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Application of Artificial Neural Networks, Support Vector Machine and Multiple Model-ANN to Sediment Yield Prediction

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Abstract
Sediment yield is important for maintaining soil health, reservoir sustainability, environmental pollution, and conservation of natural resources. The main aim of the present work is to develop four machine learning models, artificial neural networks (ANNs), radial basis function (RBF), support vector machine (SVM) and multiple model (MM)-ANNs for forecasting daily sediment yield. These models were applied to the Shakkar and Manot watersheds covering 25 years (1990–2015) and 10 years (2000–2010) of rainfall and discharge data, respectively. Results showed that the MM-ANNs model satisfactorily predicted sediment yield and outperformed the other models providing the highest correlation coefficient (0.921, 0.883) and Nash-Sutcliffe efficiency (0.744, 0.763) and the lowest relative absolute error (0.360, 0.344) and root mean square error (23,609.5, 269,671.5) for the Shakkar and Manot during the test period, respectively. Hence, the MM-ANNs model can be successfully used for sediment prediction.

Keywords Machine learning models · Sediment yield · ANN · RBF · SVM · Multiple model

1 Introduction

Watershed sediment load is an ecological hazard and its estimation is needed for developing measures for environmental protection, sustainability of reservoirs and hydropower generation, avoiding blockage of water supply systems, flood control, and maintaining soil fertility (Lin et al. 2006; Xu et al. 2012; Men et al. 2012).

In many waterways, sediment is transported in suspension and estimation of suspended sediment (SS) is basic for designing channels, dams, and culverts (Targhi et al. 2017). Awareness of potential sediment loads is important for programmes for water resource

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management and environmental protection (Melesse et al. 2011). In fact, runoff and sediment yield models are regarded as the core components of the watershed planning and management tasks implemented through the concepts used for decision support by various resource managers. Soil erosion, which is directly related to issues with transporting sediments, continues to be a major ecological concern worldwide. Continuous monitoring of soil erosion and transport of sediments, however, can be a repetitive and highly demanding task; hence detailed models for forecasting these important decision-making parameters (Gajbhiye et al. 2014, 2015).

In the last decades, artificial intelligence techniques have been applied in water resources management, especially for modelling processes with limited knowledge (Yoon et al. 2011; Chau and Wu 2010; Hsu et al. 1995). Such techniques include artificial neural networks (ANNs), and support vector machine (SVM). Neural networks are particularly useful for forecasting as they handle hydrological time series nonlinearity and uncertainty when modeling input vectors (Peng et al. 2017; Khan et al. 2005; Dhanya and Kumar 2010). Hydrologists have used ANNs since the 1990's. Over the past two decades many studies have been conducted on the efficiency of ANNs in hydrological process modeling.

Artificial neural networks have been applied in almost all branches of science. ANNs are well known for their ability to model nonlinear systems, such as precipitation-runoff, stream flow, and time series analysis (ASCE 2000). Specific applications are rainfall-runoff modeling (Chen et al. 2013; Tfwala et al. 2013; Nourani et al. 2012), groundwater management and forecasting (Lee et al. 2012; Gorelick and Zheng 2015; Nourani et al. 2008; Adamowski and Chan 2011), streamflow forecasting (Anctil et al. 2004; Besaw et al. 2010; Meshram et al. 2019a), rainfall forecasting (Chiang et al. 2004; Nasseri et al. 2008a, 2008b; Tao et al. 2018; Mirabbasi et al. 2019), suspended sediment prediction (Alp and Cigizoglu 2007; Kisi and Shiri 2012; Meshram et al. 2019b), and water quality management (Palani et al. 2008; Faruk 2010). Smith and Eli (1995) used an ANN back propagation model to estimate the peak discharge and the peak time resulting from a single pattern of rainfall. Jain and Indurthy (2003) applied ANN models for the predictions of event-based discharge and compared them to other conceptual and linear model systems. Sarkar and Kumar (2012) used ANN models for a simulation of the event-based rainfall runoff. Iraji et al. (2020) predicting reservoirs volume reduction using Artificial Neural Network (ANN). Some studies focusing on ANN-event based sediment yield modelling and concentration of sediments have been reported (Tayfur and Singh 2006; Rai and Mathur 2007; Singh et al. 2017).

The ANN will learn from the examples the careful behavior between input and output without physical interference (Wei et al. 2012; Ramezani et al. 2014). Alp and Cigizoglu (2007) contrasted the method of feed-forward back-propagation (FFBP) and the radial base functions (RBF) for regular sediment prediction. A soft computational technique was used by Ab. Ab Ghani et al. (2011) to predict sediment loads in three Malaysian rivers. The propagated feedback (schemes) ANNs architecture was used without any restriction to an extensive database compiled from measurements in different rivers in Langat, Muda, Kurau. Chang et al. (2012) assessed the efficiency of three soft computing techniques, namely neural feed forward neural network (FFNN), the adaptive neuro-fuzzy inference system (ANFIS) and gene-expression programming (GEP). Buyukyildiz and Kumcu (2017) used ANFIS, SVM, and ANN models to assess the suspended sediment load. Sharghi et al. (2018) indicated the superiority of emotional ANN (EANN) over FFNN. Nourani et al. (2019) compared Wavelet-M5 model with individual ANN and M5 models.

SVM is one of the machine learning methods utilized in hydrology and has proved to be an alternative to ANNs. SVM is used for hydrologic forecasts, such as precipitation (Behzad et al. 2009;Okkan and Serbes 2012), stream flows (Asefa et al. 2006;Liu et al. 2014), sediment (Misra et al. 2009; Azamathulla et al. 2010; Ebtehaj et al. 2016), and groundwater fluctuations

(Shiri et al. 2013; Barzegar et al. 2017) and has been found to perform better than ANNs.Yoon et al. (2011) found that prediction error of SVM for forecasting flood stage was less than the ANN models. Lin and Jhong (2015) developed the application of a multi-objective genetic algorithm SVM for hourly rainfall prediction in the Tsengwen River Basin, Taiwan. In addition to the above studies, Tayfur and Singh (2006) and Hung et al. (2009) studied the SVM model and all of them demonstrated the reliability of the model in terms of performance competencies.The main aim of the present paper is to investigate the ability of multiple model feed forward ANNs (MM-FNN) model and compare it with the single feed forward ANNs, radial basis function and SVM for daily sediment yield prediction. To the best knowledge of the writers, the capability of MM-FNN model which combines the accuracy of FFNNs, RBF and SVM methods has not been previously investigated for suspended sediment prediction.

The remaining part of the paper is presented as below. 2nd section briefly defines different types of prediction methods (ANNs, RBF, SVM, MM-ANNs). The study area and utilized data sets are described in the 3rd section. 4th section gives the utilized error measures. Determination of inputs, model development and results of models in sediment prediction are provided in the 5th section. 6th section givesthe conclusions at last.

2 Sediment Prediction Using Hybrid Learning Architecture

2.1 Artificial Neural Networks (ANNs)

The ANN architecture comprises three layers, i.e., input, output, and hidden layers as presented in Fig. 1. It can be given as below:

$$\gamma_j = f\left(\sum_i \omega_{ij}\mathcal{X}_{ij}\right) \tag{1}$$

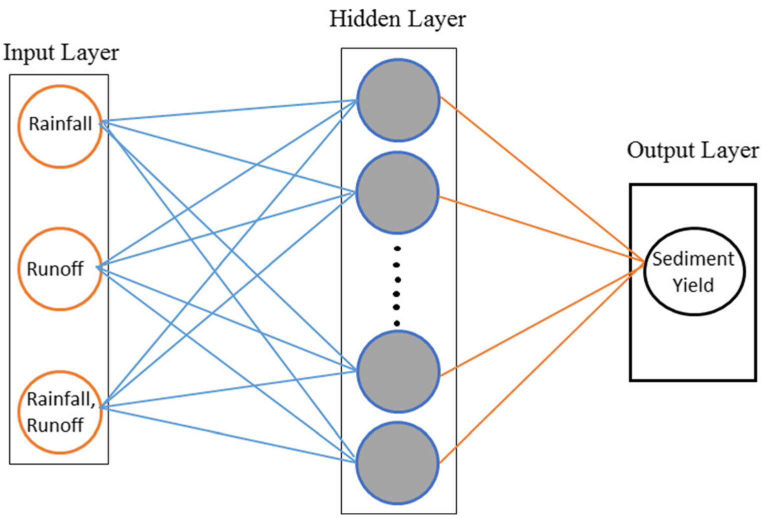

Fig. 1 A schematic structure of FNN type of ANNs

where γ_j, $f(.)$, $\mathcal{X}_{ij}$and $\omega_{ij}$are the output of node j, the transfer function, the signal of input from i^{th} node in the previous layer to j^{th} node and weight between j^{th} node and i^{th} node, respectively. In this study, feed forward ANNs (FNN) was utilized by employing Levenberg-Marquardt training algorithm.

2.2 Radial Basis Function (RBF)

RBF has been brought into ANNs due to their privately tuned reaction saw in organic neurons. Their premise lies in the interpolation of multivariate capacities. A correct RBF mapping goes through each datum point. A distinctive number of hidden layer neurons and spread constants were investigated in this examination.

2.3 Support Vector Machine (SVM)

SVM devises a computationally proficient method for learning and isolating hyper planes in a high dimensional component space (Vapnik 1995). SVM builds an N dimensional hyper-plane that isolates information into two classifications. SVM models are identified with neural systems. An SVM accomplishes higher arrangement rates in contrast with other characterization strategies. There are two types of SVM: straight SVM and non-direct SVM (Vapnik 1999). The straight SVM was utilized here.

SVM is a cutting edge classifier and can speculate direct characterization limits in a multi dimensional space (Cortes and Vapnik 1995; Cortes and Vapnik 1998; Vapnik 1998). SVM is configured by hyperplane (Cortes and Vapnik 1995) that implies the choice limits named "support vectors" (Fig. 2). The forecasting is done in light of these choice limits. In SVM, exactness is achieved in the estimation of class expectation concerning another informational index which is shaped using an ideal choice limit from the preparation information. Subsequently, the exactness rate is broken down by getting class precision (Cortes and Vapnik 1995). A basic interpretation of the SVM calculation is given afterwards. Given a training set $D = \{x_i\ \gamma_i\}_{i=1}^{n}$with input vectors $x_i = \left(x_i^{(1)}, \ldots\ldots.x_i^{(n)}\right)^T \epsilon \mathbb{R}^n$ and target labels $\gamma_i \in \{-1, +$

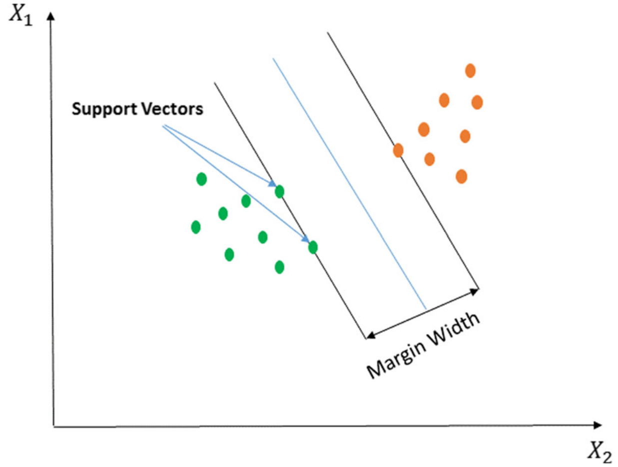

Fig. 2 A schematic representation of SVM

1} the SVM classifier, as indicated by Vapnik's unique plan, fulfills the accompanying conditions

$$w^T \varnothing(x_i) + \beta \geq +1 \quad if\ \gamma_i = +1 \tag{2}$$

$$w^T \varnothing(x_i) + \beta \leq -1 \quad if\ \gamma_i = -1 \tag{3}$$

which is equivalent to

$$\gamma_i \left[w^T \varnothing(x_i) + \beta \right] \geq 1 \qquad i = 1, 2, 3 \ldots\ldots. n$$

where w, β are the weight vector and the bias, respectively. Nonlinear function $\varnothing(.) : \mathbb{R}^2 \rightarrow \mathbb{R}^{n_k}$ maps info or estimation space to a high-dimensional, and potentially unending dimensional, highlight space (Min and Lee 2005).

Application is led with a vector which can be part direct as 1 or - 1 with a class portrayal in view of Eqs. 2 and 3 (Cortes and Vapnik 1998). The hyperplanes of specimens are not discovered by only adjoining the line. For a superior speculation they should persevere inside a specific separation. The separation of the closest specimens on the two sides of the limit is the edge which ought to be as high as feasible for an ideal speculation (Cortes and Vapnik 1998).

2.4 Multiple Model (MM-FNN)

The proposed multiple model (MM) architecture is made up of two phases (Fig. 3). In the principal layer, an artificial neural system is utilized as a classifier, which recognizes the input space into various component groups. The second layer comprises SVM, RBF and FNN which function as regressors. The proposed multiple model inputs [i.e., SVM output (Model-1), RBF output (Model-2), FNN output (Model-3)] were selected. In addition, the proposed multiple model cannot just lessen the CPU time caused by exorbitant training data yet to additionally enhance the expectation exactness.

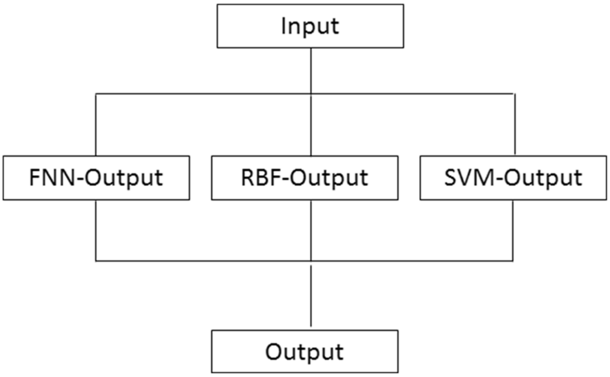

Fig. 3 Illustration of the proposed multiple model-FNN for sediment yield forecast

3 Study Area and Data Collection

Narmada basin has a region of 98,796 km^2 which is about 3% of the aggregate land zone of the nation with the most extreme width and length of 161 and 923 km. It is situated in east longitudes from 72°38′ to 81°43′ and north latitudes from 21°27′ to 23°37′. Narmada is the biggest west streaming waterway of peninsular India. It ascends from Maikala close to Amarkantak in Anuppur area of Madhya Pradesh, at a height of around 1057 m. The aggregate length of the stream is 1312 km and for the initial 1079 km it streams in Madhya Pradesh. The significant piece of basin is secured with agri-business accountingfor 56.90%. Water bodies cover 2.95% of the aggregate basin region.

For this study, two watersheds were chosen considering the available data of rainfall, runoff and sediment. A brief description of these watersheds is given as follows:

Shakkar watershed (2220 km^2) in Narsinghpur district and Manot watershed (4884 km^2) in Mandla district of Madhya Pradesh, India. Figure 4 shows these watersheds.

Daily data utilized in the present study cover rainfall (mm)-runoff (mm) and suspended sediment (MT) for the period of 1/1/1990–31/12/2015 for Shakkar watershed and 1/1/2000–31/12/2009 for Manot watershed. Out of the total data of rainfall, runoff, and sediment, 80% of data were utilized for calibration of the models and the 20% was used for model testing. Figure 5 illustrates the measured data of Shakkar and Manot sites. Table 1 sums up their statistical parameters.

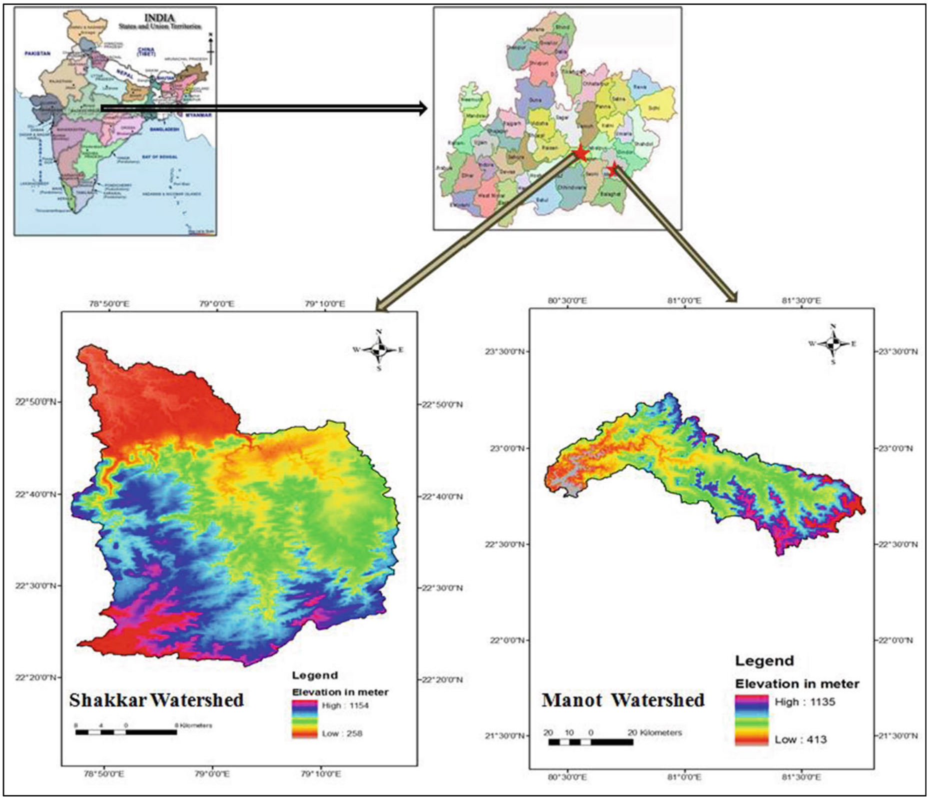

Fig. 4 Location map of the study area

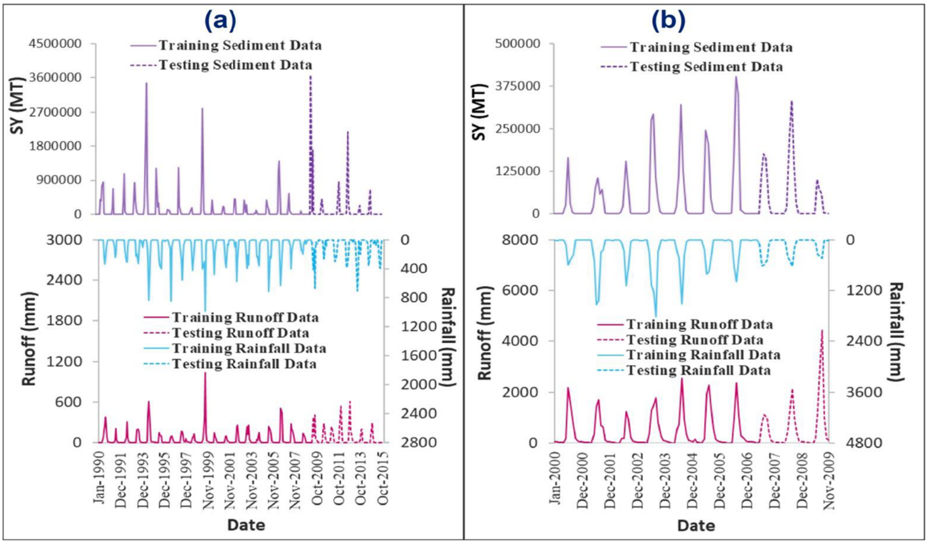

Fig. 5 Time series of measureddata utilized for **(a):** Shakkar Station and **(b):** Manot Station. SY: Sediment yield

4 Experimental Details

4.1 Model Development

Four machine learning models, FNN, RBF, SVM and MM-FNN, were implemented and assessed in sediment yield prediction utilizing daily data of rainfall-runoff and sediment data from 2 stations situated in the Narmada Basin. Before model implementation, data set was split in two subsets, training (80%) and test (20%) and program codes were employed via MATLAB for simulations. As provided in Tables 2, 3 input combinations were employed (i.e., rainfall was used as Model-1, runoff was used as Model-2, rainfall and runoff were used as Model-3).

To develop an optimal SVM model, the penalty term magnitude, the error margin deviation or width, and parameters of Gaussian radial basis function were determined for the SVM models and the optimal values of the target parameters were chosen. To obtain the optimal FNN models, data were normalized first and the models were calibrated by the LM method and

Table 1 The statistical properties of utilized data

Station	Data	Period	Count	Minimum	Maximum	Median	Mean	Standard deviation
Shakkar	Rainfall (mm)	Jan 1990-Dec 2015	312	0.0	983.0	0.0	87.6	163.1
	Runoff (mm)			0.0	1038.2	5.5	56.4	117.1
	SY (MT)			0.0	3,682,721.8	11.2	125,989.3	426,968.9
Manot	Rainfall (mm)	Jan 2000-Dec 2009	120	0.0	1824.4	7.3	204.5	372.3
	Runoff (mm)			1.9	4441.4	72.9	465.8	750.6
	SY (MT)			4.4	404,047.7	682.8	42,559.2	85,651.3

SY- Sediment Yield, MT- Metric Tonne

Table 2 Input combinations used for prediction of suspended sediment

No.	Input combinations	Models		
		FNN	RBF	SVM
1	Rainfall	FNN1	RBF1	SVM1
2	Runoff	FNN2	RBF2	SVM2
3	Rainfall, Runoff	FNN3	RBF3	SVM3

“tansig” and “linear” activation functions were set for the hidden and output layer, respectively. The quantity of hidden layer neurons was set to 1 first and then increased till the best model was obtained. To construct the MM-FNN model, the SVM, RBF, FNN outputs were used as input.

4.2 Evaluation Criteria

In this paper, four error measures were utilized to assess the quality of prediction models: Correlation Coefficient (CC), Relative Absolute Error (RAE), Root Mean Square Error (RMSE), and Nash-Sutcliffe Efficiency (NSE).

$$CC = \frac{n(\sum PQ) - (\sum P)(\sum Q)}{\sqrt{\left[n\sum P^2 - (\sum P)^2\right]\left[n\sum Q^2 - (\sum Q)^2\right]}} \tag{4}$$

$$RAE = \frac{\sum_{i=1}^{n} |P_i - Q_i|}{\sum_{i=1}^{n} |\overline{Q} - Q_i|} \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (P_i - Q_i)^2} \tag{6}$$

Table 3 Comparative performance of FNN models

Station	Model	Model structure	Training				Testing			
			CC	RAE	RMSE (MT)	NSE	CC	RAE	RMSE (MT)	NSE
Shakkar	FNN1	1–15-1	0.695	0.907	286,464.7	0.443	0.348	1.064	551,019.8	−0.070
	FNN2	1–17-1	0.950	0.213	119,382.2	0.903	0.815	0.768	494,025.8	0.140
	FNN3	2–2-1	0.877	0.386	184,332.8	0.769	**0.870**	**0.530**	**288,039.9**	**0.708**
Manot	FNN1	1–1-1	0.832	0.398	47,848.9	0.691	0.780	0.479	55,038.1	0.556
	FNN2	1–2-1	0.860	0.463	45,488.5	0.720	0.572	0.630	68,784.4	0.306
	FNN3	**2–4-1**	**0.843**	**0.421**	**47,024.0**	**0.701**	**0.782**	**0.465**	**54,176.7**	**0.570**

$$NSE = \left| 1 - \left[\frac{\sum_{i=1}^{N} (Q_i - P_i)^2}{\sum_{i=1}^{N} \left(Q_i - \overline{Q}\right)^2} \right] \right|, -\infty \le NSE \le 1 \tag{7}$$

Where n is the total quantity of data; $Q_i$and P_i are the measured and predicted data of sediment, respectively; and $\overline{Q}$ is the mean measured data.

5 Results and Discussion

The first step in building a prediction model, such as ANN (RBF/FNN) and SVM, MM-FNN, is the determination of input variables or factors. There are no set guidelines in the choice of input factors for building these models (Bowden et al. 2005; Affandi and Watanabe 2007; Firat 2008; Wang et al. 2009). In the current work, three models were implemented to search the model accuracies with respect to different input combinations. These are summed up in Table 2.

5.1 Sediment Yield Estimation with ANN

The two most prevalent neural network designs, feed forward ANNs (FNN) and radial basis function (RBF), were used for regression purposes. In the current work, three models (M1–M3) having different inputs were calibrated and evaluated using ANNs (FNN and RBF) models. The quantity of hidden nodes was gradually increased from 1 to 10 and LM algorithm was applied via the MATLAB ANN toolbox for FNN simulation.

Table 3 illustrates the accuracy of FNN models with distinct quantity of hidden neurons. The execution of FNN shifted as per the quantity of hidden neuron. In the training stage of the Shakkar Station, the FNN2 model with seventeen hidden neurons provided the best CC, RAE, RMSE and NSE while the FNN3 obtained the best CC, RAE, RMSE and NSE values (0.870, 0.530, 288,039.9 and 0.708, respectively) in the testing stage. In the training stage of the Manot Station, also FNN2 (2 hidden neurons) gave the best CC and NSE values (0.860 and 0.720, respectively), and FNN1 (one hidden neuron) the best RAE (0.398), while FNN3 (4 hidden neurons) provided the best RMSE (47024).The FNN3 provided the best CC, RAE, RMSE and NSE statistics (0.782, 0.465, 54,176.7 and 0.570, respectively) in the test stage.

According to the performance statistics in the test stage, the FNN3 (2–2-1) and FNN3 (2–4-1) models were chosen for Shakkar and Manot (Fig. 6).

Table 4 displays the results of RBF models comprising various quantities of hidden neurons (between 1 and 100). In the training and test stages of the Shakkar Station, the RBF3 model having72 hidden nodes gave the best CC, RAE, RMSE and NSE (0.913, 0.320, 156,514.3, 0.834 for training and 0.895, 0.556, 304,028.5, 0.674 for testing, respectively). In the training and testing phases, the RBF1 with 19 hidden neurons obtained the best CC, RAE, RMSE and NSE values (0.859, 0.327, 44,046.9, 0.738 for training and 0.578, 0.600, 74,219.1, 0.193 for testing, respectively).

According to the performance statistics in the test stage, the RBF3 (3–72–1) and RBF1 (1–19-1) models were chosen for the Shakkar and Manot watersheds, respectively.

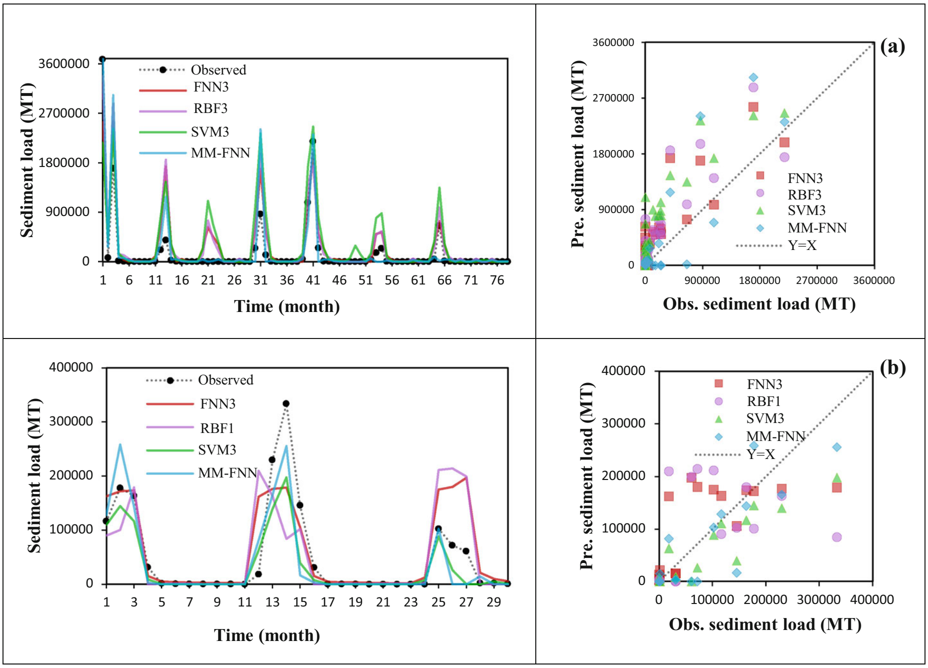

Fig. 6 Sediment yield of the testing phase by FNN, RBF, SVM, and MM-FNN, and scatter diagrams at 2 gauging stations **(a):** Shakkar and **(b):** Manot

5.2 Sediment Yield Prediction with SVM

Like ANN, the data utilized for SVM simulation were the data at time t. The C, ε and γ parameters were pre determined for SVM. Table 5 sums up the accuracy of the SVM for the training and test stages of Shakkar and Manot stations. It is observed that in the training stage

Table 4 Comparative performance of RBF models

Station	Model	Model parameters	Training				Testing			
			CC	RAE	RMSE (MT)	NSE	CC	RAE	RMSE (MT)	NSE
Shakkar	RBF1	HN: 49; r: 78.1 BF: Gaussian	0.689	0.564	278,197.5	0.475	0.264	1.105	589,735.7	−0.226
	RBF2	HN: 39; r: 77.8 BF: Gaussian	0.885	0.350	179,210.7	0.782	0.764	0.969	499,359.3	0.121
	RBF3	**HN: 72; r: 55.8 BF: Gaussian**	**0.913**	**0.320**	**156,514.3**	**0.834**	**0.895**	**0.556**	**304,028.5**	**0.674**
Manot	**RBF1**	**HN: 19; r: 59 BF: Gaussian**	**0.859**	**0.327**	**44,046.9**	**0.738**	**0.578**	**0.600**	**74,219.1**	**0.193**
	RBF2	HN: 21; r: 8.8 BF: Gaussian	0.885	0.311	39,986.1	0.784	0.509	0.658	76,120.9	0.151
	RBF3	HN: 78; r: 62 BF: Gaussian	0.918	0.264	34,107.6	0.843	0.539	0.666	84,458.1	−0.046

HN: hidden neurons, r: spread value, BF: basic function

Table 5 Comparative performance of SVM models

Station	Model	Model parameters	Training				Testing			
			CC	RAE	RMSE (MT)	NSE	CC	RAE	RMSE (MT)	NSE
Shakkar	SVM1	C: 1437.42, ε: 0.03, γ: 86.75	0.664	0.596	287,663.3	0.438	0.247	1.109	566,245.6	−0.130
	SVM2	C: 3.71, ε: 0.01, γ: 3.12	0.913	0.290	157,562.6	0.832	0.783	0.973	515,649.8	0.063
	SVM3	**C: 3.05, ε: 0.01, γ: 4.67**	**0.901**	**0.322**	**169,621.5**	**0.804**	**0.803**	**0.794**	**395,821.9**	**0.448**
Manot	SVM1	C: 2.14, ε: 0.06, γ: 1.09	0.857	0.331	44,508.1	0.732	0.631	0.544	68,403.5	0.314
	SVM2	C: 5.61, ε: 0.06, γ: 0.61	0.883	0.311	40,471.5	0.779	0.526	0.654	74,506.8	0.186
	SVM3	**C:381.79, ε:1.94e+09, γ: 3.37**	**0.901**	**0.265**	**37,409.2**	**0.811**	**0.937**	**0.339**	**40,952.6**	**0.754**

C: Magnitude of penalty term, ε: width/deviation of the error margin, γ: Gaussian radial basis function parameter

of Shakkar, SVM2 had the lowest RMSE and RAE, and the highest CC and NSE. Nevertheless, SVM3 got the best CC, RAE, RMSE and NSE in the test stage. For the Manot Station, the SVM3 had the best values of CC, RAE, RMSE and NSE in the training and test stages (Fig. 6).

5.3 Comparison of Prediction Models

We investigated the ability of the MM-FNN model for sediment yield prediction and compared with FNN, RBF and SVM models. The accuracies of the FFBP, RBF, SVM and MM-FNN models were compared using CC, RAE, RMSE and NSE. Table 6 presents the training and test results of the Shakkar and Manot stations.

In Table 6, it is shown that MM-FNN model acquired the best CC, RAE, RMSE and NSE in the training and testing stages for the both stations. The new model considerably improved the accuracy of FNN, RBF and SVM models with respect to RMSE (NSE) by 47% (7%), 54% (13%) and 121% (47%) for Shakkar and by 35% (35%), 74% (85%) and 2% (2) for Manot in

Table 6 Comparative performance of optimal models

Station	Model	Training				Testing			
		CC	RAE	RMSE (MT)	NSE	CC	RAE	RMSE (MT)	NSE
Shakkar	FNN	0.877	0.386	184,332.8	0.769	0.870	0.530	288,039.9	0.708
	RBF	0.913	0.320	156,514.3	0.834	0.895	0.556	304,028.5	0.674
	SVM	0.901	0.322	169,621.5	0.804	0.803	0.794	395,821.9	0.448
	MM-FNN (3–16-1)	0.909	0.305	160,494.5	0.825	0.921	0.360	269,671.8	0.744
Manot	FNN	0.843	0.421	47,024.0	0.701	0.782	0.465	54,176.7	0.570
	RBF	0.859	0.327	44,046.9	0.738	0.578	0.600	74,219.1	0.193
	SVM	0.901	0.265	37,409.2	0.811	0.937	0.339	40,952.6	0.754
	MM-FNN (3–18-1)	**0.913**	**0.190**	**35,519.7**	**0.830**	**0.883**	**0.344**	**40,226.5**	**0.763**

the testing stage. Results indicated that the MM-FNN model might provide an alternative to the FFBP, RBF and SVM models for predicting suspended sediment.

6 Conclusion

In this paper, the applicability of new multi-mode neural network, MM-FNN, model was investigated and compared with the performances of FNN, RBF and SVM in predicting sediment yield. The MM-FNN model was found to provide better prediction results than did other models in two stations. The MM-FNN model provided the highest CC and NSE and the lowest RAE and RMSE in both training and testing data sets. By implementing new model scheme, improvements obtained for the single models (FNN, RBF and SVM) with respect to RMSE and NSE were 47% (7%), 54% (13%) and 121% (47%) for the Shakkar Station and by 35% (35%), 74% (85%) and 2% (2) for the Manot Station in the testing stage, respectively. Thus, MM-FNN models are recommended as an alternative model to the FNN, RBF and SVM in predicting sediment yield.

Compliance with Ethical Standards

Conflict of Interest All Authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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