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Artificial neural network modeling for predict performance of pressure filters in a water treatment plant

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ABSTRACT

Pressure filters are popular in small municipal water treatment plants. One of the principles for designing and using the various units of water treatment plants is the ability of assigning and predicting the performance of those units under different and various conditions that could be verified by making pilot scale tests and could be modeled by means of available programs and software such as artificial neural network. The goals of this study that was conducted to predict pressure filter efficiency are: (1) evaluations of pressure filter efficiency for turbidity removal under different conditions such as turbidity of raw water, filtration rate and filter pressure changes; (2) statistical analysis of results and determination of the minimum and maximum and maximum effluent turbidity from filter; (3) application of Artificial Neural Network as a suitable model of filter efficiency for turbidity removal; and (4) determination of considered model index for the prediction of similar filters efficiencies. For approaching those goals, pilot designation, sampling and analysis were done for 1,300 samples, and the maximum and the minimum effluent turbidity from filter were determined based on statistical analyses. Different structure of Artificial Neural Network were evaluated based on results, and the best structure was selected and its indexes was proposed for future studies; for example the best value for different network schemes like momentum coefficient and training rate were 0.5 and 0.2, respectively.

Keywords: Water treatment; Pressure filter; Performance prediction; Modeling; Artificial neural network (ANN); Turbidity removal

1. Introduction

Pressure filters, as one of the filtration alternatives, have many advantages such as high rate of treatment, less space occupied, low price. There are constructed using metal frameworks of cylindric shape, with a vertical or horizontal configuration. Pressure filters are not generally employed in large treatment works because of size limitations. They are popular in small municipal water plants.

In water treatment processes because of complicated and nonlinear relationships between a number of physical, chemical and operational parameters, using of analytical models that have the ability to capture underlying relationships using examples of the desired input-output mapping is very suitable. Artificial Neural Networks (ANN) has been increasingly applied in the area of environmental and water resources engineering.

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The main advantage of Artificial Neural Networks over physically based models is that they are data-driven. The ANN modeling approach does not require a description of how the processes occur in either the micro or macro environments, but only the knowledge of important factors that governed the process. This situation makes the ANN modeling approach a rational choice for process modeling and controlling in water treatment.

The removal of turbidity and color to produce water that is aesthetically acceptable to consumers is a very important component of water treatment. The purpose of this research is to study the performance of pressure filters on removing the turbidity from water according to several parameters such as different turbidities, varieties of filtration rates, and different pressures, and to use these results to introduce the artificial neural network model as a powerful tool in predicting the performance of full scale plants. The reason of using pressure filters in this research is the lack of enough investigations on this kind of filters in the past, and also the need for studying the performance of these filters according to several parameters simultaneously. Moreover in this research, the neural network has also been used for modeling the results and providing an acceptable pattern to utilize the data, which as an important part of this research, will be analyzed further. The neural networks, which are inspired from the biological neural networks, are made of some parallel simple operational elements. The structure of neural networks are determined by the type of the connections between components, so we can build an artificial structure similar to the natural ones, and assigning the communication type between the components by adjusting the value of each connection, known as connection weights. After adjusting, or in another term, training the neural network, a specific result can be obtained by providing a specific input. The network adapted due to input and target contrast, until the network results and target do match [1,2]. Zhang and Stanley developed ANN models for predicting treated water turbidity and color, respectively, at the Rossdale Water Treatment Plants (WTP) in Edmonton, Alberta, Canada [3]. Gagnon et al. developed an ANN model for predicting the optimal alum dosage for the Ste-Foy WTP in Quebec, Canada [4]. Joo et al. developed a similar model for Chungju WTP in Korea, and van Leeuwen et al. developed an ANN model for the prediction of optimal alum dosage based on jar tests conducted on surface waters collected in southern Australia [5]. In all this studies, the raw water quality was more stable, not changing, e.g. when an unusual condition occurs, such as a heavy rain, the storm water brings high turbidity to water source. Based on these concepts, a project was initiated to study the potential capacity of ANN and Adaptive Network-Based Fuzzy Inference System (ANFIS) process control in WTP. The adaptive ANFIS was developed by Jang [6]. Guan and Shang have been shown the ANN model is better than the ANFIS model to be used to achieve the optimal predicting model for the optimal PAC dosing in real time when the storm water brings high turbidity to water source; also have been shown two simulation tools, ANN and ANFIS, were developed that enabled operators to obtain real-time PAC dosage more easily [7].

2. Materials and method

2.1. Pilot plant

A pressurized pilot filter with a circular area, metal made with 4 mm thickness, was used in this research. Prior to use, the interior surface of the filter was painted with two layers of epoxy, and then, all of the mechanical parts such as influent and effluent pipes, valves, barometer, nozzles, etc., were installed in appropriate places. Give a flow diagram of the filter with all the auxiliary equipment-valves, pressure meters, pump etc. In Table 1, the characteristics of the filter used are shown. Characteristics of the silica layers are provided in Table 2 [8].

The main variables in this research are the influent turbidity, filtration rate, and influent pressure. The influent water with different turbidities and flows and operational pressures were studied. The characteristics of the variables are provided in Table 3 [8].

Table 1
The characteristics of the filter used in this research

Tem	Unit	Value
Filter diameter	cm	60
Filter kind	–	Steel
Bed height	cm	105
Bed material	–	Silica
Total filter height	cm	140
Maximum pressure	m	30
Allowable head loss	m	2–4
Number of nozzles per square meter	Number	50

Table 2
The characteristics of the filter layers

Layer number	Layer thickness (cm)	Grain sizes (mm)
1	60	0.4–0.5
2	15	0.8–1.2
3	10	3–10
4	10	10–25
5	10	25–39

Table 3
The characteristics of the input parameters

Turbidity [NTU]	Filtration rate (m^3/m^2 day)	Pressure (mwc)	Turbidity (NTU)	Filtration rate (m^3/m^2 day)	Pressure (mwc)
10	8.5	0.2	100	76.5	1.5
11	13	0.2	125	85	2
12	17	0.2	165	102	2.8
13	24	0.2	285	143	4.5
15.7	25.5	0.255	390	153	5.5
33.3	42.5	0.5	600	198	8.5
50	56	0.8	790	221	10
90	63	1	–	306	15.5

The sampling and necessary tests examining were performed due to standards method mentioned in "Standard Methods" [9] and by using the portable turbidity meter, model HACH-2100, in seven months period, and under different conditions based on influent variables. All samples were collected after backwashing the filter and putting it in the circuit and in the operational period, in the time period 10–630 min. The acceptable head loss to begin the backwashing process was between 2 and 4 m, which 0.2 m was due to constant head loss and the remainder was caused in the operational period. After analytical calculations and analysis, the effluent turbidities from the filter, which were exceeded 1,300 samples, were sorted in a minimum and maximum probable value [8].

2.2. *Artificial Neural Network*

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The back-propagation neural network (BPN) is the most representative learning model for the ANN. The feed-forward, back-propagation architecture was developed in the early 1970s by several independent sources (Werbor; Parker; Rumelhart, Hinton and Williams). This network is used more than all others combined. It is used in many different types of applications. This architecture has spawned a large class of network types with many different topologies and training methods. Generally, the neural network is created for two phases, commonly referred to as the 'training phase' and the 'production phase'. The network parameters (or weights) are initially set to random value. During the training phase sample data containing both–inputs and desired outputs–are processed to optimize the network's output in order to minimize deviation. The neural network is operated using back-propagation networks. Back-propagation neural networks generally have a layered structure with an input layer, an output layer, and one or more hidden layers. Units in the input layer represent the possible influential factors that affect the network outputs and have no computation activities, while the output layer contains one or more processing units that produce the network outputs. Layers between the input and output layer are called hidden layers and may contain a large number of hidden processing units. As the name of this kind of network indicates, propagation takes place in a feed-forward manner from the input layer to the output layer, compares the network outputs with known targets, and propagates the error back to the network using a learning mechanism to adjust the weights and biases. Nodes in the input layer represent possible influential factors that affect the network outputs and have no computation activities, while the output layer contains one or more nodes that produce the network output. Hidden layers may contain a large number of hidden processing nodes [10]. Simple processing unit of an artificial neural network is shown in Fig. 1.

Among the several algorithms used in artificial neural networks, the "Multilayer Perspetron Algorithm" with "Back Propagation Training Algorithm" is prevalent in engineering fields. This algorithm is used in this research to update the parameters used in artificial neural network. This method works by minimizing the errors while adjusting the network parameters. In this method, the mean square of errors is used as a scale to measure the teaching data, and those parameters minimizing the error, are then measured [1]. In neural networks and in the training period of the network, the mean square of errors and nomination coefficient, which are defined by Eqs. (1) and (2), are used, while during the test period, the mean error percentage, as is provided in Eq. (3), is used.

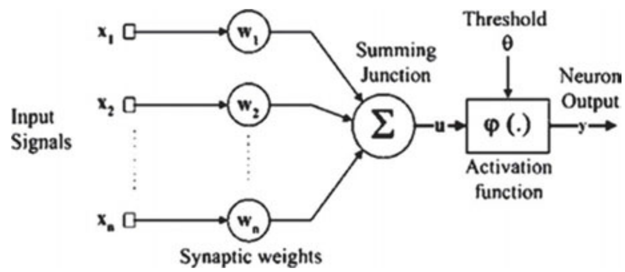

Fig. 1. Mathematical model of a neuron.

$$\mathrm{MSE} = \frac{1}{p}\sum_j \left(t_j - o_j\right)^2 \tag{1}$$

$$R^2 = 1 - \frac{\sum_j \left(t_j - o_j\right)^2}{\sum_j \left(oj\right)^2} \tag{2}$$

$$\mathrm{MPE} = \frac{1}{p}\sum_j \left(\frac{t_j - o_j}{t_j} \times 100\right) \tag{3}$$

where MSE = mean square errors; R^2 = nomination coefficient; MPE = mean error percentage; p = number of input data; j = counter of data in process; t = actual output and o = predicted output.

Data used as input to an artificial neural network, should be in a numeral form and in a specific range, like (0, 1) or (–1, 1) [1, 7]. To achieve this goal, the beneath equations are used sequentially to normalize the data for an artificial neural network. By using these terms, the output results will also be in the range of (0, 1) or (–1, 1), which can be converted to their original form by using the inverse type of Eqs. (4) and (5). The variables used in Eqs. (4) and (5) are defined as below.

$$x_N = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

$$x_N = 2\,\frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1 \tag{5}$$

where x_N = the normalized data; $x_{\min}$ = the minimum value in whole data; x = the unnormalized data and $x_{\max}$ = the maximum value in whole data.

In this research, Eq. (5) has been used to normalize the data, due to use of Tan-Sigmoid transfer function. The input data used in neural network pattern include input turbidity, output turbidity including minimum and maximum probable values, input pressure, filtration rate, and network outputs from filter including minimum and maximum probable values of turbidity.

The most important stage in ANN is selection of model architecture. The neural network used in this study possesses one input layer, two hidden layers and one output layer. The input data are being processed while passing through the first hidden layer, and the results are used as the input data for the next hidden layer, and after being analyzed for final processing, are passed to the last layer. Data come out from the last layer are known as the output data. A schematic of the network architecture used is presented in Fig. 2. While developing an artificial neural network model, available data are divided into two groups. One group is used for network training and the remaining is used for investigating the network generality ability. The TRAINGDM training function in MATLAB has been used in this research. A summary of used network characteristics is presented in Table 4 [1,2].

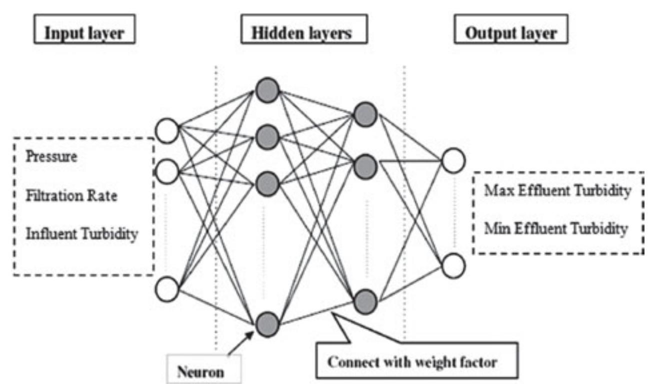

Fig. 2. Schematic architecture of artificial neural network in use.

Table 4
The characteristics of artificial neural network in use

Item	Characteristic
Number of hidden layers	Two layers
Total number of layers	Four layers
Network algorithm	Multilayer Perceptron
Training algorithm	Back propagation
Transfer function	Tan-Sigmoid
Training function	TRAINGDM

3. Results and discussion

After setting up the filter successfully and sampling the effluent from the filter for different input conditions such as different turbidities, influent filtration rate, and the filter pressure, the output results were statistically analyzed. These results, which are determined according to 1,300 samples in different situations, have been used randomly as the artificial neural network inputs, after being normalized by Eq. (5) [8]. A figure with raw data, i.e. turbidity versus operation time are missing; furthermore, the effect of various operation parameters is not shown in the existing figures.

The goal of using artificial neural network in this study is to provide a pattern for predicting the minimum and maximum values of probable turbidity in outputs of pressure filter systems. The network used for this pattern contains three types of input parameters including filtration rate, influent turbidity, and filter pressure and also two output parameters including minimum and maximum probable turbidity. In this study, the MATLAB software was used for training and testing the data in the artificial neural network [1]. To create different situations and finding the optimum condition, the neuron numbers in the training layer was increased from 8 to 15 to obtain the most accurate outputs. After successfully training the network with a fraction of data, the network was tested with the remaining data and statistical analyzes was finally used to compare the obtained results. After investigating and controlling different neural network conditions, such as number of hidden layers and number of neurons in each, 3-11-11-2 was determined as the best network structure, in which 3 and 2 are referred to input and output layers variables, respectively, and 11-11 is the number of neurons in two hidden layers. Among 68 sets of data which were obtained by statistically analyzing the laboratory data, 59 sets were used randomly for training and verifying procedures and the remaining were used for testing the trained network errors. Moreover, the best values of momentum coefficient optimum range and training rate coefficient were determined after investigating different conditions, to be 0.5 and 0.2, respectively. These values were used in different structures, such as the final structure. To determine the optimum range of each of these coefficients, each was evaluated in the range of 0.1–0.9. In Table 5, the results of investigating some of different structures of artificial neural network are provided. The results for the best conditions are also provided in Table 6. Diagrams were plotted according to these results, shown in Figs. 3–6. In Fig. 3, efficiency changes (error value) is shown for artificial neural network training and verifying stage. In Figs. 4–6, the correlation diagrams for training, verifying, and network testing stages, have been shown, and the experiment results are compared to the predicted results from the artificial neural network in each stage. The dispersal diagrams show that the neural network model has been truly trained and has a high accuracy in predicting the minimum and maximum probable turbidities in output.

Table 5
The results of investigating some of different structures of artificial neural network in test

Network structure	Nomination coefficient (R^2)	Mean error percentage for maximum output turbidity (MPE) (%)	Mean error percentage for minimum output turbidity (MPE) (%)
3-11-11-2	0.987	4.2	5.3
3-10-10-2	0.974	6.1	7.2
3-9-9-2	0.93	6.2	8.1
3-8-6-2	0.90	9.3	11.2
3-8-8-2	0.65	22.3	29.2

Table 6
The results of the best pattern from investigating several neural network structures

Item	Characteristic
Network structure	3-11-11-2
Training rate	0.2
Momentum coefficient	0.5
Number of training cycles	2,000
Transfer function	Tan-Sigmoid
Training period	41 s
Target error value	0.0001

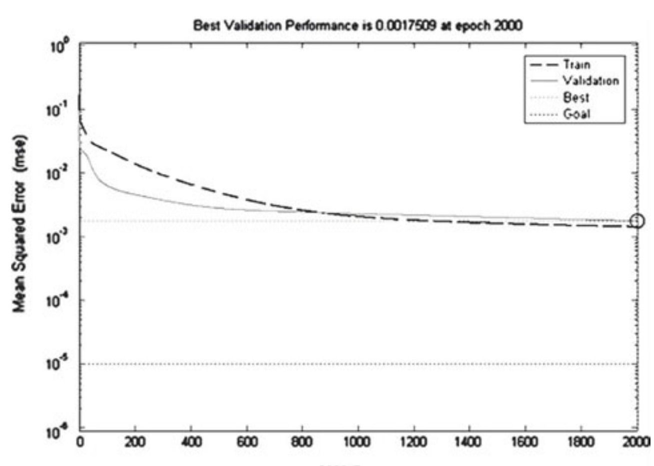

Fig. 3. Efficiency changes in training and verifying stage.

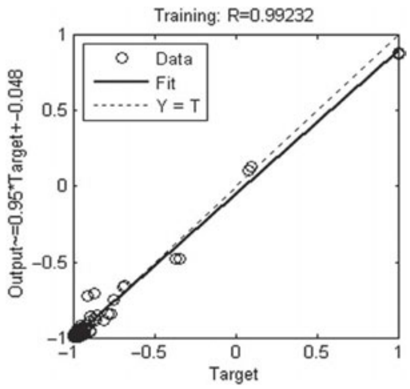

Fig. 4. Correlation diagrams for training stage.

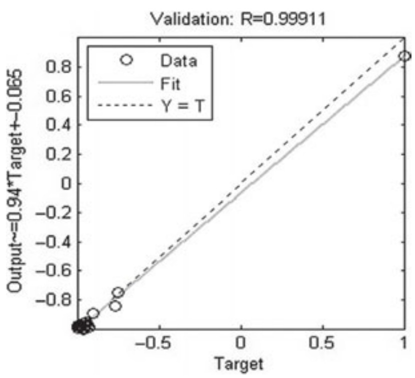

Fig. 5. Correlation diagrams for verifying stage.

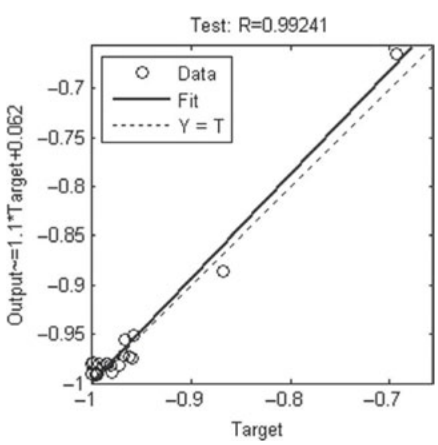

Fig. 6. Correlation diagrams for testing stage.

4. Conclusions

The beneath results were obtained from this study, in which the pressure filters efficiency and providing a pattern to show this efficiency due to artificial neural network, was investigated. Whereas the most important feature of a neural network with a high generality ability, is the ability of predicting the unseen numeral outputs accurately, we truly beneficiated this feature of an artificial neural network, and the multilayer Perceptron structure with Back Propagation Training Algorithm has been shown to be a useful tool for predicting the output turbidity from pressure filters. In this study several network architectural parameters such as momentum coefficient and training rate were investigated in different conditions. The best conditions were 0.5 and 0.2, respectively, and several neural network structures with different number of neurons were investigated to determine the optimum condition. The 3-11-11-2 structure for the artificial neural network was finally determined as the optimum pattern. According to training and testing dispersal diagrams, the output turbidities were predicted with a high accuracy, and the slop of diagrams and of interpolating functions were close to 1 and 0, respectively, showing the suitability of this pattern for predicting the pressure filters performance. It is concluded from the optimum pattern dispersal diagrams that the provided neural network is truly trained and has a high accuracy in predicting the minimum and maximum probable turbidities in output. The low values of errors for this model in several stages such as training, testing, and verifying, represents the high accuracy of experimental results and selection of appropriate variables, which can be used by other researchers in any other places with the same conditions of this pattern.

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