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Modelling of Daily Suspended Sediment Concentration Using FFBPNN and SVM Algorithms

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ABSTRACT

The river is an essential resource of fresh water on the earth, and its management is very challenging. Sedimentation and erosion is a very complex process of the river system. Suspended sediment concentration (SSC) plays a key role in this process. Therefore, water resources planning and management are essential for this. Generally, the sediment concentration estimated by direct measurement, but this process is costly and cannot apply in all rivers. It is essential to develop some technology that can predict the suspended sediment concentration. So, in this study, a feed forward back propagation neural network (FFBPNN) and support vector machine (SVM) were used to predict the suspended sediment concentration. One year of daily data was collected from the river Ganga at Varanasi cross-section. The performance of the model estimated for training and validation stages based on root mean square error (RSME), Coefficient of correlation (R) and Nash–Sutcliffe model efficiency (NSE). The performance of applied model indicated that FFBPNN (RSME = 176.2, R = 0.955 and NSE = 0.912) for validation is more precise for suspended sediment load prediction than SVM (RSME = 222.1, R = 0.930 and NSE = 0.864). This study shows that the soft computing technique is a robust tool for SSC prediction.

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1. Introduction

The sediment transport mechanism in any river system is a nonlinear and complex process in terms of space and time. Therefore, estimation and prediction of suspended sediment concentration for the river are essential for managing water resources. In addition, the transport of sediment causes damage to the riverbank, hydraulic structure, agricultural land and water quality. Furthermore, sediment deposition due to soil erosion caused by the river into the dams and Reservoir reduces their capacity. Because of this decrease in the availability of water takes place and affect electricity generation, regression and other domestic and business use. Recently, this subject is getting more intriguing by its natural impacts.

The usual practice of estimating sediment load is the direct method. In this method, the sediment load measured directly by using hydrological instruments. But it is costly, and also it is not possible to reach every river stream. So there is a need for an indirect estimation method. Therefore, many researchers have developed and worked with the soft computing tool to estimate suspended sediment load. In this method, the analysis divided into types of variables; dependent and independent variables. First is independent variables, which measured with field experiments and field data collection. Second dependent variables predicted using data techniques like Artificial Neural Networks (ANN), Support Vector Machine (SVM), neuron fuzzy, M5 model trees, sediment rating curve, multilinear regression, and wavelet method [1,2]. ANN, SVM and sediment rating curve are widely used to estimate SSC in rivers and other soft computing methods used for estimation of SSC in river basin [3]. Moreover, some of the soft computing technique like gene-expression programming (GEP) ad model tree (MT) also frequently used in the water quality monitoring field [4].

ANN used successfully in the area of water resources. Nagy [5] developed an ANN computational model for accurate estimation of SSC in rivers by using flow discharge data. Many researchers have used ANN [6–9] method for estimating and forecasting SSC. ANN has given a perfect prediction. The comparison of the sediment rating curve with ANN for the estimation of daily SSC found that the AAN provides a more accurate estimate compared to the sediment rating curve [10–16].

Also, SVM has used successfully to predict SSC during this era [17–19]. Many other researchers have used SVM [20,21], Wavelet method [22], neuron-fuzzy method, and linear regression to estimate suspended sediment transport. Many researchers like; Mahanta et al. [23], Cobaner et al. [24], Kakaei et al. [25], Yadav et al. [26] etc., have used and compared different soft computing methods. Majority of work shows that the SVM and ANN have given accurate result. Tasar et al. [27] have demonstrated that ANN is better for sediment modelling than M5 tree and regression. Also, researchers like; Mahanta et al. [23], Kakaei et al. [25], etc., have shown that the ANN technique works better for sediment analysis. While Himanshu et al. [22], He et al. [27] have shown that the SVM technique works llbetter for suspended sediment load modelling.

Most of the studies on sediment modelling flow discharge used as input variables [23,28–32]. Some researchers used flow discharge and rainfall data as an input variable [3,22,26]. However, the water level of the river has also impacted the sediment transport process. With the increase in the river's water level, the river will submerge the larger area around it. Those inundated areas will accelerate the sedimentation transport process. So, in the alluvial river like; river Ganga, the water level or stage of the river should be considered as an input for modelling daily SSC. In this study, all three parameters (flow discharge, rainfall and water level) considered, which can significantly impact SSC modelling. For this, the two most popular methods FFBPNN and SVM, are used and compared for predicting suspended sediment load of river Ganga at Varanasi region.

2. Study area

The river Ganga originates as Bhagirathi from the Gangotri glaciers, Uttarakhand, India and joins the sea at the Bay of Bengal. Ganga flow in India is about 2525 kilometres. During their travel, it crosses five states of India: Uttrakhand, Uttar Pradesh, Bihar, Jharkhand, and West Bengal. River Ganga comes from the youngest mountain of the Himalayas at an elevation of 7010m. The Ganga watershed spreads over an area of 1,086,000 km^2. Ganga went with a lot of sediment from the higher elevation to the lower elevation and deposited in the plain. This sediment creates the Gangetic Plains plan. Estimation of suspended sediment load of the river is a complex phenomenon.

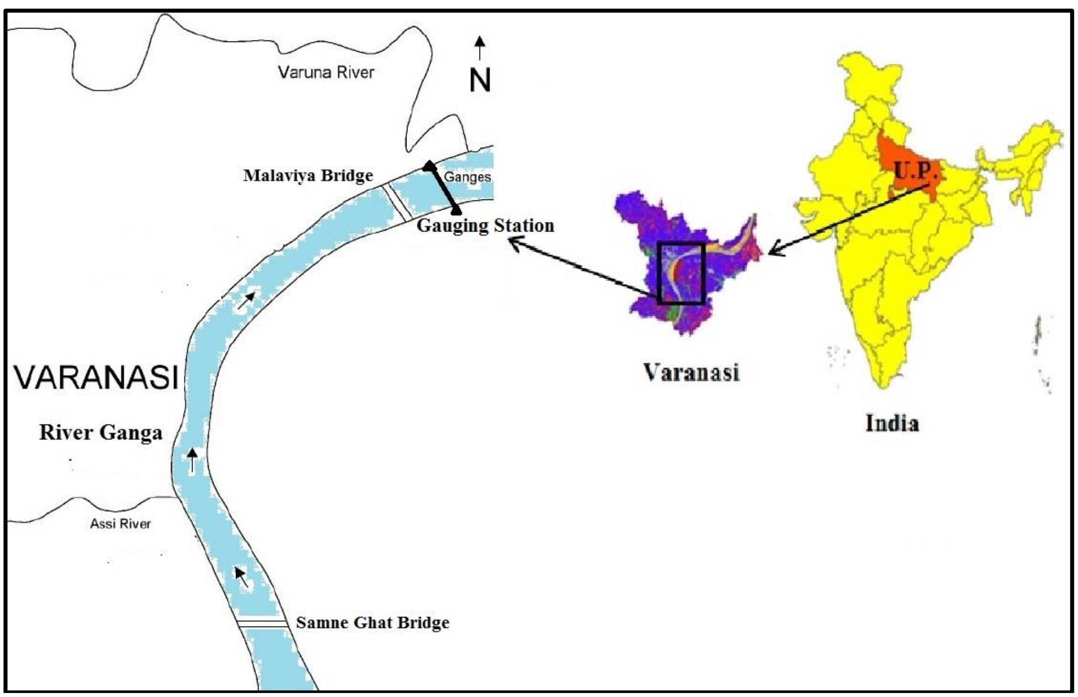


Fig. 1. The plan view of the study area near Varanasi.

Varanasi district of Uttar Pradesh, India, is selected for the sediment load study. Varanasi city situated between the watercourses Ganga and the Varuna River; the mean elevation is 80.71 m. Soil erosion also prevailed in this area [33]. Varanasi city is located near the river Ganga, as shown in fig. 1, and Gauge station near Raj Ghat. This area selected for the sediment load study of river Ganga. The latitude and longitude of this cross-section were 25° 19' 29.45" N 83° 2' 9.17" E and 25° 19' 17.15" N 83° 2' 16.99" E. In the year 2016, Varanasi hit by the worst floods after several years. The consequences of the flood are to increase in diseases, infrastructure loss, and damage of crops and carry a lot of sediment. For this, estimating the SSC of 2016 to 2017 is essential for the present work. One year of daily data used to estimate suspended sediment concentration.

3. Data collection

One year daily data collected from the gauge station at Varanasi. Central Water Commission (CWC) operates a Varanasi gauge station near the Raj Ghat. In this study, the daily data of river discharge (Q) in m^3/s, rainfall in mm, river water level (Stage of the river) in m, and SSC (gm/l) collected from May 2016- April 2017. The rainfall data procured from the Indian Metrological Department (IMD), India. The maximum and minimum ranges of all these variables given in table 1. The Indian summer monsoon starts from June to September, with large areas of India receiving more than 90% of their total annual precipitation [34]. Therefore, the maximum water discharge is in the monsoon period. River discharge is increasing rapidly from the first week of July to September month. After mid-October, flow discharge decreases and reaches a minimum flow, and the lowest flow discharge received in May [35]. May month is very dry, and the river width also becomes very. But in the time of summer monsoon, the width of the river becomes very high. Velocity is maximum when the discharge becomes maximum.

Table 1
The maximum, average and minimum range of input and output data set.

	Input data Set			Output data set
Range	Discharge (m^3/s)	Rainfall (m)	Water level (m)	Suspended Sediment Concentration (mg/l)
Maximum	30838.84	174	72.56	1860
Average	2754.76	3.62	61.12	227.92
Minimum	74.3	0	57.57	20

4. Methodology

4.1. Soft computing model

There is two soft computing method used for prediction of total SSC with their performance. Methods are as follows:

- Feed forward back propagation neural network (FFBPNN)
- Support vector machine (SVM)

4.1.1. Artificial neural network

An ANN works like a human brain and design motivated by the neurons system. Human brains gather information, and based on information brain conclude. As the brain and collect information in the training process and based on the training in a plot, the validation process results are helpful for any Complex problem, pattern recognition forecasting optimization and simulation.

The ANN is information processing, which simulates the current understanding of the biological nervous systems. The processing units, called neurons of an ANN, are arranged in layers and are connected by links of variable strengths called weights. Most units in neural networks transform their net input by using a function called an "activation function". Activation function, sometimes called transfer or squashing function, yield a value called the unit's "activation." This activation value is fed to one or more other units. Activation functions for the hidden units are needed to introduce. In this study, two network functions have been selected and given below:

4.1.2. Feed forward back propagation

There is a number of a method for ANN modelling and learning process. A multilayer feed forward back propagation is commonly used for prediction modelling. It consists of three layers, every layer inter-connected with some with the weight value. The first layer input is the input layer, the second layer is a hidden layer, and the third layer is the output layer. All three layers contain neurons, and they are inter-connected in fig. 2 [36].

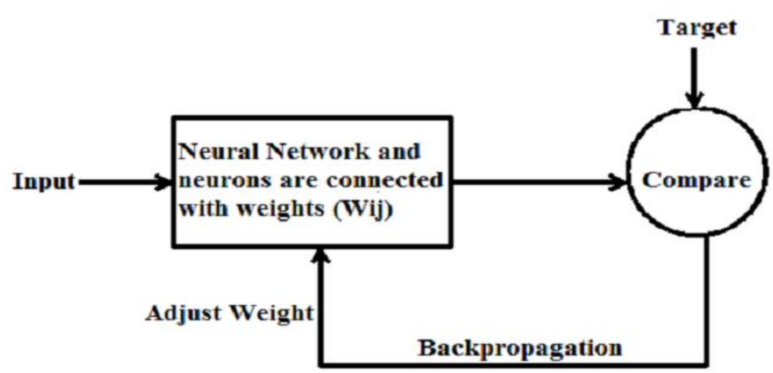


Fig. 2. Working process of feed forward back propagation neural network.

4.1.3. Support vector machine

The SVM is the most well-known technique used in machine learning calculations. They were amazingly mainstream around the time they were created during the 1990s and keep on being the go-to technique for a high-performing estimation with minor tuning. In addition, this used for various practical problems [37].

In machine learning, SVM is a supervised learning technique used for classification and regression analysis. It defines the class of the given data set. In the SVM decision boundary separates the different class's data. It plots the margin line, and this line decides the correct hyperplane. It can handle linear and nonlinear problems. In the SVM kernel function, the low dimensional feature space converted to the high dimensional feature space, where the nonlinear data easily separated into different classes. The mapping of data becomes easy in this method. The variety of data can be handled and based on their similarity to the classification is done. The hyperplane separates the different class data. SVM may acquire optimal global result with the help of the solution of convex quadratic programming. It can minimize the upper bound limit and plot low fluctuation results.

Whenever information lacks tag, focused learning is beyond the jurisdiction of the mind. Unsupervised learning comes in the picture for a new approach, which endeavours to discover characteristic bunching of the info to gatherings. After that, plot further information to these shaped gatherings. The support vector clustering [38] calculation, made by Hava Siegelmann and Vladimir Vapnik, applies the help vector measurements created in the help vector machines design to order unlabeled information. It is a standout amongst the most utilized bunching calculations in modern applications.

4.2. Model development

There are some steps for developing a model for FFBPNN and SVM; they are as follows:

- Selection of input data and output data
- Selection of training and testing data
- Selection of network type and other parameters

4.2.1. Selection of input data and output data

Input data is independent data, and output data is secondary data. There is some relationship between input data and output data. ANN fined the complex relationship between them and then provided a prediction model. ANN model is a combination of three layers, the first layer is an input layer, where a different set of data introduced in the network, the second layer is a hidden layer, where data processing will be done based on various network weights, and biases value and the third layer is the output layer, where the final result of the network will come out. So the separation of input data and output data from the data set should be very careful. Important input variable will give a more precise result. Here the complete four data set containing 365 different data. Three data sets selected for the input layer and one data set chosen for the output layer shown in the table. 1.

Discharge, rainfall and river water level is the major controlling factor of the SSC. The combination of 3 input parameters decides the SSC quantity. Selected input and output parameters help create a better training and validation model for the prediction of SSC. The data set normalized between the ranges of -1 to 1. Equation 1 used for the data normalization.

$$N_d = 2 \times \frac{O_d - O_{min}}{O_{max} - O_{min}} - 1 \quad (1)$$

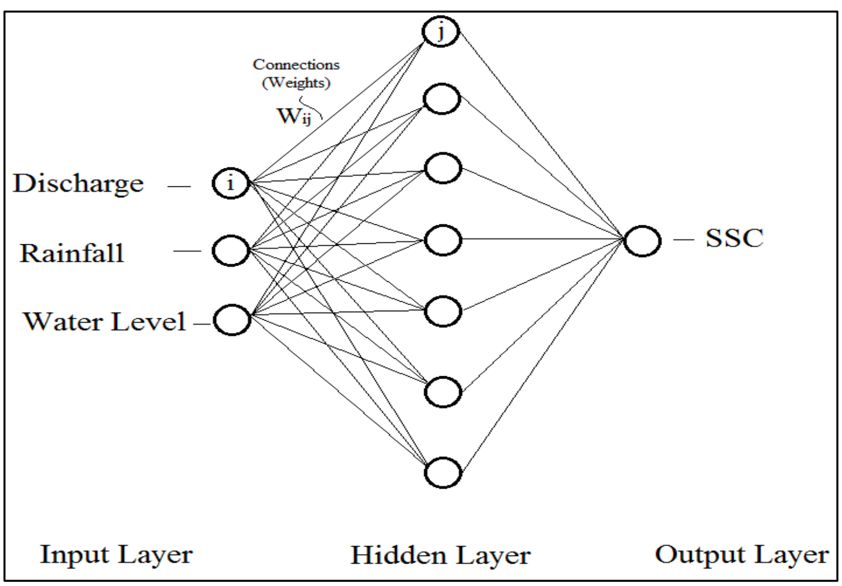
Where, N_d = Normalized data, O_d = Original data, O_{max} = Maximum value of original data and O_{min} = Minimum value of original data.

4.2.2. Selection of training and testing data

Several network functions are available in the ANN. Still, feed forward the back propagation neural network performed as a better function than the conventional statistical and stochastic method. ANN is used successfully in the field of discharge-suspended sediment load. It also used in the field of sediment yield modelling. FFBP is given acceptable simulation for sediment load [39]. The Neural Network training conducted using feed forward back propagation. Complete data set were separated into two parts. The first is the training data set, and the second is a validation data set. Total one year daily data with three different input variables used. 77% of data selected for training from the data set, and 27% of data chosen for validation. One input variable contains 265 data for training and 100 data used for the validation. The selection of training and testing data are random from the data set. Random data selection gives more accurate validation result.

4.2.3. Selection of network type and another parameter

In the FFBPNN network, data prediction is straightforward. The network contains three input node with one output node, as shown in fig. 3. After selecting the input and output node further, start selecting the hidden layer. Goh [40] suggested that the selection of hidden layer depends upon desired output. If the output is a continuous function, then a number of the hidden layers will be one, and if the desired output is discontinuous, then the number of the hidden layers will be two. There is no strict rule for a selection of hidden layer. It may depend upon the size of the problem, and the quality of training pattern changes from time to time, but [40,41] suggested that sometimes the hidden layer depends on the size of input and output variable. A number of the hidden layer changes from time to time but [41] suggested that the number of neurons in the hidden layer is commonly one more than two times of input neurons. So, this is not true all time, but this rule considered at some point. After all, there is no fixed rule for selecting neurons in the hidden layer. It mainly depends upon the trial and error method.



Note: SSC- Suspended sediment concentration

Fig. 3. ANN structure of a 3-7-1 FFBP neural network.

Root mean square error (RSME), Coefficient of correlation (R) and Nash–Sutcliffe model efficiency (NSE) value has continuously observed at the time of training (calibration) and validation (testing) to avoid excess training and over fitting. Once training has done, the second step is to simulate the output using the calibration network. Then, compare the target and computed value. If the error is less than this network preserved as a trained network, it is ready for validation. The network architecture selection based on the network performance, and these performances checked based on performance function root mean square error, shown in table 2-4. The best ANN illustrated in fig. 3.

4.3. Performance evaluation of model

The data set separated into two parts for the training (calibration) and validation (testing), and the performance of the network during training and validation evaluated based on the performance index of the RSME, R and NSE shown in equation 2 to 4 [42].

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{n}(S-L)^2}{N}} \tag{2}$$

Where N = Number of observation, S = observed sediment, and L= Computed sediment load data.

$$\text{Nash–Sutcliffe model efficiency (NSE)} = 1-\frac{\sum(S-L)^2}{\sum(S-\bar{S})^2} \tag{3}$$

Were, S = observed sediment data, $\bar{S}$ = Mean of observed sediment data and L= Computed sediment data.

$$\text{Coefficient of correlation (R)} = \frac{\sum(S-\bar{S})(L-\bar{L})}{\sqrt{\sum(S-\bar{S})^2\,\sum(L-\bar{L})^2}} \tag{4}$$

Where, S = observed sediment load data, $\bar{S}$ = Mean of observed sediment load data, L= Computed sediment load data and $\bar{L}$ = Mean of computed sediment load data.

5. Result and discussion

Two mathematical models perform the SSC prediction FFBPNN and SVM. Three input combination used for desired output (SSC). The training and validation result for FFBPNN and SVM in table 2 and 3, respectively. The models of FFBPNN and SVM tested based on RMSE. In the FFBPNN, the best model is FFBPNNS 5. Model FFBPNNS 5 has the lowest RMSE of training and validation values of 70.87 and 176.2. The best network structure is 3-7-0-1(3 input, seven nodes of hidden layer, and 1 output) given in fig. 3. The maximum error is given by the FFBPNNS 1 model number, where the total node of the hidden layer is 3, where RMSE of training and validation values of 140.9 and 229.1.

Table 2
Comparison of RMSE for different Training and validation FFBPNN structure.

Model No.	FFBPNN structure	RMSE	
	I/P- Hidden layer- O/P	Training	Validation
FFBPNNS 1	3-3-0-1	140.9	229.1
FFBPNNS 2	3-4-0-1	110.5	222.3
FFBPNNS 3	3-5-0-1	102.3	209.4
FFBPNNS 4	3-6-0-1	87.3	180.2
FFBPNNS 5	3-7-0-1	70.87	176.2
FFBPNNS 6	3-3-4-1	95.6	197.5
FFBPNNS 7	3-4-5-1	92.3	184.8
FFBPNNS 8	3-5-6-1	120.0	213.7
FFBPNNS 9	3-6-7-1	78.4	180.3
FFBPNNS 10	3-7-8-1	80.8	188.6

Note: Feed forward the back propagation neural network structure (FFBPNNS)

In the SVM, the best SVM model is SVMS 6. Model number SVMS 6 has the lowest RMSE of training and validation values, 80.4 and 222.1, respectively. The best SVMS 6 network structure is 3 - 0.5 – 01 -0.3 – 1 (input- Gamma-C-Epsilon –output) shown in table 3. The maximum error observed in model number SVMS 9, where RMSE value of training and validation value 125.3 and 251.9, respectively

Table 3
Comparison of RMSE for different Training and validation SVM structure.

Model No.	SVM structure	RMSE	
	I/P- Gamma-C-Epsilon -O/P	Training	Validation
SVMS 1	3 - 0.5 – 01 -0.1 - 1	120.6	246.6
SVMS 2	3 - 0.5 –03 - 0.1 - 1	110.3	241.9
SVMS 3	3 - 0.5 – 04 -0.1 - 1	105.6	237.2
SVMS 4	3 - 0.5 – 05 -0.2 - 1	103.1	238.7
SVMS 5	3 - 0.5 – 01 -0.4 - 1	96.4	232
SVMS 6	3 - 0.5 – 01 -0.3 - 1	80.4	222.1
SVMS 7	3 - 0.5 –0 2 -0.2 - 1	90.2	226.4
SVMS 8	3 - 0.5 – 04 -0.2 - 1	95.8	234
SVMS 9	3 - 0.5 – 08 -0.3 - 1	125.3	251.9
SVMS 10	3 - 0.5 – 03 -0.4 - 1	112.7	241.8

Note: Support vector machine structure (SVMS)

From table 4-5, it can be observed that the model FFBPNNS 5 and model SVMS 6 perform better than any other FFBPNN and SVM model. The FFBPNN training value of R and NSE are 0.988 and 0.976, respectively, for model FFBPNNS 5. The performance of model number

FFBPNNS 5 is the best out of 10 models. After training the same model number tested for validation, it found that the model value of R and NSE are 0.955 and 0.912, respectively, where it gives the best performance.

Table 4
Performance of FFBPNN Model during Training and Validation.

Model No.	FFBPNN structure	Tanning		Validation	
	I/P- Hidden layer- O/P	R	NSE	CORREL	NSE
FFBPNNS1	3-3-0-1	0.952	0.906	0.933	0.870
FFBPNNS 2	3-4-0-1	0.969	0.939	0.931	0.866
FFBPNNS 3	3-5-0-1	0.971	0.942	0.937	0.877
FFBPNNS 4	3-6-0-1	0.983	0.966	0.951	0.904
FFBPNNS 5	3-7-0-1	0.988	0.976	0.955	0.912
FFBPNNS 6	3-3-4-1	0.979	0.958	0.942	0.887
FFBPNNS 7	3-4-5-1	0.981	0.962	0.950	0.902
FFBPNNS 8	3-5-6-1	0.963	0.927	0.939	0.881
FFBPNNS 9	3-6-7-1	0.985	0.970	0.951	0.904
FFBPNNS 10	3-7-8-1	0.954	0.910	0.948	0.898

The performance of the SVM model seen in table 5, where the model number SVMSL6 is the best performer. At the time of training, the value of R and NSE are 0.981and 0.963, respectively. After achieving the good train model, the network simulated. The validation performance is also well in the model number SVMSL6, where the value of R and NSE are 0.930 and 0.864, respectively.

Table 5
Performance of SVM Model during Training and Validation.

Model No.	SVM structure	Tanning		Validation	
	I/P- Gamma-C-Epsilon -O/P	R	NSE	R	NSE
SVMS 1	3 - 0.5 – 01 -0.1 - 1	0.962	0.925	0.892	0.795
SVMS 2	3 - 0.5 –03 - 0.1 - 1	0.963	0.927	0.898	0.806
SVMS 3	3 - 0.5 – 04 -0.1 - 1	0.964	0.929	0.909	0.826
SVMS 4	3 - 0.5 – 05 -0.2 - 1	0.967	0.935	0.915	0.837
SVMS 5	3 - 0.5 – 01 -0.4 - 1	0.970	0.940	0.918	0.842
SVMS 6	3 - 0.5 – 01 -0.3 - 1	**0.981**	**0.963**	**0.930**	**0.864**
SVMS 7	3 - 0.5 –0 2 -0.2 - 1	0.978	0.956	0.921	0.848
SVMS 8	3 - 0.5 – 04 -0.2 - 1	0.972	0.944	0.914	0.835
SVMS 9	3 - 0.5 – 08 -0.3 - 1	0.960	0.921	0.889	0.790
SVMS 10	3 - 0.5 – 03 -0.4 - 1	0.965	0.931	0.898	0.806

Table 6
Comparison of Result between FFBPNN and SVM.

Model No.	Model Structure	Training			Validation		
		RMSE	R	NSE	RMSE	R	NSE
FFBPNNS 4	3-7-0-1	70.87	0.988	0.976	176.2	0.955	0.912
SVMS 5	3 - 0.5 – 01 -0.3 - 1	80.4	0.981	0.963	222.1	0.930	0.864

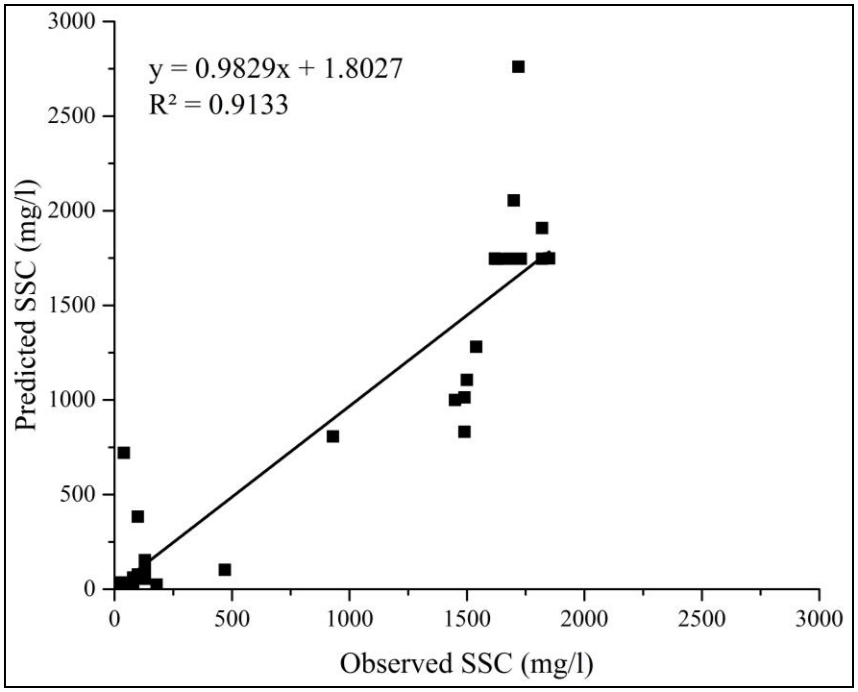


Fig. 4. Performance of FFBPNN model for SSC.

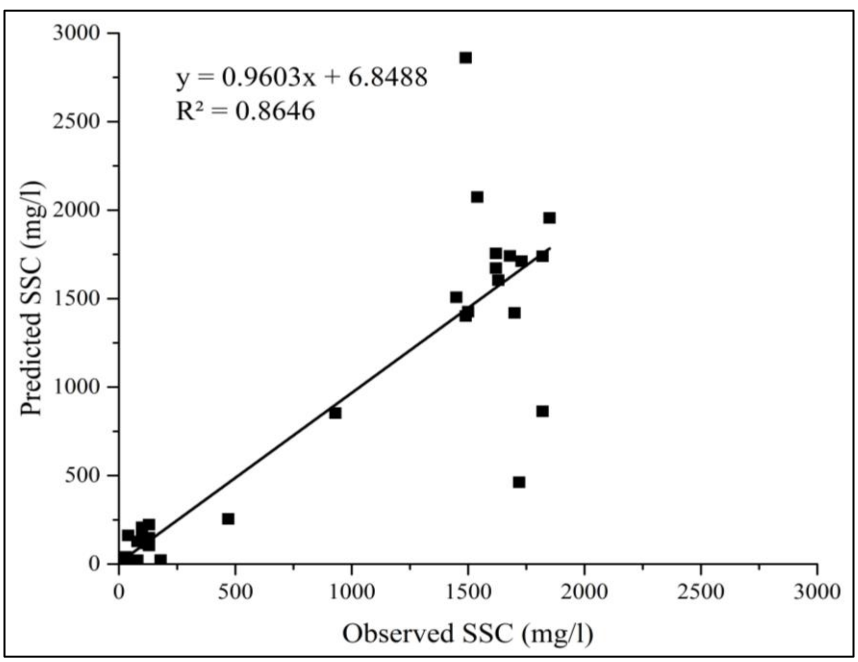


Fig. 5. Performance of SVM model for SSC.

The comparison of both models FFBPNN, and SVM has shown in table 6. The best network structure for FFBPNN and SVM model structure are 3-7-0-1 and 3 - 0.5 – 01 -0.3 – 1, respectively. In training, RMSE, R and NSE are 70.87, 0.988, and 0.976, respectively, for the FFBPNNS 5 model. In Validation, RMSE, R and NSE are 176.2, 0.955 and 0.912, respectively, for the FFBPNNS 5 model. . In training, RMSE, R and NSE are 70.87, 0.988, and 0.976, respectively for the FFBPNNS 5 model. In training, RMSE, R and NSE are 80.4, 0.981 and 0.963, respectively, for the SVMS 6 model. In the validation, RMSE, R and NSE are 222.1, 0.930, and 0.864, respectively for the SVMS 6 model. The SSC observed data and predicted data from the FFBPNN model. The scatter plot of SSC prediction using the FFBPNN model for the validation period was plotted against observed and predicted SSC (fig. 4). The best fit line obtained is y = slope * x + intercept, where the slope is 0.9829 and intercept is 1.8027. R-square value is 0.9133, which is near to 1:1 line. The scatter plot of SSC prediction using the SVM model for the validation period was plotted against observed and predicted SSC (fig. 5). The slope is 0.9603, and the intercept is 6.8488. R-square value is 0.8664. The predicted and observed SSC value is very much similar in the FFBPNN model. It also observed that the value of FFBPNN and SVM are with significant variation, the overall model performance of FFBPNN is better than SVM.

6. Conclusion

The present study aimed to compare two models (FFBPNN and SVM) to predict daily SSC for river Ganga river near Varanasi city. ANN used with feed forward back propagation technique and SVM used with radial basis technique. One year of daily data used for the model development. Trial and error method used for the selection of best model structure based on RMSE. Model performance estimated based on NSE, R-square and R-value.

Model performance of training stage indicated that the FFBPNN model predicted the SSC rate with RMSE, R, and NSE are 70.87, 0.988, and 0.976, respectively. At the validation stage, RMSE, R and NSE are 176.2, 0.955 and 0.912, respectively. The training shows minor error as compared to the validation stage. Based on minor error in the training stage, it can say the model trained adequately. The SVM model performance in the training stage predicted the SSC rate with RMSE, R and NSE are 80.4, 0.981 and 0.963, respectively. For the validation stage prediction of SSC RMSE, R and NSE are 222.1, 0.930, and 0.864, respectively. The error difference in the training and validation stage of the SVM model is higher than the FFBPNN model. On behalf of model performance, it concluded that the model performance of the FFBPNN is better compared to SVM. The result of the study showed that the ANN model was an essential tool in daily SSC prediction. It can be considered as a modelling tool for the prediction of the river SSC. This work is helpful for the precise data and better model selection for the prediction of daily SSC in the large river.

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