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Research Article

ARTIFICIAL NEURAL NETWORK SIMULATION OF ADVANCED BIOLOGICAL WASTEWATER TREATMENT PLANT PERFORMANCE

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ABSTRACT

Artificial neural network (ANN) simulation of chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP) removal efficiencies of an advanced biological wastewater treatment process is presented in this study. Seven input parameters (predictors) were used: influent COD, TN, and TP concentrations, internal recycle (IR) and return activated sludge (RAS) ratios, wastewater temperature, and total hydraulic retention time (HRT) of process reactors. Results showed that open-source ANN tools can easily be employed for quick and reliable simulation results. ANN with the logistic, the sinc, and the Elliot functions can be confidently employed for predicting COD, TN, and TP removal efficiencies. Mean square errors were $5.54*10^{-7}$, $2.06*10^{-4}$, and $2.26*10^{-3}$, respectively, for COD, TN, and TP removal efficiencies. Besides, wastewater temperature was found to be the major factor that determines the performance of a wastewater treatment system while RAS ratio, HRT, and influent wastewater characteristics are also effective on the performance.
Keywords: Wastewater treatment, biological nutrient removal, treatment performance, artificial neural networks.

1. INTRODUCTION

Treatment of wastewaters prior to discharge is one of the main components of urban infrastructure systems, the importance of which, among others, has been escalating gradually due to increasing trends in population density of large cities. Considering the increasing trends in land, workforce, and energy costs as well as awareness of materials/energy recovery from wastewaters, the design and efficient operation of wastewater treatment systems has become a great challenge for environmental engineers.

Wastewater treatment systems mostly employ complex physical, chemical, and biochemical processes in various steps [1]. Today, the treatment objectives are usually accomplished in three main steps as primary, secondary, and tertiary treatment. Primary treatment step usually comprise physical processes like screening, grit removal, and primary sedimentation, while biochemical processes (activated sludge processes) in addition to physical processes are employed in secondary treatment step. The existence of a tertiary step depends on the treatment objectives and is accomplished mostly by physical and chemical processes.

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The design and efficient operation of a wastewater treatment system as a whole is a very complicated task for environmental engineers that require expertise in all physical, chemical, and biochemical treatm ent processes. Although computer-aided methods such as activated sludge modeling tools [2-5] are usually adopted for the purpose of design, operation, and optimization of modern wastewater treatment plants, these deterministic modeling tools require knowledge on a great number of treatment plant parameters, influent wastewater parameters, and model parameters, and these models usually require hours of calculation time, if not days, to complete simulation tasks. Most of the time, engineers need to test several scenarios on a wastewater treatment plant in both the design and operation phases and these deterministic modeling tools does not meet the requirements for quick simulation results due to their huge input requirements and long run times. Therefore, empirical modeling tools become more useful for these cases when quick simulation results are needed. Artificial neural networks (ANNs), with their ability to learn and mimic engineering systems in wide range, can be used for this purpose.

An artificial neural network is a black-box modeling tool [6], which employs processing units for learning and simulating complicated engineering systems. Artificial neural networks do not need to be taught complex physical, chemical and biochemical phenomena. Instead, they learn and mimic the engineering system in an empirical manner. This feature of ANNs make it possible to obtain quick simulation results no matter how complicated the engineering system of interest is, if the ANN is well-trained prior to simulation.

The outputs of many environmental engineering processes including biological wastewater treatment can be easily simulated by a well-trained ANN. For instance, Şamlı et al [7] reported the use of ANN for predicting chlorophyll-a concentrations in a coastal region while Bayram et al [8] employed ANN modeling for dissolved oxygen concentrations in a watershed. Sakiewicz et al [9], in a newer study, employed ANN modeling for monitoring the effects of plant operating parameters in a biogas-wastewater treatment system and performed sensitivity analyses. They concluded that plant operating parameters are more effective on the performance than influent wastewater characteristics, which proves that artificial neural network modeling tools also provide the opportunity to evaluate the effects of several parameters, and prioritize them as major and minor parameters. Mohammad et al [10] reported training of a multilayer ANN for chlorophenol removal from wastewater while Mojiri et al [11] achieved optimization of an anammox process enhanced with biochar adsorption using ANN simulations. Artificial neural networks can also be used to predict the outcome of specific treatment processes as described by Ribeiro et al [12]. Papers by Han et al [13] and Qiao et al [14] describe successful implementation of ANN modeling tools for process control. They achieved implementation of a multiobjective fuzzy neural network controller for a wastewater treatment process, which aims at improving operational efficiency to satisfy the effluent quality standards and reduce the energy costs, and then employed that controller for multiobjective process operation.

A number of sample studies exists pertaining to the prediction of wastewater treatment plant performance by artificial neural networks [15-19]. For instance, Güçlü and Dursun [20] built a number of ANN architecture for predicting mixed liquor suspended solids (MLSS) concentration, as well as effluent chemical oxygen demand (COD) and suspended solids (SS) concentrations in a large-scale, Turkish wastewater treatment plant concluding that the ANN models are reliable tools for predicting wastewater treatment plant performance. The more the number of data points are, the more accurate the model results are. In a newer study, Nasr et al [21] applied ANN modeling to an Egyptian wastewater treatment plant for predicting effluent COD, biochemical oxygen demand (BOD), and total suspended solids (TSS) using operating data gathered over a period of one year. The authors reported that correlation coefficients between measured and predicted effluent concentrations reached up to 0.90, and that ANN can be used as an effective tool for analysis and diagnosis purposes. Tümer and Edebali [22] applied an ANN modeling tool for predicting TSS removal efficiency in a Turkish wastewater treatment plant using influent pH, temperature, COD, TSS, and BOD collected over four months as input parameters. They tested a number of different ANN arc hitectures to obtain best simulation results concluding that logistic function offers the most accurate results. In another study, Türkmenler and Pala [23] used influent pollutant concentrations and wastewater flowrate to predict effluent BOD concentrations by ANN reporting that ANN modeling tools can be used effectively for forecasting the performance of an advanced biological wastewater treatment plant. Review of current literature on ANN modeling of wastewater treatment plants reveals that most of the studies were performed using real treatment plant data, which offers a very narrow range of input parameters leading to a limited-range of applicability of results. Besides, operating parameters in real treatment plants like recycle ratios are extremely difficult to change during operation, and most of these studies were performed by neglecting the effects of several operating parameters on the treatment plant performance. Therefore, current literature lacks scenario-based studies, which also account for the effects of several plant operating parameters.

The motivation of this study comes from the need for sample studies that describe the application of open-source modeling tools like artificial neural networks for predicting advanced biological wastewater treatment plant performance depending on a great number of operating and influent wastewater parameters. The main purpose is to build, train and employ an ANN model for predicting the performance of a conventional A^2O process depending on influent wastewater characteristics such as chemical oxygen demand (COD), total nitrogen (TN), total phosphorus (TP) as well as temperature, and plant operating parameters such as internal recycle (IR) ratio, return activated sludge ratio (RAS), and total hydraulic retention time (HRT) of process reactors. Plant performance data was obtained using an open-source activated sludge modeling tool based on activated sludge model no. 3 (ASM3) extended with biological phosphorus removal processes. The data set was comprised of 2187 data points, which, to the author's knowledge, offers the most comprehensive simulation data in the literature. Artificial neural networks built with several activation functions were then employed for training to predict COD, TN, and TP removal efficiency of the wastewater treatment process, and testing the accuracy of ANN model. Sensitivity analyses were also performed with ANN model to determine the major and minor factors that characterize the behavior of the treatment process for COD, TN, and TP removal efficiency.

2. MATERIALS AND METHODS

2.1. Process Configuration

A conventional wastewater treatment plant configuration was used for simulation purposes. The treatment system is an A^2O process and the configuration is composed of an anaerobic, an anoxic, and an aerobic reactor followed by a secondary settling tank. The flowchart of the process is shown in Fig. 1. Primary effluent (also called influent wastewater from now on) was fed to the anaerobic reactor. The return activated sludge was taken from the bottom of the settler to the inlet of anaerobic reactor while an internal recycle was reserved to recycle nitrate from aerobic reactor to anoxic reactor. The influent flowrate was constant at 1800 m^3/h and the waste activated sludge was taken from the bottom of the settler at a flowrate of 18 m^3/h. The hydraulic retention time of the secondary settling tank was 4 hours.

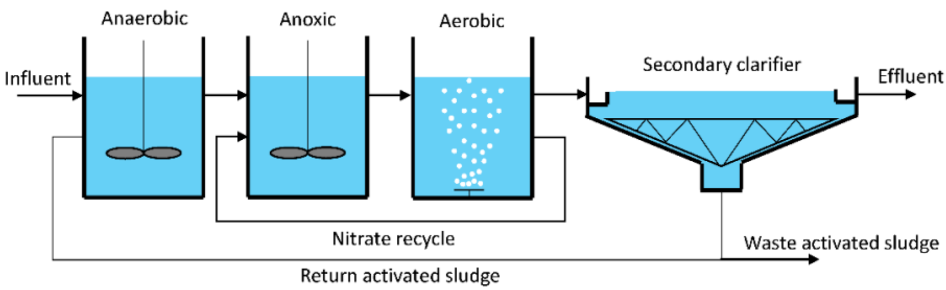

Figure 1. Flowchart of the wastewater treatment process

2.2. Activated Sludge Model

Activated sludge model no.3 (ASM3) by Gujer et al [5] extended with biological phosphorus removal processes [24] was used to simulate the A^2O process given in Fig. 1. Simulations were performed using an open-source MS Excel Visual Basic for Applications (VBA) tool called bioXL3p, which has been developed as an extended version of previous bioXL3 software [1]. The tool is an MS Excel add-in with a friendly user interface and it is equipped with several additional functionality to build and apply various simulation scenarios.

Based on seven operating and influent wastewater parameters given in Table 1, a total of 2187 scenarios were created and simulations were performed to determine steady-state COD, TN, and TP removal efficiencies of the system. To obtain volumes of process reactors in the simulations, the HRTs of the anaerobic, the anoxic, and the aerobic reactors were assumed to be 9%, 18%, and 73% of total HRT of the process reactors, respectively.

Table 1. Influent wastewater and operating parameters for the wastewater treatment process

Parameter	Value
Influent	
Chemical oxygen demand (COD)	300; 400; 500 mg/L
Total nitrogen (TN)	30; 40; 50 mg/L
Total phosphorus (TP)	2; 3; 4 mg/L
Internal recycle ratio (IR)	2; 3; 4
Return activated sludge ratio (RAS)	0.8; 1.0; 1.2
Total hydraulic retention time of process reactors (HRT)	5.0; 7.5; 10.0 h
Wastewater temperature (T)	5; 15; 25 °C

For all simulations, influent concentrations of several model components were calculated using the fractionation data for primary settled wastewater presented in Rössle and Pretorius [25]. The component concentrations in all simulations are shown in Table 2.

Table 2. Influent component concentrations for bioXL3p tool

Component	Concentration	Remarks
Dissolved oxygen	0 mg/L	Constant
Soluble inert organics	0.075 * [COD]	Calculated in each simulation based on influent COD. Refer to Table 1.
Readily biodegradable organics	0.325 * [COD]	Calculated in each simulation based on influent COD. Refer to Table 1.
Ammonium + ammonia nitrogen	0.69 * [TN]	Calculated in each simulation based on influent TN. Refer to Table 1.
Nitrite + nitrate nitrogen	0 mg/L	Constant
Dissolved nitrogen	0 mg/L	Constant
Phosphate phosphorus	0.55 * [TP]	Calculated in each simulation based on influent TN. Refer to Table 1.
Alkalinity	5 mmol/L HCO_3	Constant
Autotrophic biomass	0 mg/L	Constant
Heterotrophic biomass	0 mg/L	Constant
Phosphorus accumulating biomass	0 mg/L	Constant
Particulate inert organics	0.05 * [COD]	Calculated in each simulation based on influent COD. Refer to Table 1.
Slowly biodegradable substrate	0.55 * [COD]	Calculated in each simulation based on influent COD. Refer to Table 1.
Organics stored by heterotrophs	0 mg/L	Constant
PHAs stored by PAO	0 mg/L	Constant
Polyphosphates	0.125 * [TP]	Calculated in each simulation based on influent TP. Refer to Table 1.

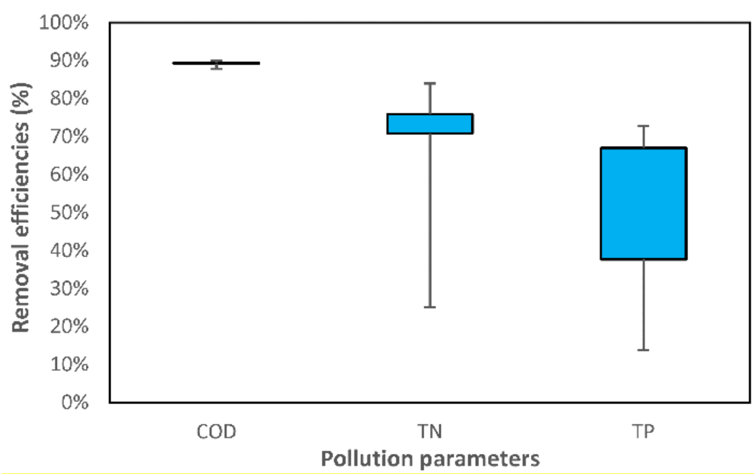

Figure 2. Removal efficiencies of A²O process calculated by activated sludge modeling

The removal efficiencies of the process for COD, TN, and TP are shown in Fig. 2. Besides, steady-state sludge retention times (SRT) and mixed liquor suspended solids (MLSS) concentration were calculated for each scenario. The average MLSS concentrations in process reactors changed between 2032 and 8772 mg/L while sludge retention times changed between 9.4

and 23.0 days. Average COD removal efficiency was calculated as 89.4%±0.5% with minimum and maximum values of 87.9% and 90.4%. Minimum and maximum TN removal efficiencies were 25.1% and 86.6% with an average value of 70.6%±14.1%. Calculated average TP removal efficiency was 61.0%±22.6%. The TP removal efficiencies ranged from 13.8% to 88.3%.

2.3. Artificial Neural Network

Another open-source MS Excel VBA-based tool [26] was used for artificial neural network simulations. The tool allows selection of the number of input neurons, output neurons, and hidden neurons as well as the number of hidden layers in addition to percent of training samples, number of epochs, and learning rate. The tool also offers a number of activation functions for hidden and output neurons [27] as well as user-defined steepness coefficients [28].

An artificial neural network model has been established with the topology given in Fig. 3. For all simulations, the input data was normalized between 0 and 1. Since the output data is composed of COD, TN, and TP removal efficiencies calculated between 0 and 1, normalization was not performed for output data. Randomly selected 70% of the samples (simulation results from activated sludge model) was used for training while the remaining 30% was used to validate the simulation results. The learning rate was 0.75 with 2000 epochs. Ten hidden neurons were employed for all simulations. Although a number of activation functions has been used effectively for various simulation works with ANNs (a detailed discussion of these functions can be found in Sibi et al [29]), three activation functions, namely the logistic, the Elliot, and the Sinc functions, were employed for simulating wastewater treatment plant performance in this study. Features of these activation functions are shown in Table 3.

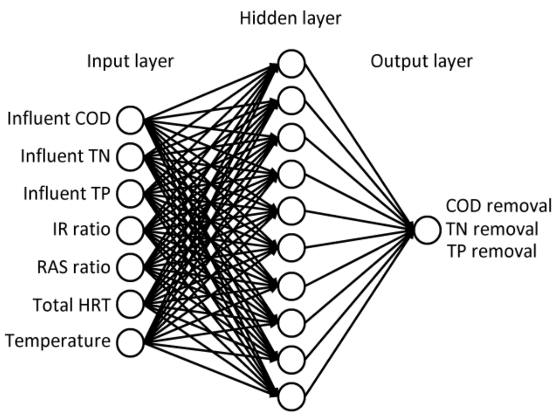

Figure 3. Artificial neural network topology

Table 3. Activation functions used

Activation function	Mathematical expression	Derivative	Spanning range
Logistic	$y = \dfrac{1}{1+e^{-x}}$	$y' = y(1-y)$	0<y<1
Elliot	$y = \dfrac{0.5x}{1+\|x\|} + 0.5$	$y' = \dfrac{1}{2(1+\|x\|)^2}$	0<y<1
Sinc	$y = \begin{cases} 1 & \Leftrightarrow \quad x = 0 \\ \dfrac{sinx}{x} & \Leftrightarrow \quad x \neq 0 \end{cases}$	$y = \begin{cases} 0 & \Leftrightarrow \quad x = 0 \\ \dfrac{cosx}{x} - \dfrac{sinx}{x^2} & \Leftrightarrow \quad x \neq 0 \end{cases}$	-0.2172≤y≤1

The artificial neural network tool starts the learning process by randomly selecting the training data and assigning random initials to weights and biases of each neuron in the structure. Therefore, the tool converges to a different set of weights and biases each time it is run. The point of convergence may be a local or a global minimum for mean square error, and the neural network is, therefore, run 25 times for each activation function, summing up to 75 simulations (25 times for each of three activation functions) for each of COD, TN, and TP removal efficiencies.

3. RESULTS AND DISCUSSIONS

3.1. Artificial Neural Network Simulation

Training of the artificial neural network given in Fig. 3 was the main step of this study. Randomly selected 70% of the samples (results of activated sludge modelling) were selected in each training session, while the remaining 30% was used for validation. Since the artificial neural network (ANN) simulation tool [26] randomly selects the training data and starts the learning process with a random set of weights and biases for neurons, it converges to a different set of final weights and biases each time. This final solution can be a local or global maxima, and the neural network simulation, therefore, was performed 25 times for each activation function and for each of COD, TN, and TP removal efficiencies in order to obtain the most accurate solutions.

Average mean square error (MSE) between measured (activated sludge modeling results) and predicted chemical oxygen demand (COD) removal efficiencies were calculated as $5.54*10^{-7}\pm1.67*10^{-7}$, $8.83*10^{-7}\pm1.51*10^{-7}$, and $7.46*10^{-7}\pm2.40*10^{-7}$, respectively with the logistic, the Elliot, and the sinc functions. On the other hand, the coefficients of determination (R^2) calculated for COD removal efficiency were 0.9832±0.0049 with the logistic function, 0.9696±0.0051 with the Elliot function, and 0.9766±0.0079 with the sinc function. Statistics for COD removal efficiency are shown in Fig. 4. The MSE values with the logistic function were the lowest (Fig. 4.b). Besides, the logistic function provided the strongest correlation between measured and predicted COD removal efficiencies (Fig. 4.a).

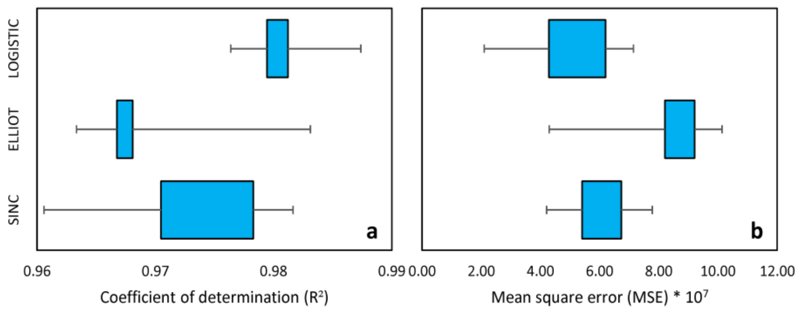

Figure 4. Statistics for COD removal. **a.** Coefficients of determination, **b.** Mean square errors

A visual inspection of correlation plots between measured and predicted values of COD removal efficiency (Fig. 5) also reveals the superiority of the logistic function (Fig. 5.a) in COD removal prediction over the Elliot (Fig. 5.b) and the sinc functions (Fig. 5.c). In correlation plots, the red line represents perfect fit, the blue dots represent the correlation plots, and the black line is a regression line. The regression line in Fig. 5.a is the closest one to perfect fit with a $R^2 = 0.9935$. Besides, the measured versus predicted COD removal efficiencies are more concentrated around the perfect fit with logistic function.

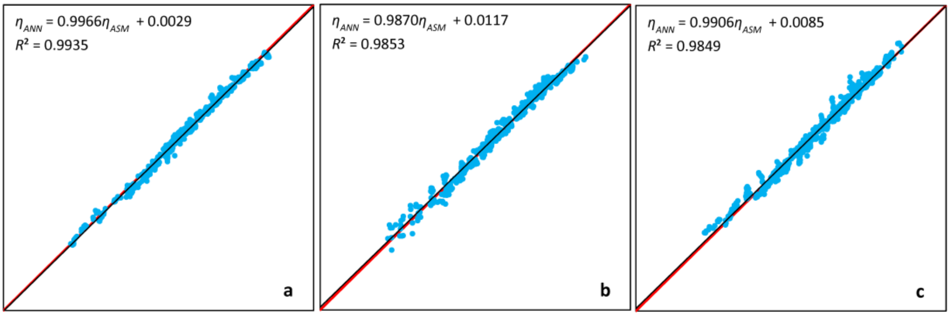

Figure 5. Correlation plot for COD removal efficiency with **a.** logistic function, **b.** Elliot function, **c.** sinc function

Statistics for predicted total nitrogen (TN) removal efficiency is shown in Fig. 6. For TN removal, the neural network did not show a noticeable difference in prediction performances with the logistic, the Elliot, and the sinc functions (Fig. 6.a) though the Elliot function produced slightly lower MSE values (Fig. 6.b). Average values of determination coefficient were calculated as 0.9924±0.0015, 0.9918±0.0014, and 0.9932±0.0014, respectively, with the logistic, the Elliot, and the sinc functions. On the other hand, average MSEs were calculated as $3.02*10^{-4}\pm0.57*10^{-4}$, $1.59*10^{-4}\pm0.32*10^{-4}$, and $2.06*10^{-4}\pm0.31*10^{-4}$, respectively. The Elliot function was slightly better than others in terms of calculated MSE.

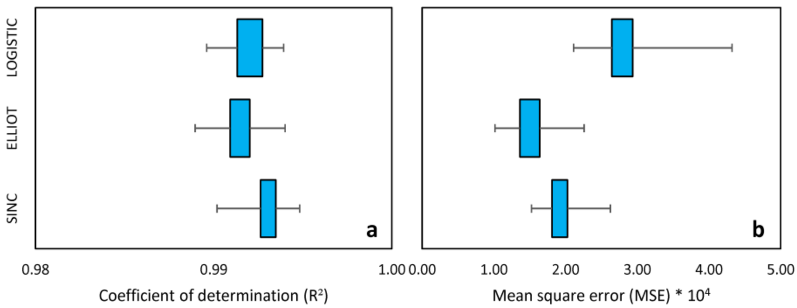

Figure 6. Statistics for TN removal. **a.** Coefficients of determination, **b.** Mean square errors

Correlation plots for TN removal are shown in Fig. 7, which are the results of the neural network simulation with the lowest calculated MSEs using the logistic, the Elliot, and the sinc functions. The coefficients of determination were acceptable with the logistic and the Elliot function (Fig. 7.a&7.b). In contrast, predicted TN removal efficiencies with the sinc function were more concentrated around the perfect fit (Fig. 7.c). Considering the very small discrepancy between the MSE values with the Elliot and the sinc functions, one can conclude that a neural network with the sinc function shows the best performance for predicting TN removal efficiency.

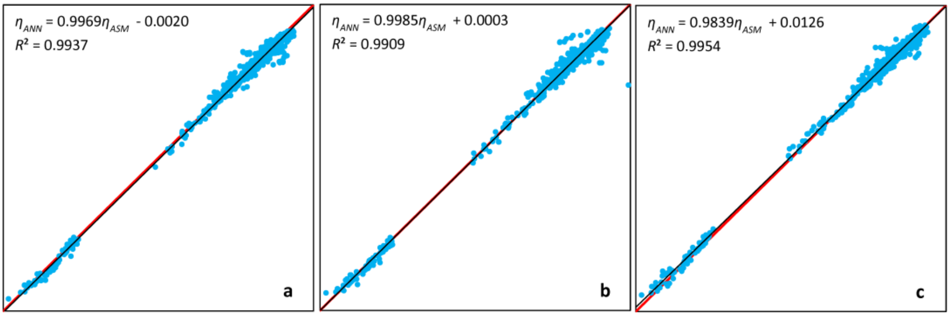

Figure 7. Correlation plot for TN removal efficiency with **a.** logistic function, **b.** Elliot function, **c.** sinc function

Fig. 8 shows coefficients of determination and MSE values calculated for TP removal efficiency with the logistic, the Elliot, and the sinc functions. Calculated R^2 values were 0.9405±0.0213, 0.9581±0.0055, and 0.9502±0.092, respectively (Fig 8.a). The highest coefficient of determination was obtained with the Elliot function. MSE values (Fig. 8.b) were conforming to the coefficients of determination, and were calculated $6.23*10^{-3}\pm1.98*10^{-3}$, $2.26*10^{-3}\pm0.34*10^{-3}$, and $3.3*10^{-3}\pm0.72*10^{-3}$, respectively. The Elliot function also provided the lowest MSE values.

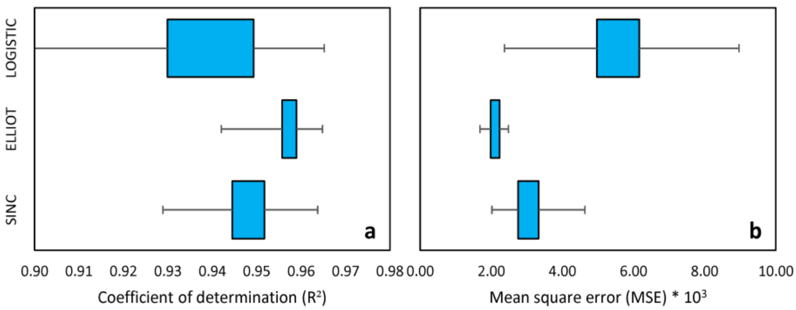

Figure 8. Statistics for TP removal. **a.** Coefficients of determination, **b.** Mean square errors

The mean square errors calculated for TP removal efficiency were considerably higher compared to COD, and TN removal. The resulting prediction accuracy of ANN for TP removal was lower, though it is still acceptable. A visual inspection of Fig. 9 reveals the prediction capability for TP removal. The results with the Elliot function were somewhat concentrated around the perfect fit (Fig. 9.b) compared to the logistic (Fig. 9.a) and the sinc (Fig. 9.c) functions, which suggests that, together with Fig. 8, the Elliot function would be the best choice for TP removal simulation with the artificial neural network.

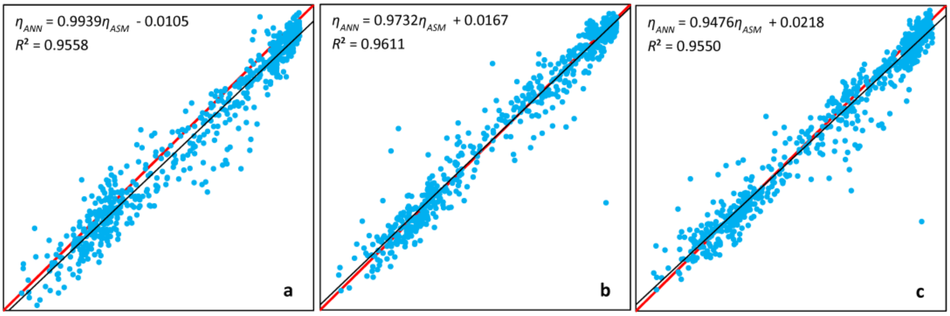

Figure 9. Correlation plot for TP removal efficiency with **a.** logistic function, **b.** Elliot function, **c.** sinc function

3.2. Sensitivity Analyses

COD removal efficiency of the A^2O process was very stable and did not show considerable changes with respect to any of the influent wastewater or operating parameters. COD removal efficiencies were between 87.9% and 90.4% under all conditions. The results showed that none of the input parameters incorporated in the models have a distinctive effect on COD removal efficiency. Fig. 10 shows surface maps for COD removal efficiency by logistic-ANN. It is clear that the effects of influent TN (Fig. 10.a) and TP concentrations (Fig. 10.b) as well as IR (Fig. 10.c) and RAS ratios (Fig. 10.d) on COD removal efficiency was negligible. On the other hand, hydraulic retention time (HRT) was one of the parameters that influence COD removal slightly (Fig. 10.f). COD removal efficiency increased by an average of 0.12% per hour with increasing HRT. The major effective parameter on COD removal was the wastewater temperature (Fig. 10.e). COD removal efficiency increased from 88.7% at 5°C to 89.6% 25°C for an influent COD of 300 mg/L, from 88.9% at 5°C to 89.9% at 25°C for 400 mg/L influent COD, and from 89.1% at 5°C to 90.1% at 25°C for 400 mg/L influent COD. An increase of 20°C in wastewater temperature lead to approximately 1% increase in COD removal efficiency of the A^2O process.

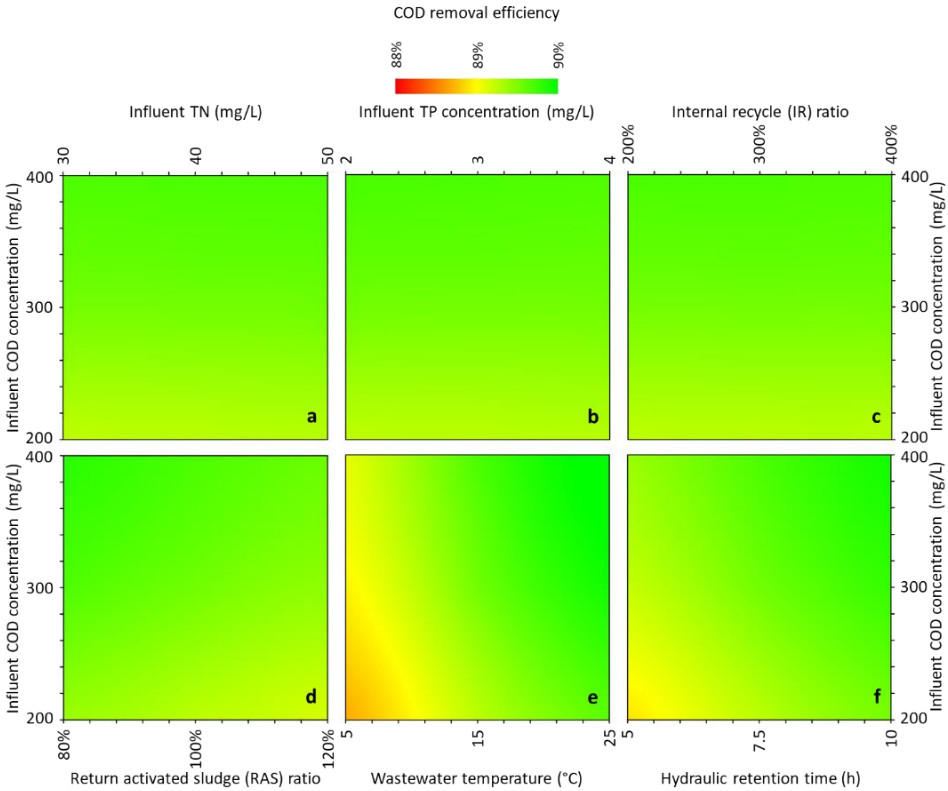

Figure 10. Surface maps for COD removal efficiency calculated by logistic-ANN with respect to influent COD and **a.** influent TN concentration, **b.** influent TP concentration, **c.** internal recycle ratio, **d.** return activated sludge ratio, **e.** wastewater temperature, **f.** hydraulic retention time

TN removal efficiency by the sinc-ANN was mainly influenced by influent TN concentration (Fig. 11). TN removal efficiency dropped by an average of 0.19% per 1 mg/L of increase in influent TN concentration. This reduction was steeper for lower influent COD concentrations (Fig. 11.a) with an average of 0.26% per mg/L with increasing influent TN concentration at an influent COD of 300 mg/L. One can conclude that TN removal efficiency is a function of influent C:N (COD:TN) ratio. Influent TP concentration (Fig. 11.b) and IR ratio (Fig. 11.c) did not affect TN removal efficiency considerably. The effects of RAS ratio and HRT were also a function of influent TN concentration (Fig. 11.d & 11.f). A 10% increase in RAS ratio results in an average of 0.45% increase in TN removal efficiency. This rate of increase was considerably higher at high influent TN concentrations (around 0.57% per 10% increase in RAS ratio). For HRT, similar trends were observed. TN removal efficiency rose by an average of 0.40% per hour with increasing HRT. Again, the rate of change was steeper at high influent TN concentrations (Fig. 11.f). The major parameter that affects TN removal efficiency was wastewater temperature (Fig. 11.e). TN removal improved by an average of 0.70% per 1°C increase in wastewater temperature. Results showed that the improvement in TN removal was higher at lower influent TN concentration (around 0.80% per 1°C). One can conclude that wastewater temperature is a major predictor of TN removal efficiency while RAS ratio and HRT influence TN removal slightly.

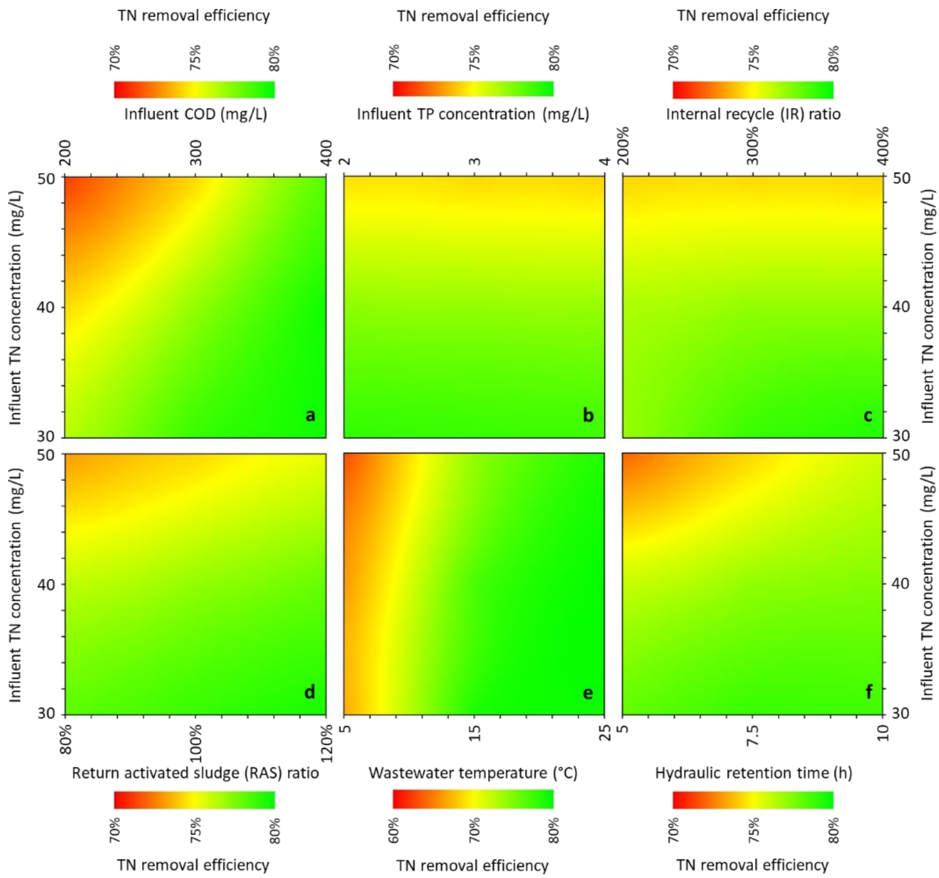

Figure 11. Surface maps for TN removal efficiency calculated by sinc-ANN with respect to influent TN concentration and **a.** influent COD, **b.** influent TP concentration, **c.** internal recycle ratio, **d.** return activated sludge ratio, **e.** wastewater temperature, **f.** hydraulic retention time

TP removal efficiency by the Elliot-ANN is summarized in Fig. 12. The results showed that TP removal efficiency was mainly influenced by influent COD (Fig. 12.a) with a reduction in removal performance by approximately 0.16% per mg/L increase in influent COD. This effect is different than what is expected as the system's response in terms of TP removal since the addition of readily biodegradable substrate to increase TP removal efficiency is a common application. The most probable reason for this behavior can be seen by examining the COD fractionation given in Table 2. A total of 60% of influent COD was assumed to be in particulate form, almost 10% of which is inert in all simulations. Particulate COD is considered to be slowly biodegradable substrate in activated sludge modeling. This is why TP removal efficiency does not increase with increasing influent COD. TP removal was also a function of influent TN concentration (Fig. 12.b). Similar to the effects of influent COD, TN had also a negative impact on TP removal. Average decrease in TP removal efficiency was 0.42% per mg/L increase in influent TN concentration, and this rate of change was steeper at high influent TP concentrations. IR ratio showed a negative effect on TP removal performance (Fig. 12.c) with an average decrease of 2.4% per 100% increase in IR ratio. RAS ratio had a similar effect on TP removal (Fig. 12.d) with an average decrease of 0.32% per 10% increase in RAS ratio. The effect of wastewater temperature was somewhat different than other input parameters (Fig. 12.e). Drastic reductions were observed in TP removal in all influent TP concentrations as the wastewater temperature increased from 5°C to 15°C. Average rate of reduction was 5.5%/°C. Above 15°C, on the other hand, TP removal improved with increasing wastewater temperature at an average rate of 2.7%/°C. This unexpected reduction in TP removal efficiency between 5°C and 15°C was probably a result of sudden increase in nitrifying activity and TN removal efficiency (Fig. 11.e). Finally, TP removal efficiency increased by an average of 18.1%/h with increasing total HRT of process reactors (Fig. 12.f). One can conclude that influent COD, wastewater temperature, and HRT are the major factors that influence TP removal efficiency of an A²O process while influent TN concentration is a minor factor. The effects of IR and RAS ratios were negligible.

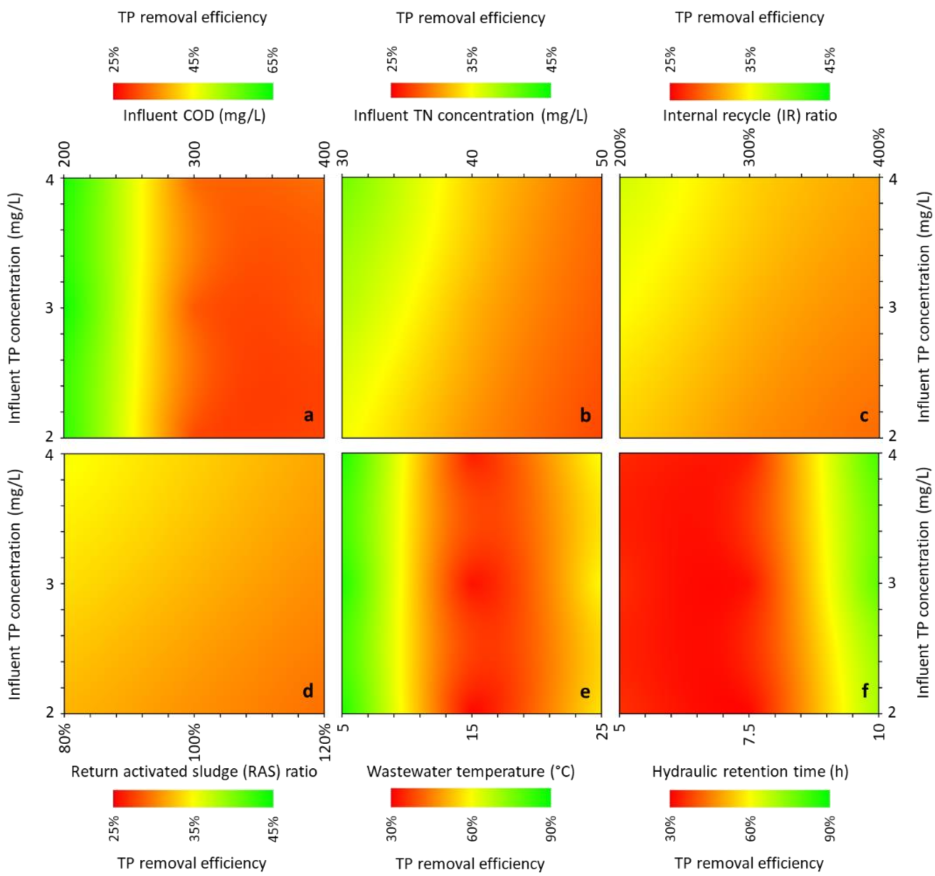

Figure 12. Surface maps for TP removal efficiency calculated by Elliot-ANN with respect to influent TP concentration and **a.** influent COD, **b.** influent TN concentration, **c.** internal recycle ratio, **d.** return activated sludge ratio, **e.** wastewater temperature, **f.** hydraulic retention time

3.3. Simulation of Real Wastewater Treatment Systems

The simulation process presented in this study was accomplished in two steps: Activated sludge modeling and artificial neural network simulation. Open-source tools were used for simulation in both steps. In the first step, an activated sludge modeling tool was used to obtain

COD, TN, and TP removal efficiencies of an A^2O process depending on several factors including the design/operating parameters such as hydraulic retention time, internal recycle ratio and return activated sludge ratio, as well as influent wastewater characteristics such as influent COD, TN, and TP. In the second step, artificial neural network simulations were performed using the design/operating parameters and influent wastewater characteristics.

The implication of the simulation method presented in this paper can be viewed from two standpoints. In the eyes of a design engineer, the objective is to determine the dimensions of all process reactors in addition to several possible operating strategies. This process requires several inputs including wastewater characterization and a deep understanding of biological wastewater treatment systems. Depending on influent wastewater characteristics, the design engineer usually needs to build and operate a pilot-scale system or run an accurate model like activated sludge models to determine optimum dimensions, both of which takes tremendously long times to accomplish. Instead, the design engineer can employ a well-trained artificial neural network to test several dimensions of process reactors and select the optimum configuration. On the other hand, determining optimum internal recycle, return activated sludge, or waste activated sludge ratio is the main objective in the eyes of an operating engineer. The operating engineer usually needs to test several scenarios to determine optimum recycle ratios and waste sludge flowrate to adjust sludge retention time (SRT). Testing these scenarios on full-scale systems can be very costly most of the time. Besides, employing deterministic models like activated sludge models is a very slow and tiring process to test various scenarios. Instead, the operating engineer can use real wastewater characterization and removal efficiencies from full-scale treatment plant for training artificial neural network and can use the network to obtain really fast various operating scenarios.

4. CONCLUSIONS

Performance of artificial neural network for simulation of biological wastewater treatment process was evaluated in this study. For this purpose, a total of 2187 data points, which are composed of influent chemical oxygen demand (COD), total nitrogen (TN), and total phosphorus (TP) concentrations, internal recycle (IR) and return activated sludge (RAS) ratios, wastewater temperature, total hydraulic retention time (HRT) of process reactors, and corresponding steady-state COD, TN and TP removal efficiencies, were obtained for an A^2O process using an open-source MS Excel activated sludge modeling (ASM) tool. The data set, along with ASM-predicted COD, TN, and TP removal efficiencies, were then used as samples to train and evaluate the performance of artificial neural network (ANN) for predicting the COD, TN, and TP removal efficiencies. An open-source MS Excel tool for backpropagation neural network was employed for simulations. The neural network simulations were performed with the most-commonly used activation functions for each of COD, TN, and TP removal efficiencies, namely the logistic, the Elliot, and the sinc functions.

The use of ANN, in this study, for predicting COD, TN, and TP removal efficiencies of an advanced biological wastewater treatment process shows, especially for operating engineers, how easily open-source ANN tools can be employed for simulating various scenarios on the treatment process with operating parameters obtained from full-scale plant and influent wastewater characteristics to obtain really fast results.

Following conclusions can be withdrawn from the results of this study:

- Artificial neural network modeling tools can be confidently used to predict COD, TN, and TP removal efficiency of a wastewater treatment process with satisfactory ease and speed of calculations.
- All of the logistic, the Elliot, and the sinc functions can be used in neural network modeling tools for wastewater treatment process simulations once the key predictors of treatment performance are provided.

- The logistic-ANN provides the best simulation results for COD removal efficiency of a biological wastewater treatment plant. Wastewater temperature is a major factor that affects COD removal in a biological wastewater treatment plant.
- For the prediction of TN removal, one should select the sinc function to use in neural network simulation to obtain the most accurate simulation results. TN removal efficiency of a biological wastewater treatment plant is a function of mainly wastewater temperature with minor contributions from RAS ratio and HRT.
- For the prediction of TP removal, the Elliot function is the one that provides the most accurate simulation results. TP removal efficiency of a biological wastewater treatment plant is a function of mainly influent COD, wastewater temperature, and HRT. Influent TN concentration is a minor factor that affects TP removal performance.

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