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Comparison of Empirical Methods and Neural Network Technique in Predication of Suspended Sediment: a Case Study of Armand River, Karoon Basin, Iran

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Abstract: Prediction of suspended sediment discharge in rivers is an important process for water resources improvement and managements. In practice sediment yield is usually calculated from direct measurement of sediment concentration of river or indirectly using sediment transport equations. Since direct measurement cannot be performed for all stream gauges, indirect methods are preferred. In this study, predictions of suspended sediment load for Armand River in Iran using selected empirical equations were made based on 772 sets of data. This research examines whether a neural network technique (MLP) can predict the suspended sediment discharge in the river better than the empirical formulae such as Toffaleti, Chang-Simons-Richardson, Einstein, Lane-Kalinske, Brooks and Bagnold. The results showed that MLP has good performance to estimate suspended sediment in comparison with aforementioned equations. The results revealed that MLP using velocity, area, depth, hydraulic ratio as input parameters and also considering 4 units in input layer, 2 in hidden layer and 1 in output layer shows the best performance among all of the models of neural network. Evaluation of the results showed RMSE=0.027 and R^2= 0.90, which is recorded the highest determination coefficient.

Key words: Empirical methods · Artificial Neural Network · Armand River · Iran

INTRODUCTION

Improving knowledge on suspended sediment yields, dynamics and water quality is one of current major environmental challenges addressed to scientists and hydropower managers [1]. Indeed, estimates of suspended sediment load are essential to investigate about river transportation. Especially the time and the relation between time and suspended sediment discharge are important because the depletion and increasing in the sediment amount occur during flood seasons [2] and also Chen *et al.* [3] found that the fine suspended sediment concentrations had pronounced seasonal and spring-neap tidal variations. Although the existence of suspended sediment causes a lot of problems in rivers but in contrast there are some agricultural hills slope maintenance practices which can modify sediment erosion in the basin and in the future in rivers [4]. Estimation of sediment load is required in practical studies for the planning, designing, operation and maintenance of water resources structures [5]. The sediments transportation monitoring requires a good sampling technique which is very lengthy and costly. Because of this, some formulae were developed from 1950 up to now to predict and estimate the sediment load in rivers [6]. Shirin and Kisi [7] applied convenient Gene Expression Programming (GEP), Nero-Fuzzy (NF) and Artificial Neural Network (ANN) techniques and compared with each other. Comparison of results indicated that the wavelet conjunction models significantly increased accuracy of single GEP, NF and ANN models in suspended sediment estimation. Kisi [8] demonstrated the evidence of ANN ability in Daily River suspended sediment concentration modeling. Beside these methods, sediment rating curve showed good results in predication of suspended sediment for 3 days ahead [9]. Bisantino *et al.* [10] have compared the field data with those predicted from four formulae (Ackers-White, Engelund-Hansen, Yang and Van Rijn). They illustrated that for low sediment loads, the formulae results are not reliable or at least less reliable. Nourani *et al.* [11] developed two ANN models for semi-distributed modeling of suspended sediment load process of the Eel River watershed located in California, USA. The results demonstrate that although the predicted

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sediment load time series by both models are in satisfactory agreement with the observed data, the geomorphologic ANN model performs better than integrated model because of employing spatially variable factors of the sub-basins as the model's inputs. Therefore, the model can operate as a non-linear time-space regression tool rather than a fully lumped model. Based on the results of Cobaner *et al.* [12] the Nero-Fuzzy models perform better than the other methods such as empirical ones in daily suspended load estimation. On the other hand, what Kisi [13] showed in his research which proposed Neural Differential Evolution (NDE) models to estimate suspended sediment concentration in river is not consistent with [12]. The emergence of ANN technology has given many promising results in the field of hydrology and water resources and also sediment hydraulics to solve the nonlinear system complexity problem [14, 15]. The hydrological characteristics of the river such as spatio-temporal changes of sediment concentrations and difficulties for their estimation encouraged using the ANN models. Rai and Mathur [16] in his research about modeling sediment load during storm events found the Neural Network technique as a suitable estimation tool in two catchments in the USA. One of the most different researches that were done by Cigizoglu and Kisi [17] approved the higher performance of Range-Dependent Neural Network (RDNN) in comparison with conventional ANN applications. Most of the studied transport models are based on simplified assumptions that are valid in ideal Laboratory conditions only and may not be true for much complicated natural river systems. Models based on more sophisticated theoretical solutions require a large number of parameters that are impossible or difficult to collect for a natural river system [18]. Tena *et al.* [19] found that calculations of sediment load are based on continuous discharge and turbidity records, the latest calibrated with direct suspended sediment sampling that covered the whole range of observed hydraulic conditions. Gao [20] found that in practice, the empirical equation can be used to estimate the maximum possible bed-load transport rates during high flow events, which is useful for various sediment-related river managements. Kisi [13] compared three methods of neural network with each other and the results indicated that the NDE models give better estimates for suspended sediment in river than NF, NN and RC techniques. In this research, predictions of suspended sediment for Armand river located in Chahar-Mahal-Bakhtiari Province were made and analyzed using the selected empirical equations and NN technique and also the results were compared with each other the same as what Roushangar *et al.* [21] have done in their study.

MATERIALS AND METHODS

Study Area: Application of six suspended sediment estimation formulae was tested in Armand River in Iran. Sediment discharge and sediment concentration and also flow discharges series for the stations are used to develop and verify models' performances. Armand Station is located in Armand River at 50° 46' Latitude 31° 40' Longitude. The drainage area of this river is about 9986 km^2 and the station that these data are used from, is located in 1082 m height. This river is located in North Karoon Basin. The basin is one part of Zagros mountainous lands and is covered by limestone and marl soils and semi-dense forests. The mean annual rainfall of the basin is about 500 mm. Fig. 1 shows the location of study area in Iran.

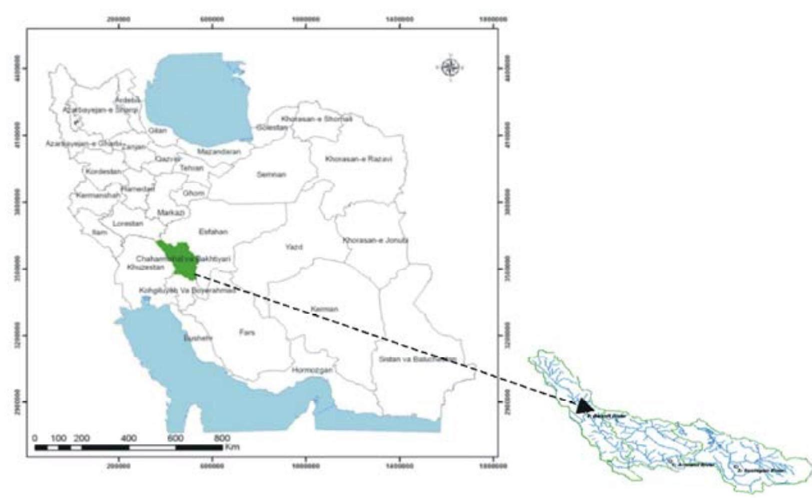

Fig. 1: The location of study area in Iran.

Table 1: Descriptions of abbreviations which are used in suspended sediment formulae.

	Abbreviations	descriptions
1	$\overline{u_y}$	The average local velocity at distance y from the bed
2	$u_* = \sqrt{\dfrac{\tau o}{S_f}}$	The shear velocity
3	S_f	The density of the water
4	S_e	The slope of the energy grade line
5	R	The hydraulic radius
6	g	The acceleration due to gravity
7	y	The distance from the bed
8	v	The kinematic viscosity of the water
9	K_s	The roughness of the bed
10	x	A corrective parameter
11	$\Delta = \dfrac{K_s}{X}$	The apparent roughness of the surface
12	δ	The thickness of the laminar sub layer of a smooth wall
13	g	The acceleration due to gravity
14	y	The distance from the bed
15	k	Van-Karman coefficient equal to 0.4
16	ω	The fall velocity
17	q	The flow discharge
18	q_{sw}	The suspended sediment discharge
19	C_a	As the suspended sediment concentration in water depth a
20	S_g	Assumed as the ratio of water density to sediment density
21	$\overline{u}$	The mean velocity
22	τ	The shear stress
23	q_{sm}	The sediment discharge
24	S	The bed slope

Data Sources: The range of all data used in this study lie within the range of data used in the development of the selected equations. This is illustrated in Table 1. A 44 years (1967-2009) data was collected for the study area. Abnormal distribution of data have such effects that may lead to high fluctuations in figures and reduces the reliability of analytical results, thus normalization of data is necessary. At first step imperfect data were eliminated and then the missing data were estimated using interpolation method.

The river under study is categorized as a small river with aspect ratio more than 5. Data covers flow velocities from 0.66 m/s to 4.12 m/s and flow depths from 0.91 to 1.5 m.

Artificial Neural Networks: Artificial Neural Network (ANN) is a massively parallel-distributed information processing system that has certain performance characteristics resembling to the biological arrangement of Neurons in human brain [22]. An ANN establishes a data-driven nonlinear relationship between inputs and outputs of a system [23]. Thus, Neural Networks (NN) has been successfully applied in a number of diverse fields including water resources. In the hydrological forecasting context, (ANNs) may offer a promising alternative for rainfall–runoff modeling [24, 25-27], stream flow prediction [28,17, 29-32]. There are few published studies in the field of suspended sediment prediction using artificial intelligence methods such as neural networks and fuzzy logic approaches. Tayfur [33] reviewed the ANN-based modeling in hydrology over the last years and reported that about 90% of the experiments extensively use the multi-layer Feed-forward Neural Networks (FNN) trained by the standard Back

Propagation (BP) algorithm. Maier and Dandy [34] reviewed 43 articles dealing with use of the ANN model for estimation of water resources variables.

The neural network typically consists of an input layer, an output layer and a layer of nonlinear processing elements, known as the hidden layer. The ANN has several algorithms used in forecasting and modeling processes. In this study, the feed forward back propagation algorithm was selected for modeling the suspended sediment concentration. The most commonly used ANN in hydrological predictions is the BP algorithm [35]. BP is a supervised learning technique used for training the neural networks. Basically, it is a gradient descent technique to minimize some error criteria. The BP network structure in this study includes a three-layer learning network consisting of an input layer, a hidden layer and an output layer.

Improving the Generalization Level in Model: One of the most important and effective problems that occurs during neural network training is over fitting. The error on the training set is driven to a very small value, but when new data is presented to the network, the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations [36]. The feed forward back propagation algorithm is a widely applied three layers network type consisting of an input layer, a hidden layer and an output layer. The determination of the number of nodes in a hidden layer providing the best training results was the initial process of the training procedure. The suspended sediment concentration estimation was carried out with the BP through considering the width and depth and also the area of the river, river discharge and velocity as associate inputs of the network. Various hidden nodes numbers were tried for the BP algorithm.

Model Evaluation: The performances evaluation criteria were the root mean square errors (RMSE) and the coefficient of determination (R^2) expressed between estimated and observed suspended sediment concentration as:

$$r^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - y_i')^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{1}$$

Where d_i is the difference between *i*th estimated and *i*th observed values of suspended sediment concentration and *N* is the number of observations. The coefficient of determination used to evaluate the performance of the models is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - y_i')^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{2}$$

Where y_i and y_i are the *i*th observed (actual) and estimated values of y and $\bar{y}$ is the mean of the observed values of y; and N is the number of observations.

Suspended Sediment Formulae: The finer particles of the sediment load of streams move predominantly as suspended load. Suspension as a mode of transport is opposite to what Chang_Simons_Richardson [37] called surface creep and to what they refined as the heavy concentration of motion immediately at the bed. In popular parlance this has been called bed load, although as defined in this publication bed load includes only those grain sizes of the surface creep which occur in significant amounts in the bed.

Chang-Simons-Richardson [37] derived a sediment transport model in which, they assumed the below formula valuable

$$\varepsilon_s = KU_* \frac{y}{D}(D - y) \tag{3}$$

And also defining the amount of ε_s equal and $\beta KD\xi U_*(1-\xi)^{1/2}$ introducing ξ=y/D, shear stress may be determined as; c_y the concentration in water depth y, is estimated as;

$$\frac{C_y}{C_a} = \left(\frac{d-y}{y}\frac{a}{d-a}\right)^z \tag{4}$$

In which the concentration of these particles at y is c_y. y is the variable of integration, the dimensionless distance of any point in the vertical from the bed, measured in water depth d, with;

$$z = \frac{v_s}{0.4u_*} \tag{5}$$

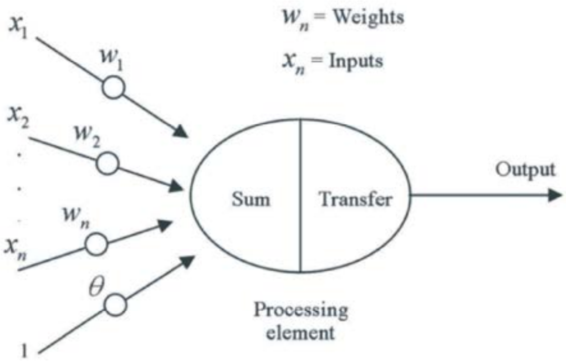

Fig. 2: Basic concepts of artificial neuron (after Yang, 2009).

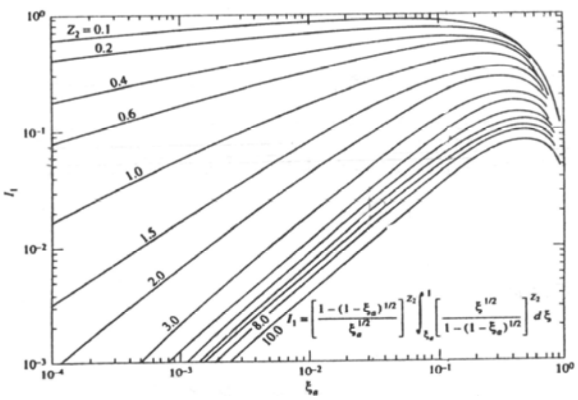

Fig. 3: I_1 vs.ξa (ξ in water depth a) to determine the amount of I_1 for individual depths (Yang, 1940).

Also replacing Equation (3) in Equation (4), Equation 6 would be obtained:

$$\frac{C}{C_a} = A_1\left[\frac{\xi^{1/2}{}_a}{1-\left(1-\xi_a\right)^{1/2}}\right]^{z_2} \tag{6}$$

The suspended sediment discharge would be estimated in the form of

$$q_{sw} = \gamma D C_a\left(V I_1 - \frac{2U_*}{K} I_2\right) \tag{7}$$

In this equation there are two factors $I_1$and I_2 that can be obtained either from the graphs I_1-ξ (Fig. 3) or I_2-ξ (Fig. 4).

The performance of Chang-Simons-Richardson to estimate the suspended sediment is evaluated using RMSE and R^2.

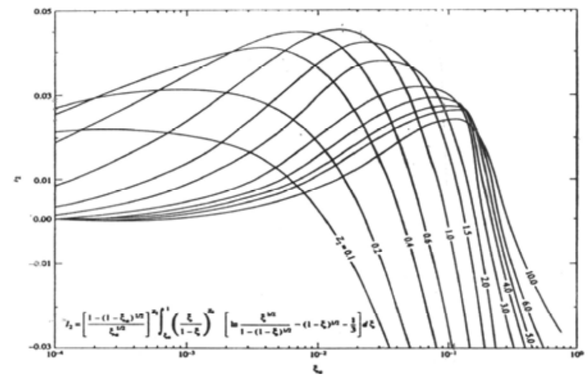

Fig. 4: I_2 vs. ξa (ξ in water depth a) to determine the amount of I_2 for individual depths (Yang, 1940).

Bagnold [38] derived a stream-based sediment transport model. In that model, Bagnold assumes the sediment is transported in two modes, i.e., the bed load transport and the suspended transport. The bed load sediment is transported by the flow via grain to grain interactions; the suspended sediment transport is supported by fluid flow through turbulent diffusion. The suspended sediment rate can be calculated using the below formula [3];

$$g(S_g - 1)q_{sm} = 0.01\tau(\bar{u}^2/\omega_s) \tag{8}$$

Brooks [39] derived a sediment transport model in which he takes the Semi-logarithmic velocity distribution into account and also determined that suspended sediment discharge depends on suspended sediment concentration. The suspended sediment rate can be calculated as:

$$\frac{q_{sw}}{C_{md}q} = T_B\left(k\frac{V}{U_*}, Z_1, E\right) \tag{9}$$

where Z_1, is a function of $Zi = \frac{\omega_i V}{C_Z RS}$

C_z is the factor which depends on temperature. $E=e^{-(kv/U^*)-1}$ and C_{md} is the suspended sediment concentration in y=D/2 numbers.

The hydraulics of uniform flow includes basically the description of the velocity distributions and of the frictional loss for turbulent flow. Einstein has found that in describing sediment transport the velocity distribution in open-channel flow over a sediment bed is best described by the logarithmic formulas based on V. Karman's similarity theorem with the constants as proposed by Keulegan [40]. He gives the vertical velocity distribution as

$$\frac{\bar{u}_y}{u_*} = 5.50 + 5.75\log_{10}\frac{(yu_*)}{\nu} = 5.75\log_{10}\left(9.05\frac{yu_*}{\nu}\right) \quad (10)$$

For Smooth Boundaries And:

$$\frac{\bar{u}_y}{u_*} = 8.50 + 5.75\log_{10}(\frac{y}{k_s}) = 5.75\log_{10}(30.2\frac{y}{k}) \quad (11)$$

The transition between the two, including the rough and smooth conditions, may all be combined in the form:

$$\frac{\bar{u}_y}{u_*} = 5.75\log_{10}(30.2\frac{Vx}{k_s}) = 5.75\log_{10}(30.2\frac{y}{\Delta}) \quad (12)$$

subscript (x) is given in Fig. 1 as a function of k_s/δ.

The integral of suspended load moving through the unit width of a cross section may be obtained by combining Equations 10 and 11.

$$\int_y^d C_y\bar{u}_y dy = \int_y^d C_a\left(\frac{d-y}{y}\frac{a}{d-a}\right)^z 5.75u_*\log_{10}(30.2y/\Delta)dy \quad (13)$$

Lane-Kalinske [41] derived a suspended sediment transport model in which their approach was based on $\varepsilon_s=\varepsilon_m$, they assumed that $\beta=1$ and introduced this Equation

$$\varepsilon_s = kU_*\frac{y}{D}(D-y) \quad (14)$$

The average of this parameter is obtained

$$\bar{\varepsilon}_s = \frac{\int_0^D \varepsilon_s dy}{D} = \frac{kU_*}{D^2}\int_0^D (yD-y^2)dy \quad (15)$$

Introducing the abbreviation

$$P_L = \frac{\bar{C}}{C_a} \quad (16)$$

Suspended sediment discharge is estimated as:

$$q_{sw} = qC_aP_L\exp\left(\frac{15\omega a}{U_*D}\right) \quad (17)$$

Toffaleti [42] derived a suspended sediment transport from Einstein and Chain formulae and also used deep integration of concentration profile multiplied by velocity profile. The total velocity profile is obtained from

$$U = (1+\eta_v)V(Y/R)^{\eta_v} \quad (18)$$

in which U is the velocity in water depths of Y in relation to bed and η_v is an explanatory parameter

$$\eta_v = 0.1198\times 0.00048T_F \quad (19)$$

T_F is the temperature in Fahrenheit.

Toffaleti divided the vertical depth into four parts and estimated the suspended sediment concentration for each part separately. Introducing the abbreviation

$$Zi = \frac{\omega_i V}{C_Z RS} \quad (20)$$

$$C_Z = 260.67 - 0.0667T_F \quad (21)$$

If the assumed amount of Z_i become more than η_v, so it can be supposed that it is equal to 1/5 η_v and the suspended sediment discharge for upper zone in the vertical profile would be defined

$$q_{SUi} = Mi\frac{(R/11.24)^{0.244Zi}(R/2.5)^{0.5Zi}\left[R^{\eta_1} - (R/2.5)^{\eta_1}\right]}{\eta_1} \quad (22)$$

For the median one

$$q_{Smi} = Mi\frac{(R/11.24)^{0.244Zi}\left[(R/2.5)^{\eta_2} - (R/11.24)^{\eta_2}\right]}{\eta_2} \quad (23)$$

for the below zone

$$q_{SLi} = Mi\frac{(R/11.24)^{\eta_3} - (2di)^{\eta_3}}{\eta_3} \quad (24)$$

with

$$Mi = \frac{43.2Pi(1+\eta_v)VC_{Li}}{R^{\eta_v - 0.756Zi}} \quad (25)$$

and

$$\eta_1 = 1 + \eta_v - 1.5Zi \quad (26)$$

$$\eta_2 = 1 + \eta_v - Zi \quad (27)$$

$$\eta_3 = 1 + \eta_v - 1.756Zi \quad (28)$$

In Equation 25, P_i is the percentage of sediments with d_i diameter; C_{Li} must be calculated for each diameter in water depths Y. Total suspended sediment load discharge per unit in the river would be equal with all suspended sediment load discharges in the parts.

RESULTS AND DISCUSSION

A difficult task with MLP is choosing the number of nodes in each of the layer. There is no theory yet to determine that how many hidden units must be considered for each function. In this study, the three layer MLP is used and common trial and error method is used to select the number of nodes, specially the hidden nodes. The input data were standardized before being entered to the model. The sediment concentration data were also normalized in the same way. After training step, the weights were saved and used to test data for each neural network and also models.

The Neuron in the output layer represents suspended sediment flux (Fig. 2). The number of Neurons in the hidden layers was determined by a trial-and-error method. Neurons in the input layer represent input variables. In this study, 20 input combinations, which fell in four groups, were used (Table 2). The networks in different groups were designed to compare the performances of different sets of causal variables; while those in the same group were designed to examine the degree of number of the parameters effect between the inputs and the outputs. The network in group 1 used the width of the river beside other parameters in each sub group. In this group the second sub group with three input parameters has the best simulation in comparison with others. Among all of the simulations in Table 2, it can be recognized that in the 9th and 5th and also 8th subgroups, there is the most ability to simulate the flux as an output. In addition individuals were tested and it was seen that W lonely has good ability to predict Q_s. Evaluation of this simulation showed that velocity, area, depth and hydraulic ratio, flow discharge, width and also velocity, area, depth, flow discharge considered within two groups can simulate the sediment discharge with RMSE equal 0.032 and 0.027, respectively. Also determination coefficient was equal 0.81 and 0.90 for each group, respectively (Fig. 2; the best network in suspended sediment discharge). During the training process the best results were determined with the optimization function as gradient descent and momentum equal to 0.9 and also interval offset equal to 0.5.

Table 2: Performance of MLP as a neural network.

Network Type	Decoration	RMSE	R^2
W Q_w	(2 1 1)	0.081	0.32
W Q_w V	(3 4 1)	0.067	0.51
W Q_w V A	(4 1 1)	0.066	0.54
W Q_w V A D	(5 1 1)	0.066	0.55
W Q_w V A D RH	(6 1 1)	0.032	0.81
Q_w V	(7 1 3)	0.057	0.62
Q_w V A	(2 3 1)	0.056	0.64
Q_w V A D	(3 1 1)	0.044	0.79
Q_w V A D RH	(4 2 1)	0.027	0.90
V A	(5 5 1)	0.049	0.67
V A D	(6 1 1)	0.042	0.68
V A W	(2 1 1)	0.053	0.67
V A D RH	(3 3 1)	0.059	0.58
A Qw	(3 1 1)	0.077	0.46
A D	(4 2 1)	0.042	0.68
A W	(5 3 1)	0.042	0.68
A D RH	(2 2 1)	0.042	0.68
D RH	(2 4 1)	0.041	0.69
D W	(2 5 1)	0.040	0.70
D Qw	(3 3 1)	0.066	0.54

Table 3: Evaluation of suspended sediment estimation formulae.

Formulae	Observed annual mean suspended sediment discharge	Estimated annual mean suspended sediment discharge	RMSE	R^2
Toffaleti	391.33	180.27	0.084	0.65
Chang-Simons-Richardson	391.33	173.74	0.052	0.41
Einstein	391.33	18.45	0.059	0.48
Lane-Kalinske	391.33	180.87	0.088	0.71
Brooks	391.33	1206.34	0.042	0.35
Bagnold	391.33	59.95	0.082	0.61

Table 3 shows that Bagnold, Brooks, Einstein, Chang_Simons_Richardson, Lane-Kalinske and Toffaleti equations with five input parameters cannot estimate the suspended load accurately. Input parameters of this formula are both morphological and hydrological and in comparison with the 5th group (2nd sub group) and the 8th and 9th groups (2nd sub group) of neural network, Bagnold cannot estimate the suspended sediment flux as well. But about Brooks it must be mentioned that this formula can estimate the suspended sediment discharge more accurate than the first subgroup. In comparison with the first group (1st sub group) and 3rd group (14th sub group) of neural network, Einstein can estimate the suspended sediment flux as well (Tables 2 & 3). The 5th group (the second sub group) and the 8th and 9th group (the second sub group) of neural network, estimate the suspended sediment flux more accurate than Lane _ kalinske. In comparison with the 5th group (the second sub group) and the 8th and 9th group (the second sub group) of neural network, Toffaleti cannot estimate the suspended sediment flux as well. Also the results of the application of Chang_Simons_Richardson formula with ANN shows that the accuracy of the formula is high when just two parameters (width and river discharge) are entered in to ANN model.

Comparison between Tables 2 & 3 highlights the difference among the estimation methods for suspended sediment in the river. One of the most advantages about ANN is that there is not any exact function to enter specific parameters as input into the model and this matter can be a kind of positive point of this model over other methods. So because of this as it is illustrated in Table 2, some groups of input parameters are tested to predict the suspended sediment discharge.

The performance of all models presented clearly in Fig. 5 through 11. Results indicate that the Chang-Simons-Richardson method performs poor than the artificial neural networks and it cannot estimate the nonlinear suspended sediment flux with high accuracy, due to their simple structure. Also it is clearly showed that Bagnold, Toffaleti and Lane-Kalinske have better

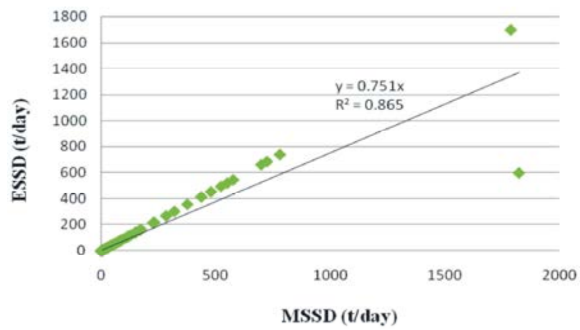

Fig. 5: Performance of MLP to estimate suspended sediment discharge (MSSD: measured suspended sediment discharge; ESSD: estimated suspended sediment discharge)

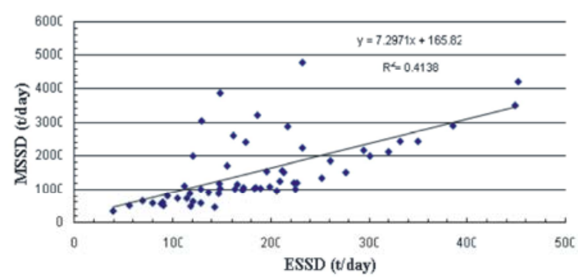

Fig. 6: Performance of Chang-Simons-Richardson to estimate suspended sediment discharge.

estimation in comparison with other formulae. These three formulae have rather good agreement with the measured data. Although in some of the researches in recent years, the over and under estimation of empirical formulae has been proved [43, 17]. But in this study it is shown that how good these empirical formulae can estimate the suspended sediment discharges and it is understood that these two kinds of methods ANN and empirical formulae estimated the suspended sediment discharges with about the same accuracy. In addition the high performance of MLP in this study is consistent with the results found by Singh *et al.* [44] and Melesse *et al.* [45], but the result of this study is not consistent with Khatibi *et al.* [46], Piotrowski *et al.* [47] and Oehler *et al.* [48]. Also the ability of equations is also approved and shown as

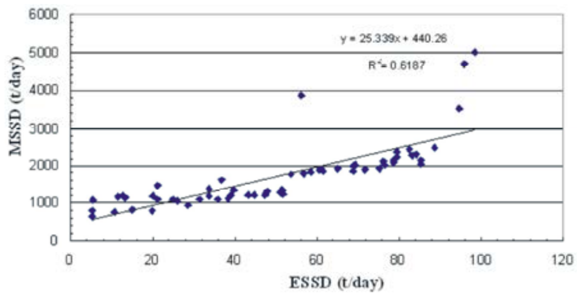

Fig. 7: Performance of Bagnold in estimation of suspended sediment discharge.

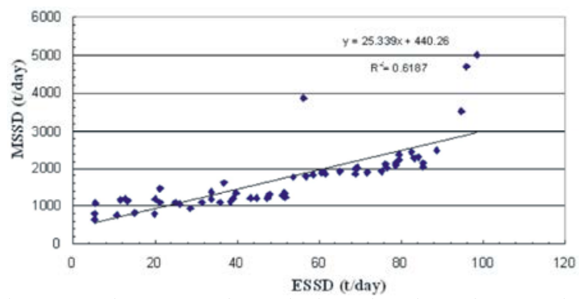

Fig. 8: Performance of Brooks in estimation of suspended sediment discharge.

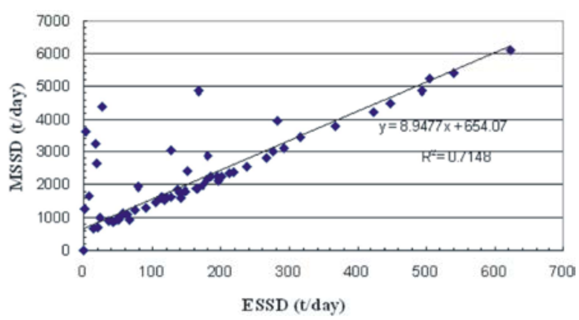

Fig. 9: Performance of Lane-Kalinske in estimation of suspended sediment discharge.

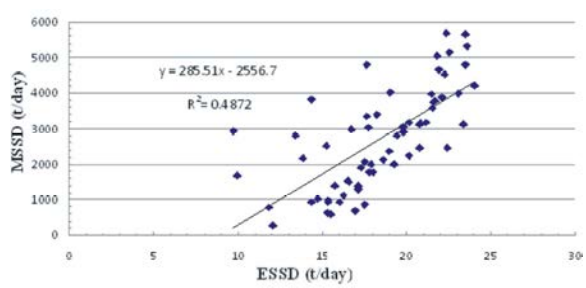

Fig. 10: Performance of Einstein in estimation of suspended sediment discharge.

accurate as ANN. This is the matter which is not consistent with what others have shown. Configuration of BP in this study shows the highest statistical performance in the sediment estimation when the velocity,

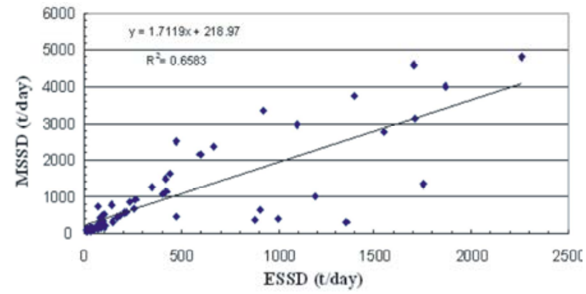

Fig. 11: Performance of Toffaleti in estimation of suspended sediment discharge.

depth, hydraulic ratio, river discharge, width and area were used as input variables in the network. This result is also not consistent with Mustafa *et al.* [49]. According to Brikundavyi *et al.* [50], the performance of the BP was found to be superior to conventional statistical and stochastic methods in continuous flow series forecasting. The superiority of artificial neural networks over a conventional empirical method here can be attributed to their capability to capture the nonlinear dynamics and generalize the structure of the whole data set [51]. Obviously, using artificial neural networks for modeling sediment estimation can be more reliable than the empirical methods.

CONCLUSIONS

This study focused on estimation of the suspended sediment discharge in Armand River. From the evaluations of the selected sediment transport equations and ANN (using MLP as the type of network), it was observed that ANN performed well when tested against field data in comparison with empirical methods. In this study the ANN methodologies were applied to estimate the weir daily-based suspended sediment discharge using morphological and hydrological parameters as input variables. ANN can generate a better fit to the observed suspended sediment flux when an individual river discharge is used as the input parameter; especially this can be observed using width as the only input parameter. A, q_w, D and V as the entrances to ANN together create better simulation in comparison to using individual parameters. The results of the evaluations showed that empirical formulae cannot be introduced as accurate models for suspended sediment estimation, so further studies needed to develop a model that can estimate the suspended sediment discharge up to its importance accurately.

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