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PREDICTING THE EVOLUTION OF SUSPENDED SEDIMENT CONCENTRATION USING ARTIFICIAL NEURAL NETWORK

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Abstract: *This paper presents the results of a study aimed to obtain an artificial neural network (ANN) model in order to find the evolution of suspended sediment concentration (SSC) with respect to time by knowing the concentration of the suspended sediment at an earlier time, in a given stress field. Data obtained from an annular flume experiments using three artificial sediments (alumina, silica and kaolin) and a natural sediment obtained from river Rhine are used in this study to derive the model parameters. The experimental data of alumina is used to find the model and for its validation the data of silica, kaolin and Rhine mud are used. The results are presented in terms of various statistical parameters. It is observed that the obtained ANN model provides satisfactory results for all the tested sediments.*

Keywords: *Artificial neural network; suspended sediment; concentration; bed shear stress; flow depth.*

INTRODUCTION

Suspended sediments in a river flow contain pollutants and toxic contaminants which are harmful to human life and aquatic flora (Edwards, 1969, Brookes, 1986). Fine suspended sediments are prime factors for the transport of nutrients and contaminants such as heavy metals and micro-organics (Cigizoglu and Kisi, 2006). Flood water, poorly managed agriculture practice and mineral extraction may result in an increase in suspended solids and sedimentation in the rivers (Wood and Armitage, 1997). The suspended sediments in the rivers deposit at low velocity regions such as floodplains and reservoirs. The phenomenon of deposition of the suspended sediments is complex by nature. It depends on many factors like mineralogical composition, particle size, bulk density, organic matter, pH, bed shear stress, temperature, flow depth and salinity. Available literature explains effects of the deposition on dredging, water quality, storage capacity of reservoir, flooding etc., (Mehta and Partheniades, 1975, Mehta et al., 1989). Hence, estimation of suspended sediment concentration (SSC) in rivers and reservoirs is one of the most important hydrologic data in solving engineering problems such as hydraulic design, to improve water quality and water resources management (Hsu and Cai, 2010).

Deposition process of suspended sediments and evolution of its concentration may be predicted

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by experimental (Krone, 1962, Mehta and Partheniades, 1975, Haralampides et al. 2003, etc.) and numerical studies (Nicholson and O'Connor, 1986, Hung et al. 2009, Lu and Wang, 2009, etc). In addition, artificial neural networks (ANNs) have been successfully applied to estimate the sediment concentration and discharge of suspended sediment in a river flow (Jain, 2001, Nagy et al. 2002, Agarwal et al. 2005, Cobaner et al. 2009, Ulke et al. 2009). Recent studies showed that ANNs are capable of modeling and forecasting of complex engineering problems and also capture the physical process involved in the system (Jain et al. 2004, Sudheer, 2005, Jain and Kumar, 2009). Therefore, in the present study, ANN is used to predict the evolution of the SSC when a sediment is allowed to deposit in a given flow field.

However, the SSC at a given height is decreased with time and is a complicated function of several sediment and fluid characteristics. In the present study, it is assumed that the deposition of suspended sediment in the initial stages is influenced by these characteristics and thereafter the subsequent changes in the SSC level is dictated by the time lag values of SSC. Thus, the factors (flow and sediment) remaining constant, the SSC at time t, C_t, is a function of the SSC values at previous time levels (C_{t-1}, C_{t-2}, C_{t-3}, C_{t-4}, etc.). Therefore, the main objective of the present study is to find an ANN model between the SSC values at different time levels. Following statistics are used to evaluate the performance of the ANN model: (a) Nash-Sutcliff efficiency (E), (b) correlation coefficient, R, (c) average absolute relative error, *AARE*, (d) root mean square error, *RMSE*, and (e) threshold statistics, *TS*. These parameters are defined in the Appendix-1.

DATA FOR THE ANALYSIS

The data were obtained from the experiments conducted in an annular flume located at Theodor-Rehbock laboratory, Universität Karlsruhe, Germany. Three artificial sediments such as alumina (d_{50}=0.7 μm), silica (d_{50}=3.5 μm) and kaolin (d_{50}=2.06 μm) and a natural sediment collected from river Rhine (d_{50}=15 μm) were used to study the deposition of cohesive sediments in freshwater.

Experimental Setup

The schematic diagram of the annular flume is shown in Figure 1. The annular flume has an outer diameter of 1.2 m and a channel width of 0.375 m. Flows are generated by rotating the inner cylinder having a mean diameter of 0.45 m with the help of an electric motor. Flows in the flume generate a centrifugal force which results in strong secondary currents. However, effects of the side wall and the secondary currents are not considered in the analysis. Average bed shear stress (N/m^2) can be calculated by using the following empirical formula (Hillebrand, 2008),

$$\tau = 0.073\,(2\,\pi\,r\,f)^{1.527} \qquad (1)$$

In Equation 1, 'r' and 'f' are radius (m) and rotational frequency (s^{-1}) of the inner cylinder, respectively. All the experiments were conducted using two different flow depths (0.20 m and 0.275 m). Two different rotational frequencies (10/60 s^{-1} and 22/60 s^{-1}) corresponding to bed shear stresses of 0.008 N/m^2 and 0.027 N/m^2, respectively, were used to conduct the experiments with alumina, silica and Rhine mud. The experiments with kaolin were conducted in the flow field corresponding to the bed shear stress of 0.027 N/m^2. Initial suspended sediment concentration for Rhine mud was 0.35 g/l and it was 1.00 g/l for other sediments. Suspended sediment concentration was measured at 0.10 m flow depth from flume bottom at every 10 sec till the sediment concentration reaches equilibrium state.

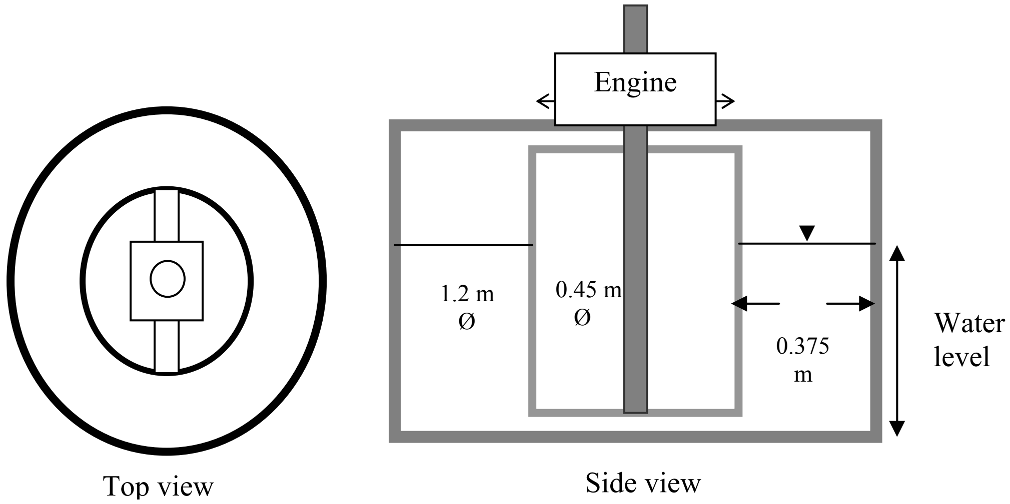

Fig. 1. Schematic diagram of annular flume.

ANN MODEL

A feed forward artificial neural network is trained using back propagation training algorithm (Rumelhart et al. 1986, Spreecher, 1993). The back propagation method contains the Levenberg-Marquardt algorithm (LM). The algorithm will be stopped if the number of iterations is reached 10,000. The ANN model consists of three layers-input, hidden and output. The general architecture of the ANN model is P-H-1, where, P is the number of input neurons and H is the number of hidden neurons.

The number of time lag concentrations (i.e. input neurons) is obtained by plotting the partial auto-correlation (PAC) versus the number of lags (Figure 2) using the whole experimental data. From Figure 2, it is observed that the first time lag is very significant due to its highest PAC value. Similarly, it is observed that the second time lag PAC value is also an important one compared to the other time lags. Hence, it is decided to take two time lag concentrations of the suspended sediment as input parameters.

The ANN network is trained by varying the hidden neurons from 1 to 10. The network topography is fixed by adopting trial and error procedure. As stated earlier, data of alumina is used for training process with different hidden neurons to obtain an optimum ANN architecture and the results are obtained in terms of statistics.

The statistical results for different architectures are presented in Table 1. The values of E, R, $RMSE$, TS_5, TS_{25}, TS_{50} and TS_{100} for all the hidden neurons are almost same except for single and double hidden neurons. From the statistical results given in Table 1, it is difficult to select an optimum ANN architecture because all the given statistics are with similar values. However, the values of $AARE$ are different for different hidden neurons. Thus, the $AARE$ values of all the architectures are compared and it is observed that 2-4-1 architecture is having the least *AARE*=0.514. Therefore, it is selected as the optimal architecture. The structure of optimum ANN model consists of two neurons in the input layer, four neurons in the hidden layer, and one neuron in the output layer.

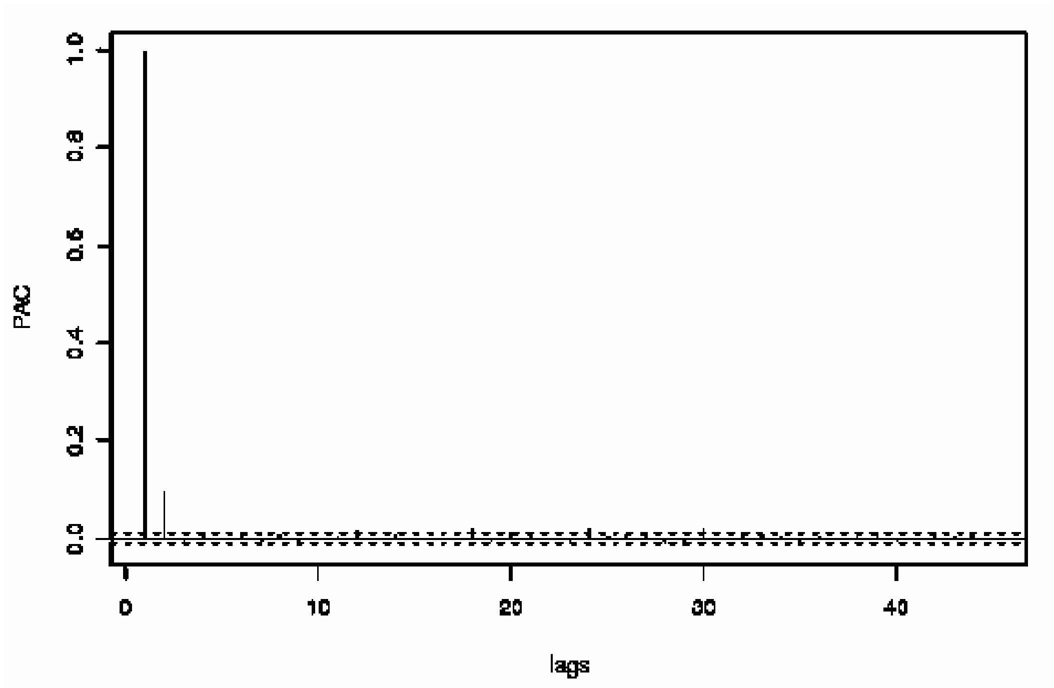

Fig. 2. Partial autocorrelation versus number of lags.

Table 1. Statistical results of different ANN architectures during training.

P-N-1	*E*	*R*	*AARE*	*RMSE*	TS_5	TS_{25}	TS_{50}	TS_{100}
2-1-1	0.969	0.985	14.452	0.015	12.35	76.25	99.32	100
2-2-1	0.997	0.999	2.181	0.004	88.32	100	100	100
2-3-1	0.999	0.999	0.875	0.003	98.68	100	100	100
2-4-1	0.999	0.999	0.514	0.003	99.70	100	100	100
2-5-1	0.999	0.999	0.578	0.003	99.71	100	100	100
2-6-1	0.999	0.999	0.574	0.003	99.73	100	100	100
2-7-1	0.999	0.999	0.566	0.003	99.71	100	100	100
2-8-1	0.999	0.999	0.583	0.003	99.70	100	100	100
2-9-1	0.999	0.999	0.591	0.003	99.40	100	100	100
2-10-1	0.999	0.999	0.594	0.003	99.66	100	100	100

Model Performance

The experimental data of silica, kaolin and Rhine mud are used to validate the ANN model and the obtained statistical results are given in Table 2. It is observed that the ANN model is performing well because the obtained statistics of silica, kaolin and Rhine mud are satisfactory. The efficiency, *E* and correlation coefficient, *R* of all the tested sediments are almost equal and are similar to the training process. The *AARE* values of the tested sediments are higher than that of the alumina. However, the variation in *RMSE* and TS_5 values are marginal.

The *RMSE* values and threshold statistics are more or less same for silica and kaolin. Whereas, kaolin attains the highest *AARE* value compared to other sediments. The Rhine mud is having lowest *AARE* and *RMSE* values among the tested sediments because the SSC of Rhine mud is low and it is known from the training process that the ANN model perform very well for small concentrations. When the three sediments (silica, kaolin and Rhine mud) tested together the *AARE* and *RMSE* values are decreased compared to silica and kaolin and increased compared to Rhine mud, but, not much variation is observed in case of other statistics. The scatter plots between the observed and predicted concentrations for silica is shown in Figure 3, for kaolin is shown in Figure 4 and for Rhine mud it is shown in Figure 5. Similarly, for all the sediments tested together, the scatter plot is shown in Figure 6. These figures are showing best fit between the observed concentration and predicted concentration which indicates the ANN model is capable to predict the evolution of SSC.

Table 2. Performance statistics of ANN model during testing.

Sediment	*E*	*R*	*AARE*	*RMSE*	TS_5	TS_{25}	TS_{50}	TS_{100}
Silica	0.998	0.999	0.905	0.007	98.42	100	100	100
Kaolin	0.998	0.999	1.670	0.007	98.37	100	100	100
Rhine mud	0.995	0.998	0.713	0.001	99.81	100	100	100
All sediments	0.999	0.999	0.883	0.005	99.14	100	100	100

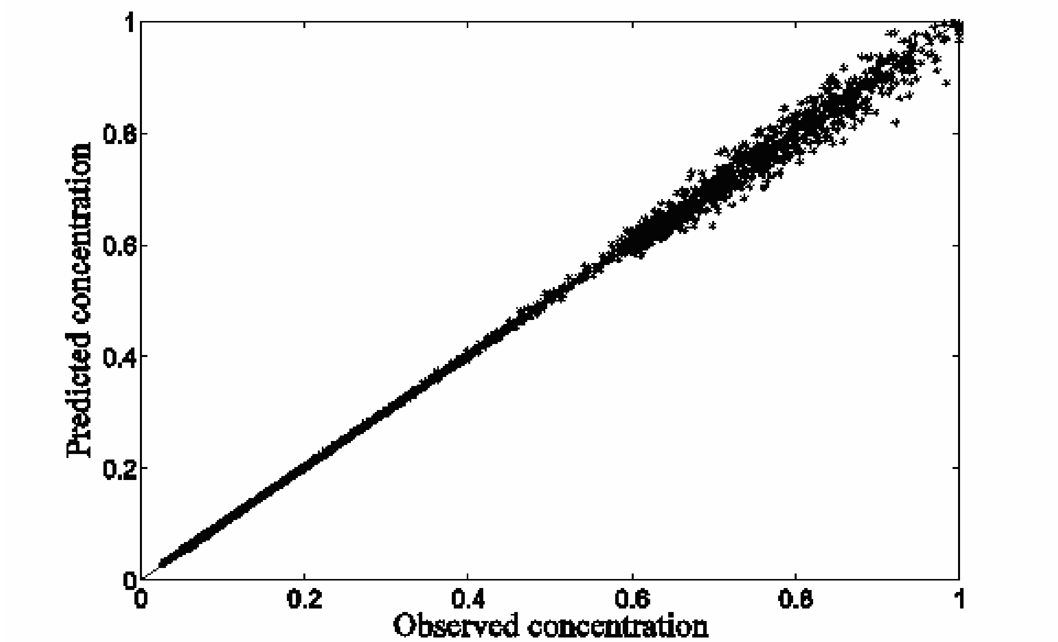

Fig. 3. Scatter plot between the observed and predicted concentrations of silica.

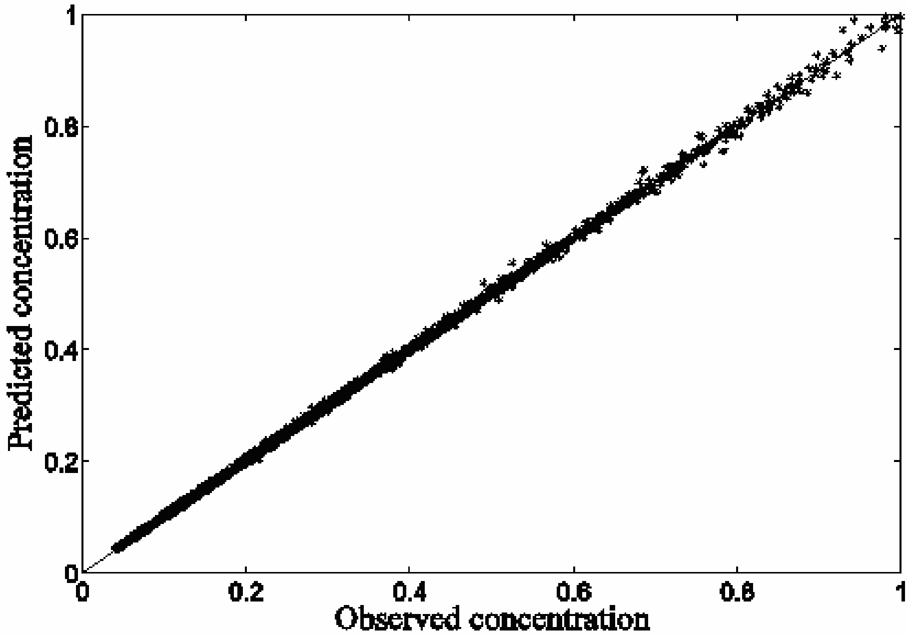

Fig. 4. Scatter plot between the observed and predicted concentrations of kaolin.

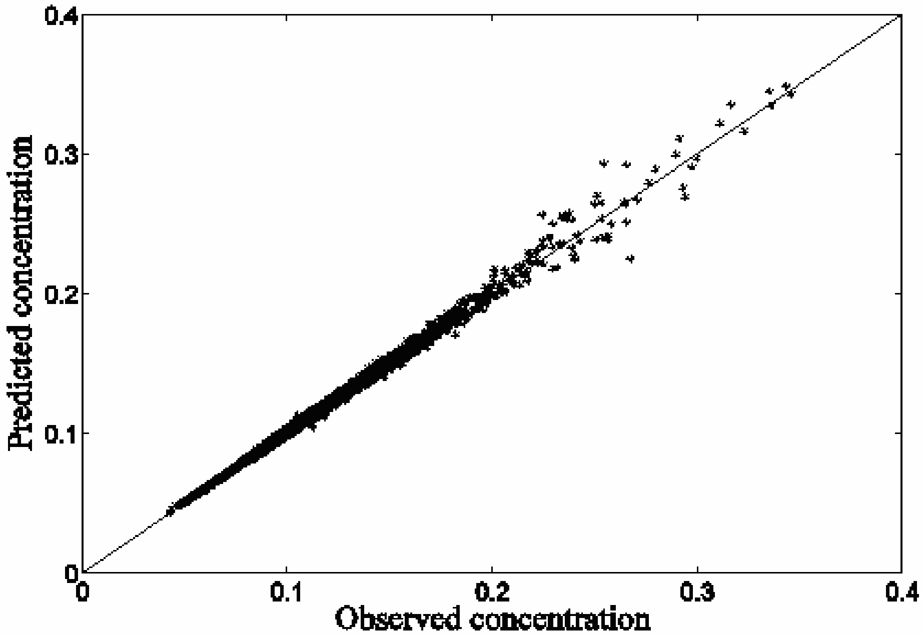

Fig. 5. Scatter plot between the observed and predicted concentrations of Rhine mud.

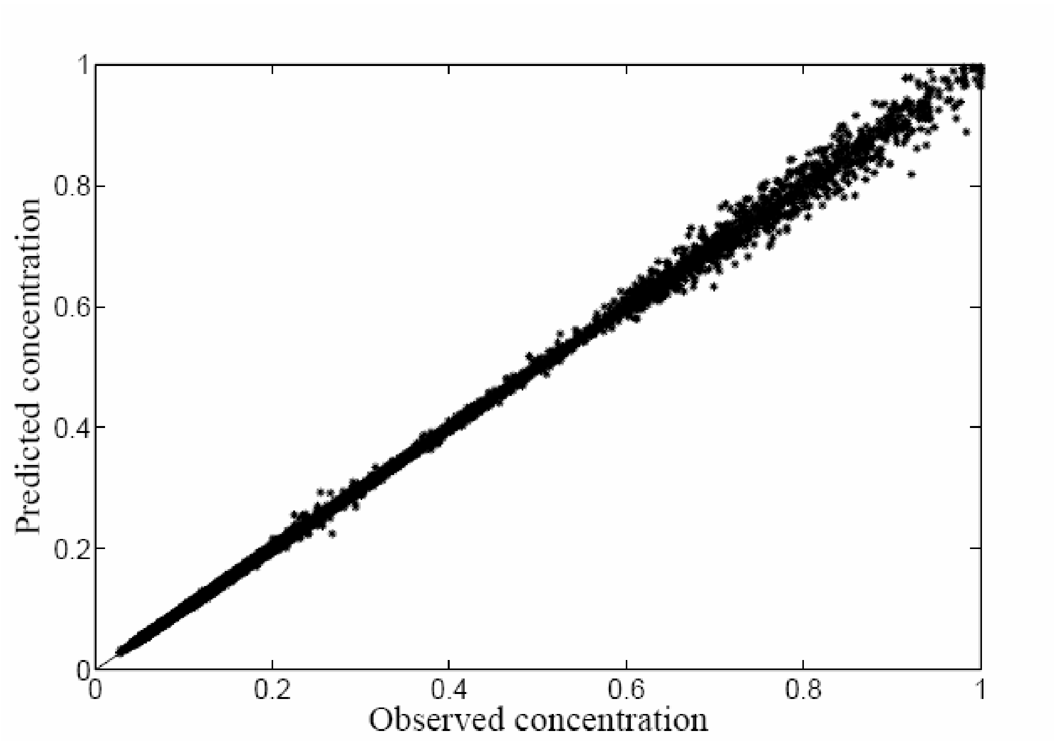

Fig. 6. Scatter plot for all the sediments tested together.

From the above figures it is clearly observed that the ANN model is capable of predicting the evolution of SSC of any suspended sediment in different stress fields. The experimental data is obtained from different stress fields using various sediments. Although, SSC is influenced by sediment and flow characteristics, from the presented results, it can be noted that ANN successfully captures the physical process involved in the sediment deposition.

CONCLUSIONS

The present study was focused to find the evolution of suspended sediment concentration (SSC) from the time lag concentrations of the suspended sediment in a given flow field by using artificial neural network (ANN). Data obtained from the experiments conducted in an annular flume with various sediments (alumina, silica, kaolin and Rhine mud) were used in this study to develop and validate the ANN model. The results were presented in terms of various statistical parameters. For predicting the evolution of SSC, satisfactory results were obtained by using the ANN model and a good fit was observed between the observed and the predicted concentrations. Therefore, using this model the SSC at any time *t* can be obtained by knowing the two earlier time step concentrations of the suspended sediment in a given stress field.

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REFERENCES

Agarwal, A., Singh, R.D., Mishra, S.K. and Bhunya, P.K. 2005. ANN-based sediment yield models for amsadhara river basin (India). *Water SA*, 31 (1), 95-100.

Brookes, A. 1986. Response of aquatic vegetation to sedimentation downstream from river channelisation works in England and Wales. *Biological Conservation* 38, 352-367.

Cigizoglu, H.K. and Kisi, O. 2006. Methods to improve the neural network performance in suspended sediment estimation. *J. Hydrology*, 317, 221-238.

Cobaner, M., Unal, B. and Kisi, O. 2009. Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hudro-meteorological data. *J. Hydrology*, 367, 52-61.

Edwards, D. 1969. Some effects of siltation upon aquatic macrophyte vegetation in rivers. *Hydrobiologia,* 34, 29-37.

Haralampides, K., McCorquodale, J.A. and Krishnappan, B.G. 2003. Deposition properties of fine sediment. *J. Hydraulic Engineering*, 129 (3), 230-234.

Hillebrand, G. 2008. *Transportverhalten kohaesiver sedimente in turbulenten stroemungen–untersuchungen im offenen kreisgerinne*. Ph.D. Thesis, Universitaet Karlsruhe (TH), Germany.

Hsu, Y.S. and Cai, J.F. 2010. Densimetric monitoring technique for suspended-sediment concentrations. *J. Hydraulic Engineering*, 136 (1), 67-73.

Hung, M.C., Hsieh, T.Y., Wu, C.H. and Yang, J.C. 2009. Two-dimensional nonequilibrium noncohesive and cohesive sediment transport model. *J. Hydraulic Engineering*, 135 (5), 369-382.

Jain, A. and Kumar, S. 2009. Dissection of trained neural network hydrologic model architectures for knowledge extraction. *Water Resources Research*, 45 (7).

Jain, A., Sudheer, K.P. and Srinivasulu, S. 2004. Identification of physical processes inherent in artificial neural network rainfall runoff models. *Hydrological Processes,* 18 (3), 571-581.

Jain, S. K. 2001. Development of integrated sediment rating curves using ANNs. *J. Hydraulic Engineering*, 127 (1), 30-37.

Krone, R. B. 1962. *Flume studies of the transport of sediment in estuarial shoaling processes.* Final report to San Francisco district, U.S. Army Crops of Engr., Washington, D. C.

Lu, Y.J. and Wang, Z.Y. 2009. 3D numerical simulation for water flows and sediment deposition in dam areas of the three gorges project. *J. Hydraulic Engineering*, 135 (9), 755-769.

Mehta, A.J., Hayter, E.J., Parker, W.R., Krone, R.B. and Teeter, A.M. 1989. Cohesive sediment transport I: Process description. *J. Hydraulic Engineering*, 115 (8), 1076-1093.

Mehta, A.J. and Partheniades, E. 1975. An investigation of the depositional properties of flocculated fine sediments. *J. Hydraulic Research*, 13 (4), 361-381.

Nagy, H.M., Watanabe, K. and Hirano, M. 2002. Prediction of sediment load concentration in rivers using artificial neural network model. *J. Hydraulic Engineering*, 128 (6), 588-595.

Nicholson, J. and O'Connor, B.A. 1986. Cohesive sediment transport model. *J. Hydraulic Engineering*, 112 (7), 621-640.

Rumelhart, D.E., McLelland, J.L. and PDP Research Group. 1986. *Parallel distributed processing, explorations in the micro structure of cognition*, *Vol. I: Foundations*, MIT Press, Cambridge, Mass.

Spreecher, D.A. 1993. A universal mapping for a Kolmogorov's superposition theorem. *Neural Networks*, 6 (8), 1089-1094.
Sudheer, K.P. 2005. Knowledge extraction from trained neural network river flow models. *J. Hydrologic Engineering,* 10 (4), 264-269.
Ulke, A., Tayfur, G. and Ozkul, S. 2009. Predicting suspended sediment loads and missing data for Gadiz River, Turkey. *J. Hydrologic Engineering*, 14 (9), 954-965.
Wood, P.J. and Armitage, P.D. 1997. Biological effects of fine sediment in the lotic environment *Environmental Management*, 21 (2), 203-217.

APPENDIX

The following equations are used to compute the various statistical parameters such as *E, R*, *AARE*, *RMSE* and *TS*.

Nash-Sutcliff efficiency (E)
$$= 1-\frac{\sum_{t=1}^{N}\left(C_p(t)-C_{oa}\right)^2}{\sum_{t=1}^{N}\left(C_o(t)-C_{oa}\right)^2} \quad \text{(A-1)}$$

Correlation coefficient *(R)*
$$= \frac{\sum_{t=1}^{N}\left(C_o(t)-C_{oa}\right)\left(C_p(t)-C_{pa}\right)}{\sqrt{\sum_{t=1}^{N}\left(C_o(t)-C_{oa}\right)^2\left(C_p(t)-C_{pa}\right)}} \quad \text{(A-2)}$$

Average absolute relative error (*AARE*)
$$= \frac{1}{N}\sum\left|\frac{C_p(t)-C_o(t)}{C_o(t)}\right|\times 100 \quad \text{(A-3)}$$

Root mean square error (*RMSE*)
$$= \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(C_p(t)-C_o(t)\right)^2} \quad \text{(A-4)}$$

and

Threshold statistics (TS_x)
$$= \frac{n_x}{N}\times 100 \quad \text{(A-5)}$$

where, N is total number of data points, $C_p(t)$ is predicted concentration at time t, C_{pa} is average predicted concentration, $C_o(t)$ is observed concentration at time t, C_{oa} is average observed concentration, and n_x is number of data points whose absolute relative error is less than x percent.