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PSO-ANN's based suspended sediment concentration in Ksob basin, Algeria

Baazi Houria*, Kalla Mahdi and Tebbi Fatima Zohra

Natural Hazards and Territory Planning Laboratory (LRNAT), Hadj Lakhdar University, Batna (UHLB), Algeria.

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Suspended sediment concentration estimation has a major influence on river basin planning and management. Prediction of such parameter with artificial neural network (ANN) has shown its performance, because of this, Back Propagation Neural Network model trained with particle swarm optimization (PSO) is used to forecast the daily sediment concentration for Ksob river, Tebessa using 22 years data set from Morsott gauging station; the recorded daily suspended sediment concentrations and correspondent daily discharges were used to train the ANN model. PSO is used to allow ANN architecture to be easily optimized. Simulation of both ANN and PSO-ANN models has shown more accurate results compared with the traditional sediment rating curve.

Key words: Ksob basin, Algeria, sediment rating curve, neural networks, particle swarm optimization.

INTRODUCTION

The estimation of sediment yield is of crucial importance, especially to ensure the efficient operation of hydraulic structures management and also for environmental issues. For many years, suspended sediment concentrations have been collected in gauging stations and to estimate sediment concentrations during periods when samples are not collected, relations between sediment concentrations or load and stream flows are developed and known as sediment rating curve (SRC) (Asselman, 2000; Cohn et al., 1989; Horowitz, 2002). This technique has been use for a long time despite errors involved in using it (Walling, 1977).

Artificial neural network (ANN) is an alternative and complementary set of techniques to traditional models (Abrahart et al., 2005; Cigizoglu, 2008). They may be treated as an universal approximators (ASCE, 2000) and most of their attractive features are self-learning, self-adapting, good robustness and capability of dealing with non-linear problems (Dhar, 2010), without the physics being explicitly provided to them (Nagesh, 2004).

Among many successful bio-inspired Swarm Intelligence, the well known approach particle swarm optimization (PSO) which was inspired from the social behaviors of birds flocking or fish schooling and was developed by Kennedy and Eberhart (1995). It is similar to Genetic Algorithms (GA) in the sense that is a population-based search method.

Combining ANN and Swarm Intelligence has received much attention in several engineering issues in order to overcome single model deficiencies (Chen, 2014). In the present study, an hybrid model of a ANN combined with particle swarm optimizer (PSO) in order to improve ANN

*Corresponding author. E-mail: Inondation100@gmail.com.

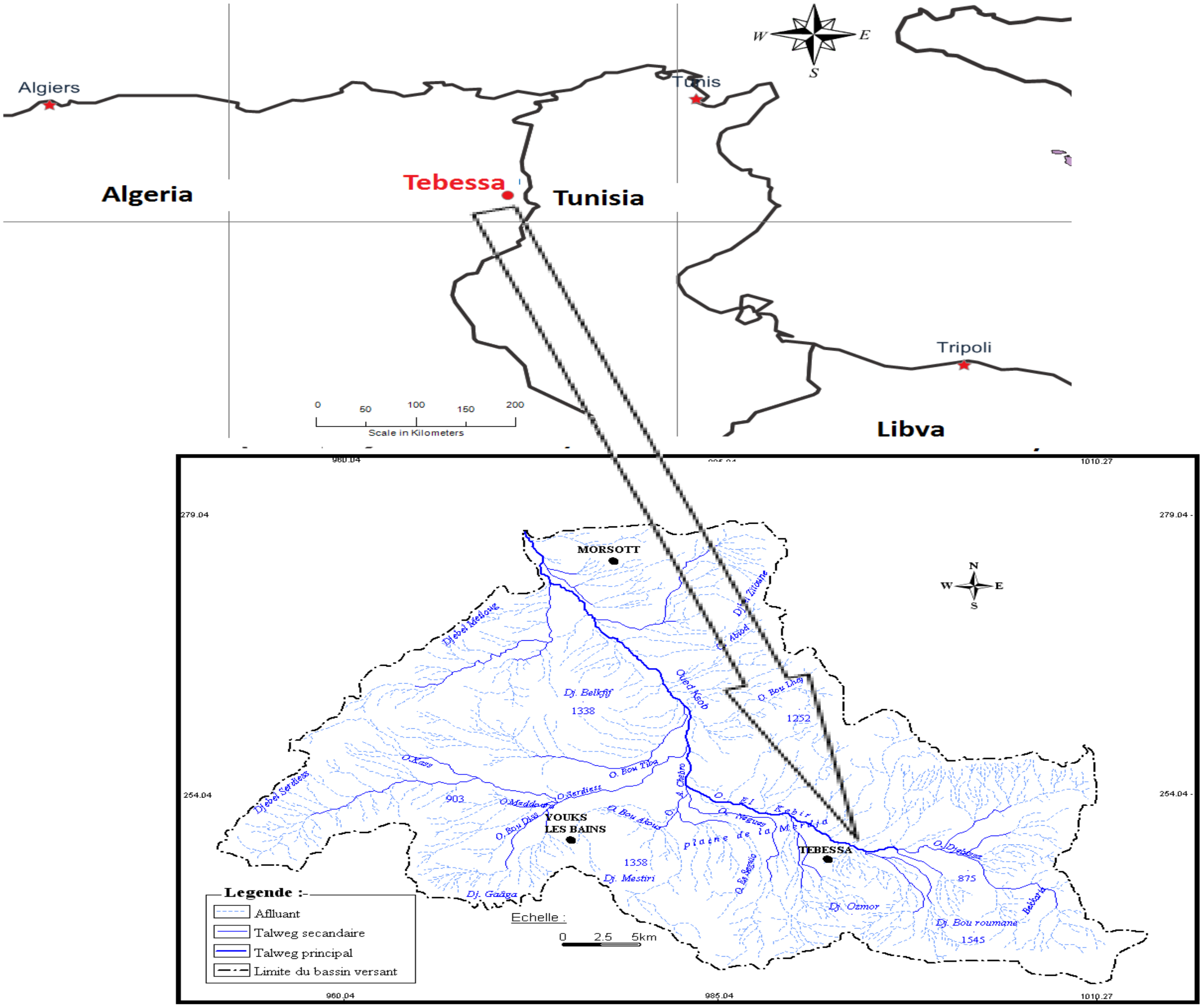

Figure 1. Ksob basin location map.

training for suspended sediment modelling of Morsott gauging station data in the Ksob basin of Tebessa town, Algeria.

Study area

The Ksob catchment (1304 km^2) is located in the extreme northeast of Algeria (Figure 1). It is a sub –basin of Wadi Medjerda, and a part of the Sahara Atlas. It is wedged between of 35° 21` to 35° 43 N and longitude 7° 43` to 8° 21` E. The region is characterized by semi-arid climate with very hot and dry summer and very cold and wet winter. Inter annual average rainfall is about 339 mm. These rains are often in stormy form. The annual average temperature is around 16°C with a maximum in July (25.87°C) and a minimum in January (6.52°C).

Vegetation consists of forests, maquis and reforestation, the remaining area is divided between agricultural lands and wastelands. The development of agriculture is heavily compromised by soil characteristics, runoff, and intensity of human action. The basin consists mainly of old and recent alluvium, clay, sand stone and limestone gravel. These formations gave good soil permeability.

METHODS

Sediment rating curve

A sediment rating curve (SRC) is a relationship established between sediment concentration, *C*, and water discharge, *Q*, or

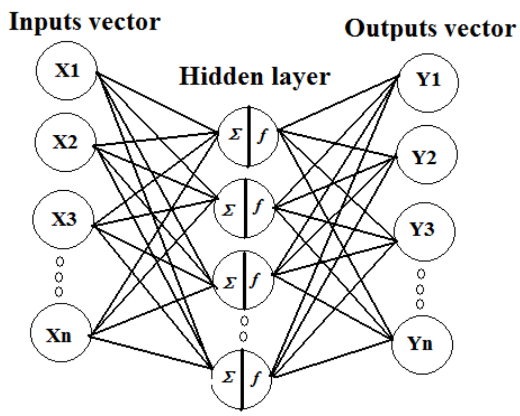

Figure 2. MLP architecture.

between sediment load Q_s, and discharge Q. It is a 'black box' type model not directly related to any physical parameters (Tebbi et al., 2012) and having a standard form of:

$$C = aQ^b \tag{1}$$

Or

$$Q_S = a'Q^{b'} \tag{2}$$

Coefficients a, a' and b, b' are empirically determined where a represents the sediment concentration for a discharge of 1.0 m^3s^{-1}, a' represents the sediment load for a discharge of 1.0 m^3s^{-1} and b and b' reflect load response to changes in discharge and typically fall in the range of 1 to 2 or possibly higher (Julien, 2010).

Large number of studies were conducted to estimate suspended sediment yields using SRC method in Algerian rivers (Achite and Ouillon, 2007; Khanchoul et al., 2010; Khanchoul and Jansson, 2008; Terfous et al., 2001; Touaibia et al., 2001). Most of these studies preferred the form of Equation (2) of the method ($Q_s=a'Q^{b'}$).

Artificial neural networks

Artificial neural networks (ANN) consist of layers of interconnected artificial neurons (Figure 2). A neuron (also called a "node" or "unit") is the basic unit of an artificial neural network, simulating a biological neuron. It performs a weighted sum of inputs and passes this to an activation function to produce the output of the neuron. A multi-layer perceptron is feedforward neural network that consists of neurons arranged in a distinct layered topology. The input layer nodes serve to introduce the values of the input variables. The hidden and output layer neurons are each connected to all of the units in the preceding layer.

For most applications fully-connected networks are better. There is usually some weight associated with every connection. Input layer represents the non processed information that is introduced into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input units and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden units and output units (Sivanandam and Deepa, 2006). To adjust the weights, the most common learning algorithm is called Back Propagation.

ANN are being used alone or hybridized increasingly to predict and forecast water resources variables and have seen significant activity in various hydrology related areas such as rainfall-runoff (Kim, 2005), stream flow (Dolling and Varas, 2002), ground water (Daliakopoulos et al., 2005; Sreekanth et al., 2009), precipitation forecasting and water quality issues (Eslamian and Lavaei, 2009; Shamim et al., 2004), and for designing optimal strategies in reservoir operation (Chandramouli and Deka, 2005; Chaves and Chang, 2008; Hasebe and Nagayama, 2002). Also, ANN have been widely used for sediment transport modeling (Abrahart et al., 2008; Adib and Tagavifar, 2010; Chutachindakate, 2009; Cigizoglu and Alp, 2006; Cigizoglu and Kisi, 2006; Firat and Güngör, 2010; Kisi, 2007; Liu et al., 2013; Rajaee et al., 2011; Wang et al., 2008).

In Algeria, Boukhrissa et al. (2013) investigated the ability of ANN models to improve the accuracy of streamflow-suspended sediment relationships in daily and annual suspended sediment estimation for the El Kebir catchment and shown that the ANN models have the highest efficiency to reproduce the daily sediment load and the global annual sediment yields.

Kisi (2012) using daily stream-flow and suspended sediment concentration data from two stations on the Eel River in California, found that Least Square Support Vector Machine performs better than ANN models. Kisi et al. (2012a) applied Genetic Programming technique for estimating the daily suspended sediment load in two stations in Cumberland River in U.S.; results were comparecd with those of the Adaptive Neuro-Fuzzy Inference System, Artificial Neural Networks and Support Vector Machine, Genetic Programming give beter accuracy. Most of actual studies attempt to improve ANN models accuracy by hybridization with several evolutionary techniques.

Ramezani et al. (2014) used an ANN approach to predict sediment for Maroon River in Iran by optimizing the ANN connection weights with social based algorithm (SBA). Kisi et al. (2012b) compared neural networks with Artificial Bee Colony algorithm model with those of the Neural Differential Evolution, Adaptive Neuro-Fuzzy, Neural Networks and Rating Curve models using data from two stations, Rio Valenciano Station and Quebrada Blanca Station results showed that the ANN-ABC was able to produce better results than other models.

Kisi (2005) found that neuro-fuzzy gives better estimates than neural networks. Using 11-year data (1994 to 2004) of Doiraj River located in Iran, Kalteh (2013) applied both ANN and SVM models for predicting suspended sediment load and found that ANN models based on a quasi-Newton method named Broyden, Fletcher, Goldfarb and Shanno (BFGS) algorithm has a better performance comparing with other models.

Particle swarm optimization

The basic particle swarm optimization (PSO) algorithm consists of three steps, namely, generating particle's positions and velocities, velocity update, and finally, position update. First, the positions, $X_{id}(k)$ and velocities, $V_{id}(k)$ of the initial swarm of particles are randomly generated.

The positions and velocities are given in a vector format for the i_{th} particle at time k. The second step is to update velocities of all particles at time $k+1$ using the particles objective or fitness values, which are, function of the particles current positions in the design space at time k.

The fitness function value of a particle determines which particle has the best global value in the current swarm, P_{best}^{id}, and determines the best position of each particle over time, p_{id}, that is, in current and all previous moves.

The velocity update formula uses these two pieces of information for each particle in the swarm along with the effect of current motion, $v_{id}(k)$, to provide a search direction, $V_{id}(k+1)$, for the next iteration.

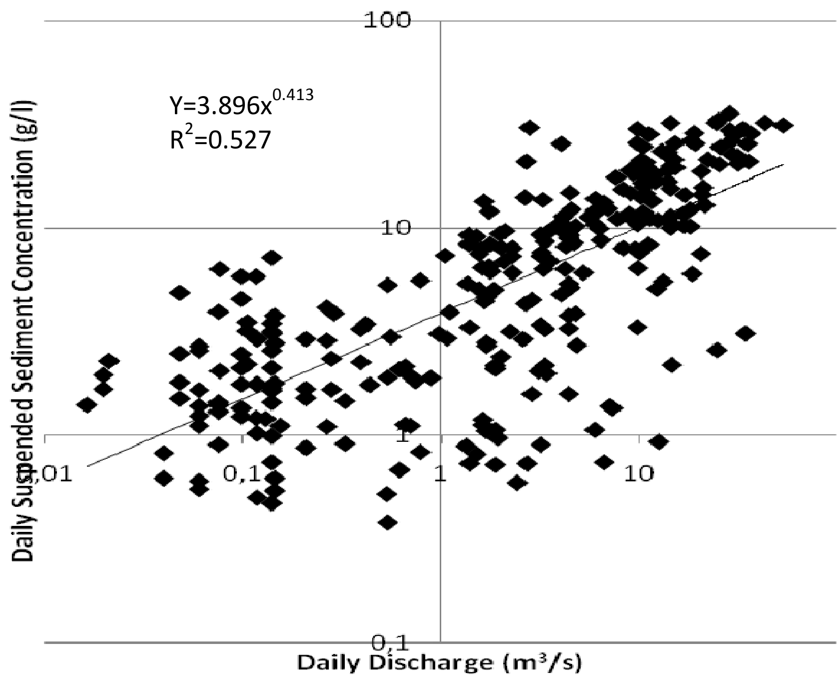

Figure 3. Sediment Rating Curve for Morsott station (1976-2002).

$$\vec{V}_{id}(k+1)=W\times\vec{V}_{id}(k)+C_1\times\varphi_1\times(P_{best}^{id}-P_{id}(k))+C_2\times\varphi_2\times(G_{best}^{id}-P_{id}(k)) \quad (3)$$

Where i=1,2,…n . n is the number of particles. d=1,2,3,…m, m is the number of input variables to be optimized. W=weights trading off the impact of the local best and global best solutions' on the particle's total velocity. C_1, C_2 Position update is the last step in an iteration. φ_1, φ_2 samples a uniform random distribution [0,1].

$$X_{id}(k+1) = X_{id}(k) + V_{id}(k+1) \quad (4)$$

The three steps of velocity update, position update, and fitness calculations are repeated until a desired convergence criterion is met.

RESULTS AND DISCUSSION

Figure 3 is constructed using 294 data of both mean daily suspended sediment concentrations and mean daily discharges of Morsott gauging station in the period of 02/1975 to 10/2002. Goodness of sediment rating curve fit using Equation (1) is checked using coefficient of determination R^2. R^2 obtained for the best fit by a single curve is 0.527 and corresponding root mean square error is 6.0359 g l^{-1}.

ANN model

To be able to compare SRC method and other methods we used daily discharges (m^3/s) as the unique inputs in ANN_BP model. Matlab's neural network fitting tool creates a two-layer feed-forward with sigmoid hidden neurons and linear output neurons and it is trained with Levenberg-Marquardt backpropagation algorithm. Also training, validation and test sets are sampled respectively taking 70, 15 and 15%. Number of neurons in hidden layer is taken as 3. Figure 4 compares outputs of the ANN_BP model and observed suspended sediment concentrations.

PSO- ANNmodel

For combining particle swarm optimization algorithm and BP_ANN algorithm using a Matlab® code, the first step is initialization of random particles that represents a set of weights, and then simulating neural network, then evaluate fitness value of initialized particles. Determination of optimal solution individual Pbest and global Gbest according to the fitness value of each particle, and updating the velocity and position of particles according to Formulas (3) and (2). Best particle of current particles is stored. Repeat iteration until maximum number of iteration is met (Figure 5).

Estimating suspended sediment concentration by SRC, ANN and PSO_ANN's respectively enable us to estimate suspended sediment concentrations in the Ksob basin. Figure 6 shows linear regression between observed and simulated concentration using different transfer functions and different training algorithms of PSO_ANN model for test period. We can observe that R^2 is improved about.

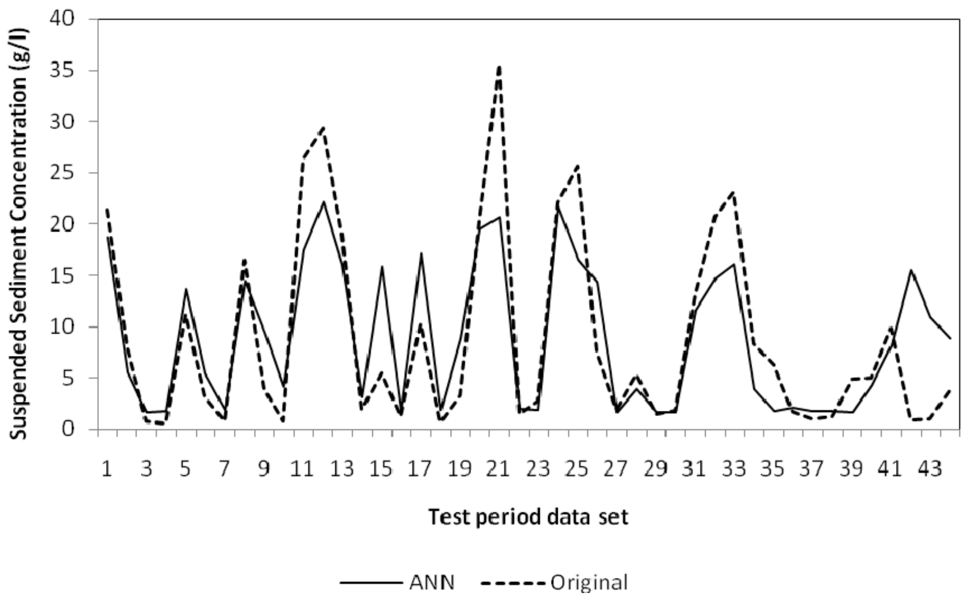

Figure 4. Simulated vs. observed mean daily suspended concentrations using ANN-BP model (Test period).

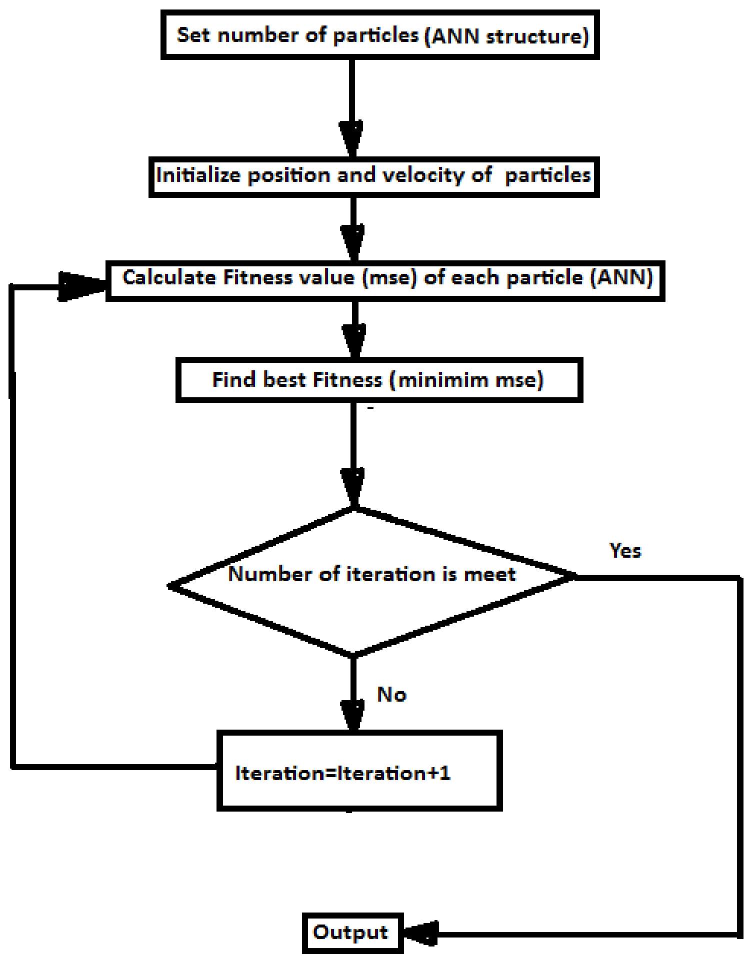

Figure 5. Flow chart of PSO-ANN's model.

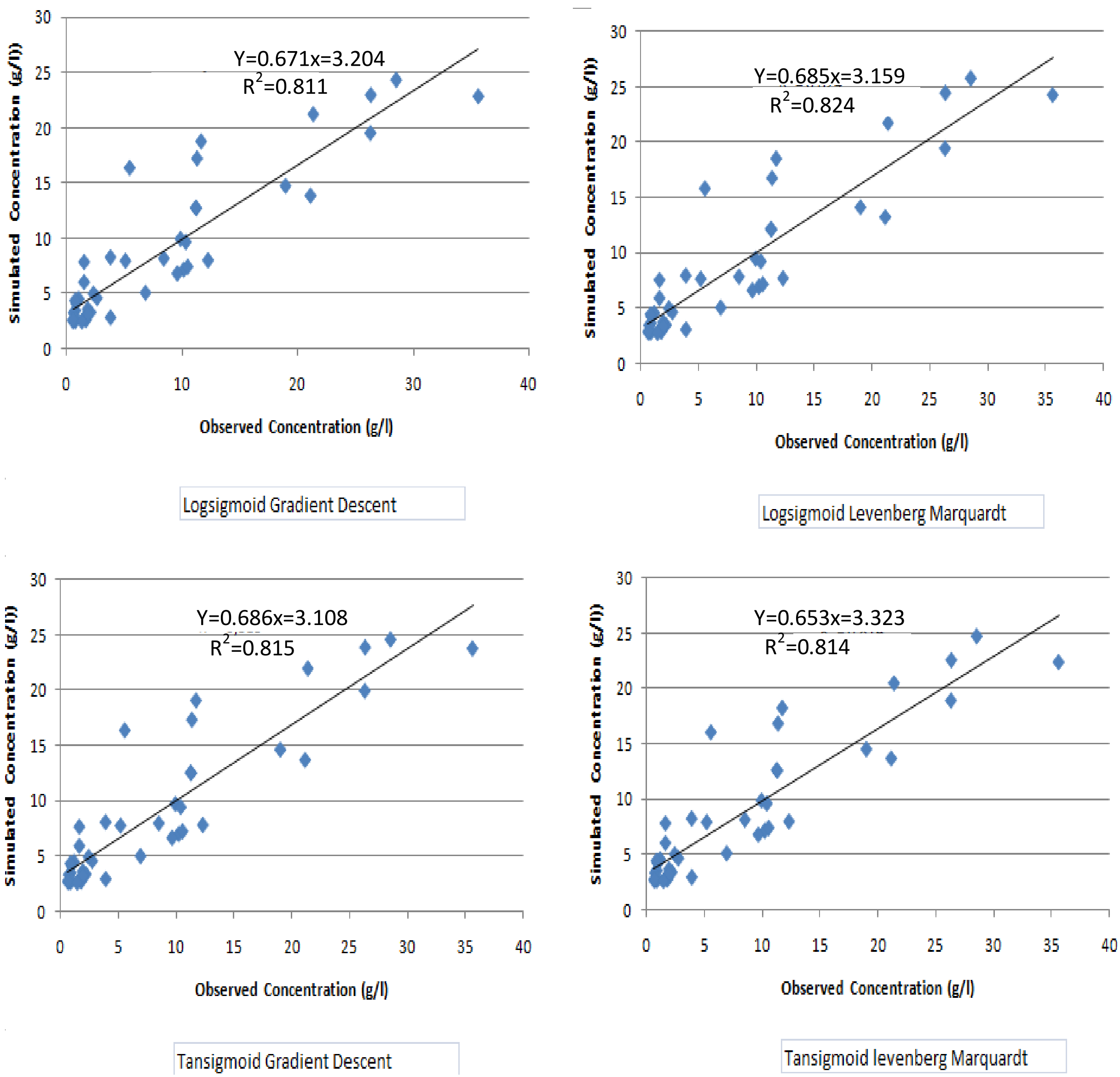

Figure 6. Simulated vs. observed suspended concentrations using PSO_ANN's model (test period).

Table 1. Models performances.

PSO-ANN (Test period)			ANN			SRC	
	RMSE	**R^2**		**RMSE**	**R^2**	**RMSE**	**R^2**
LOGGD	4.0962	0.8118					
LOGLM	3.9737	0.8247	Train	5.375	0.602	6.036	0. 527
TANGD	4.0264	0.8158	Test	5.307	0.689		
TANLM	4.1422	0.8141	Validation	4.090	0.678		

Table 1 indicates models performances using R square coefficient and root mean square error and shows that using hybrid ANN_BP model with principal transfer functions in hidden layer and training algorithms at test period for same sample improves RMSE and R^2; results show that PSO-ANN's improves ANN's model at least RMSE 21% and R^2 18% and both ANN and PSO-ANN model are better than SRC model.

Conclusion

Sediment rating curve, neural networks back propagation and hybrid PSO based neural networks models were employed in this study in order to model suspended sediment concentrations in Ksob river using Morsott gauging station data. Compared with the ANN model, PSO-ANN' appears to be more suitable for suspended sediment concentration modeling. Due to the lack of data, multiple linear regression and recurrent ANN's models were not considered, the proposed model based on PSO can be further investigated with several improved PSO models also other models in future studies.

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Conflict of Interest

The authors have not declared any conflict of interest.

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