Predicting the performance of multi-media filters using artificial neural networks
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ABSTRACT
The impact of flow rate and turbidity on the performance of multi-media filtration has been studied using an artificial neural network (ANN) based model. The ANN model was developed and tested based on experimental data collected from a pilot scale multi-media filter system. Several ANN models were tested, and the best results with the lowest errors were achieved with two hidden layers and five neurons per layer. To examine the significance and efficiency of the developed ANN model it was compared with a linear regression model. The $R^2$ values for the actual versus predicted results were 0.9736 and 0.9617 for the ANN model and the linear regression model, respectively. The ANN model showed an R-squared value increase of 1.22% when compared to the linear regression model. In addition, the ANN model gave a significant reduction of 91.5% and 97.9% in the mean absolute error and the root mean square error, respectively when compared to the linear regression model. The proposed model has proven to give plausible results to model complex relationships that can be used in real life water treatment plants.

Key words | artificial neural networks, influencing factors, multi-media filtration, water treatment

INTRODUCTION
Water resources management has recently emerged as an imperative solution to the prevailing and intensifying shortages in water supplies. The colossal growth of the world’s population has directly contributed to the shortage of water around the globe whilst alternative water resources are being sought to meet growing demands (Elfaki et al. 2015). The use of treated wastewater has emerged as a viable water resource in recent times (Hamoda et al. 2004). Despite its promising outlook, the objective and use of the treated wastewater must be clearly identified before treatment can begin. Depending on the reuse application, the type and reliability of the treatment process may differ from one purpose to the other. The current limitations of standard secondary treatments for domestic and industrial wastewaters have transpired as a result of the requisite standards of quality and discharge. With more stringent environmental requirements, additional and advanced treatment of secondary effluents is necessary. These processes may include a series of unit operations such as coagulation/flocculation, sand/multi-media filtration, and membrane separation technologies (Chae et al. 2009; Jenkins et al. 2011; Sadeddin et al. 2011; Elbana et al. 2012; Gao et al. 2012; Elfaki et al. 2014; Muthuraman & Sasikala 2014; Ramavandi 2014). The multi-media filtration process is still considered to be a reliable and economic process, in spite of the wide use of membrane separation for tertiary stages of treatment. From an economic standpoint, multi-media filtration is considered an inexpensive process that is capable of promoting the quality of secondary effluents (Aslan and Cakici 2007), and which has been employed for various purposes such as desalination pretreatment, filtration and disinfection of river water and storm water, and the removal of nutrients and heavy metals (Aslan & Cakici 2007; Jenkins et al. 2011; Marti et al. 2013; Puig-Bargués et al. 2012; Corral et al. 2014; Nitzsche et al. 2015).

Multi-media filters utilize different granular particles, e.g. gravel, anthracite and graphite, with varying granule sizes, to remove suspended solids from influents (Elbana et al. 2012; Gao et al. 2012; Elfaki et al. 2014; Reddy et al. 2014). In a multi-media filter, the inconsistent flow rate and the highly variable quality of the influent have a direct impact on the efficiency of the filtration process. Mathematical modeling and computer simulations should be utilized as means of prediction, optimization and control of the
filtration process (Puig-Bargue’s et al. 2012). Artificial neural networks (ANNs) have evolved to help predict and control the effluent quality in water and wastewater plants. ANNs function by relating input and output factors and using them to identify recurrent patterns and, ultimately, predicting treatment results by the end of their learning process. (Gumrah et al. 2000; Puig-Bargue’s et al. 2012; Yoon et al. 2013; Arnavat & Bruno 2015; Bagheri et al. 2015; Beucher et al. 2015; Kalogirou et al. 2015). This intelligence-based approach performs similarly to a human brain and is widely used where there is a need to resolve non-linear connections for complex processes with results that are difficult to achieve, e.g. in the fields of neurology, medicine, engineering and security (Bagheri et al. 2015; Kalogirou et al. 2015). Research shows that the use of ANNs in wastewater treatment plants was successful in terms of modeling, simulation and controlling treatment processes (Bagheri et al. 2015).

In this study, the impact of flow rate and turbidity on the performance of multi-media filtration has been studied using an ANN-based model. The ANN model was developed and tested based on experimental data collected from a pilot scale multi-media filter system. ANN modeling is useful in mapping the relationship between independent and dependent variables, especially in cases of complex relationships (Smith 2001). The ANN model is expected to optimize the multi-media filtration process without requiring tedious parameter estimation procedures.

**METHODOLOGY**

**Experimental set-up**

The pilot scale multi-media filter system used in this study is represented in **Figure 1**. A 10.2 cm diameter and 120 cm long PVC pipe (Harvel Co., USA) was used to build up the filter. The filter consisted of four layers of different material with varying granular sizes: anthracite (0.8–1.6 mm), coarse sand (0.71–1.18 mm), fine sand (0.4–0.8 mm) and gravel. As
seen in Figure 1, each layer had a different thickness, and the top space of 30 cm above the anthracite layer was allocated for influent water retention during the filtration process.

The suspension was prepared by mixing clay (Fila Group Co.) with tap water to achieve the required influent turbidity level. Continuous mixing was maintained to ensure a homogeneous feed. Influent was consequently pumped to the system using a 0.75 HP pump (CEAM 70/5, Lowara Co., Italy). The influent and effluent tanks had a capacity of 150 liters each; additionally, each had low and high flow level switch sensors (LVH-200, Omega Engineering Co., USA) at 15 cm from the bottom and 10 cm from the top of the tank to avoid below minimum levels and flooding, respectively. All sensors are connected to the control panel (FLECK7700 SXT, Pentair Water Co., USA) to facilitate system shutdown when needed. Four needle type flow valves (Hyward, USA) were used in the set-up: V1, V2, V3 and V4. V1 is a three-way valve to which both influent and effluent tanks are connected; water from the influent tank passes through the valve to the filter and back to the effluent tank. V2, on the other hand, is a global recirculating valve that allows a portion of the effluent back to the influent tank to ensure proper mixing and simultaneously control characteristics of the influent. As seen in Figure 1, V3 was used to control the flow rate of the influent fed to the filter. To measure the flow rates of the influent and effluent, flow meters (FL50002, Omega Engineering Co., USA) were employed. Once reaching unacceptable filtered water quality, the system is shut down and is set to the backwash mode. After closing the filter’s inlet and outlet ports, water will be fed to the filter for backwash through the backwash flow valve V4.

**Operating conditions**

A breakthrough turbidity of 5 NTU was set for determining the efficiency of the filtration process. To study the effect of varying operational conditions, the filter was tested with three different influent flow rates (1.8, 2.8 and 4 liters/minute) representing different flow ranges (low, medium and high, respectively) in an attempt to simulate real life situations and operating conditions in treatment plants. Additionally, turbidity was increased at a 5 NTU increment between 10 and 30 NTU inclusive to evaluate the efficiency of the process at filtering water with higher initial turbidity. The turbidity of the influent and effluent were measured for 264 samples using a portable turbidity meter (Hatch-2100P), and the breakthrough time (BT) was recorded. The BT was considered as the time when the effluent turbidity reached 5 NTU.

**Artificial neural network**

The developed ANN model was tested based on the actual collected experimental data. The ANN Toolbox of Visual Gene Program was used to build the model through four steps: (i) determination of model inputs, (ii) network geometry and parameters, (iii) model output, and (iv) training/testing period (Jung & McDonald 2011). The architecture of the network chosen was the multi-layer feed-forward ANN with a back-propagation training algorithm. In a multi-layer feed forward ANN, all layers are adaptive and the network is not allowed to take cycles from later layers back to earlier layers, which makes it easy to represent more functions with a multi-layer network and to approximate any continuous function from the inputs to the outputs to a certain degree of accuracy. The back propagation training algorithm is a gradient algorithm that represents how the error would be distributed in the output over the different hidden units, with the intent of minimizing the total squared error of the training data. A multilayer neural network consists of input, hidden, and output layers; each hidden layer has several nodes that serve in processing the input data. All nodes in a network are connected between the different layers, forming the architecture of the network. An illustration of the ANN chosen for this study is shown in Figure 2.

Different structures, in addition to trial and error tests of ANN models, were tested to find the best model for predicting the effluent quality of the multi-media filter with the fewest errors. To find the best architecture for the ANN models, different numbers of nodes in each hidden layer were tested. The lowest error was obtained when two hidden layers with 5 nodes per layer was used. In order to evaluate the robustness of the developed ANN model, two different scenarios that can take place in an actual treatment plant were applied; the first scenario was increasing the influent flow rate, and the second was increasing the influent’s turbidity. The ANN was trained subsequently on learning a pattern from the data provided. Influent turbidity, flow rate and time were introduced as parameters of the input layer; meanwhile, the effluent’s turbidity and filtration time were introduced to the ANN’s output layer as output parameters.

An important step in training and testing an ANN is data partitioning. The data to be introduced have to be divided into training sets and validation sets. While running the actual experiments on the multi-media filter, the influent’s turbidity, flow rate and the effluent’s turbidity and time to filtration were measured and recorded. The values
obtained were analyzed graphically to determine the BT. Eighty per cent of the data obtained were thereafter fed to the ANN as a training set, and the remaining 20% were used to validate the ANN model. A comparison between the predicted and actual results will therefore validate the accuracy of the network. It is important to note that the validation data have to be different from the training data, and that training should not continue for a long time to avoid over learning (Arnavat & Bruno 2015).

**Data verification**

To validate the performance of the ANN model, a comparison between predicted and actual data were performed and the mean absolute error (MAE), root mean square error (RMSE), and Coefficient of multiple determination ($R^2$) were calculated. MAE is the mean absolute value of the differences between the observed results ($O$) and the predicted results ($P$) for a number of samples ($n$) as shown in Equation (1):

$$\text{MAE} = \left[ \frac{1}{n} \sum_{i} (O - P_i) \right]$$

Equation (1)

RMSE, on the other hand, is the average of the squared differences between the observed ($O$) and predicted ($P$) results as shown in Equation (2):

$$\text{RMSE} = \left[ \frac{1}{n} \sum_{i} (O - P_i)^2 \right]^{0.5}$$

Equation (2)

The $R^2$ value was determined to measure how far the predicted values are from the actual values by using Equation (3):

$$R^2 = \frac{SSR}{SST}$$

Equation (3)

where

$$SSR = SST - SSE$$

$$SST = \sum (y - \bar{y})^2$$

$$SSE = \sum (y - x)^2$$

where ($y$) is the actual value, ($\bar{y}$) is the average for all actual values and ($x$) is the predicted value from the model.

To visually examine the goodness of the prediction model, the actual versus predicted results for the BT plot is observed. The perfect model would have an $R^2$ value of 1; the closer the value obtained is to 1, the greater the accuracy of the model would be considered.

**Linear regression**

Linear regression is a statistical technique that determines the linear relationship between a single dependent variable and one or more independent variables (Allison 1999). To determine the best possible combination of variables that would result in the lowest error and variation in the developed regression model, best subset analysis was performed. Stepwise linear regression was carried out to
compare its outputs with the outputs of the ANN model. In order to best fit the dependent variables to the independent ones in stepwise linear regression, the back elimination procedure was used. BT was the response (dependent) variable, meanwhile flow rate and turbidity were the independent variables. For comparison purposes, the input and output parameters chosen were the same ones used in the ANN model. Analysis of variables was performed using the RStudio software to determine the R-squared value and the p-value of the data analyzed upon elimination of statistically insignificant variables. The most appropriate model was the one with a p-value less than 0.05, which means that the null hypothesis is rejected (i.e. $\beta = 0$), and that there is a significant relationship between the variables in the linear regression model and an R-squared value for the model higher than 0.9 (0.9–1).
RESULTS AND DISCUSSION

ANN performance

As shown in Figure 3, the increase in the influent turbidity had an impact on the filter performance. It was found that the treated volume decreased drastically as the turbidity of the influent increased from 10 to 30 NTU. On the other hand, the impact of the influent flow rate on the performance of the filter showed no clear trend (Figure 3). Consequently, using ANN to predict the final turbidity of the effluent in the multi-media filter was a reasonable approach to optimizing the filtration process.

Figures 4–8 show the actual and predicted effluent turbidity under different running conditions. Figure 4(a) shows that after 6 hours of running the filter at the lowest flow rate (1.8 l/min) and turbidity (10 NTU), breakthrough was still not achieved. However, increasing the flow rate to 2.8 l/min and 4.0 l/min decreased the time of breakthrough to 3.2 hours, as shown in Figure 4(b) and 4(c). ANN results showed a very similar predicted trend to the actual trend obtained from experimental results. Figure 5 reveals that increasing the turbidity from 10 to 15 NTU showed the same trend with respect to BT and flow rate; moreover, the predicted results also exhibited the same trend as the actual ones. Figure 6(a)–(c) show a significantly shorter BT at the three flow rates tested for both actual and ANN results. The same trend is expected to be witnessed for the remaining six combinations, where it is expected that the filtered water volumes will decrease proportionally with the increase in flow rates and turbidity. Despite the extremely fast BT
witnessed at high turbidity values (Figures 7 and 8), the results still show a good similarity between the actual and the ANN predicted data. Several ANN models were tested, and the best results with the lowest errors were achieved with 2 hidden layers and 5 neurons per layer. The MAE, the RMSE and the $R^2$ were 0.476, 0.654 and 0.9736, respectively.

Comparison between ANN and linear regression performance

Stepwise linear regression with back elimination procedure, resulted in Equation (4), which can be used to predict the BT:

$$\text{Log(Breakthrough Time)} = (3.701 - 0.02394Q - 0.07942(Ty)^2 + 0.0001868 (Ty)^3)$$  \hspace{1cm} (4)

where $(Q)$ is the flow rate (l/min) and $(Ty)$ is the turbidity (NTU). Since the relation between the BT versus flow rate and turbidity cannot be modeled using linear coefficients alone, a full model was considered that consisted of the logarithmic value of the BT versus the linear, quadratic and cubical coefficients of the independent variables. Several models were tested; as mentioned earlier, any coefficient with a $p$-value higher than 0.05 was eliminated. Therefore, the final relationship between BT and the independent variables that yielded the best $R$-squared value was the chosen model for linear regression. The predicted BT for both the ANN and linear regression models were obtained:

The $R^2$ value for both models is presented in Figure 9(a) and (b). Although the prediction of the quality of effluent
from a tertiary mixed-media filtration process is very complex, the figures demonstrate that the ANN was able to learn the relation between the influent parameters (time, flow rate, and turbidity) and the effluent turbidity. As can be noted from the figures above, the R-squared value for the BT predicted through the ANN was higher than that predicted through the linear regression. Additionally, MAE and RMSE were also compared between ANN and linear regression; the results are presented in Table 1.

As seen in Table 1, the ANN results showed an R-squared value increase of 1.22%, in addition to a very significant reduction of 91.5% and 97.9% in MAE and RMSE respectively. In conclusion, the ANN’s performance exhibited superior prediction abilities in comparison with stepwise linear regression.

### CONCLUSIONS

A set of 15 operational conditions were run on a multimedia filtration unit to study the effect of changing flow rate and initial turbidity on filtration capacity. The results of the filtration tests showed that effluent turbidity is inversely proportional to the increase in flow rate. Moreover, as initial turbidity increased, the volume of treated water with an acceptable turbidity level decreased. The ANN designed and trained to predict the outcomes of the multi-media filtration system showed very similar predicted results to the actual experimental results, therefore proving the sturdiness and efficiency of the model. Although the number of hidden layers required in multi-layer feed forward ANN may be large, the comparison of predicted BT obtained from linear regression and ANN showed that ANN yielded results of higher accuracy, where the R² value for the actual versus predicted BT was higher for the ANN model with a value of 0.9736. Supplementary research and tests are recommended for further optimization of the filtration process, such as using additional data points or real case studies. Also, different techniques other than linear regression can be compared with the developed prediction model to examine its efficiency. Nevertheless, the results obtained in this study proved that the use of ANNs in predicting the outcomes of multimedia filters is a favorable and cost effective step towards advancement of filtration processes.

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