MODELLING OF SUSPENDED SEDIMENT
In Nile River using ANN

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Abstract: Artificial neural network (ANN) prediction models can be considered as an efficient tool in predictions once they are trained from examples or patterns. These types of ANN models need large amount of data which should be at hand before thinking to develop such models. In this paper, the capability of ANN model to predict suspended sediment in 2-D flow field is investigated. The data used for training the network are generated from a pre-verified 2-D hydrodynamic and a 2-D suspended sediment models which were recently developed by the authors. About two-thirds of the data are used for training the network while the rest of the data are used for validating and testing the developed ANN model. Field data measured by hydraulic research Institute are used to compare the results of the ANN model. The conjugate gradient learning algorithm is adopted. The results of the developed ANN model proved that the technique is reliable in such field compared to both the results of the previously developed models and the field data provided that the trained network is used to generate prediction within the range of training data.

1 INTRODUCTION

The subject of sediment transport in alluvial streams gains its importance with the increasing of water resources utilization. Extensive researches had been done in this field. Generally, laboratory investigations to predict sediment transport are time-consuming, costly and even not possible for many practical engineering problems. Therefore, mathematical models for predicting sediment transport were developed using different techniques. Several one dimensional models were developed, see for example (Thomas and Prasuhn, 1977), (Bhallamudi and Chaudhry, 1991) and (Guo and Jin, 1999). Examples of 2-D models include those developed by (Lin and Shen, 1984), (Van Rijn, 1986), (Celik and Rodi, 1988), (Van Rijn et al., 1990) and (Elfiky et al., 2003). Instead of mathematical model, a relatively new computational tool, ANN, can be used to predict the suspended sediment load.

Although many applications in the field of Hydraulic Engineering are available such as (Karunanith et al., 1994) and (Dibike et al., 1999) very few applications in the field of sediment transport were published. (Nagy, 1999) used ANN to estimate the natural sediment discharge in rivers in terms of sediment concentration. (Jain, 2001) used the ANN approach to establish an integrated stage-discharge-sediment concentration relation. Also, ANN approach can successfully model the hysteresis effect that is associated with unsteady flow in open channels. (Nagy et al., 2002) used the ANN approach to estimate the natural sediment discharge in rivers in terms of sediment concentration.

In the present paper, ANN, is used to predict the suspended sediment load in terms of the flow depth, the velocities components in x and y directions and the sediment carrying capacity. Since, the method learns from examples, a large set of data should be available. Practically, field data of different rivers should be used to train and validate the ANN but it is not available at the time being at the author hands

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Therefore, the developed SED-2 numerical model by (Elfiky et al., 2003) is used to generate the required data for training and verification of the ANN to test and prove its capability to predict the suspended sediment concentration once it gets trained.

2 OVERVIEW OF ANN

Artificial Neural Network (ANN), is a structure composed of a number of interconnected units (artificial neurons) Each neuron has an input/output characteristics and implements a local computations or function, (Schalkoff, 2002). Hence, the overall ANN of interconnected neurons displays a corresponding functionality. A neural system should be capable of storing information through training. Thus the objective of training the ANN is to develop an internal structure enabling the ANN to correctly identify or classify new similar patterns. Thus, neural network is a dynamic system, its state changes over time in response to external inputs or an initial unstable state. Various types of ANN are in use and could be reviewed from (Schalkoff, 2002). Most of the applications of ANNs in fields of water Engineering were reviewed in (Negm, 2002). In this paper, the multilayer feedforward network or the multilayer perceptrons is used in modeling suspended sediment concentration in river flow.

A typical ANN consists of three layers (4-10-1) is shown in Figure 1. The input variables determine the number of neurons in the input layer and the input data vectors are applied to the input layers from an external source. A bias neuron is normally used with input of unity to shift or scale the activation function. The output layer is where the output are processed and are sent to an external source for further analysis or extra treatments or plotting, .etc. The layers between the input and the output are hidden where the entire processing are not accessible. The most common nonlinear transfer functions are the sigmoidal functions including the logistic and the hyperbolic tangent. The latter function is given by Equation (2)

$$Oh_j = \exp(Ih_j) - \exp(-Ih_j) \big/ \exp(Ih_j) + \exp(-Ih_j) \qquad (1)$$

where Ih_j is The input to the neuron j of the hidden layer and given by

$$Ih_j = \sum_{j=1}^{m} x_i w_{ij} + b_j \qquad (2)$$

where x_i is the input of the neuron i in the input layer with m is the number of neurons in the input layer and b_j is the bias of the unit. The w_{ij} is the weights vector of the connections between the neurons of the input layer and the neurons of the hidden layer.

The outgoing singnal from the hidden neuron is then combined with the weights of the connections between the neurons of the hidden layers and those of the output layer yielding the output of the output layer, Oo_k, using a linear combine function defined by Eq. (3).

$$Oo_k = \sum_{j=1}^{n} Oh_j C_{jk} + b_k \qquad (3)$$

in which C_{jk} is weight of the connection between neuron j of the hidden layer and neuron k of the output layer and b_k is the bias to the neuron k.

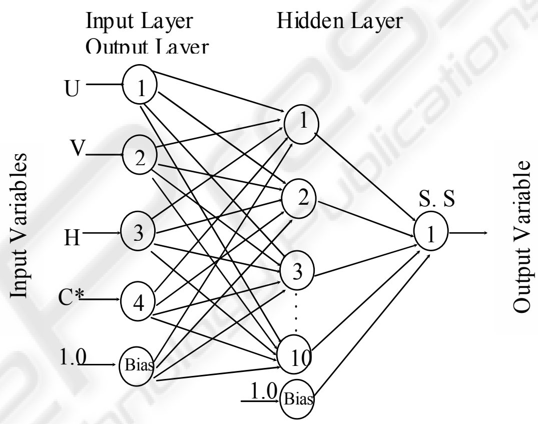

Figure 1: Typical three layers Feed-Forward ANN.

Training the network involves the determination of the weight vectors w_{ij} and C_{jk} such that the sum of squares of the error between the actual value of the output and the desired value of the output is minimal. The network weights are randomly assumed within a particular range. Then they are updated.

3 COLLECTION OF DATA FOR TRAINING, VALIDATION AND TEST

The numerical sediment transport model (SED-2) developed by (Elfiky et al., 2003) was used to generate the suspended sediment load ((kg/m.sec) for a canal reach of 830 m long. The two basic inputs of the SED-2 model (velocities) was obtained by running the HYD-2 model by Elfiky et al., 1997). The inputs to the SED-2 model include the velocities in x and in y directions and the flow depth. The output of the model is the suspended sediment concentration. Figure 2: shows a definition sketch for the reach where the model was applied. The reach is confined between cross section (1) at KM 57.000 and cross section (2) at KM 57.830 on El-Noubaria canal. Also, El-Nasser canal was included in the simulation using SED-2. Each canal was simulated separately using the ANN because the change in the flow direction at the canal junction was misunderstood by the network leading to very poor neural network model. The effective total number of generated data points are 963 for El-Nubraia canal reach.

4 COLLECTION OF FIELD DATA

The collected field measurements at two cross-sections on EL-Nubaria main canal are used to compare the model results. The data were collected by the Hydraulic Research Institute (HRI), National Water Research Center NWRC), Delta Barrages, Egypt on November, 1998, (Saad et al., 1999). The average velocity and the suspended sediment load were measured at two stations along both of Sec. (1) at KM 57 and Sec. (2) at KM 57.83 on EL-Nubaria canal, see Figure 2.

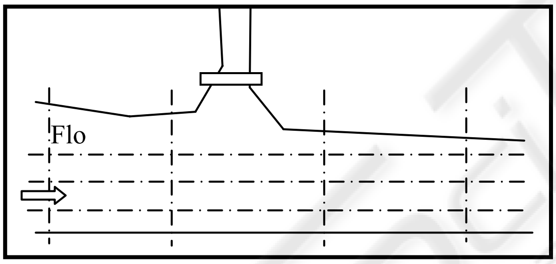

Figure 2: Definition sketch for the canal reach where the SED-2 numerical model was applied.

5 BUILDING THE NETWORK

Many factors affect the accuracy of the network. The most important factors will be discussed in the following paragraphs.

Normalization of Data ensures that each input contributes equally to the decision or the prediction made by the network. If the input values were not normalized, an input data, which have large numbers, will be more significant than that which has small numbers. Several methods could be used for normalization. One of these methods the zero-mean unit-standard deviation normalization method in which the mean and the standard deviation for each field is determined. Each field is then normalized such that the mean value for the field becomes zero and the values at plus and minus one standard deviation are mapped onto plus and minus one.

According to the Neural Connection software, the normalized input data, which are provided to the neural network, are classified into three sets, i.e. training, validation and test data sets. The training data is used to train the proposed ANN and is taken as 70% of the total records (2/3 of the data may be enough for large set of data). Validation data is used to monitor neural network performance during training phase and it represents 15% of total input data. Test data is used to test the performance of a trained ANN in generating the required prediction. The test data set is unseen data to the ANN model and represents 15% of the total utilized records by the present application.

The choice of the connections weights have a large effect on the performance of the network. The best initial values of the connections weight are found by trial and errors by conducting many computer experiments and the correlation coefficient, R, between the target and the output of the proposed network is computed for each experiment. Also, the root mean square error, rmse, is computed. The values of the weights that generate output with maximum R and minimum rmse are chosen. In the present application, the best initial weights was assumed to be in the range $\pm$ 12.2.6.

Generally, increasing the number of neurons in the hidden layer improves the performance of network on the training data, but not necessarily on the validation data. If so many hidden neurons are used in a network, the network will have enough weights to exactly represent all the training patterns. Such network will be poor network because it will be able to generalize the solution. This means that the network is overtrained. As the total number of hidden units is increased from one, the network performance on the validation data increases rapidly. This is because each new hidden unit starts to represent one of the underlying features in the data set. As more units are added, performance levels off. At that point, the training should stop. However, adding further units may then cause a decrease in performance because the power of generalization is lost and the network begins to learn the noise present in the data. It is always better to use as few neurons as possible to achieve the desired result. Generally, the number of neurons depends on the complexity of the data and on both the number of input and output variables. From experience, a rough initial estimation to the number of neurons in the hidden layer may be the geometric mean of the neurons in both input and output layers. The procedure is achieved by conducting many computer experiments. In the present application, the best number of neurons in the hidden layer is 10. The results of the conducted experiments are presented in Figure 2 in terms of R and rmse. The best value of R and the minimum value of rmse are when the network has a size of 4-10-1. It should be noted a similar figure to figure 3 is prepared to select the optimal value of each of the important factors affecting the ANN performance but not presented here to avoid repetition.

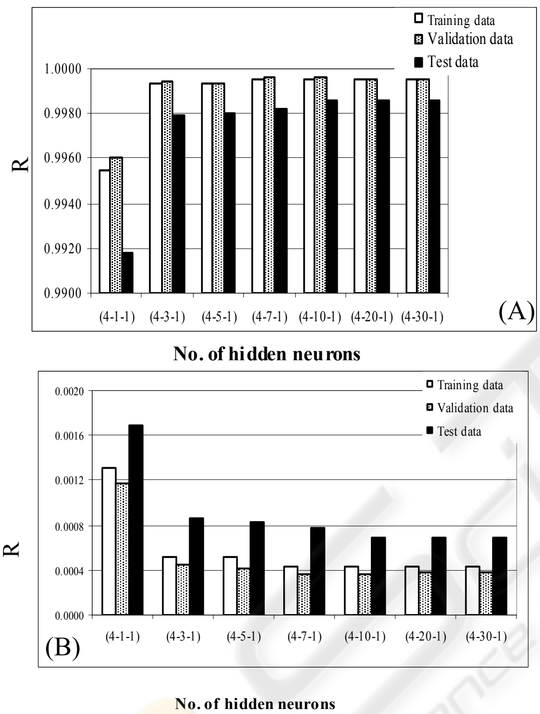

Figure 3: Typical performance of the proposed network in terms of (a) R and (b) rmse.

In most of the application one hidden layer will produce enough accuracy. However, more than one hidden layers can be used based on the complexity of the data structures. This can be achieved by conducting several computer experiments using single and multiple hidden layers and then a decision is taken based on the performance of the network. In this application, one hidden layer is found to be enough.

The type of activation functions used in the hidden layer is chosen by trials. In this application the tansh activation function is found to be the best one compared to the linear or the sigmoid.

The learning algorithm affects highly the performance of the networks. In the present application, the conjugate gradient is used to prevent the network from being trapped in a local minima. Unlike back-propagation, the conjugate gradient method does not proceed along the direction of the error gradient, but in a direction orthogonal to the one in the previous step. This prevents future steps from influencing the minimization achieved during the current step. In addition to the above factors, the maximum number of updates is important which is fixed when the validation error reaches to each minimum during training process. Keeping in mind the above discussed factors, building the network for the present application is well represented, see Figure 4.

6 RESULTS OF THE DEVELOPED NETWORK

Results of the developed network are presented in three figures. Figure 5 presents the comparison between the ANN estimation and the values predicted from the previously developed numerical model (SED-2) for training data set. The correlation coefficient, R is 0.9993. Clearly, perfect agreement is obtained for this set and this expected because the generated data from the numerical model was used to train the network. The very few data points which seem to deviate from the line of perfect agreement are those points where the velocities are affected by the entering flow to the El-Nasser canal and hence the suspended sediment is also affected because a remarkable portion of suspended sediment flow to El-Naser canal. It should be noted that El-Nasser canal was not included in the simulation using the neural network, in spite of its inclusion in the numerical model, because its inclusion interrupts the performance of the network. Figure 6 presents the ANN results for validation and test data versus those of the numerical model. The correlation coefficient is (R=0.9993) for validation data and equals (R=0.9992) for test data. The correlation coefficient for all data set is 0.9993. Figure 7 represents the variation of the residuals for all the three data sets versus the network predictions. The residuals seem to be distributed around the line of zero error, uncorrelated with the ANN outputs (estimated and predicted) and of very small values. The correlation coefficient of the residuals with the network prediction is very small and equals -0.0272. In this figure, the high values of the residuals are for the points that affected by El-Nasser canal where the velocity component in x direction is suddenly affected (because it changes its direction and becomes in y direction as the flow enters El-Nasser canal) and the suspended sediment load is in turn reduced compared to the upstream sections.

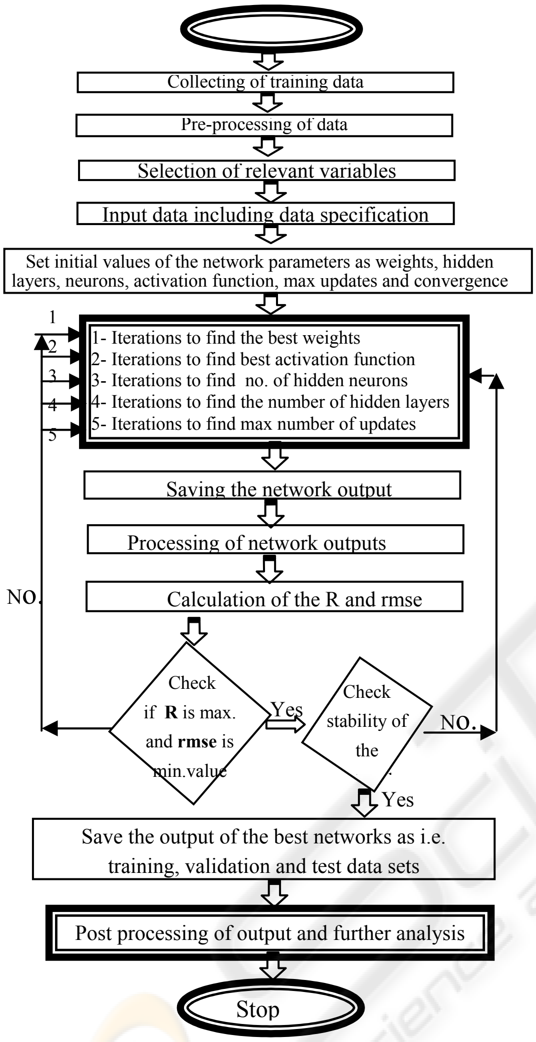

Figure 4: Flowchart showing the basic steps of building a neural network for an application.

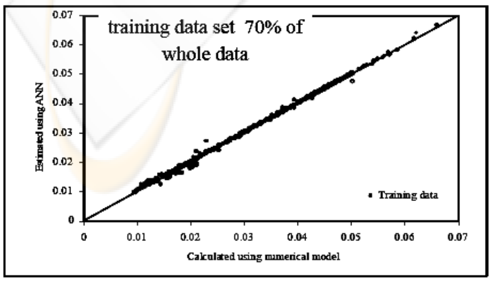

Figure 5: Comparison between predictions of ANN and those of SED-2 numerical model.

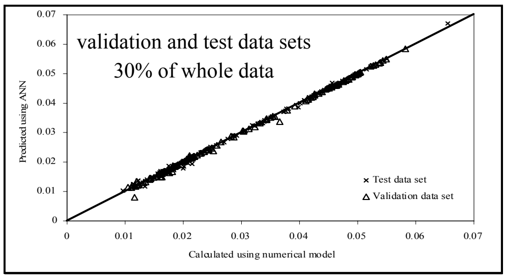

Figure 6: Comparison between predictions of ANN and those of SED-2 numerical model.

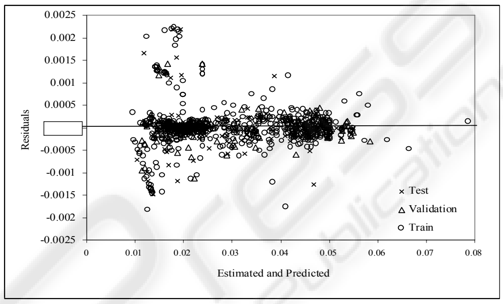

Figure 7: Variations of the residuals of all ANN data with the estimated values.

7 COMPARISONS

The collected field data at the two cross sections, 1 and 2 are compared to both the predicted values using the numerical model and the neural network model in Figures 8 and 9 for sections (2) and (1). Clearly, good matching is observed between the field data and the models results at section (2). At Sec. (1), there are a great agreement at the left and right stations while a gab is noticed between the models results and the field data in the middle station, perhaps due to the inflow boundary effect, Elfiky et al.8). Comparisons between results of ANN model and the numerical model at other sections as (3) and (4) indicate very great agreement (not presented here to reserve space).

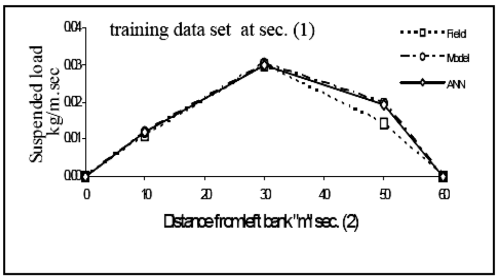

Figure 8: Comparison between predictions of ANN, SED-2 numerical model and field data.

Comparisons between results of ANN model and those of numerical model at the longitudinal sections as L.S.1, L.S.2 and L.S.3 show also very close agreement between both results. Indicated in Fig. 10.

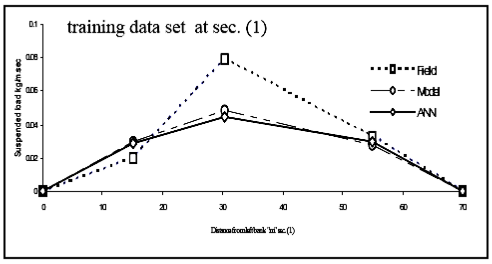

Figure 9: Comparison between predictions of ANN, SED-2 numerical model and field data.

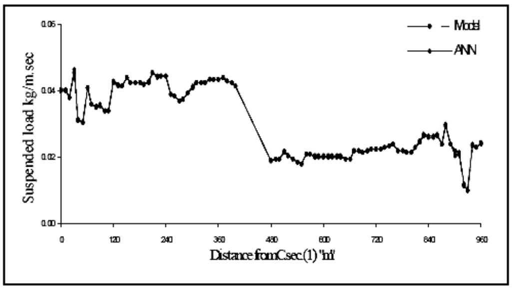

Figure 10: Comparison between prediction of ANN and those of SED-2 numerical model at L.S.1.

8 CONCLUSION

A multilayer feedforward artificial neural network (4-10-1) is used to estimate the suspended sediment concentration efficiently based on four inputs including the depth of flow, the components of flow velocities in x and y directions and the sediment carrying capacity. Since, the field data are very limited, a 2-D numerical model (SED-2) was used to generate the required training and validation data for the developed neural network. The present paper proved that the ANNs are a powerful computational tool for computing the suspended sediment concentration in rivers provided that the trained and verified network should be used to predict values within the training range otherwise, poor predictions are obtained.

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