1. 10.5 percent of total area of Mandya district covers the concern basin. Entire Lokapavani river basin is occupied by four taluks named Nagamangala, Mandya, Srirangapatna and Pandavapura taluks. The location of Lokapavani river basin at Mandya district is also shown in figure 2.

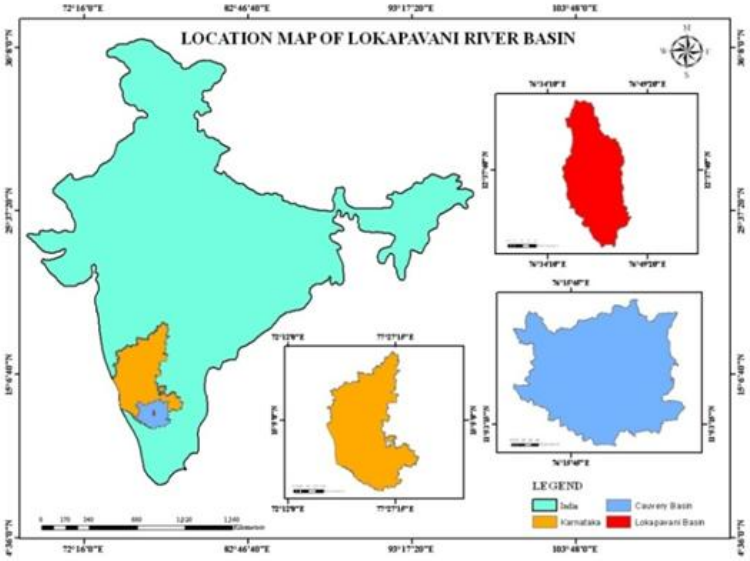

Figure 1: Location of Lokapavani river basin over India and Karnataka state

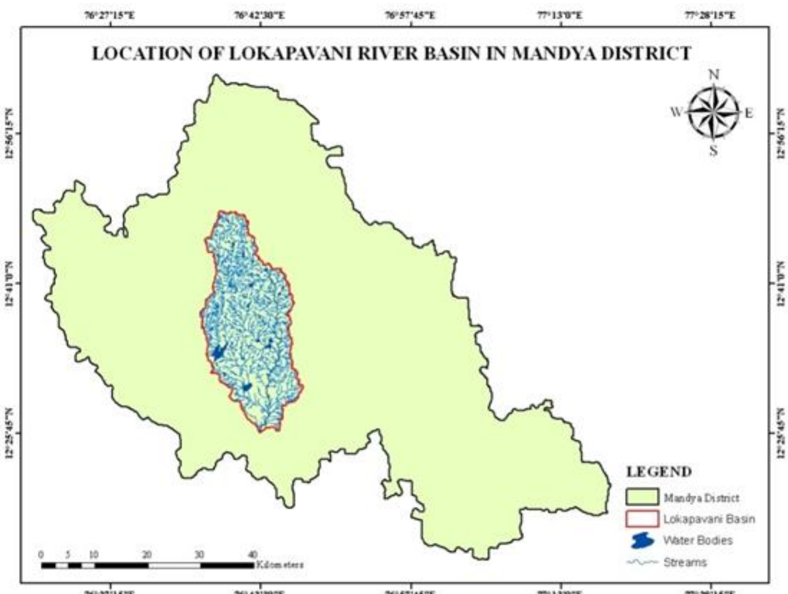

Figure 2: The location of Lokapavani river basin at Mandya district

IV. Materials and Methods

1.1. Data And Methods

In this study the data available at a river gauge station and also 5 rain gauge stations located across Lokapavani river basin are used. Thus, 360 simultaneously measured water and sediment discharges data as well as daily rainfall are considered. In ANN approach, to train the network some data indicating the problem conditions is initially selected and then other data is used to test and validate the network performance. The most important point while selecting the training dataset is to have the data which contains a wide range of available dataset. In this paper, 80% of whole data is considered as training data and 10% is selected for both testing and validation data. The other essential point in ANN is to normalize the data before importing into the network. Data normalization helps to have a better training and faster network especially when the variation range of input data is high. Generally, importing the raw data decreases the speed and the accuracy of the network [15]. To normalize the data in this study, the below equation is used.

$$X_n = 0.8\left[\frac{X_i - X_{\min}}{X_{max} - X_{min}}\right] + 0.1 \qquad (1)$$

After training, testing and validation dataset selection, the neural network was designed. MATLAB software is used to model and design the neural network. Out of 360 data, 288 data has been employed as training data and 36 data has been selected as testing data as well as validation data. The ANN structure is designed considering one input layer, two hidden layer and one output layer. Logistic Sigmoid is selected as the activation function of ANN. The input data for ANN modeling has contained daily water discharge, accumulative water discharge and accumulative rainfall data. To achieve an appropriate structure of artificial neural network, various networks have been designed and trained by different number of neurons and epoch. The result of different implemented networks is given in Table 1.

Table 1: Statistical results of MLP using LM training algorithm in the year 2006-07

Network	No of Hidden Layers	No of Neurons	Epoch	R2	RMSE	r2	bias	rmse
LM1-2006	2	3	1000	0.857005028	0.053746274	0.607359658	0.028292181	0.184261597
LM2-2006	2	3	2000	0.87065061	0.051240815	0.685877333	0.016801714	0.178033237
LM3-2006	2	3	3000	0.856376953	0.054099888	0.576037963	0.053689105	0.190467871
LM4-2006	2	3	5000	0.872744134	0.050919213	0.658721308	0.026257548	0.178985822
LM5-2006	2	6	1000	0.866987334	0.051852317	0.664893569	0.034773494	0.179530146
LM6-2006	2	6	2000	0.871985562	0.051443785	0.642326741	0.010332389	0.177646837
LM7-2006	2	6	3000	0.868525011	0.053514939	0.729161835	0.050514677	0.195331798
LM8-2006	2	6	5000	0.867033756	0.052095621	0.628311754	0.023628798	0.17776842
LM9-2006	2	8	1000	0.882056223	0.049028771	0.720492219	0.001930919	0.177456365
LM10-2006	2	8	2000	0.868742347	0.053245968	0.72637174	-0.024074417	0.198933632
LM11-2006	2	8	3000	0.868566894	0.052028274	0.682447861	0.063335339	0.194245868
LM12-2006	2	8	5000	0.875419494	0.050603037	0.648034181	0.042822428	0.189036397
LM13-2006	2	10	1000	0.861333348	0.053120909	0.601371765	0.043691167	0.188294833
LM14-2006	2	10	2000	0.867269405	0.052221289	0.612342565	0.024283214	0.17046125
LM15-2006	2	10	3000	0.87197974	0.051048313	0.700061696	0.042083411	0.186860707
LM16-2006	2	10	5000	0.877485344	0.049955224	0.682535801	0.028690198	0.177882292

As Table 1 shows selecting the different number of neuron and epoch have a significant impact on the quality of results. The number of neurons and epoch has been changed from 3 to 10 and from 1000 to 5000 respectively. After statistical investigation it was found that the most efficient network is resulted when the number of neurons is 8 and the number of epoch is 1000. Evaluation of different performed ANN has been done using statistical analysis. For this purpose, 5 statistical factors including R^2, RMSE, r^2, bias and rmse have been used. R^2 shows the correlation between the data. Larger value of R^2 and of course closer to 1 expresses a higher correlation between the observed and estimated data. RMSE indicates that how estimated data are deviated from observed data. Small value of RMSE shows less deviation between estimated and observed data which claims more accurate results. Nash coefficient (r^2) is a statistical index that demonstrates the ratio of fit in hydrology models. (r^2) ranges between one and negative infinity i.e. $(-\infty, 1]$. When r^2 is close to 1, it means a better efficiency of the model. The model will correspond with the mean of data, if r^2 equals zero. And if r^2 obtains a negative value, it shows that the mean of data is more efficiency than the model itself. Bias aims as relative skew; i.e. if the ratio average of estimated values to observed values equals 1 then the estimated data are unbiased otherwise they are skewed. The relative skew is a criterion to evaluate the efficiency of estimated data. Smallest relative skew and of course closer to zero demonstrates more accurate estimation. In addition, the bias values are placed at the interval of $(-\infty, +\infty)$. Root mean square error rmse is like as bias, a criterion to assess the efficiency of estimated data. The $rmse$ value closer to zero indicates efficiency estimation. rmse varies from zero to $+\infty$ i.e. $[0, +\infty)$. Indeed, whatever X_{est} is closer to X_{obs}, hence, $\frac{X_{est}}{X_{obs}}$ would be closer to 1, consequently, the error value goes toward zero, therefore $rmse$ reduces, and then it can be concluded that more appropriate estimation has been placed.

V. Results and Discussion

5.1 Results Obtained From ANN

According to the statistical parameters, among the implemented ANNs applied Levenberg Marquardt (LM) training algorithm, the most fitted estimate values have been resulted from the network having 8 numbers of neuron and 1000 epoch. The concern network has represented the highest value of correlation coefficient (R^2= 0.88), the least value of RMSE (RSME ≈ 0.05), the closest r^2 value to 1 (r^2 = 0.72), the minimum value of bias and of course close to zero (bias = 0.002) and the lowest rmse value (rmse = 0.18). A comparison is done between measured values of suspended sediment and those of estimated by ANN model based on standard line to evaluate the performance of ANN model in suspended sediment estimation. Figure 3 shows the perfect line of agreement for ANN performance.

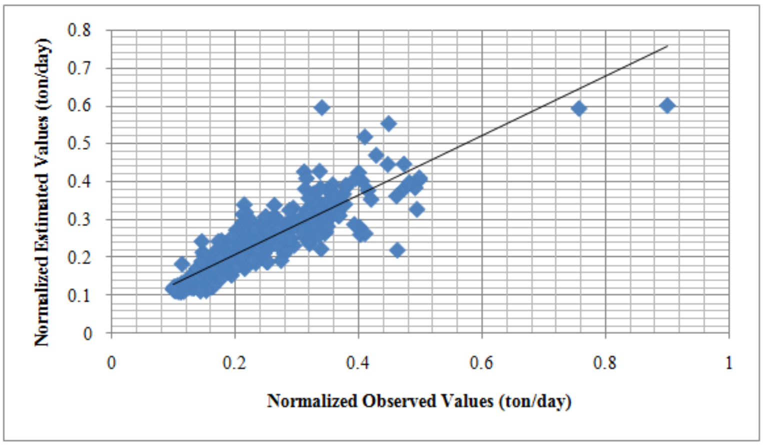

Figure 3: Perfect line of agreement between observed and estimated data using ANN

The dispersion of the estimated and observed data around the standard line with 45 degree gradient has seen less in figure 3 which means ANN model was successful to estimate the suspended sediment in the year 2006-07. However, the monthly average estimated suspended sediment using ANN and observed data is graphed in figure 4. According to the graph, less fluctuation has been noted between observed suspended sediment data and estimated suspended sediment data using ANN model.

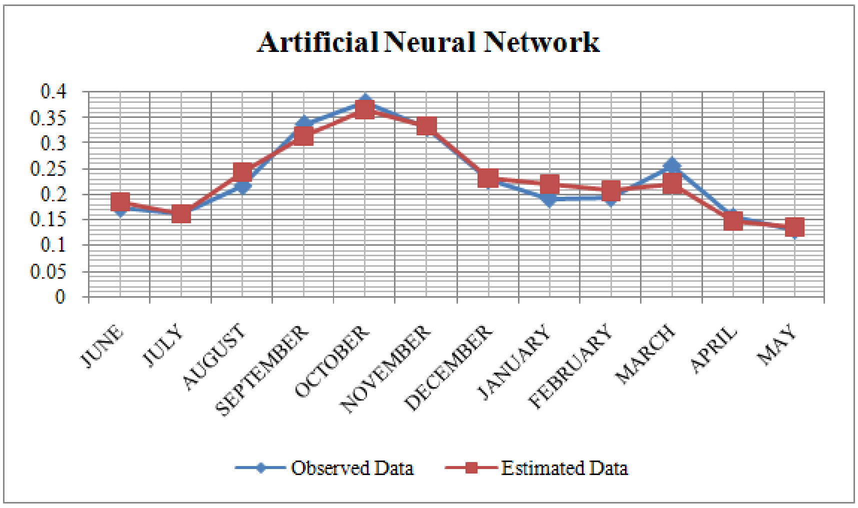

Figure 4: Estimated suspended sediment using ANN and observed data

5.2 Results Obtained From SRC

In order to compare the results of ANN with those of Sediment Rating Curve (SRC), the suspended sediment has also been estimated using SRC modeling. In SCR modeling, a regression equation is usually extracted between corresponding water and sediment discharges. Therefore, to determine and to draw the sediment rating curve, fitted exponential equation has been recommended by various experts (Graf, W.H., 1984). Generally, sediment exponential equation is as follows:

$Q_s = aQ_d^b$ (2)

In this equation *a* and *b* are the coefficients and Q_s and Q_d are sediment discharge (ton/day) and water discharge (m^3/s) respectively. Sediment rating curve has been drawn using sediment discharge (ton/day) and water discharge (m^3/s) data for Lokapavani river basin. The sediment rating curve for the year 2006-07 is illustrated in figure 5. Checking the position of observation spots on the graphs shown in figure 3, represented a wide range of daily water discharge changes which was a reflection of the hydrological regime of Lokapavani river basin.

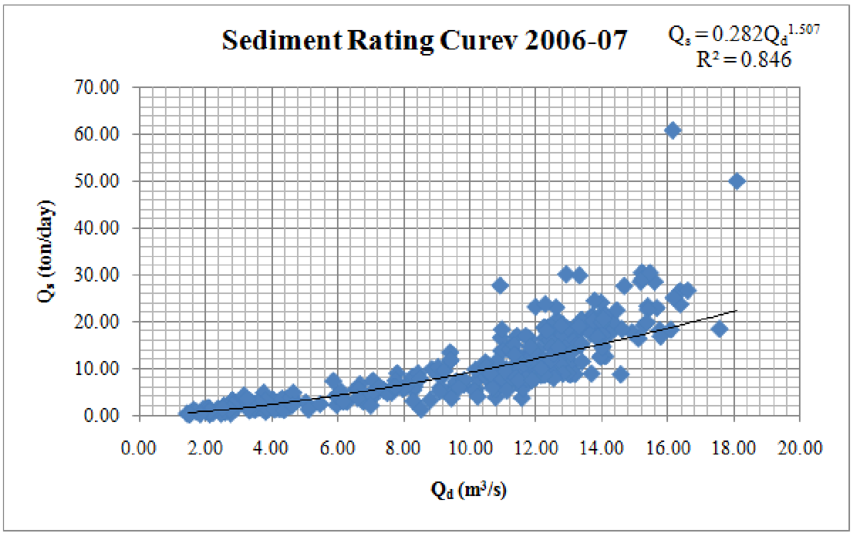

Figure 5: Sediment rating curve in the year 2006-07

For the year 2006-07, the minimum water discharge (Q_d) was equal to 1.46 m^3/s and the maximum Q_d was 18.11 m^3/s; the range of suspended sediment has also followed by hydrological regime and it varied from 0.32 ton per day to 60.89 ton per day in the year 2006-07. The coefficients of sediment rating curve equation were calculated as a=0.282 and b=1.507. The coefficient of determination was also recorded as R^2=0.846. The graph line has been drawn between observed data and estimated suspended sediment using SRC model which is illustrated in figure 6. Based on the presented graph, a significant variation has been observed between measure suspended sediment data and those of estimated using SRC; especially from September to November.

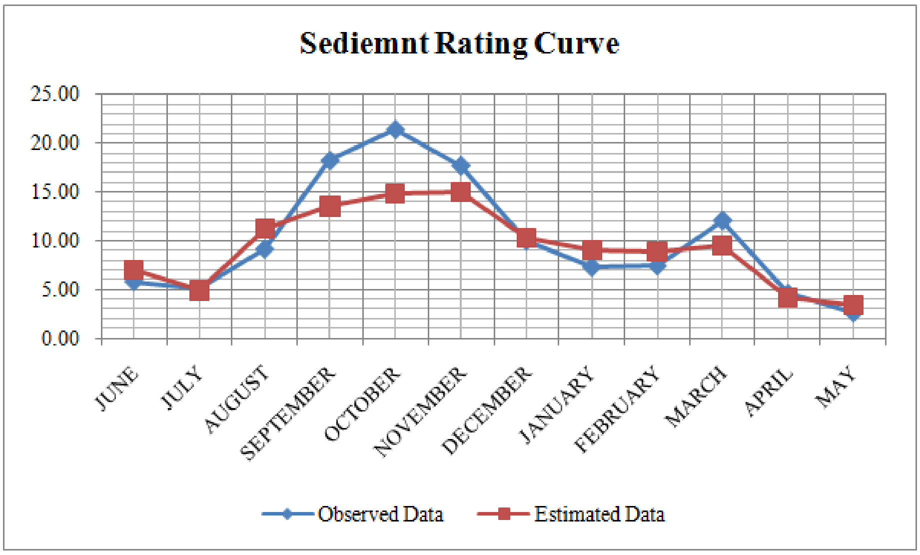

Figure 6: Estimated suspended sediment using SRC and observed data

VI. Conclusion

In this paper in order to determine the best method for estimating the suspended sediment at Lokapavani river basin located at Mandya district, Karnataka state, India, corresponding data of water discharge and suspended sediment concentration and rainfall data were collected and analyzed for the year 2006-07. For this purpose two different models including ANN and SRC have been applied. Hence, suspended sediment rating was curved for suspended sediment discharge at Lokapavani river basin, during 2006-07. The sediment rating curve was developed by establishing power relation between daily water discharge as independent variable and corresponding daily suspended sediment discharge as dependent variable. The value of determination coefficient (R^2) was 0.846.

MATLAB software was used to design and to develop the ANNs. MLP network which is one variety of ANN models was taken for this study. Logistic sigmoid function was selected as transfer function for all developed ANNs. LM was also selected as training algorithm for MLP networks. To evaluate the different developed MLP networks, statistical parameters such as coefficient of determination (R^2), Nash Coefficient (r^2), Root Mean Square Error ($RMSE$), bias were used. Therefore, according to the statistical parameters of artificial neural networks performed using Levenberg Marquardt (LM) training algorithm for the year 2006-07, the best estimation of suspended sediment at Lokapavani river basin was done via the network designed with 8 neurons at 1000 epoch. The value of R^2 was equal to 0.88, $RMSE$ value equaled to 0.05, the value of r^2 was equivalent to 0.72, the value of $rmse$ and $bias$ was 0.18 and 0.002 respectively. To compare the artificial neural network model using Levenberg Marquardt training algorithm with sediment rating curve model in the year 2006-07, the coefficient of determination was considered. The R^2 value of artificial neural network with Levenberg Marquardt training algorithm (0.88) was closer to 1 compared to the value of R^2 obtained from sediment rating curve model (0.846). It means MLP network was more capable to result the most accurate suspended sediment estimation in comparison with SRC model.

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