# Effect of Particles on Flow Structures in Secondary Sedimentation Tanks Using Neural Network Model

*Mostafa Y.El-Bakry* * *,D.M.Habashy* * * and Mahmoud Y.El-Bakry* * ,* * ***

**Abstract**— Sedimentation tanks are designed for removal of floating solids in water flowing through the water treatment plants. These tanks are one of the most important parts of water treatment plants and their performance directly affects the functionality of these systems. Flow pattern has an important role in the design and performance improvement of sedimentation tanks. In this work, the neural network model is used to study the particle-laden flow in a rectangular sedimentation tank which used the Kaolin as solid particles. The neural network simulation has been designed to simulate and predict the Shear stress coefficient at the bottom of tank for various inlet concentrations and maximum streamwise velocity along the channel. The system was trained on the available data of the two cases. Therefore, we designed the system for finding the best network that has the ability to have the best test and prediction. The proposed system shows an excellent agreement with that of an experimental data in these cases.

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## 1 INTRODUCTION

Solids removal is probably the main process in water purification method in filtration plants. The most significant phase of this process is the separation of sludge and suspended particles from water by means of gravity. In these basins, the turbid water flows into the basin at one end and the cleaner water is taken out at the other end by decanting. Obviously, the water must flow in the tank long enough for appropriate particles deposition. The performance of these sedimentation tanks directly affects the filtration basin's efficiency. Sedimentation tanks are divided into two main categories. The primary settling tanks have a low influent concentration and the flow field in them is not influenced much by concentration field due to the negligible buoyancy effects. The secondary or final settling tanks have a higher influent concentration and they are usually placed after the primary and activation tanks Tamayol *et al.*[1]. So they usually contain activated sludge and hence, the size of particles would grow and flow field is influenced by concentration distribution. Generally, the sedimentation tanks are characterized by several hydrodynamic phenomena, such as density waterfalls, bottom current and surface return currents, and are also sensitive to temperature fluctuations and wind effects. Various studies have been conducted to find the effects of particles on the flow and hydraulics of settling tanks. Imam and McCorquodale [2]solved flow

*Physics Department, Faculty of Science, Benha University, Egypt mail: oelbakre@yahoo.com
**Physics Department, Faculty of Education Ainshams University
***Physics Department, Faculty of Science University of Tabuk

equations with a constant turbulent eddy diffusivity assumption.

Celik and Rodi [3] and Stamou and Rodi [4] used k-ε turbulence model to predict the flow field in settling tanks. Kerbs [5]developed one and two dimensional models

for clarifier modeling. He observed that worse sludge quality causes stronger density current and thus increases the tendency for short circuiting between the inlet and the outlet. Zhou *et al.*[6] applied a 3-dimensional fully mass conservative clarifier model, based on modern computational fluid dynamics theory. They observed that the upward buoyant flow occurs in the tank with deep sludge blanket and a short circuiting flow appears near the water surface and flow regime is strongly affected by the sludge blanket in the tank. Mazzolani *et al.*[7] developed numerical models for the prediction of turbulent flow and suspended solid distribution in the sedimentation tank. They found that increasing the concentration in region between discrete settling and hindered settling, results in an increase in settling velocities of the faster particles. In addition, the application of the three distinct settling models in the numerical analysis of the transport in a rectangular sedimentation tank, yields highly different predictions of solid distribution and removal rate. On the other hand, the main features of the hydrodynamic field are qualitatively similar. Tamayol and Firoozabadi [8] studied the effects of different turbulent models on the flow field. Tamayol *et al.*[9] also studied the hydrodynamics of secondary settling tanks while using baffles for increasing their performance. They found that it is required to calculate the concentration profiles in the tank, as well as the velocity

profiles. Also their results showed that both Reynolds and Froude numbers are important in determination of the degree of importance of buoyancy forces in sedimentation tanks. In tanks with low buoyancy forces, the problem is due to short circuiting between the inlet and outlet, while in the tanks which are highly stratified, the problematic phenomenon is bottom density currents. The design of tanks with high deposition rate and hydraulic efficiency requires complete investigation of the effect of particles on the flow hydrodynamics. In addition, the investigation of the physics of sedimentation and its effects on the hydrodynamics of sedimentation tanks are rare. Asgharzadeh et al.[10] studied the effect of particles on hydrodynamics of flow field in secondary sedimentation tanks experimentaly and numerically.

In this work, we introduce the artificial neural network (ANN) for modelling the Shear stress coefficient at the bottom of tank for various inlet concentrations and Maximum streamwise velocity along the channel using the data obtained from Asgharzadeh et al.[10].
Neural networks are widely used for solving many problems in most science problems of linear and non-linear cases [11-20]. Neural network algorithms are always iterative, designed to step by step minimise (targeted minimal error) the difference between the actual output vector of the network and the desired output vector [21-23]. The data obtained by [10] is chosen to be carried out using the neural networks .

The present work offers neural network to simulate and predict the unknown data of the shear stress coefficient and maximum streamwise velocity along the channel as a function of distance of at the bottom of tank at various inlet concentrations. The rest of paper is organized as follows; Sec. 2 describes the artificial neural network . Section 3 presents the proposed system. Section 4 shows the obtained results. Finally, Sec. 5 concludes the work.

## 2 Artificial Neural Network

Bourquin et al. [24,25] and Agatonovic-Kustrin and Beresford[26] described the basic theories of ANN modeling. An ANN is a biologically inspired computational model formed from several of single units, artificial neurons, connected with coefficients (weights) which constitute the neural structure. They are also known as processing elements (PE) as they process information. Each PE has weighted inputs, transfer function and one output. PE is essentially an equation which balances inputs and outputs. There are many types of neural networks designed by now and new ones are invented every week but all can be described by the transfer functions of their neurons, by the training or learning algorithm (rule), and by the

connection formula. A single-layer neuron is not able to learn and generalize the complex problems. The multilayer perceptron (MLP) overcomes the limitation of the single-layer perceptron by the addition of one or more hidden layer(s)Fig.(1). The MLP has been proven to be a universal approximator Cybenko [27]. In Fig. (1), a feedforward multilayer perceptron network was presented. The arriving signals, called inputs, multiplied by the connection weights (adjusted) are first summed (combined) and then passed through a transfer function to produce the output for that neuron. The neuron transfer function, f, is typically step or sigmoid function that produces a scalar output(O) as follows

$$O = f \left( \sum_i W_i I_i + b \right) \qquad (1)$$

where $I_i$, $W_i$ and b are i th input, i th weight and bias, respectively.
The activation (transfer) function acts on the weighted sum of the neuron's inputs and the most commonly used transfer function is the sigmoid (logistic) function. The way that the neurons are connected to each other has a significant impact on the operation of the ANN (connection formula). There are two main connection formulas (types): feedback (recurrent) and feedforward connection. Feedback is one type of connection where the output of one layer routes back to the input of a previous layer, or to same layer. Feedforward does not have a connection back from the output to the input neurons. There are many different learning rules (algorithms) but the most often used is the Delta-rule or backpropagation (BP) rule.
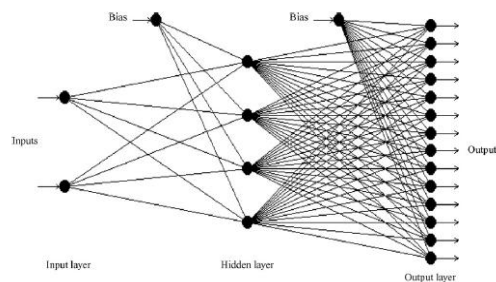


Fig.(1). Schematic representation of a multilayer perceptron feedforward network consisting of two inputs, one hidden layer with four neurons and 14 outputs.

A neural network is trained to map a set of input data by iterative adjustment of the weights. Information from inputs is fed forward through the network to optimize the weights between neurons. Optimization of the weights is made by backward propagation of the error during training or learning phase. The ANN reads the input and output values in the training data set and changes the value of the weighted links to reduce the difference between the predicted and target (observed) values. The error in prediction is minimized across many training cycles

(iteration or epoch) until network reaches specified level of accuracy. A complete round of forward–backward passes and weight adjustments using all input–output pairs in the data set is called an epoch or iteration.

## 3 Modeling Shear Stress Coefficient and Maximum Streamwise Velocity Using ANN

Shear stress coefficient $C_d$ and maximum streamwise velocity $U_{max}$ can be simulated and predicted at different inputs using ANN. we choose to internally model the problem with two individual neural networks trained separately using experimental data. The first ANN was configured to have distance at bottom tank $X/L_o$ and $C_{in}$ (0,400 and 800) as inputs while the output is Shear stress coefficient $C_d$ . The second ANN was configured to have distance at bottom tank $X/L_o$ and $C_{in}$ (0,400 and 800) as inputs while the output is maximum streamwise velocity $U_{max}$ . Fig.(2) represent a block diagram of the two ANN based modeling.
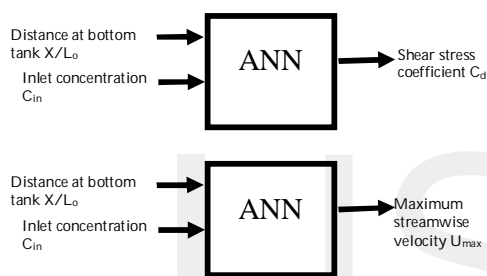


Fig.(2): Block diagram of the two ANN based modeling.

The performance of the previous two models is examined by using the mean square error (MSE) .The proposed ANN was trained using the Levenberg–Marquardt optimization technique. This optimization technique is more powerful than the conventional gradient descent techniques. The Levenberg–Marquardt updates the net- work weights using the following rule:

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \qquad (2)$$

where J is the Jacobian matrix of derivatives of each error with respect to each weight; $J^T$ is the transposed matrix of J; I is the identity matrix that has the same dimensions as those of $J^T J$; $\mu$ is a scalar changed adaptively by the algorithm and e is an error vector. $\Delta W$ is a measure for the rate of learning of the network i.e. when $\Delta W$ tends to zero this means that the network has been learnt (ready to predict the unseen values).Then the adjustment for the weights is done by Eq. (2) to reduce the error value.

## 4 Results

The proposed ANN models were applied to simulate the shear stress coefficient $C_d$ (referred to as model1) and maximum streamwise velocity $U_{max}$ (model 2). By employing the above mentioned proposed models with different values of the ANN parameters we have obtained different numbers of hidden neurons for the ANN models. The results obtained by the two models are discussed in the following: The first ANN having three hidden layers of 67 , 86 and 94 neurons (model1) and second network having 90 , 77 and 80 neurons(model2) respectively with one neuron in the output layer. Network performance was evaluated by plotting the ANN model output against the experimental data and analyzing the percentage error between the simulation results and the experimental data Fig. (3). In the training process, 196 and 657 epochs was found to be sufficient, Fig. (3), with respect to the minimum mean sum square error (MSE) of $2.3939 \times 10^{-12}$ and $9.8191 \times 10^{-13}$ respectively. For all networks, the function which describes the nonlinear relationship is given in appendix.
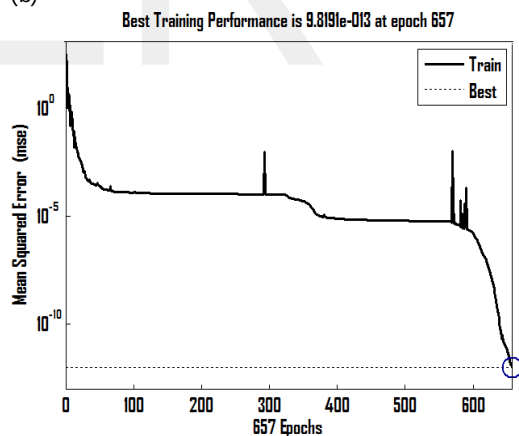
(a)
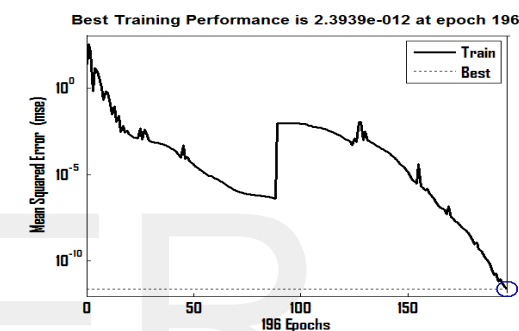


(b)



Fig. 3: Performance using ANN model, where epochs are the number of training
(a) Shear stress coefficient $C_d$
(b) Maximum streamwise velocity $U_{max}$

The above mentioned details of the proposed ANN model (model1) are carried out and simulated two the experimental data of the distance at bottom tank $X/L_o$ and Shear stress coefficient $C_d$ using the obtained function which is given in appendix. The proposed $C_d$ is trained using ANN model on three cases of inlet concentration $C_{in}$. The values of these cases are 0, 400 and 800 Fig.(4) . After the training , the

obtained system is predicted the behavior of inlet concentration $C_{in}$=1000 Fig.(4). It is found that as shown in Fig. (4), the obtained results (simulated and predicted) are provided to demonstrate good agreement with the experimental data[10].
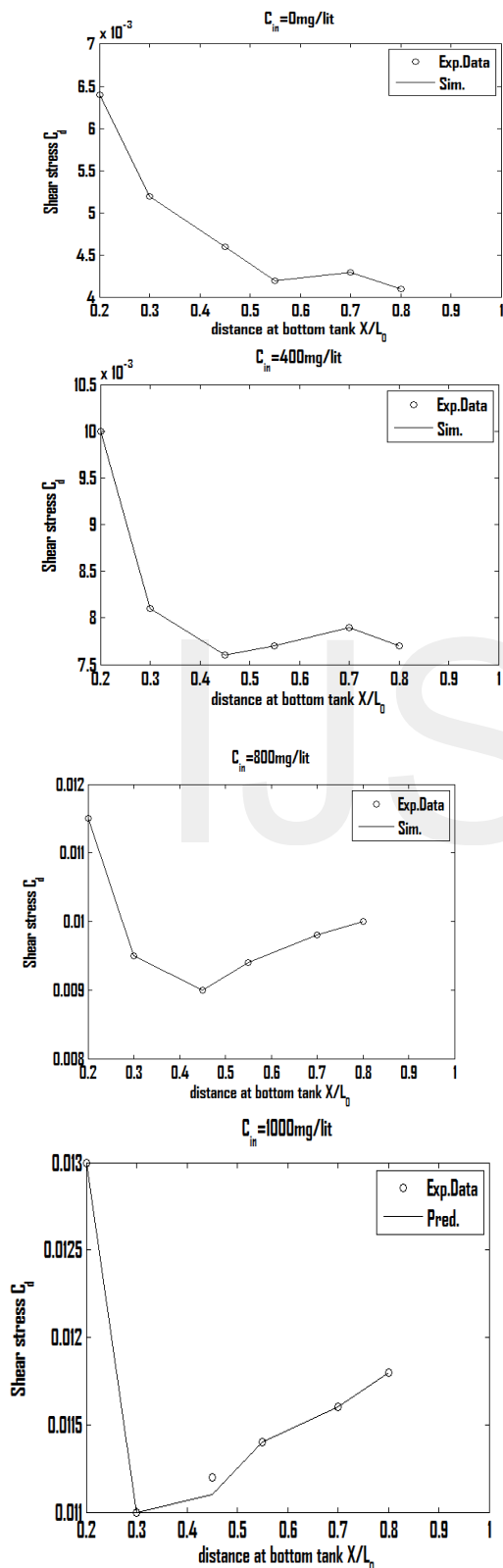
Also, ANNs are chosen to be applied on the maximum streamwise velocity $U_{max}$ (model2) at different values of inlet concentration $C_{in}$. The training values inlet concentration $C_{in}$ are 0, 400 and 800 as shown in Fig.(5). The predicted value of inlet concentration $C_{in}$ = 1000 is in Fig(5). The simulation and predicted results from the obtained function which is given in appendix are best fitting with the experimental data. It is noted from Fig(4) and Fig(5) that, the proposed ANN model shows excellent results matched well the experimental data.



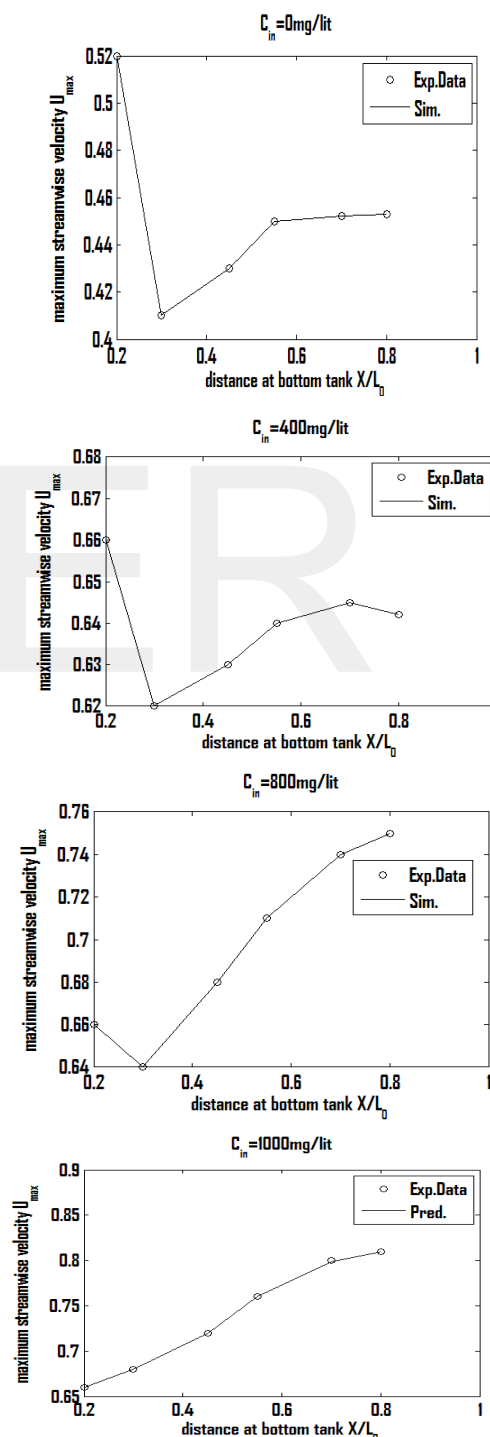Fig. 4. ANN simulation and prediction of shear stress coefficient.



Fig. 5. ANN simulation and prediction of maximum streamwise velocity $U_{max}$

## 5 Conclusion

In this work, a method was proposed to model the Shear stress coefficient $C_d$ at the bottom of tank for various inlet concentrations and maximum streamwise velocity along the channel $U_{max}$ using ANN. For training and testing the network, several numerical cases with combinations of input variables and output data are generated. The validity of the applied predicted methods was investigated in several cases to ensure the effectiveness to establish the results with less permissible error. It can be concluded by analyzing the results that the artificial neural network can predict the shear stress coefficient $C_d$ at the bottom of tank for various inlet concentrations and maximum streamwise velocity along the channel $U_{max}$ accurately with minimum relative error. The trained ANN network shows excellent results matched with the experimental data in the two cases of the shear stress coefficient $C_d$ and maximum streamwise velocity $U_{max}$. The designed ANN introduce a powerful model and shows a good match to the experimental data. Then, the capability of the ANN techniques to simulate and predict the experimental data with almost exact accuracy recommends the ANN to dominate the modelling techniques in fluid mechanics.

## Appendix

The equation which describe shear stress coefficient and maximum streamwise velocity is given by:

$C_d$ and $U_{max}$ =Pureline [net. LW{4,3} logsig(net. LW{3,2} logsig(net.LW{2,1} logsig(net. IW{1,1} A +net. b{1})+net. b{2})+net. b{3})+net. b{4}], Where
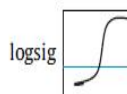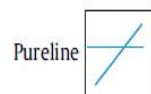


A =$X/L_o$ is the input
net. IW{1,1}: linked weights between the input layer and first hidden layer.
net. LW{2,1}: linked weights between the first hidden layer and the second hidden layer.
net. LW{3,2}: linked weights between the second hidden layer and third layer.
net. LW{4,3}: linked weights between the third hidden layer and output layer.
net . b{1}: is the bias of the first hidden layer.
net . b{2}: is the bias of the second hidden layer.
net . b{3}: is the bias of the output layer.
net. b{4}: the bias of the output layer.

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