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Forecasting suspended sediment load using regularized neural network: Case study of the Isser River (Algeria)

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Abstract

In the management of water resources in different hydro-systems it is important to evaluate and predict the sediment load in rivers. It is difficult to obtain an effective and fast estimation of sediment load by artificial neural network without avoiding over-fitting of the training data. The present paper comprises the comparison of a multi-layer perception network once with non-regularized network and the other with regularized network using the Early Stopping technique to estimate and forecast suspended sediment load in the Isser River, upstream of Beni Amran reservoir, northern Algeria. The study was carried out on daily sediment discharge and water discharge data of 30 years (1971–2001). The results of the Back Propagation based models were evaluated in terms of the coefficient of determination (R^2) and the root mean square error (*RMSE*). Results of the comparison indicate that the regularizing ANN using the Early Stopping technique to avoid over-fitting performs better than non-regularized networks, and show that the overtraining in the back propagation occurs because of the complexity of the data introduced to the network.

Key words: *artificial neural network, Beni Amran reservoir, early stopping, Isser River, sediment load*

INTRODUCTION

Among the most critical environmental hazards that hydrologists are dealing with nowadays is sediment load in watersheds. An effective and fast estimation of flow and flux in watersheds are ones of great interests for large number of engineering applications to protect hydraulic infrastructure from different disasters such as: stability problems, the loss of water storage in reservoir and the deterioration of water quality.

The processes of flow and sediment load are complex in Algeria, due to rainfall regime which is infrequent, intense and occurs in the coastal belt, as well as the shortage of data and the difficulty of daily direct measurement. According to REMINI [2004] and REMINI *et al.* [2009] the erosion rate is between 2000 and 4000 t·km^{-2}·year^{-1}. The average annual amount of deposited sediment in dams increased from 20 million m^3 in the 1980's to 35 million m^3 in the 1990's and reached 45 million m^3 in 2000 [SERBAH 2011].

Increasing suspended sediment load and its sedimentation in Algeria led hydrologists to research the phenomenon of suspended sediment discharge and its relation with some of hydro-climatic parameters, such as rainfall, runoff, land cover, and sediment concentration in different rivers. Among the researchers were, for instance: TERFOUS *et al*. [2001], BENKHALED and REMINI [2003], ACHITE and MEDDI [2004], LARFI and REMINI [2006], LEFKIR *et al*. [2006], BOUCHELKIA *et al*. [2013], who studied the quantification of suspended sediment discharge and explained the phenomena of flow and suspended sediment load in different areas.

During the last twenty years hydrologists started applying artificial intelligence techniques to estimate and predict different hydrological phenomena. Among the techniques were: Adaptive Neural Network Fuzzy Inference System (ANFIS) [BAE *et al*. 2007; KISI 2005], Genetic Programme (GP) [AYTEK, KISI 2008; SAVIC *et al*. 1999] and Artificial Neural Network (ANN) [ABRAHART *et al*. 2001; ASCE 2000a, b; SOLOMATINE *et al*. 2003; ZHU *et al*. 2007].

Recently hydrologists have compared different artificial intelligence techniques in search for novel methods to improve the ANN training and to avoid the over-fitting that occurs in the networks. The overtraining of the used data may result in deterioration of generalization properties of the model and, when applied to novel measurements, lead to its unreliable performance [PIOTROWSKI, NAPIORKOWSKI 2013]. The early stopping criterion is one of the most common methods used in artificial neural network to avoid over-fitting because of its simplicity of understanding and implementation [LIU *et al*. 2008; PRECHLET 1998].

This study attempts to apply the early stopping technique to estimate and forecast the sediment discharge, and presents the comparison results of non-regularized and regularized neural networks in the case of the Isser River, upstream of Beni Amran reservoir, situated in northern Algeria.

MATERIALS AND METHODS

STUDY AREA

The study area comprises the watershed of the Isser that is located at 36°52’N~35°52’N and 3°56’E~2°52’E, northern Algeria, upstream Beni Amran reservoir. Its total area is 4140.9 km^2 and its length of the principal Thalweg is 437.7 km. The basin has Mediterranean climate, cold and wet in winter, hot and dry in summer, and the average rainfall is about 800 mm per year. This basin joins the great mountain range Kabylie and is separated by the Krachema massif into two perimeters: low and middle Isser. The Oued Isser is mainly controlled by six gauging stations; there are two main stations – Latreille upstream station and Lakhdaria downstream station, and four hydrometric stations in each sub-basin (Fig.1). The basin’s lithology is extremely sensitive to erosion because it is largely formed of marls. The basin is divided into five sub-basins; each is controlled by a hydrometric station on the river [PNUD 1987].

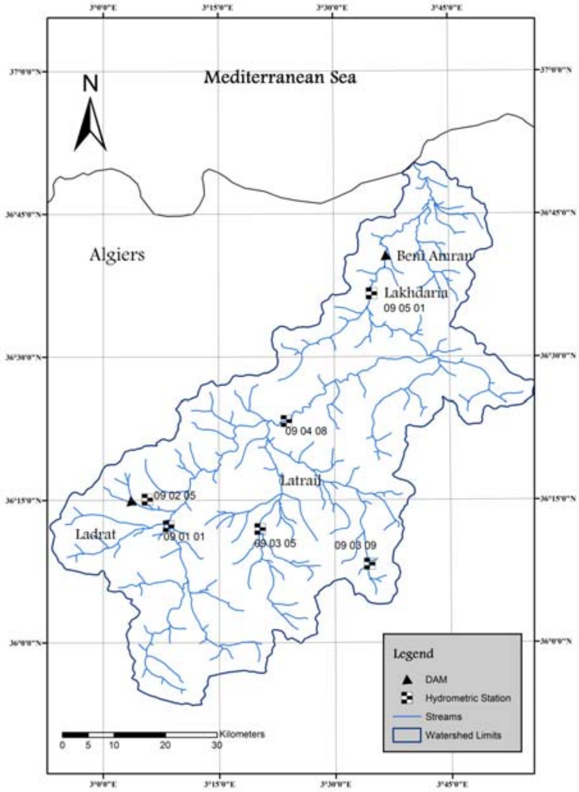

Fig. 1. Map of the Isser watershed and Lakhdaria hydrometric station; source: own elaboration

USED DATA

The daily data sets comprised of water discharge (m^3·s^{-1}) and suspended sediment discharge (kg·s^{-1}) from the period between 1 September 1971 and 31 August 2001. The data used in this article come from the National Agency of Water Resources (ANRH).

Table 1. The statistical parameters of applied data set

Data set	Data type	Mean	Std	Min	Max
Training set	WD, m^3·s^{-1}	22.20	47.84	0.005	800.00
	SSD, kg·s^{-1}	280.73	1 525.00	0.00056	23 250.00
Validation set	WD, m^3·s^{-1}	8.08	26.00	0.0262	575.20
	SSD, kg·s^{-1}	320.98	1 775.30	0.004	20 681.00
Testing set	WD, m^3·s^{-1}	4.90	16.97	0.010	359.10
	SSD, kg·s^{-1}	124.01	992.75	0.002	15 600.00

Explanations: WD – water discharge, SSD – suspended sediment discharge.
Source: own study.

The data series were divided into three sets; we used twenty four years for training period (80%) from 1 September 1971 to 31 August 1995 and three years (10%) for the cross validation from 1 September 1995 to 31 August 1998 to avoid over training in our networks, and the last three years (10%) were used for testing period from 1 September 1998 to 31 August 2001. This helped us to assess the performance of the model.

Because of different measurement units, we have applied normalization using equation (1) to prevent the effect of extreme values of the data sets and to match the sigmoid type of transfer function, which has a range of values varying from 0 to 1. The input and output data were normalized using the following transformation equation:

$$Y_{norm} = Y_i / Y_{\max} \qquad (1)$$

where: Y_{norm} = the normalized dimensionless variable; Y_i = the observed value of variable; $Y_{\max}$ = the maximum value of the variables.

ARTIFICIAL NEURAL NETWORK

ANN is one of the mathematical models for forecasting by using pattern matching and comparison procedures [FISCHER 1998]. ANN models are developed by training the network to represent the relationships and processes that are inherent within the data. They are non-linear regression models, which need a set of interconnected simple processing nodes or neurons to perform an input-output mapping. Inputs for each neuron are taken either externally or are derived from other neurons. Then, each neuron passes its inputs through an activation or transfer functions such as a logistic or sigmoid curve [SOLOMATINE *et al*. 2003]. One of the common methods used in ANN is Feed Forward Back Propagation (FFBP). It is a supervised learning technique used for training data by minimizing the error of the data. It consists of an input layer, hidden layer and an output layer.

THE LEVENBERG MARQUARDT ALGORITHM

The Levenberg–Marquardt algorithm (LM) is a network training function. It is an approximation to Newton's method [MARQUARDT 1963], it provides a numerical solution to the problem of minimizing a nonlinear function over a space of parameters for the function. It is a popular alternative to the Gauss–Newton method of finding the minimum of a function. It is easy, robust and has stable convergence. This algorithm is the most popular function used in back propagation for predicting hydrological parameters.

METHOD TO PREVENT OVER-FITTING

In the last twenty years a number of techniques have been developed to avoid over-fitting that occurs during neural network training. Among applied techniques were: Weight Decay and Noise Injection [PIOTROWSKI, NAPIORKOWSKI 2013; ZUR *et al*. 2009], Optimized Approximated Algorithm [LIU *et al*. 2008] and Early Stopping [PIOTROWSKI *et al*. 2014; PRECHLET 1998; ZUR *et al*. 2009].

To avoid over-fitting, in the present paper we used one of the common techniques for regularizing errors in ANN, the so-called 'Early Stopping' [HAYKIN 1999; PRECHLET 1998]. We applied the Early Stopping criterion based on Prechlet's criterion [PIOTROWSKI, NAPIORKOWSKI 2013; PRECHLET 1998], where we divided our data set into three parts: training, validation and testing. The validation set was used only to evaluate the error during training set once in a while, knowing that we used only training set for training. To avoid Early Stopping on the validation error that may still go further down after it has begun to increase, we let the training iterations finish with a condition given to our model to save the network with the lowest generalized error that was evaluated and compared in every epoch.

Table 3 shows the results of the estimated suspended sediment discharge using the Early Stopping technique. The used input combinations for the regularized network were the same as the non-regularized network in order to compare between these two applications.

MODEL PERFORMANCE EVALUATION

For evaluating the performance of the models we used two different equations to calculate the error between observed and estimated data.

COEFFICIENT OF DETERMINATION (R^2)

Coefficient of determination (R^2) describes the degree of co-linearity between simulated and measured data; R^2 describes the proportion of the variance in measured data explained by the model [MORIASI *et al*. 2006]. R^2 ranges from 0 to 100%, with higher values indicating less error variance, and values greater than 50% considered acceptable [SANTHI *et al*. 2001; VAN LIEW *et al*. 2003]. The coefficient of determination R^2 has been used for further analysis to evaluate the performance of our estimation model. It is defined as follows:

$$R^2 = \left(1 - \tfrac{S_{cr}}{S_{ct}}\right)100 \qquad (2)$$

where: S_{cr} = square sum of residues; S_{ct} = square sum of total.

ERROR INDEX (RMSE)

Several error indices are commonly used in model evaluation, including root mean square error (*RMSE*). These indices are valuable because they indicate error in the units (or squared units) of the constituent of interest, which aids in analysis of the results. *RMSE* values of 0 indicate a perfect fit [SINGH, WOOLHISER 2002]. The root mean square error was used to test the statistical significant between estimated and observed suspend sediment concentration which can be expressed as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[\left(\dot{\theta}-\theta\right)^2\right] \tag{3}$$

$$RMSE = \sqrt{MSE} \tag{4}$$

where: θ = the observed sediment discharge; $\dot{\theta}$ = the predicted sediment discharge; n = the number of observations.

RESULTS AND DISCUSSION

In general, the training, validation and testing are the fundamental steps of Neural Network process. The training set is used to train the Neural Network by minimizing the error of the data and finding its best performance, then the validation and testing sets are used for checking the overall performance of the trained network, The Feed Forward Back Propagation Neural Network is the most common algorithm for multi-layered networks, which is often used in hydrologic modeling. It consists of an input layer, two hidden layers and an output layer; the numbers of neurons in the hidden layers is a very difficult task for MLP method. The performance of the BP model was tested for two different applications. In the first application, the suspended sediment load was predicted and estimated with full iteration that was given to the BP model to assess the best performance during training period. In the second application, the sediment load was predicted using the "Early Stopping" technique, which depended on the best network during the same iterations. Different numbers of input combinations were tried by BP model and the performances were compared to each other for the best input combination that gave the best values of *RMSE* and R^2.

The *RMSE* and R^2 values of the training, validation and testing period of the non-regularized network are presented in Table 2, the BP networks are trained according to the Levenberg–Marquardt algorithm, with the input layer, two hidden layers and output layer, with full iteration (500 epochs) for each network (8 networks).

The performance values of the training period show very good results of ANN_7, _8, _4 with R^2 (88.8%, 86.3%, 71.5%) respectively. The ANN_6, _3 and _1, showed acceptable values as well with R^2 (65.6%, 64.5%, 56.3%) respectively.

The models evaluation (*RMSE* and R^2) during testing period of the first application (full epochs), shows that the network with current and previous water discharge ANN_3 (Fig. 2a) gave the best performances with the lowest *RMSE* (2.57) and the highest R^2 (84.40%), and we can notice that the performance results of ANN_3 during testing period was better than training and validation period (Tab. 2). The ANN_7, _1 and _8 gave acceptable results and values close to ANN_3, with *RMSE* (3.07, 3.32, 3.66) and

Table 2. Performances of the non-regularized networks during training, validation and testing period

ANN	Input combination	Training		Validation		Testing	
		RMSE	R^2, %	*RMSE*	R^2, %	*RMSE*	R^2, %
ANN_1	WD_t	6.50	56.3	7.62	56.7	3.32	75.5
ANN_2	SSD_{t-1}	8.07	31.1	9.76	29.9	6.29	05.8
ANN_3	WD_t, WD_{t-1}	5.91	64.5	7.62	57.7	2.57	84.4
ANN_4	WD_t, SSD_{t-1}	5.28	71.5	6.47	69.7	5.71	24.9
ANN_5	SSD_{t-1}, SSD_{t-2}	8.07	32.6	10.45	19.1	6.47	01.8
ANN_6	WD_t, SSD_{t-1}, SSD_{t-2}	5.71	65.6	9.02	40.1	4.62	49.6
ANN_7	WD_t, WD_{t-1}, SSD_{t-1}	3.27	88.8	5.50	77.9	3.07	77.7
ANN_8	WD_t, WD_{t-1}, SSD_{t-1}, SSD_{t-2}	3.61	86.3	6.99	64.1	3.66	68.4

Source: own study.

R^2 (77.7%, 75.5%, 68.4%) respectively (Fig. 2b, 2c). Both BP models with previous sediment discharge ANN_2 and the network with two previous sediment discharges ANN_5 gave the worst values because of the complexity of the data and the poor correlation between input combination and the output, contrary to the other models which proved the positive relationship between water discharge and sediment discharge.

Table 3 shows the results of the training, validation and testing periods using the Early Stopping criterion based on cross validation technique.

Table 3. Performances of the regularized networks "early stopping criteria's" during training, validation and testing period

ANN	Input combination	Epoch	Training		Validation		Testing	
			RMSE	R^2, %	*RMSE*	R^2, %	*RMSE*	R^2, %
ANN_9	WD_t	10	6.50	55.4	7.50	58.4	3.21	75.7
ANN_10	SSD_{t-1}	91	8.07	31.0	9.76	30.0	6.29	05.6
ANN_11	WD_t, WD_{t-1}	85	5.91	62.4	6.99	63.4	2.53	84.9
ANN_12	WD_t, SSD_{t-1}	07	6.10	60.9	6.47	69.0	4.11	60.1
ANN_13	SSD_{t-1}, SSD_{t-2}	11	8.21	28.7	9.76	30.3	6.28	05.2
ANN_14	WD_t, SSD_{t-1}, SSD_{t-2}	96	6.10	61.3	7.92	53.6	4.75	46.6
ANN_15	WD_t, WD_{t-1}, SSD_{t-1}	41	3.87	84.3	4.82	82.6	2.71	82.6
ANN_16	WD_t, WD_{t-1}, SSD_{t-1}, SSD_{t-2}	52	4.03	83.0	4.61	84.4	2.73	82.4

Source: own study.

The networks ANN_15, _16 gave the best performance results during training period with R^2 (84.3%, 83.0%). The networks ANN_11, _12, _14 gave acceptable values during training period with R^2 (62.4%, 60.9%, and 61.3%). We can notice that the network of the second application during training period was chosen according to cross validation technique, and the performances values were lower than in non-regularized networks in the first application with full iteration (500 epochs).

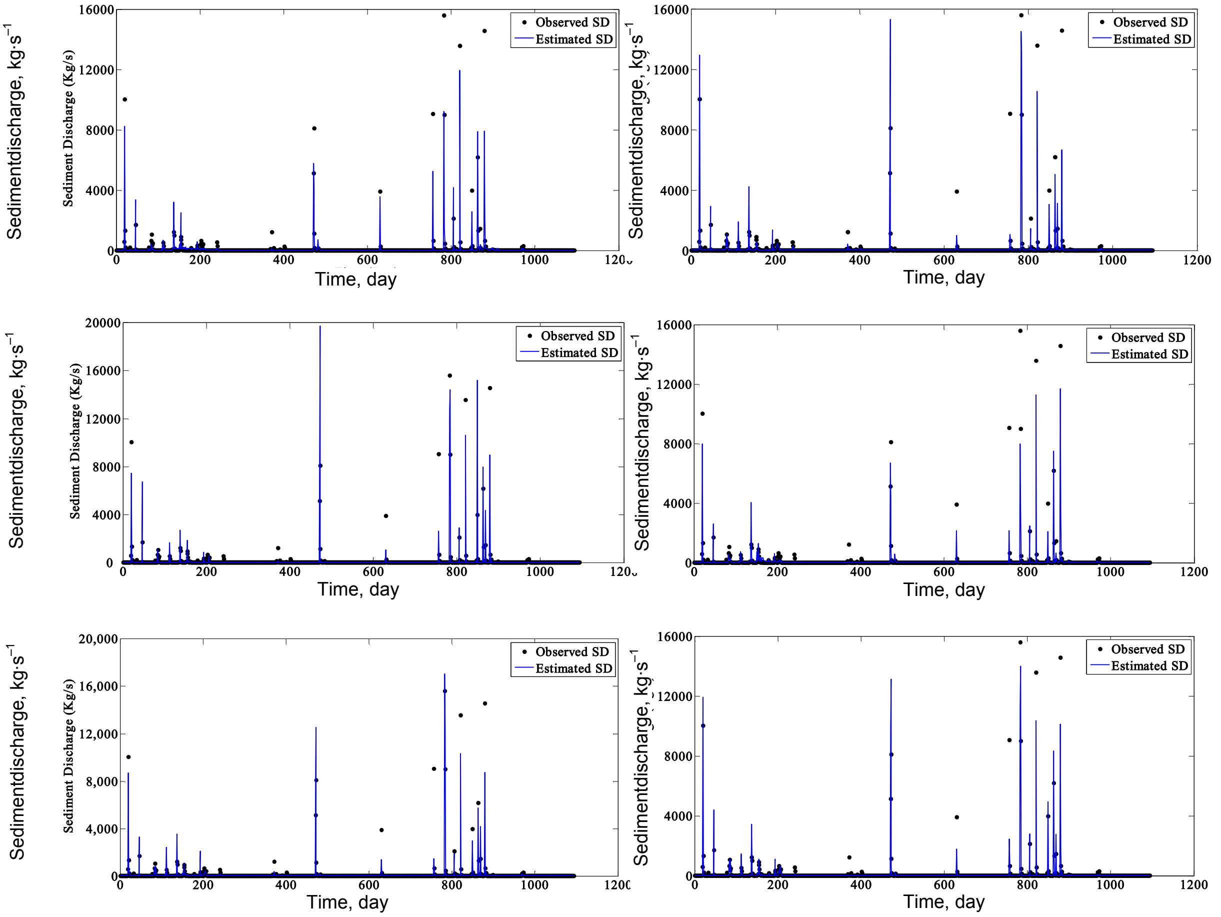

Fig. 2. The estimated and observed sediment discharge of a) ANN_3, b) ANN_7, c) ANN_8, d) ANN_11, e) ANN_15; f) ANN_16; source: own study

The validation period was used for cross validation, for effective evaluation of the model's result we didn't take under consideration the performances of the validation period (only used for cross validation), but we can see that it is clearly improved comparing with the results of the models of the validation period without regularizing the networks (Tab. 2, 3).

The *RMSE* and R^2 values of the testing period (Tab. 3) were significantly improved as well. The ANN_11 (Fig. 2d) gave the best results with *RMSE* (2.53) and R^2 (84.9%). The networks with current water discharge and previous water discharge and sediment discharge ANN_15, and the network with current water discharge, previous water discharge and two previous sediment discharges ANN_16 showed well goodness of fit (Fig. 2e, 2f), and close values to ANN_11 with *RMSE* (2.71, 2.73) and R^2 (82.6%, 82.4%) respectively. We can notice from all networks, regularized and non-regularized, that the predicted values overestimated the observed values during small events. On the contrary, during the largest events the values are underestimated. We can also notice from our results that the predicted sediment discharge showed high goodness of fit in ANN_3, _7, _8, _11, _15 and _16, opposite to the other networks that showed poor values during flood period. The results presented in Table 2 and 3 showed that over-fitting occurred in our MLP model. We can see that most of our networks were improved using cross validation technique.

The ANN_4 and ANN_12 had the same network architecture and input combinations. We see that the ANN_12 improved very well using regularizing technique with improvement of 58% comparing to the non-regularized network in the first application with full iteration. The best network that was detected using cross validation was on the epoch 07, where the error of validation set had the minimum values during all epochs of the ANN_12. The over-training in this ANN started beginning from the 8^{th} epoch as shown in Fig. 3.

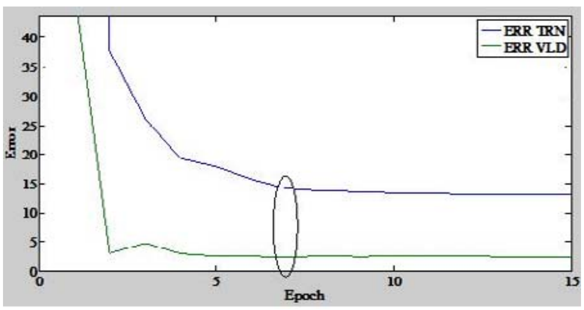

Fig. 3. The training error and validation error on epoch 08 before over-training started; source: own study

To compare our results we can present two different studies carried out on the same river. LEFKRI *et al*. [2006] estimated daily sediment transport depending on only water discharge using the fuzzy logic and the empirical model. The results indicate that fuzzy logic showed better results than the empirical model during a period of one year (1987) with 76% during validation period. Another study by LARFI, REMINI [2006] estimated the sediment discharge using the linear correlation models in large events during an observation period of 13 years. The correlation between water discharge and sediment discharge was 67.6%. The comparison with other methods shows that regularized ANN models give better results taking under consideration the long period used in our data.

Both results, of the regularized and the non-regularized networks, support the significance of developing a non-linear complex behavior model to predict sediment discharge in the river. According to our results, it is obvious that overtraining occurs in our neural network models because of the complexity and non-homogeneity of data. For example, it can be noticed in the networks, in which we used previous sediment discharge and water discharge as input that the overtraining did occur (ANN_2, _4, _5, _7, _8). We can conclude that the non-regularized MLP models are frequently exposed to overtraining.

CONCLUSION

The processes of flow and sediment load are complex in Algeria. The present study investigates the comparison between non regularized and regularized ANN using the Early Stopping technique for estimating suspended sediment load on a daily scale in the case of the Isser River, upstream the Beni Amrane reservoir.

Different input combinations including daily current and previous water discharge and previous sediment discharge were used in the ANN models to obtain the optimal input combination. The results obtained in this study indicate that over-fitting occurred in our networks, and the use of the Early Stopping technique gave better results of our predictive model comparing to non-regularizing networks. The major over-fitting occurred in our ANN model when we used previous values of sediment discharge, which reflected the complexity and big size of data that were introduced to our network. In conclusion, we have shown that forecasting suspended sediment load using the early stopping criterion in ANN training is very robust and effective.

In the future we aim to use the noise injection and optimized approximation algorithm in artificial neural network to avoid over-fitting and to improve our networks for better results.

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Prognozowanie ładunku zawiesiny z zastosowaniem regularyzowanej sieci neuronowej: przykład rzeki Isser w Algierii

STRESZCZENIE

Słowa kluczowe: *ładunek zawiesiny, rzeka Isser, sztuczne sieci neuronowe, technika Early Stopping, zbiornik Beni Amran*

Ocena i przewidywanie ładunku zawiesiny w rzekach są istotne w zarządzaniu zasobami wodnymi w różnych hydrosystemach. Trudno jest uzyskać efektywne i szybkie oszacowanie ładunku zawiesiny za pomocą sztucznych sieci neuronowych bez uniknięcia przepełnienia danymi. W niniejszej pracy porównano wyniki zastosowania wielowarstwowej sieci w dwóch wariantach – sieci nieregularyzowanej i sieci regularyzowanej z użyciem techniki Early Stopping do oceny i prognozowanie ładunku zawiesiny w rzece Isser powyżej zbiornika Beni Amran w północnej Algierii. Badania bazowały na notowaniach dobowego odpływu zawiesiny i danych dotyczących odpływu wody w ciągu 30 lat (1971–2001). Wyniki modeli opartych na metodzie wstecznej propagacji oceniono za pomocą współczynnika determinacji (R^2) i pierwiastka ze średniego błędu kwadratowego. Porównanie wyników dowodzi, że sieć neuronowa regularyzowana przy pomocy techniki Early Stopping celem uniknięcia przeładowania sprawdza się lepiej niż sieć nieregularyzowana. Wyniki wskazują, że przeładowanie wstecznej propagacji ma miejsce z powodu złożoności danych wprowadzonych do sieci.