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OUED EL ABIOD BASIN (ALGERIA): SOLID TRANSPORT ESTIMATION BY THREE ARTIFICIAL NEURAL NETWORK METHODS

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ABSTRACT

The assessment of sediment transport in river is important in water resource management such as the design and control dams and other hydraulic structures. In this paper, Three Artificial Neural Network methods are used to estimate the daily suspended sediment concentration for the corresponding daily discharge flow in the river of Oued El Abiod watershed, Biskra, Algeria. The Feed-forward Neural Networks (FFNN), generalized regression neural networks (GRNN) and the radial basis neural networks (RBNN) models are established for estimating current suspended sediment values. The two criteria RMSE and R^2 were used to evaluate the performance of applied models. The comparison of three models showed that the RBNN method provided generally the better than the other methods in estimation of suspended sediment. Therefore, the ANN model had capability to improve nonlinear relationships between discharge flow and suspended sediment with reasonable precision.

Keywords: Artificial Neural Network, Oued Abiod watershed, Generalized Regression, Suspended Sediment.

INTRODUCTION

The assessment of sediments being carried by a river is importance for planning and designing of various water resources projects. Sediment yield is defined as “the total sediment outflow from a watershed, measurable at a point of reference during a specified period of time” by American Society of Civil Engineers (Singh and Krstanovic, 1987). Sediment concentration can be defined as the mass of sediment which is entrained within a unit volume of water. In order to measure sediment concentration a variety of method has been developed (Pavelsky and Smith, 2009; Singh and Krstanovic, 1987). Classical methods of predicting sediment transport are based on the empirical formulas (e.g. regression models) which attempt to obtain relationship between sediment yield and flow discharge and thus sediment concentration and flow discharge. But the formulas obtained by the conventional methods are incapable of being fairly accurate in the prediction of sediment discharge and sediment concentration. For instance, in Algeria, Fournier formula (1960) is tested about thirty basin and the results obtained are mediocre (Remini and Hallouche, 2007). It is now realized that complex phenomena require intelligent systems. Neural network approaches have been successfully applied in a number of diverse fields including hydraulic and hydrological phenomena. Some of the hydrological applications analyzed are rainfall–runoff modeling (Wilby and al., 2003), groundwater simulation (Nourani and al., 2008), river flow modeling (Cigizoglu and Kisi, 2004; Hu and al., 2001) , and hydrological time series modeling (Jayawardena and al., 2006) and suspended sediment modeling (Aydın and Eker, 2012; Chutachindakate and Sumi, 2008; Cigizoglu and Kisi, 2006; Eisazadeh, 2013; Kisi and al., 2008; Wang and al., 2009; Zhu and al., 2007). Application the neural network for predicts suspended sediment in the different river basin in Algeria has just come into the limelight. In this study, river of Oued El Abiod watershed in upstream of Foum El Gherza dam, Biskra (Algeria), are selected for estimating sediment concentration by using several type of Neural Network: Feed-forward Back propagation, Generalized Regression and Radial Basis Function. Therefore, 600 data sets of sediment concentration have been used.

STUDY AREA AND DATA BASE

Geographical location of the Oued El Abiod Watershed

Certain areas throughout the world possess an inherent vulnerability to the processes of erosion, particularly in warm and dry climates where vegetation is sparse. One such area is the province of Biskra located at 400 km in southeast Algeria (Fig. 1). Foum El Gherza Dam is a concrete arch dam; constructed in 1950 with capacity of 47 Hm^3 in Biskra (Fig. 2), Algeria is exclusively destined for irrigation. Its initial regularized volume is estimated at 13 Hm^3. Currently its total capacity is 14.89 Hm^3, of which 10 Hm3 usable volume.

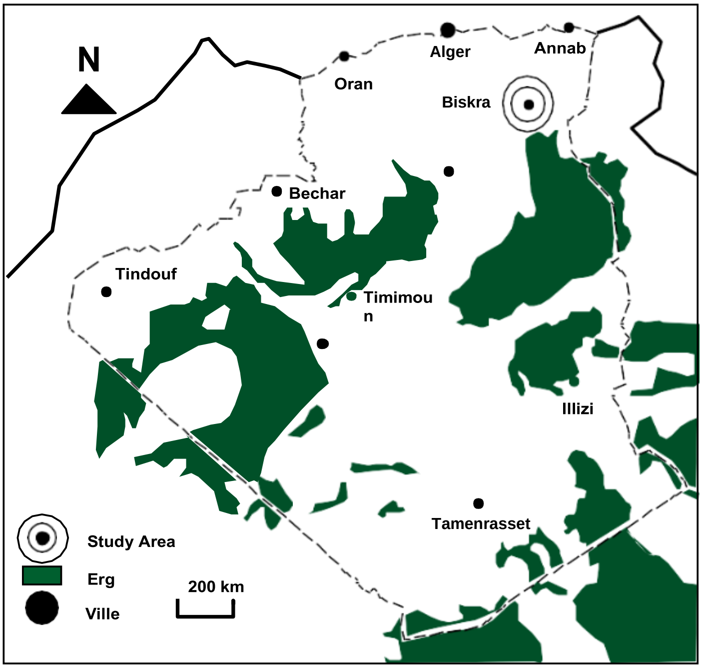


Figure 1: Geographical location of the El Abiod Watershed (Remini, 2015)

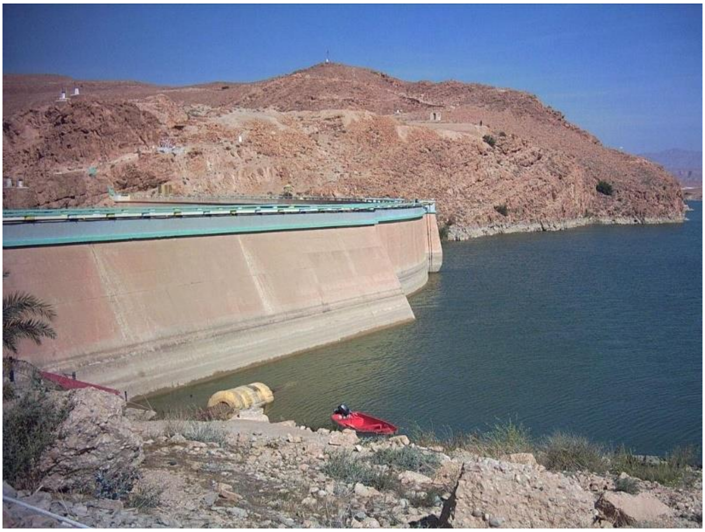


Figure 2: Foum El Gherza Dam (Photo Remini, 2007)

State of Foum El Gherza dam

Foum El Gherza Dam receives approximately 0.6 Mm^3 of sediment per year from its 1300 Km^2 Oued El Abiod watershed (Fig. 3). Hence, the rate of siltation dam attains 75% (Fig. 4). Due to the accelerated silting up of the dam, a dredging operation was carried out in 2006 to remove 4 million m^3 of mud (Fig. 5). A second dredging operation was launched in 2016 to remove 8 million m3 of mud. The dredge is currently in the dam.

Oued El Abiod watershed is located in the massif of Aures, it is part of the great watershed Chott Melrhir which consists of three main rivers: Oued El Abiod River, Chenawra River and Tkout River. Oued El Abiod watershed is characterized by arid climate, sparse vegetative cover, and high relief.

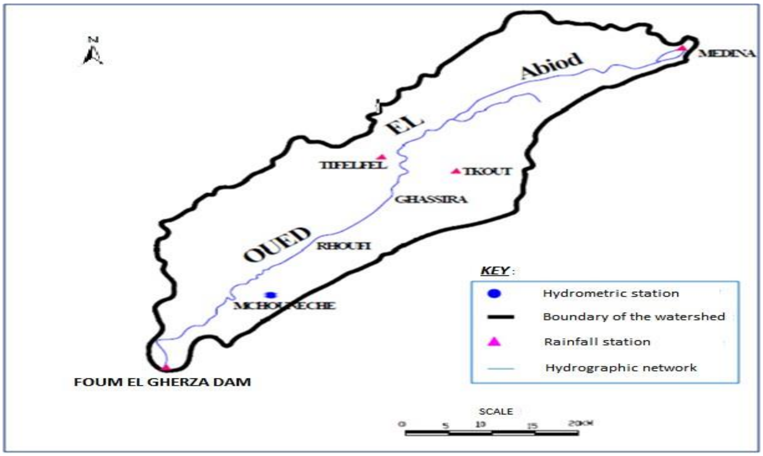


Figure 3: Located of stations in Oued El Abiod watershed

Figure 4: Progress of the sediment delta in the Foum El Gherza dam (Photo Remini, 2006)

Figure 5: Desilting of Foum El Gherza dam (Photo Remini, 2006)

DATA USED

Our database of flow discharges and suspended sediment concentration consists of 600 samples for each one (Fig.6), collected at station Mechounech (code 06-15-02) which are located in upstream of the dam Foum El Gherza. However, this study applies a daily flow discharge and suspended sediment concentration data for training the network.

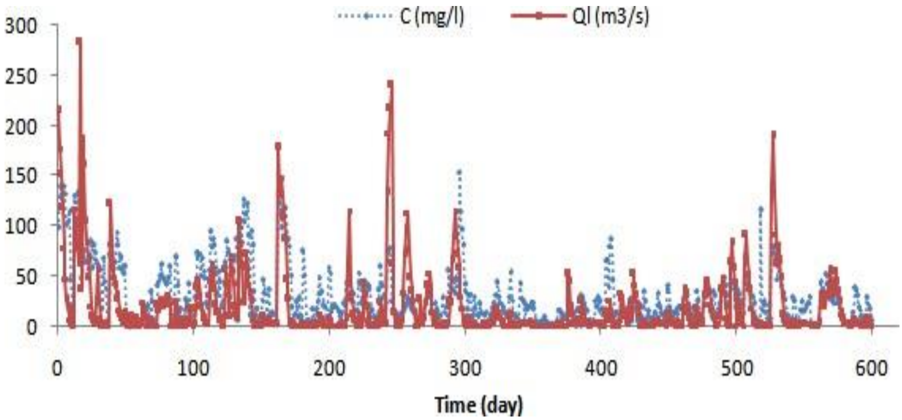


Figure 6: Suspended sediment concentration (C) and flow discharges (Ql) time series

METHODOLOGY

As a prelude, we shall provide a bird's eye view of relevant information for Artificial Neural Network. Neural network publications span multiple disciplines: neurobiology, physics, psychology, medical science, mathematics, computer science, and engineering. Since its revival in the mid 1980's, neural network is modeled on biological processes for information processing, including specifically the nervous system and its basic unit, the neuron. Signals are propagated in the form of potential differences between inside and outside of cells (neurons). Dendrites bring signals from other neurons into the cell body or soma, possibly multiplying each incoming signal by a transfer weighting coefficient. A mathematical model of the neuron is depicted in Figure 7, which shows the dendrite weights vj, the firing threshold v0 (also called the bias), the summation of weighted incoming signals, and the nonlinear function σ(.). The cell inputs are the n signals at the time instant k x1(k), x2(k), x3(k) . . . xn(k) and the output is the scalar y(k), which can be expressed as:

$$y(k) = \sigma\left(\sum_{j=1}^{n} v_j\, x_j(k) + v \qquad \textbf{(1)}$$

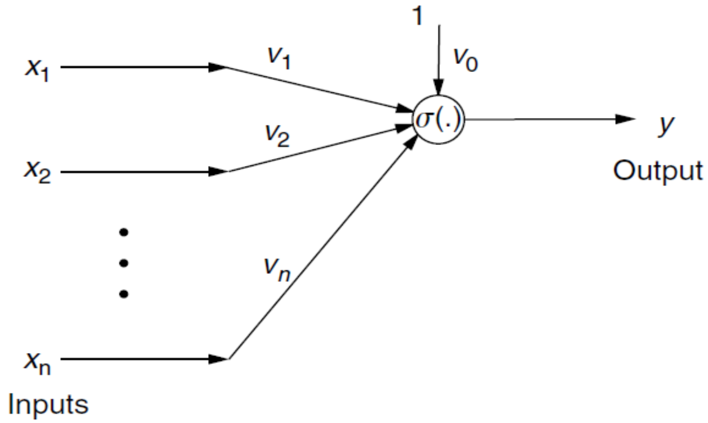


Figure 7: Mathematical model of a neuron.

The basic details and concepts of the working of an ANN can be found in (Bishop, 1995; Haykin, 1999). The input layer admits the incoming information, which is processed by the hidden layer(s), and the output layer presents the network result. During the learning process, the weights of the interconnections and the neural biases are adjusted in trial-and-error procedures, to minimize the errors. In this study, the number of input data (flow discharges) is equal to the output data (sediment concentration). The main purpose of this study is to analyze and discuss the performances of three different ANN techniques, namely, the Feed-forward Neural Networks (FFNN), generalized regression neural networks (GRNN) and the radial basis neural networks (RBNN), in the prediction and estimation of suspended sediment concentration. Tow statistical factor to evaluate the performance of the FFNN, GRNN and RBNN models in prediction of suspended sediment concentration are coefficient of determination (R^2) and root mean square error (RMSE), expressions for which are as follows:

$$R^2 = \left(\frac{\sum_{i=1}^{n} (C_{io} - \bar{C}_o)(C_{is} - \bar{C}_s)}{\sqrt{\sum_{i=1}^{n} (C_{io} - \bar{C}_o)^2 \sum_{i=1}^{n} (C_{is} - \bar{C}_s)^2}} \right)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (C_{io} - C_{is})^2} \quad (3)$$

C_{io} : Observed sediment concentration.

$\bar{C}_{io}$: Mean observed sediment concentration.

C_{is} : Estimated sediment concentration.

$\bar{C}_{io}$: Mean estimated sediment concentration.

Feed-forward neural networks (FFNN)

In this study, two-layer feed-forward networks were implemented, with a tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer, theoretical works have shown that a single hidden layer is sufficient for a FFNN to approximate any complex nonlinear function (Cybenco,1989). Neurons on the input layers are the flow discharges. The neurons on the output layer represent the suspended sediment concentration. The number of neurons (Nh) in the hidden layer varying from 5 to 1000 was employed, determined after an iterative process, since there is no algorithm available to indicate how many neurons in the hidden layer are necessary to simulate any function. The Levenberg–Marquardt algorithm was employed to train the ANN models, because it is more powerful and faster than the conventional gradient descent technique (Cigizoglu and Kisi, 2006; Hagan and Menhaj, 1994). During training the weights and biases of the network are iteratively adjusted to minimize the network performance function.

Generalized regression neural networks (GRNN)

The basics of the GRNN can be found in the literature (Specht, 1991). The GRNN consists of four layers: an input layer, a pattern layer, a summation layer, and an output layer, schematic of the GRNN is shown in Fig. 8.

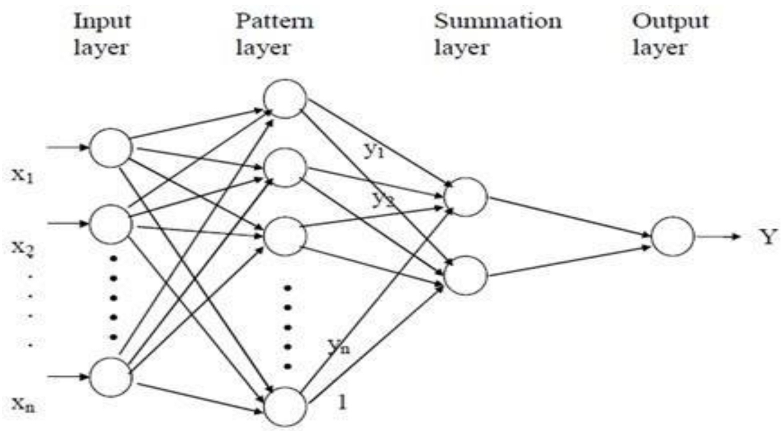


Figure 8: Schematic of the GRNN

The GRNN method is used for estimation of continuous variables, as in standard regression techniques. It is related to the radial basis network and is based on a standard statistical technique called kernel regression (Specht, 1991). The GRNN method does not require an iterative training procedure as for the FFNN method. However, the success of the GRNN method depends heavily on the spread factors (Wasserman, 1993; Specht, 1991). The larger that spread is, the smoother the function approximation. Too large a spread means a lot of neurons will be required to fit a fast changing function. Too small a spread means many neurons will be required to fit a smooth function, and the network may not generalize well. In this study, a range of spread constants (Sc) was tested order to determine the optimum smoothing factors for model inputs.

Radial basis neural networks (RBNN)

Radial basis neural networks were introduced into the neural network literature by Broomhead and Lowe (1988). The RBNN method as an artificial neural network consists of three layers: a layer of input neurons feeding the feature vectors into the network; and a layer of output neurons, and a hidden layer of RBNN neurons, calculating the outcome of the basic functions (Fig. 9). The basis function in the hidden layer produces a significant non-zero response to input stimulus only when the input falls within a small localized region of the input space. Hence, this paradigm is also known as a localized receptive field network (Lee and Chang, 2003).

The RBNN which is implemented for classification problems by using supervised training, because of certain advantages of RBNN over other artificial neural network models such as better approximation capabilities, simpler network structures and faster learning algorithms (Aik and Zainuddin, 2008). In the present study, different numbers of spread constants (Sc) are examined for the RBNN models.

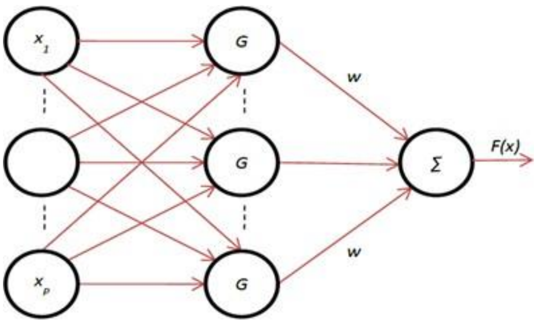


Figure 9: Radial Basis Function Neural Network Toplogy

RESULTS AND DISCUSSION

Estimation sediment concentrations using FFNN model

A difficult task with the Feed-forward Neural Network (FFNN) method is choosing the number of hidden nodes. There is no theory yet to tell how many hidden units are needed to approximate any given function. In this study, the feed-forward network with one hidden layer and different number of hidden nodes (Nh) are used. Table 1 gives the determination coefficients R^2 and RMSE for each number Nh. It can be seen from Table 1 that the FFNN whose number of hidden nodes Nh = 800 has the highest R^2 (0.868) and the smallest MRSE (10.612 mg/l).

Table 1: Values of determination coefficient R^2 and MRSE, for FFNN model.

Number hidden nodes Nh	R^2	RMSE (mg/l)
5	0.511	20.477
10	0.564	19.344
20	0.535	20.016
50	0.616	18.153
100	0.669	16.841
600	0.847	11.458
800	0.868	10.612
1000	0.595	19.218

The correlation statistic between the observed and estimated sediment concentration for different number hidden nodes are presented in figure 10 (a and b).

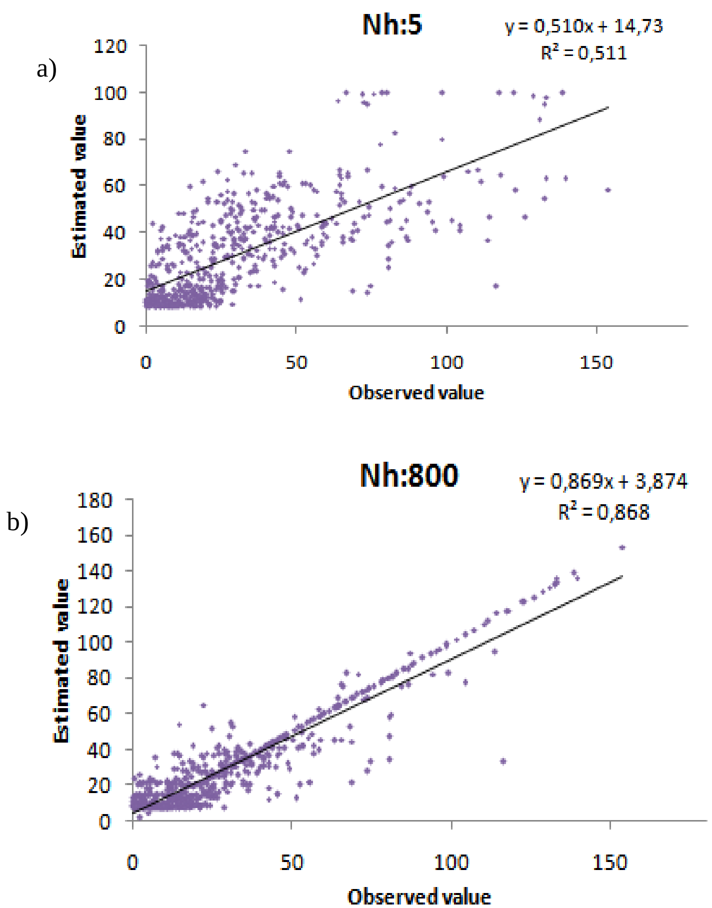


Figure 10: Linear regression of observed and estimated suspended sediments using FFNN model, (a) for Nh = 5, (b) for Nh = 800.

Estimation sediment concentrations using GRNN model

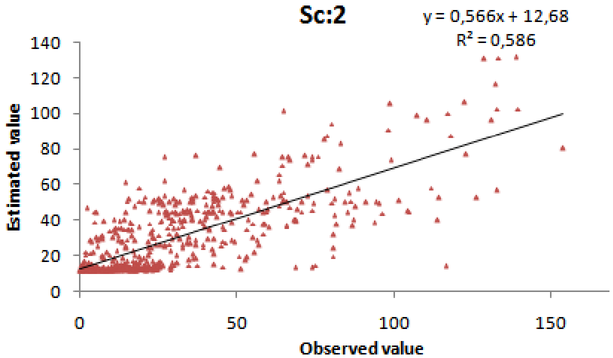
For the GRNN model, different spreads were tried to find the best one that gave the highest R^2 and minimum MRSE. The optimum spread constants were found Sc = 0.01. Therefore, the highest R^2 (0.959) and the lowest RMSE (5.925 mg/l) values were obtained for spread constants Sc = 0.01. The performance of GRNN is highly increased when the spread constants decrease for the range [2;0.01] (Table 2).

Table 2: Values of determination coefficient R^2 and MRSE, for GRNN model

Spread constants Sc	R^2	RMSE (mg/l)
2	0.586	18.855
1	0.634	17.721
0.5	0.684	16.474
0.1	0.832	12.013
0.05	0.877	10.282
0.01	0.959	5.925

Figure 11 show the correlation between the observed and estimated sediment concentration for different spread constants. Further, slightly better correlation is observed with the spread constants equal to 0.01.

a)



b)

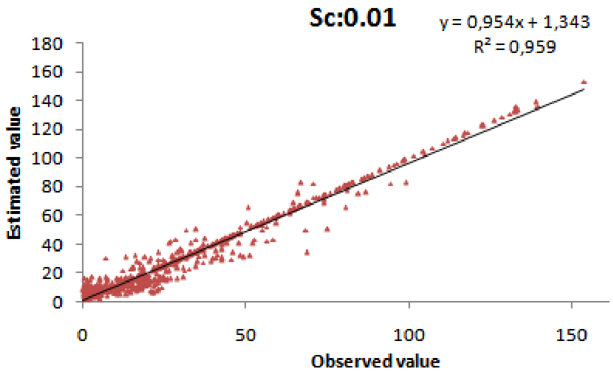


Figure 11: Linear regression of observed and estimated suspended sediments using GRNN model, (a) for Sc = 2, (b) for Sc = 0.01.

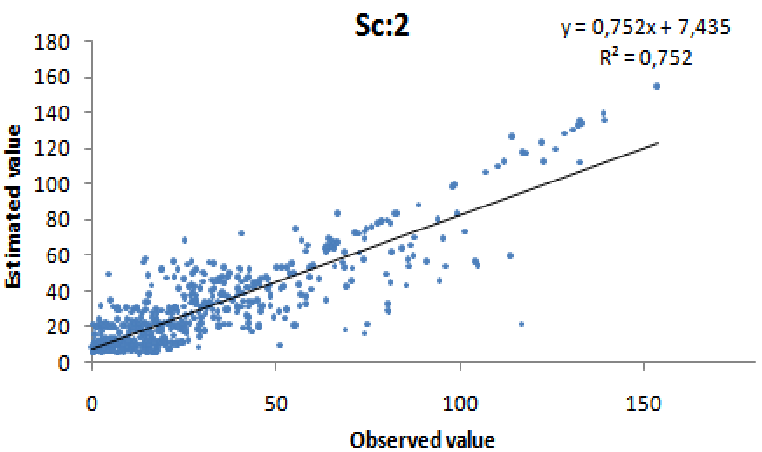
Estimation sediment concentrations using RBNN model

For the RBNN model, different spread constants were tried. Observed and predicted suspended sediment for different spread constants presented in Table 3. It is clearly evident that the performance of RBNN shows good when spread constants are decrease for the range of [2-0.01]. The spread constants that gave the highest R2 (0,967) and the minimum MRSE (5.313 mg/l) was found to be Sc=0.01. Comparison of results showed that the RBNN model could be successfully applied for sediment concentration estimation as it significantly improves the amount of prediction accuracy. The RBNN performance seems to be slightly better than that of the FFNN and GRNN models. The correlation between the observed and estimated suspended sediments for different spread constants is shown in Fig. 12.

Table 3: Values of determination coefficient R^2 and MRSE, for RBNN model

Spread constants Sc	R^2	RMSE (mg/l)
2	0.752	14.593
1	0.815	12.588
0.5	0.880	10.145
0.1	0.955	6.172
0.05	0.963	5.602
0.01	0.967	5.313

a)



b)

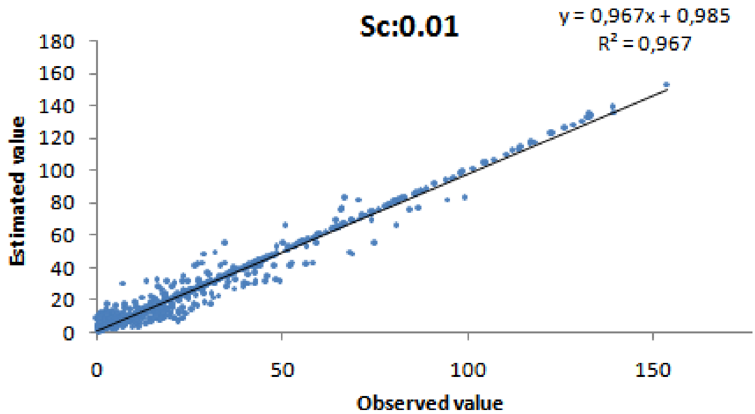


Figure 12: Linear regression of observed and estimated suspended sediments using RBNN model, (a) for Sc = 2; (b) for Sc = 0.01

CONCLUSION

This study confirmed that the assessment of the daily suspended sediment concentration in Oued El Abiod river is possible using the ANNs techniques. Two statistics factors to evaluate the performance of different techniques are employed; the determination coefficient R^2 and RMSE (root mean square of error). The highest R^2 and smallest RMSE are introduced the best method. The obtained results from the FFNN implementing with Levenberg–Marquardt algorithm indicated that the good performance of estimated sediment concentration with 800 neurons in the hidden layer with the R^2 = 0.868 and RMSE = 10.612 mg/l were obtained. The GRNN model had the best results when the spread constants are low. The amount of RMSE and R^2 in this method for spread constant equal 0.01 is 5.929 mg/l and 0.959 respectively. Same as GRNN the RBNN method gave a much better estimate when the spread constant are small. For spread constant equal 0.01, the determination coefficient R^2 and MRSE is equal to 0.967 and 5.313 mg/l respectively. The comparison of three models indicated that RBNN model performed better than the FFNN and GRNN models in estimation of suspended sediment concentration. The GRNN method ranked as the second best. The FFNN method provided the worst performance than the RBNN and GRNN models.

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