



Suspended sediment discharge modeling during flood events using two different artificial neural network algorithms

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Received: 25 April 2019 / Revised: 19 August 2019 / Accepted: 1 October 2019 / Published online: 10 October 2019
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Abstract

This paper presents modeling of artificial neural network (ANN) to forecast the suspended sediment discharges (SSD) during flood events in two different catchments in the Seybouse basin, northeastern Algeria. This study was carried out on hourly SSD and water discharge data during flood events from a period of 31 years in the Ressoul catchment and of 28 years in the Mellah catchment. The ANNs were trained according to two different algorithms: the Levenberg–Marquardt algorithm (LM) and the Quasi-Newton algorithm (BFGS). Seven input combinations were trained for the SSD prediction. The performance results indicated that both algorithms provided satisfactory simulations according to the determination coefficient (R^2) and root mean squared error (RMSE) performance criteria, with priority to the BFGS algorithm; the coefficient of determination using the LM algorithm varies between 51.0 and 90.2%, whereas using the BFGS algorithm it varies between 54.3 and 93.5% in both studied catchments, with calculated improvement for all seven developed networks with the best improvement in the Ressoul catchment presented in ANN06 with Δ_{R^2} 4.23% and Δ_{RMSE} 1.74‰, and with the best improvement presented in ANN05 with Δ_{R^2} 6.07% and Δ_{RMSE} 0.71‰ in the Mellah catchment. The analysis showed that the use of Quasi-Newton method performed better than the Levenberg–Marquardt in both studied areas.

Keywords Suspended sediment discharges · Flood events · Modeling · Artificial neural network · Levenberg–Marquardt algorithm · Quasi-Newton algorithm

Introduction

Among the major environmental problems that hydrologists are dealing with nowadays are the silting and solid transport caused by water erosion. The quantification of the suspended sediment load in catchments is of great importance as it affects directly the management of different hydro-systems as well as the catchment morphology.

An effective and accurate model for predicting the suspended sediment is the priority of most hydro-scientists to protect different hydro-systems from soil degradation, loss of storage capacity in reservoirs, stability, and the deterioration of ground water (Bouguerra et al. 2017; Bouhadeb et al. 2018).

In the last decade, scientists started dealing with different complicated nonlinear phenomenon such as SSD using artificial intelligence and machine learning due to its non-linearity behavior.

The artificial neural network is a massively parallel distributed information processing system (Zhu et al. 2007). The artificial intelligence technique is considered

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as a nonlinear machine learning dealing with complicated phenomenon.

The use of artificial neural network in hydrological modeling started in Halff et al. (1993). The application of neural network was first employed in modeling stream flow models (Zealand et al. 1999; Riad et al. 2004; Sudheer and Jain 2004; Abrahart et al. 2007; Partal 2009; Wang et al. 2009; Hassan et al. 2018), water reservoir (Golob et al. 1998; Jain et al. 1999; Bae et al. 2007; Shamim et al. 2016), water quality (Clair and Ehrman 1998; Sahoo et al. 2006; Zou et al. 2007), and suspended sediment discharge (Nagy et al. 2002; Kisi 2004; Alp and Cigizoglu 2007; Mustafa et al. 2012; Afan et al. 2015; Hassan et al. 2015; Tachi et al. 2016; Alizadeh et al. 2017; Bouzeria et al. 2017).

In the majority of studies using neural networks, the backpropagation neural network method according to Levenberg–Marquardt (LM) algorithm was the most used in training algorithms in predicting suspended sediment discharge in rivers. The choice of training algorithm is a significant aspect in artificial neural network-based model developments, and despite the popular use of LM algorithm in modeling different hydrological parameters, it has standard optimization techniques compared to the Quasi-Newton method based on the BFGS training algorithm (Broyden 1970; Fletcher 1970; Goldfarb 1970; Shanno 1970).

Hassan et al. (2018) modeled with ANN the stream flow at Patrind Hydropower station in Pakistan using Broyden, Fletcher, Goldfarb, and Shanno (BFGS) and backpropagation (BP) algorithms, and the results indicated that both methods gave accurate predictions with high values of model efficiency (more than 95%). The same author Hassan et al. (2015) compared the performance of the BFGS, BP and local linear regression (LLR)-based ANN models for the estimation of weekly sediment load in a Pakistan catchment. The study showed that BFGS method outperformed all other methods. The same methods BFGS, BP and LLR were employed by Ahmed et al. (2018) in predicting weekly sediment load in an irrigation canal, and once again the BFGS method gave the best performances.

To our knowledge, no research has been reported comparing LM and BFGS algorithms in forecasting suspended sediment discharge during flood events. The main purpose of this paper, therefore, is to compare the performance of these two training neural network algorithms in predicting the suspended sediment discharge using different input combination.

The investigation was carried out during several flood events due to the fact that the most intensive sediment transport occurs during the passage of a flood wave (Rowinski and Czernuszenko 1998). In addition, the high dynamics and the unsteadiness of the suspended sediment transportation process during flood events provide a good test of these methods. The simulation of the ANNs depended on current

and previous water discharge and two previous sediment discharge during flood events in two different valleys in the Seybouse basin, northeastern Algeria.

Site description

The Seybouse basin is located in northeastern part of Algeria between $06^{\circ}46'58''$ and $07^{\circ}58'44''$ east longitude and between $35^{\circ}47'48''$ and $36^{\circ}55'42''$ north latitude. The Seybouse basin drains an area of 6470 km^2 for a perimeter of 535 km which gives an elongated shape of the basin, with 06 hydrometric measurement stations. The Seybouse wadi starts in the junction of the main tributaries: the Cherf wadi and the Bouhamdane wadi, and the total length of Seybouse wadi is 138 km. This valley flows on a relatively low slope (1.9%), and the valley outlet flows in the Mediterranean Sea in the Gulf of Bône (Annaba) after having followed various directions (Fig. 1).

The present study was conducted in two different sub-basins of the Seybouse basin; the first one is the Ressoul catchment, which is located in maritime Seybouse between $07^{\circ}27'51''$ and $07^{\circ}36'51''\text{E}$, and the latitude between $36^{\circ}32'56''$ and $36^{\circ}40'51''\text{N}$. Its total area is 103 km^2 for a perimeter of 50 km, and the principal watercourse of the Ressoul wadi is around 25 km; the second catchment is the Mellah wadi with an area of 550 km^2 and 150 km, and the sub-basin is located in medium Seybouse between $07^{\circ}28'41''$ and $07^{\circ}58'44''\text{E}$ longitude and between $36^{\circ}12'52''$ and $36^{\circ}30'21''\text{N}$ latitude. The Seybouse basin has a predominant Mediterranean climate, which is hot and dry in summer and wet and cool in winter. The annual average rainfall in the basin between the period 1921 and 1989 varies from 330 and 1030 mm, with an average value of 550 mm on the whole basin.

Used data

Among the six hydrometric stations of the Seybouse basin, two were selected for this study: Ain Berda hydrometric station which controls the Ressoul catchment and Bouchegouf station that controls the Mellah catchment (Table 1).

The data sets of the presented research comprising instantaneous water elevations (cm) and suspended sediment concentrations (g/l) were collected from the National Agency of Hydraulic Resources (ANRH) which is managing all the hydrometric necessary measurements in watersheds and controls the water resources in different Algerian rivers by the mean of hydrometric, rainfall stations and water quality analysis. Data were collected from 1968/1969 to 1999/2000 and from 1970/1971 to 1999/2000, respectively, at Ain Berda and Bouchegouf stations.

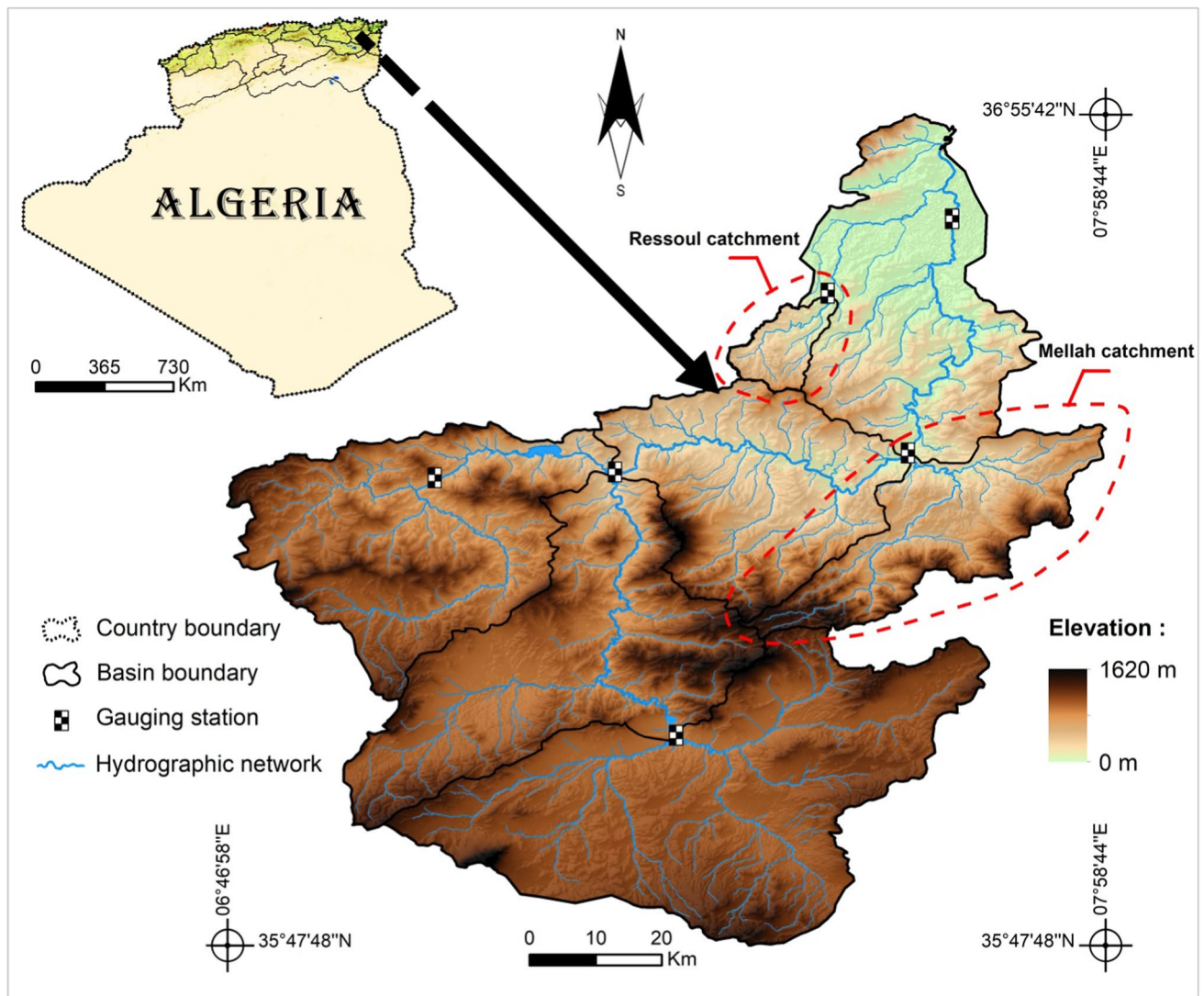


Fig. 1 Location map of the study area

Table 1 Characteristics of the two hydrometric stations used

Station name	Ain Berda	Bougegouf
Geographical coordinates		
Longitude	07°36'13"E	07°42'21"E
Latitude	36°40'55"N	36°27'57"N
Elevation (m)	72	99
Controlled area (km ²)	103	550
Observed period	1964/1965–2011/2012	1967/1968–2008/2009

Water discharge data were derived from water surface elevation data using the stage-discharge rating curves of the hydrometric stations, while the suspended sediment discharges were calculated by the following formula (1):

$$SSD = WD * SSC \quad (1)$$

where *SSD* suspended sediment discharge, *SSC* suspended sediment concentration and *WD* water discharge.

The variation of annual inflow shows significant fluctuations from one year to another in both hydrometric stations (Fig. 2); During 48 years of observation between (1964/1965–2011/2012), the station of Ain Berda observed an average annual inflow of 13.61 Hm³, which corresponds to an average flow discharge of 0.43 m³/s, with an instantaneous maximum discharge recorded on November 04, 1992, at 14 h:20 of 205.3 m³/s, whereas the inflow of Mellah catchment between (1967/1968–2008/2009) observed an average flow discharge of 2.19 m³/s at the Bougegouf hydrometric station, which corresponds to an average annual inflow of 69.13 Hm³, with an instantaneous

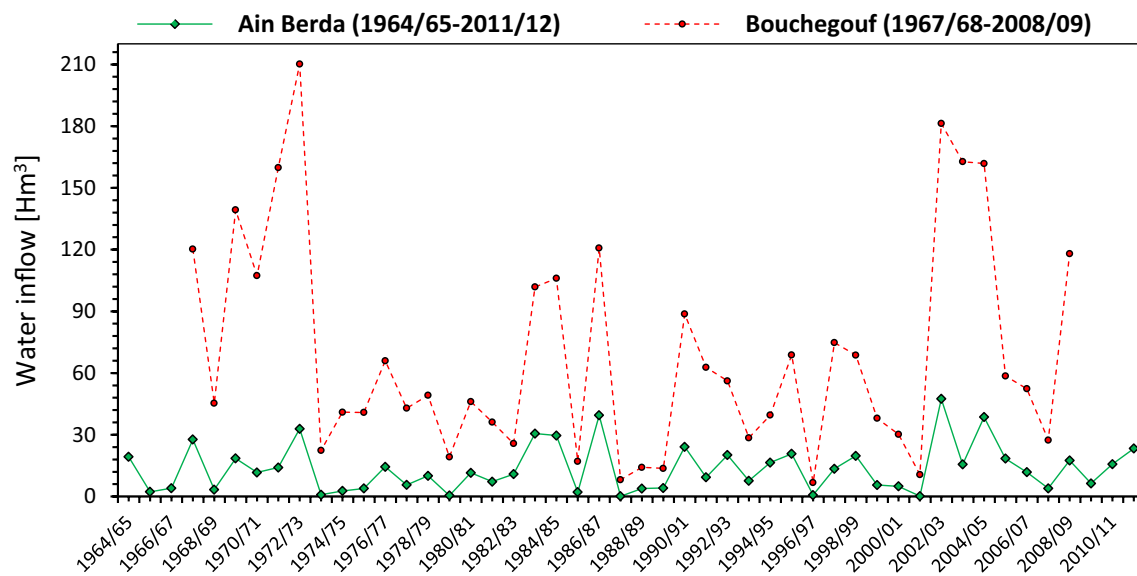


Fig. 2 Inter-annual variation of inflow in the two hydrometric stations

maximum discharge observed on April 04, 2003, at 17 h:00 of 739.8 m³/s.

The data sets were divided into two sets for both hydrometric stations; for the Ain Berda station, the first set represents the data that were introduced to the training process with 109 flood events between 1968 and 1988. The second set was used for the validation process, with 25 flood events between 1989 and 2000, whereas for the Bouchegouf station, 52 flood events between 1971 and 1989 introduced to the training process and 17 flood events between 1990 and 2000 were used during the validation process.

The used data were carried out on an hourly scale during the flood period, and 134 and 69 flood events were used in order to develop the neural network model in Ain Berda and Bouchegouf stations, respectively.

The hourly statistical parameters (min, mean, max, standard deviation and coefficient of variation) of the data are presented in Table 2.

The statistical parameters of WD and SSD used in the training process show average to high values of the variation coefficient for the SSD with Cv: 4.1% and 5.2% and average values for the WD with Cv: 2.4% and 1.9% at Ain Berda and Bouchegouf stations, respectively. The parameters used in the validation process show slightly lesser values of the suspended sediment and water discharge variation coefficient compared to the training sets with Cv: 3.46% and 2.16% at Ain Berda station and Cv: 2.9% and 1.4% at Bouchegouf station.

Correlation matrix

The input selection of the used data in both valleys was based on the correlation matrix which enables selecting the input data according to their correlation with the target which is the suspended sediment discharge. The analysis was applied to

Table 2 Statistical parameters of the tow hydrometric stations used

Data set	Variables	Minimum	Average	Maximum	SD	C.V
Ain Berda station						
Training	WD (m ³ /s)	0.001042	7.20	161.77	17.59	2.44
	SSD (kg/s)	0.000025	32.41	2732.33	133.03	4.10
Validation	WD (m ³ /s)	0.001041	5.92	118.10	12.76	2.16
	SSD (kg/s)	0.0000046	24.01	984.54	83.06	3.46
Bouchegouf station						
Training	WD (m ³ /s)	0.455	20.358	616.8	37.576	1.845
	SSD (kg/s)	0.080	140.768	17,319.744	731.883	5.198
Validation	WD (m ³ /s)	0.090	14.195	153.6	20.22	1.423
	SSD (kg/s)	0.004	77.414	2399.793	226.77	2.927

2775 individuals in Ain Berda hydrometric station and 2457 in the Bouchegouf hydrometric station, by taking into account eight variables (WD_t , WD_{t-1} , WD_{t-2} , WD_{t-3} , SSD_t , SSD_{t-1} , SSD_{t-2} , SSD_{t-3}). The correlation matrix analysis of both stations showed that the SSD_t is well correlated with the WD_t , WD_{t-1} , SSD_{t-1} and moderately correlated with both WD_{t-2} and SSD_{t-2} , contrary to the rest of parameters where the correlation did not show good linking with the SSD_t (Table 3).

Normalization

The data normalization method was applied to avoid, on the one hand, the effect of extreme values of variables in the learning process and, on the other hand, the inaccuracy which may result from the difference in the measurement units between water discharge and sediment discharge. The normalization Eq. (2) that was applied differs between 0 and 1.

$$X_{\text{norm}} = X_i / X_{\text{max}} \quad (2)$$

where X_{norm} is the normalized data set, X_i is the original data set, and X_{max} is the maximum value of the original data set.

Methods

Artificial neural network (ANN)

Artificial neural networks are flexible mathematical structures that are capable of identifying complex nonlinear relationships between input and target data sets and capable of estimating target values based on training and learning

processes (Melesse et al. 2011). ANNs are well suited to complex, nonlinear problems, where correlation between variables is often hidden and hardly noticeable (Piasecki et al. 2018). The ANN is one of the most significant techniques that were applied by researchers to deal with different hydrological phenomenon in the last twenty years.

Training algorithms

In this study, a multilayer perceptron neural network was trained with two different learning algorithms: the Levenberg–Marquardt (LM) and the Quasi-Newton (BFGS) algorithms in predicting the suspended sediment during flood events.

The Levenberg–Marquardt algorithm

The Levenberg–Marquardt algorithm (LM) is a numerical solution to the minimization of nonlinear problems, and the LM was developed by Levenberg Kenneth and Marquardt Donald in 1963 (Wilamowski and Yu 2010). The algorithm was designed to approach the second-order training speed without computing the Hessian matrix (Hagan and Menhaj 1994).

The Quasi-Newton algorithm

The Quasi-Newton algorithm (BFGS) was developed by Broyden (1970) based on the Newton method. BFGS was designed for better and fast optimization during the training process as an alternative method to the conjugate gradient

Table 3 Correlation matrix between variables in both stations

	Variables	WD_t	WD_{t-1}	WD_{t-2}	WD_{t-3}	SSD_t	SSD_{t-1}	SSD_{t-2}	SSD_{t-3}	Variables	
Ain Berda station	WD_t	1	0.948	0.853	0.747	<u>0.866</u>	0.796	0.678	0.563	WD_t	Bouchegouf station
	WD_{t-1}	0.899	1	0.948	0.853	<u>0.807</u>	0.866	0.796	0.678	WD_{t-1}	
	WD_{t-2}	0.788	0.899	1	0.948	<u>0.691</u>	0.807	0.866	0.796	WD_{t-2}	
	WD_{t-3}	0.707	0.788	0.899	1	0.567	0.691	0.807	0.866	WD_{t-3}	
	SSD_t	<u>0.813</u>	<u>0.721</u>	<u>0.598</u>	0.507	1	<u>0.869</u>	<u>0.681</u>	0.526	SSD_t	
	SSD_{t-1}	0.678	0.813	0.721	0.598	<u>0.739</u>	1	0.869	0.681	SSD_{t-1}	
	SSD_{t-2}	0.576	0.678	0.813	0.721	<u>0.567</u>	0.739	1	0.869	SSD_{t-2}	
	SSD_{t-3}	0.477	0.576	0.678	0.813	0.440	0.567	0.739	1	SSD_{t-3}	

0.813 Selected WD_t based on the high correlation with SSD_t , 0.721 Selected WD_{t-1} based on the high correlation with SSD_t , 0.598 Coefficient of correlation between two antecedent water discharge (WD_{t-2}) and current suspended sediment discharge (SSD_t), 0.866 Coefficient of correlation between current water discharge (WD_t) and current suspended sediment discharge (SSD_t), 0.807 Selected WD_{t-1} based on the high correlation with SSD_t , 0.691 Coefficient of correlation between current water discharge (WD_{t-2}) and current suspended sediment discharge (SSD_t), 0.739 Coefficient of correlation between antecedent suspended sediment discharge (SSD_{t-1}) and current suspended sediment discharge (SSD_t), 0.567 Coefficient of correlation between two antecedent suspended sediment discharge (SSD_{t-2}) and current suspended sediment discharge (SSD_t), 0.869 Selected SSD_{t-1} based on the high correlation with SSD_t , 0.681 Coefficient of correlation between two antecedent suspended sediment discharge (SSD_{t-2}) and current suspended sediment discharge (SSD_t)

> WD_t : current water discharge, WD_{t-1} : antecedent water discharge, WD_{t-2} : two antecedent water discharge, WD_{t-3} : three antecedent water discharge, SSD_t : current suspended sediment discharge, SSD_{t-1} : antecedent suspended sediment discharge, SSD_{t-2} : two antecedent suspended sediment discharge, SSD_{t-3} : three antecedent suspended sediment discharge.

algorithm (Dennis and More 1977; Hagan and Menhaj 1994).

Model development

In this present study, around 75% of the used data between (September 27, 1969, to December 12, 1988 in the Ressoul wadi) and (January 06, 1971, to Mars 23, 1989, in the Mellah wadi) have been introduced to the training set, and 25% of the data (February 15, 1989, to May 28, 2000, in the Ressoul wadi) and (January 09, 1990, to May 31, 2000, in the Mellah wadi) have been left for the validation set.

The ANN structure selected in this study consisted of multilayer perceptron (MLP) with input layer, two hidden layers and output layer (Fig. 3). LM and BFGS algorithms were applied in training the ANNs in two different study areas for better evaluation and comparison between ANNs structures and performances. The activation transfer function and number of neurons in the hidden layers were chosen based on many simulations of the neural models using different structure variations.

Table 4 represents the neural network model architectures using both based training algorithms, and the number of neurons and activation functions of each network are chosen based on the trials and errors of each model, and as it is obvious in Table 4, the number of neurons is increasing depending on the complexity of the input variables and the number of inputs. During trials, only one hidden layer was chosen for training the neural network models, and due to the increase in neurons numbers during trials, we tried to divide the number of neurons on two different layers with different activation functions

to avoid over-fitting problems that occurs generally using many neurons in the hidden layer especially when dealing with complicated phenomenon such as suspended sediment discharge.

Model evaluations

Coefficient of determination (R^2)

This enables the efficiency of a model (R^2) to be defined by formula 3:

$$R^2 = \frac{\sum (X_{i_{\text{obs}}} - \bar{X}_{\text{obs}}) * (X_{i_{\text{pred}}} - \bar{X}_{\text{pred}})}{\left(\sqrt{\sum (X_{i_{\text{obs}}} - \bar{X}_{\text{obs}})^2 * \sum (X_{i_{\text{pred}}} - \bar{X}_{\text{pred}})^2} \right)^2} \quad (3)$$

where $X_{i_{\text{pred}}}$ and $X_{i_{\text{obs}}}$ are the predicted and observed suspended sediment discharges at corresponding times and \bar{X}_{obs} is the mean of observed SSD.

Root mean square error (RMSE)

This criterion was employed to estimate the gap between the predicted and observed SSD values. The formula (4) of root mean square error (RMSE) is:

$$\text{RMSE} = \sqrt{\frac{\sum (X_{i_{\text{pred}}} - X_{i_{\text{obs}}})^2}{N}} \quad (4)$$

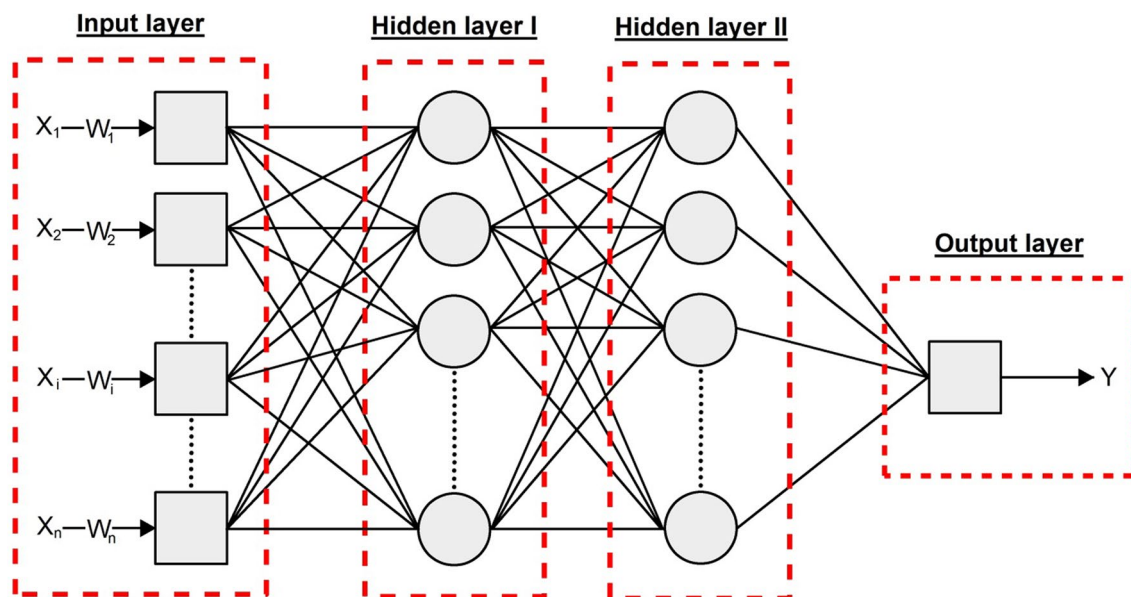


Fig. 3 Artificial neural network structure

Table 4 Neural network structures and activation functions of hidden layers

No.	Combination	Ain Berda station				Boucheougouf station			
		LM algorithm		BFGS algorithm		LM algorithm		BFGS algorithm	
		ANN structure	Activation function	ANN structure	Activation function	ANN structure	Activation function	ANN structure	Activation function
01	WD_t	3–3	L–T	3–3	L–T	3–3	L–T	3–3	L–T
02	SSD_{t-1}	3–4	L–P	3–4	L–P	4–5	L–P	3–4	L–P
03	WD_{t-1}	4–5	L–P	4–5	L–P	5–5	L–P	4–5	L–P
04	WD_t and WD_{t-1}	4–6	L–P	4–6	L–P	4–6	L–P	4–6	L–P
05	WD_{t-1} and SSD_{t-1}	5–6	L–P	5–6	L–P	5–6	L–P	5–6	L–P
06	WD_t and SSD_{t-1}	5–7	P–T	5–7	P–T	5–7	P–T	5–7	P–T
07	WD_t , WD_{t-1} and SSD_{t-1}	6–8	P–T	6–8	T–P	8–9	P–T	6–8	T–P

where T Tansig, L Logsig, P Purelin

where $X_{i_{pred}}$ and $X_{i_{obs}}$ are the predicted and observed values at corresponding times, respectively, and N is the total number of observations.

Results and discussion

The performance of the artificial neural network models based on LM and BFGS algorithms was evaluated using the root mean square error (RMSE) and correlation coefficient (R^2).

ANN according to LM algorithm

In the first application presented in this work, seven input combinations were trained using the Levenberg–Marquardt algorithm, with 1000 iterations in each neural network model to assess the best performance during the training process. Table 5 represents the structure and performance criteria of the ANN using the LM algorithm in both hydro-metric stations.

The RMSE and R^2 values presented above were obtained during the training and validation processes of the ANN according to the LM algorithm of 07 input combinations in predicting the suspended sediment discharge during flood events in the Ressoul wadi and the Mellah wadi.

The performance criteria of the training process show that the ANN trained well especially the network 07 in both studied areas with superiority to the Mellah wadi depicting the highest value of R^2 99% and the lowest RMSE 0.0043, and with R^2 93% and RMSE 0.0129 in the Ressoul wadi (Figs. 4, 5) followed by the ANN06 where they show good values in both case studies.

During the validation process, contrary to the training process the performance criteria were higher in the Ressoul wadi than in the Mellah wadi. The results of the Ressoul shows very good values in ANN07 with R^2 around 90.2% and RMSE 0.0096, followed by ANN06, ANN01 and ANN04 with R^2 (84.1, 82.1 and 80.6%) and RMSE (0.0122, 0.0129 and 0.0134), respectively. The ANN02, ANN05 and ANN03 show acceptable values with R^2 (76.5, 76 and 69.7%) and RMSE (0.0148, 0.0149 and 0.0168), respectively. The performance criteria for evaluating results

Table 5 The performance results of the ANN using the LM algorithm

No.	Combination	Ain Berda station				Boucheougouf station			
		Training		Validation		Training		Validation	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
01	WD_t	0.745	0.0246	0.821	0.0129	0.934	0.0111	0.676	0.0071
02	SSD_{t-1}	0.654	0.0287	0.765	0.0148	0.896	0.0138	0.744	0.0064
03	WD_{t-1}	0.519	0.0338	0.697	0.0168	0.883	0.0147	0.510	0.0088
04	WD_t and WD_{t-1}	0.748	0.0244	0.807	0.0134	0.933	0.0111	0.626	0.0077
05	WD_{t-1} and SSD_{t-1}	0.694	0.0270	0.760	0.0149	0.934	0.0110	0.689	0.0070
06	WD_t and SSD_{t-1}	0.839	0.0195	0.841	0.0122	0.963	0.0082	0.746	0.0063
07	WD_t , WD_{t-1} and SSD_{t-1}	0.930	0.0129	0.902	0.0096	0.990	0.0043	0.884	0.0043

Fig. 4 Observed and predicted SSD according to LM algorithm using ANN07 in Ain Berda station

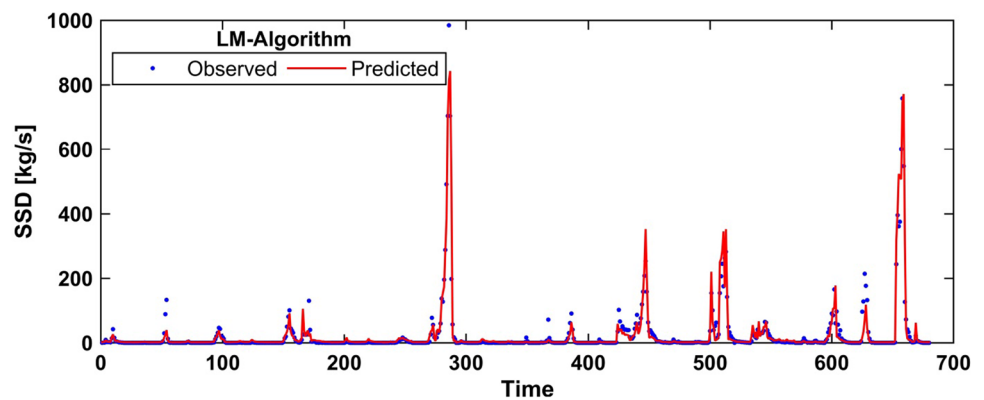
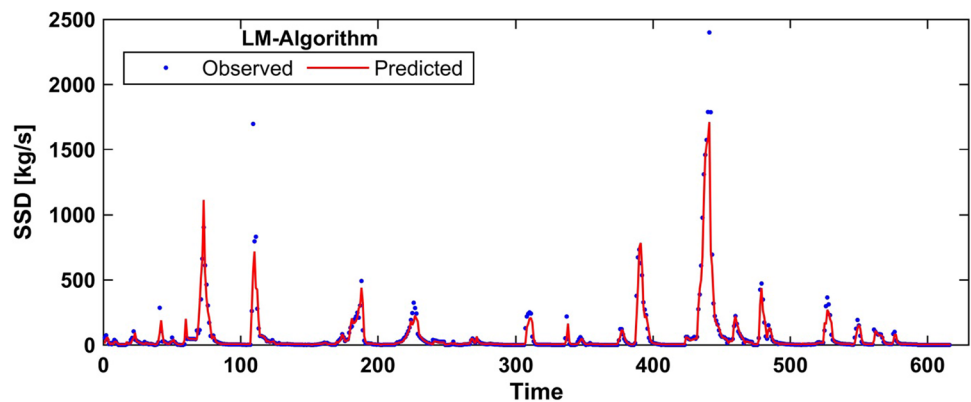


Fig. 5 Observed and predicted SSD according to LM algorithm using ANN07 in Bouchegouf station



in the Mellah wadi show its best combination in ANN07 with R^2 88.4% and RMSE 0.0043 followed by ANN06 and ANN02 with R^2 74.6%, 74.4% and RMSE 0.0063, 0.0064, respectively. After that, the average values of the combination are presented in ANN05, ANN01 and ANN04 with R^2 68.9%, 67.6% and 62.6%, and RMSE 0.007, 0.0071 and 0.0077, respectively.

The best neural network during the validation process in both hydrometric stations depends on the input combinations with the current and antecedent water discharge and the antecedent suspended sediment discharge. The results confirm that using the three inputs improves the neural network learning and minimizes the error and showed very high goodness of fit during validation period. The ANN01 with only current water discharge shows very good values, which proves the high relation between suspended sediment discharge and water discharge that was proven in the literature by many researchers. The NN models depending only on the antecedent sediment discharge or antecedent water discharge show that using the previous sediment values is better than the previous water discharge in the Ressoul wadi and vice versa in the Mellah wadi. In general, the use of ANN according to LM algorithm is very effective during flood events compared to the literature. The values that were presented in the validation set are shown to be better than the training

set due to the long series that were introduced to the training period compared to the validation period.

ANN according to BFGS algorithm

In this second application, the suspended sediments were predicted using the Quasi-Newton algorithm, with 1000 iterations for each neural network model. The obtained structure presented in Table 6 was the best for all simulations for these models. To assess the best performance during the training process, Table 6 represents the structure and performance results of the ANN using the BFGS algorithm in both Ressoul wadi (Ain Berda station) and the Mellah wadi (Bouchegouf station).

The performance results of the ANN according to the BFGS algorithm were evaluated using the R^2 and RMSE.

During the training process, the ANN according to the BFGS algorithm was evaluated by the R^2 and RMSE; the results in this application show lower values compared the LM algorithm in both stations. Most of NNs in this application were stopped before finishing the full iterations (1000) that were introduced to the models. The training stopped due to the over-fitting that appeared in the training. In the Ressoul wadi, the best results performances were presented in ANN07 and ANN06 with R^2 (83.8 and 80.9%) and RMSE

Table 6 The performance results of the ANN using the BFGS algorithm

No.	Combination	Ain Berda station				Boucheougouf station			
		Training		Validation		Training		Validation	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
01	WD_t	0.735	0.0251	0.833	0.0125	0.920	0.0121	0.688	0.0070
02	SSD_{t-1}	0.653	0.0287	0.772	0.0146	0.878	0.0150	0.758	0.0062
03	WD_{t-1}	0.519	0.0338	0.700	0.0167	0.879	0.0149	0.543	0.0085
04	WD_t and WD_{t-1}	0.742	0.0247	0.821	0.0129	0.933	0.0111	0.661	0.0073
05	WD_{t-1} and SSD_{t-1}	0.652	0.0287	0.782	0.0142	0.924	0.0119	0.750	0.0063
06	WD_t and SSD_{t-1}	0.809	0.0213	0.883	0.0104	0.939	0.0106	0.793	0.0057
07	WD_t , WD_{t-1} and SSD_{t-1}	0.838	0.0196	0.935	0.0078	0.962	0.0084	0.914	0.0037

(0.0196 and 0.0213). The ANN04, ANN01, ANN02 and ANN05 showed acceptable values during training process with R^2 (74.2, 73.5, 65.3 and 65.2%). The ANN03 with antecedent water discharge showed poor values during training process with R^2 51.9% and RMSE 0.0338. In the Mellah wadi, the performance results were higher than the results of the Ressoul wadi with R^2 (96.2, 93.9 and 93.3%) RMSE (0.0084, 0.0106 and 0.0111) which are presenting networks ANN07, 06 and 04, respectively, followed by ANN05 and 01 with R^2 (92.4 and 92%) and RMSE (0.0119, 0.0121). In general, the performance values during training process were acceptable with superiority to the data of the Mellah wadi. The performance results using the BFGS algorithm showed inferior values during training process compared to the results were obtained using the LM algorithm, because of the unfinished learning of the developed neural network models.

The best values of R^2 and RMSE during validation process were obtained by ANN07 with current and antecedent values of water discharge and antecedent values of suspended sediment discharge with 93.5% and 0.0078 for the Ressoul wadi (Fig. 6) and 91.4% and 0.0037 in the Mellah wadi (Fig. 7).

In the Ressoul wadi, the ANN06 with current water discharge and antecedent suspended sediment discharge,

ANN01 with current water discharge and ANN04 with current and previous water discharge showed very good values not far from the ANN07 and better than the networks with the same input combination according to LM, with R^2 (88.3, 83.3 and 82.1%) and RMSE (0.0104, 0.0125 and 0.0129), respectively. In the Mellah wadi, the ANN06, ANN05 and ANN02 showed good values with R^2 (79.3, 75 and 75.8%) and RMSE (0.0057, 0.0063 and 0.0062), respectively.

The ANN05, ANN02 and ANN03 of the Ressoul wadi and ANN01, ANN03 and ANN04 of the Mellah wadi were improved compared to the results in the ANN according to the LM. The performance values show acceptable values dealing with such phenomenon as suspended sediments in valleys, with R^2 (78.2, 77.2 and 70%) and (68.8, 54.3 and 66.1%), respectively. The results presented in this application using BFGS algorithm got improved compared to the results using the LM algorithm. The results obtained in this work show that the use of BFGS is more effective than the LM which is contradictory to the literature, where most researchers used the LM in training the ANN algorithm.

Error improvement using BFGS

As it was presented in the previous sections, the use of the ANN according to the BFGS algorithm showed better results

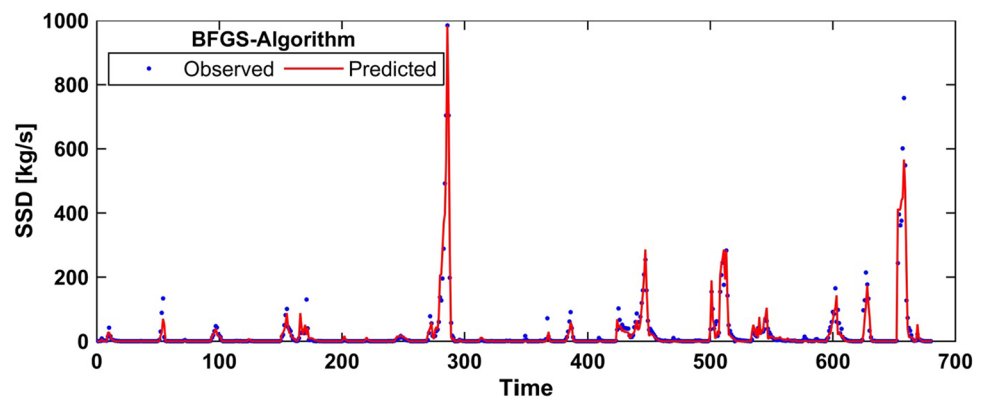
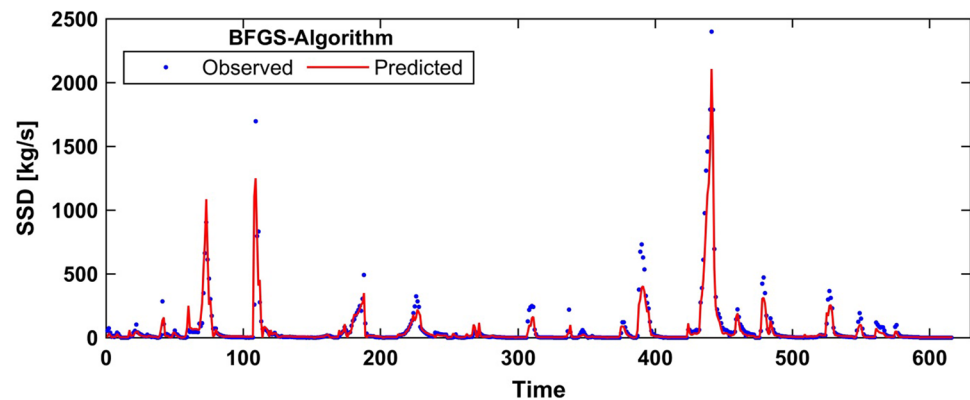
Fig. 6 Observed and predicted SSD according to BFGS algorithm using ANN07 in Ain Berda station

Fig. 7 Observed and predicted SSD according to BFGS algorithm using ANN07 in Bouchegouf station



than the use of LM algorithm in training ANN. In this section, the discussion is based on the evaluation of the used criteria improvement in this study the (R^2 and RMSE) in the ANN using the BFGS training algorithm. Table 7 represents the improvement of errors in the different input combinations between the two training algorithms in both studied areas.

As it is shown in Table 7, the best improvement results of the Ressoul wadi were obtained by ANN06 (current water discharge and antecedent suspended sediment discharge) and ANN07 (current, antecedent water discharge and antecedent suspended sediment discharge), where it showed improvement of 4.231, 3.285% in the coefficient of determination and 1.739, 1.759 ‰ in the mean squared error, respectively, and the rest of neural networks showed improvement between Δ_{R^2} (0.316 and 2.219%) and Δ_{RMSE} (0.088 and 0.707‰), whereas in the Mellah wadi the ANN05 (antecedent water discharge and suspended sediment discharge) gave the best improvement in all presented networks with 6.065% in the coefficient of determination and 0.720‰ in the root mean squared error. Followed by ANN06 with 4.779% and 0.626‰, the rest of neural networks showed improvement between Δ_{R^2} (1.178 and 3.518%) and Δ_{RMSE} (0.131 and 0.595 ‰).

The obtained improvement by using the BFGS algorithm explains the stopping criterion used in this latter to avoid overfitting that could occur in the presented models; due to

the different introduced input combinations, and the complexity of the studied phenomenon. The use of NN according to the BFGS algorithm improved the results compared to the NN according to the LM algorithm in this case study.

Figure 8 represents both the observed and predicted suspended sediments according to the LM and BFGS during flood period that was observed in the Ain Berda station between the February 6–9, 1996. It can be seen that the figure shows very goodness of fit for both networks with superiority the BFGS, especially during the peak of this flood where it is obvious that over-fitting occurred in the NN according to LM algorithm. Contrary the NN according to the BFGS algorithm showed very goodness of fit during all the flood period, knowing that the BFGS prevents the over-fitting during the training process.

Conclusion

The primary basis of this research work was the investigation of the suspended sediment discharge in the Seybouse basin during flood events. The artificial neural network models were applied with two different training algorithms: the Levenberg–Marquardt (LM) and the Quasi-Newton (BFGS), and the models were trained using different input combinations of two hydrometric stations in the Seybouse basin. It was found that training the NN according to the Quasi-Newton

Table 7 Improvement of the BFGS evaluation criteria (R^2 and RMSE) compared to the LM algorithm

No.	Input combination	Ain Berda station		Bouchegouf station	
		Δ_{R^2} (%)	Δ_{RMSE} (‰)	Δ_{R^2} (%)	Δ_{RMSE} (‰)
01	WD_t	1.214	0.445	1.178	0.131
02	SSD_{t-1}	0.652	0.206	1.386	0.174
03	WD_{t-1}	0.316	0.088	3.291	0.300
04	WD_t and WD_{t-1}	1.390	0.491	3.518	0.370
05	WD_{t-1} and SSD_{t-1}	2.219	0.707	6.065	0.720
06	WD_t and SSD_{t-1}	4.231	1.739	4.779	0.626
07	WD_t , WD_{t-1} and SSD_{t-1}	3.285	1.759	3.006	0.595

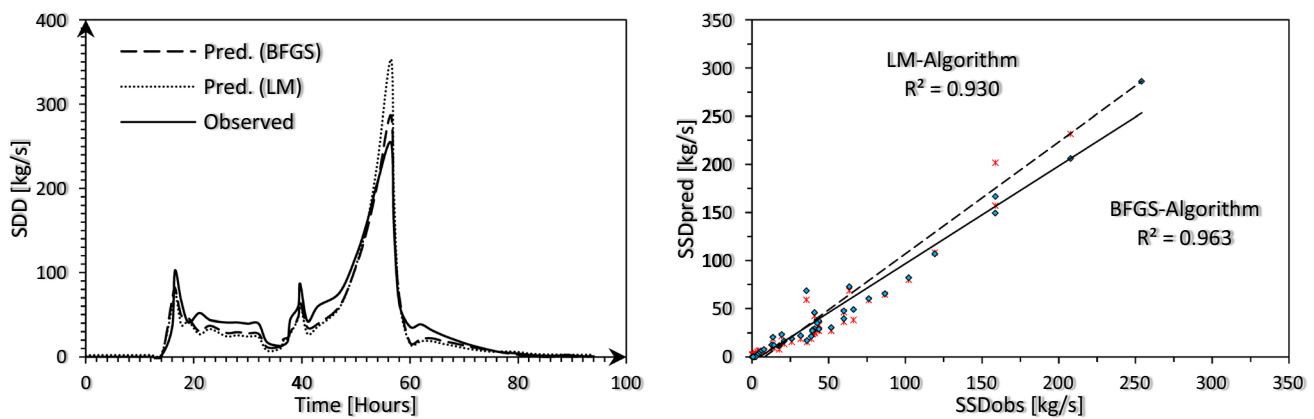


Fig. 8 Examples of flood events (February 06–09, 1996) in the Ain Berda station

algorithm gave higher values in all networks compared to the Levenberg–Marquardt in both studied areas. The best neural network was the ANN07 with current and antecedent water discharge and antecedent sediment discharge. Moreover, the forecasting of the suspended sediment discharge (SSD) depending on only current water discharge or only antecedent sediment discharge is very effective, which proves the good correlation between these last ones and the SSD. The results of the present study indicates that use of artificial neural network in forecasting the suspended sediment discharge and the use of Quasi-Newton method is very effective in training the neural networks.

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