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Dynamic Performance Analysis and Simulation of a Full Scale Activated Sludge System Treating an Industrial Wastewater Using Artificial Neural Network

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A B S T R A C T

Due to changeable nature of the industrial wastewaters, proper operation of an industrial wastewater treatment plant is of prior importance in order to keep the process stability at the desired conditions. In this mean, simulation of the treatment system behavior using artificial neural network (ANN) can be an effective tool. This paper evaluates long term performance and process stability of a full-scale integrated industrial wastewater treatment system (Faraman's industrial estate, Kermanshah) in removing organic matter over a 2-year operation. The wastewater treatment system is composed of static screens, an equalization tank, an aerobic biological tower (TF) and an activated sludge (AS) reactor. Multilayer Feed-forward Networks of ANN was used to forecast the process performance of AS system. In this study, mixed liquor suspended solids (MLSS) (mg/l) and organic loading rate (OLR) (kg COD/m^3.d) were selected as input parameters and TSS removal, COD removal and sludge volume index (SVI) as output parameters. The results showed a very good agreement between the actual and modeled data (R^2> 0.9). The ANN models provided a robust tool for predicting the performance of wastewater treatment plants and as a result, the online monitoring parameters could be applied for prediction of effluent characteristics.

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1. INTRODUCTION

Industries use water for a variety of purposes. While only a small fraction of the supplied water is used in the end product, or is lost by evaporation, the rest is converted into industrial wastewater. Indiscriminate discharge of these wastewater streams into the environment can render solids and pollute the receiving water bodies and even cause air pollution by generating obnoxious gases [1]. The increased concern about environmental issues has encouraged specialists to focus their attention on the proper operation and control of wastewater treatment plants (WWTPs). Characteristics of the industrial wastewaters vary widely depending on the function and the activity of the particular industry [2]. The type of influent for plants is also time-dependent and it is difficult to have a uniform influent to a wastewater treatment plant (WWTP) which may result in an operational risk impact on the plant [3]. Many wastewater treatment plants do not have measurement and control equipment. Therefore, there is a need in designing control strategies for the good operation of the process that may consider various types of models [4]. Traditional modeling techniques used in bioprocesses are based on mass balance equations together with rate equations for microbial growth, substrate consumption and formation of products. And since microbial reactions coupled with environmental interactions are non-linear, time variable and of a complex nature [5], traditional deterministic and empirical modeling has shown some limitations [6]. Also, predicting the plant operational parameters using conventional experimental techniques is a time consuming step and is an obstacle in the way of efficient control of such processes [3]. An effective control of a WWTP can be achieved by developing a well-experienced mathematical tool for predicting the plant performance based on past observations of WWTP performance. Owing to high precision, capability and quite promising applications in engineering [7-9] of artificial neural networks (ANNs), it can be used for modeling such WWTPs processes. ANNs are very useful in the determination and control of dynamic

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systems [10]. The ANN-based models are applied to major WWTPs. The developed models revealed to perform consistently well in the face of varying accuracy and size of input data. Using these models, the plant operators will be able to anticipate the plant effluent, given the quality of the waste stream at input locations. Hamed et al. [3], developed an ANN model to predict the performance of wastewater treatment plant. The ANN-based model was found to provide an efficient and a robust tool in predicting WWTP performance. Raduly et al. [11], simulated performance of a WWTP by ANN using 20 years of dynamic data. It showed that the ANN could reduce simulation time by a factor of 36, including the time needed for the generation of training data and for ANN training. Mjalli et al. [12], used ANN block-box modeling to acquire the knowledge base of a real wastewater plant. This study signified that the ANNs are capable of capturing the plant operation characteristics with a good degree of accuracy. The developed program is implemented and validated using plant-scale data obtained from a local wastewater treatment plant, namely the Doha West WWTP. Other successful experiences using ANN in simulation of wastewater treatment processes are exampled as antibiotic degradation in aqueous solution by the Fenton process [13], coagulation process of paper mill wastewater [10] and predicting the effluent total organic compounds (TOC) of activated sludge process in an industrial WWTP [14]. The results indicate that reasonable forecasting and control performances have been achieved through the developed model. This paper addresses the problem of how to capture the complex relationships that exist between process variables to diagnose the dynamic behavior of an activated sludge system operating in a central industrial wastewater treatment plant, Faraman's industrial estate, Kermanshah, Iran, by applying an ANN model. Safer operation and control of the plant can be achieved by developing an ANN model for predicting the plant performance based on past observations of certain key effluent quality parameters.

2. MATERIALS AND METHODS

2. 1. Faraman's Industrial Wastewater Treatment Plant

Schematic diagram of the wastewater treatment plant studied in this paper is shown in Figure 1. This plant consists of static screens, equalization tank, trickling filter (TF), primary sedimentation tank, an AS reactor and thickening sludge basin. To prevent entry of suspended solids, oil and grease into the biological systems and also to minimize fluctuations in the incoming sludge and units overload, screens and sedimentation tanks is used prior to biological treatment. Since the process is intermittent, an equalization tank is required to dampen the fluctuations in the flow and in the organic load. TF and primary sedimentation tank effluents are conducted to AS reactor.

2. 2. Biological Treatment Units

2. 1. 1. Trickling Filter (TF) The trickling filter that used in the plant consists of ceramics packing. Its characteristic is shown in Table 1. The feed was pumped from equalization tank to the top of the filter, and with the aid of nozzles, sprayed uniformly over the filter. The effluent of TF is introduced into the primary sedimentation tank.

2. 1. 2. Activated Sludge (AS) Reactor AS reactor characteristic is shown in Table 1. The system includes two parallel aeration tanks with total volume of 4400 m^3. The main advantage of this system is its relative flexibility against the toxic shocks. So that, the toxic concentration is distributed and reduced immediately thereafter it is entered into the reactor.

2. 3. Characteristics of Industrial Wastewater

The characteristic of raw industrial wastewater is shown in Table 2. The wastewater samples were collected between 8 am and 4 pm. The samples were stored in cool room at 4 °C. Table 3 lists the characteristics of the raw wastewater before and after each biological treatment system.

TABLE 1. Specification of biological treatment units in the Faraman's WWTP.

TF system		AS system	
Parameter		**Parameter**	
Type of system	Roughing Filter	Number of reactors	2
Volume (m^3)	900	Type of reactor	CSTR
Area (m^2)	81000	Volume (m^3)	2200
Type of packing	Ceramic	Depth (m)	2
Specific area of packing (m^2/m^3)	90	HRT (d)	2
Height (m)	4	Number of aerators	8

TABLE 2. Characteristics of the raw Faramn's industrial wastewater.

Parameter	Average	Maximum	Minimum
COD(mg/l)	1275.3	3950	156
BOD(mg/l)	1821.9	3100	321
TSS(mg/l)	526.6	5390	50
TDS(mg/l)	1101	1740	400
pH	6.8	9.3	4.8
T(^{0}C)	17.9	28	6
NO_3^-(mg/l)	12.3	32.7	11.5
Total phosphate(mg/l)	6.5	1	0.9

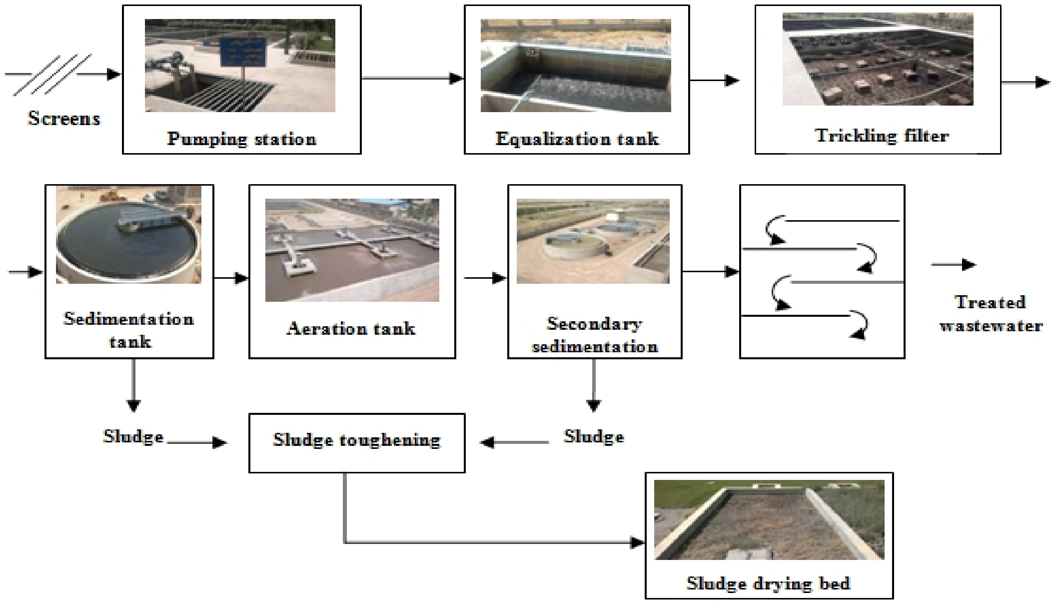


Figure 1. Schematic diagram of the studied wastewater treatment plant

TABLE 3. The characteristics of the influent and effluent wastewater of the TF and AS.

Parameter	Trickling filter		Activated sludge	
	Influent	Effluent	Influent	Effluent
TCOD	1277.5	972.9	785.2	56.3
BOD	---	50.7	344	26.2
TSS	622.3	339.5	245	20.5
pH	7.1	7.7	7.2	7.9
T(°C)	17.8	17.4	16.6	14.4

2. 4. ARTIFICIAL NEURAL NETWORK (ANN)

2. 4. 1. ANN Basis The main benefits of the neural network in comparison to other modeling programs are the nonlinearity, adaptively, evidential response, fault tolerance and uniformity of analysis and design [15]. ANNs can be classified into different categories by their network architecture, activation or transfer function and training algorithm [16, 17]. The choice of the architecture of the network depends on the task to be performed. This is specified by the neuron characteristics, network topology and learning algorithm [18]. In Figure 2 a schematic diagram of the multi-layer, feed-forward ANN model is presented.

2. 4. 2. Model Design and Network Training The performance of an ANN model mainly depends on the network architecture and parameter settings. The neuron model and the architecture of a neural network describe how a network transforms its input into an output. This transformation can be viewed as a computation. One of the most difficult tasks in ANN studies is to find this optimal network architecture. There are many heuristic techniques described in the neural network literature to perform various tasks within the supervised learning paradigm, such as optimizing training, selecting an appropriately sized network, and predicting how much data will be required to achieve a particular generalization performance [19, 20]. In this study, MATLAB NN toolbox is used for ANN applications. MATLAB NN toolbox randomly assigns the initial weights for each run each time which considerably changes the performance of the trained NN even all parameters and NN architecture are kept constant. To reach the suitable network architecture, several trials and errors have been conducted until the suitable learning rate, number of hidden layers and numbers of neurons (less than 30) per each hidden layer were reached. This process is repeated N times, where N denotes the number of hidden nodes for the first hidden layer. This whole process is repeated for changing number of nodes in the second and third hidden layers. The suitable architecture is the one which produces the minimal error term in both training and testing data. In this study, a supervised training, back propagation algorithm is selected.

Due to the convergence speed and the performance of network, the Levenberg-Marquardt training method was selected as a proper training algorithm. This is preferred compared to the other training techniques such as resilient back propagation, scaled conjugate gradient, variable learning rate back propagation and BFGS quasi-Newton [21].

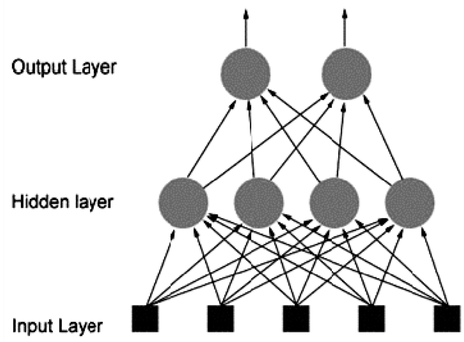


Figure 2. Schematic diagram of the multi-layer, feed-forward ANN model

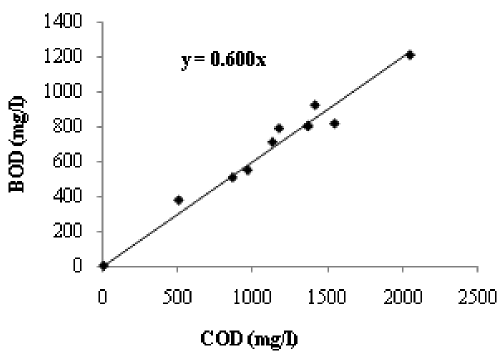


Figure 3. Relationship between COD and BOD of the raw industrial wastewater studied

Multilayer Feed-forward Networks of ANN was used to forecast the process performance of AS system in this work. The network architecture used in this study is called NN 2-n-m-l-3, where the first digit is the number of input nodes, *n* is the number of nodes in the first hidden layer, *m* is the number of nodes in the second hidden layer, l is the number of nodes in the third hidden layer and fifth digit is the number of output nodes. In this program up to 30 neurons in each hidden layer is tested and the optimal network is selected based on the root mean square error (RMSE). In a wastewater treatment plant, the most important parameters are biochemical oxygen demand (BOD), chemical oxygen demand (COD) and suspended solid (SS) which can be used to assess plant performance. In this study, mixed liquor suspended solids (MLSS) (mg/l) and organic loading rate (OLR) (kg COD/m^3.d) were selected as input parameters and TSS removal, COD removal and sludge volume index (SVI) as output parameters.

2. 5. Experimental Data Used and Analytical Techniques In this study, the performance data of 2-year operation of biological treatment units (TF and AS) in Faraman's industrial wastewater treatment plant, Kermanshah-Iran was used. In order to evaluate the performance of the system, BOD, COD, TSS, pH and temperature at influent and effluent were monitored. Other than the aforementioned parameters, nitrogen and phosphorus content of raw wastewater were characterized. All parameters were analyzed according to the Standard Methods for the Examination of Water and Wastewater [22].

3. RESULTS AND DISCUSSION

3. 1. Relationship between COD and BOD According to the COD and BOD values, relationship between COD and BOD of the wastewater (inlet stream) was obtained by linear regression (BOD= 0.6 COD), (Figure 3). The wastewater has a relatively good biological treatability considering the BOD/COD ratio of 0.6. Measurement results of the nitrogen and phosphorous indicate that the nutritional requirements for microbial growth (COD/N/P) are appropriate for biological treatment, because of the enough nitrogen and phosphorus contents in the wastewater.

3. 2. Biological Treatment Process Description Figures 4 and 5 present variations of the COD and TSS values in TF system during a 585-day period. As seen, this system has very fluctuations. In some cases, the effluent COD and TSS concentrations are more than influent values. Average COD and TSS removal efficiencies in this system were 24 and 45%, respectively. The unstable and low performance of the TF system is attributed to the variability of the quantitative and qualitative characteristics of the industrial wastewater (Table 2), sloughing of biofilm attached to the packing with time which can be caused by many factors such as high input flux or excessive biological growth, clogging in TF that occurs due to entering large amounts of non-biodegradable TSS to the filter, icing and the inappropriate feed distribution over the filter that caused the non-uniform growth of micro-organism on the surface of the packing. So, the effective surface area and performance of the system were decreased. TF effluent is then introduced into the AS system. The applied OLR for activated sludge system was varied from 0.12 to 0.652 Kg COD/m^3.d. Average COD removal efficiency obtained from the AS system was 90%. As COD removal efficiency of the WWTP was mainly obtained from AS system, long term behavior of AS was simulated by ANN in the following section.

3. 3. ANN Results (Model Testing) for AS Process In this study, 70% of whole data is specified as the training data in which the network would be adjusted according to its error.

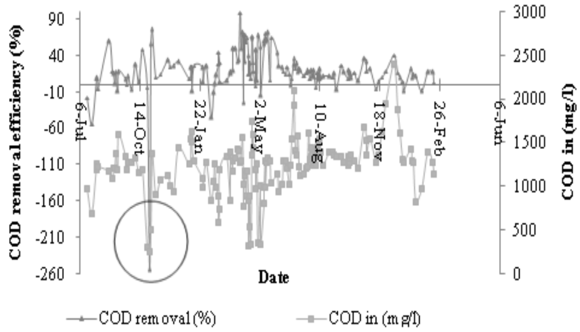


Figure 4. Variations of the influent COD concentration and COD removal efficiency versus time

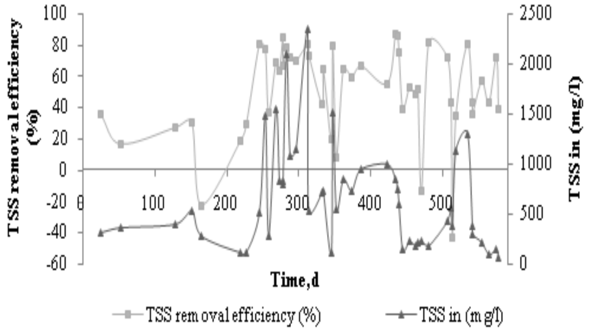
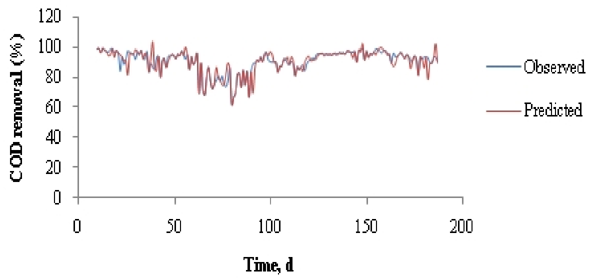


Figure 5. Variations of the influent TSS concentration and TSS removal efficiency versus time

Similarly, 15% of database is considered as the validating data which is used to measure network generalization and to halt training when generalization stops improving. Finally, the remaining 15% of the data is specified as the testing data. For the latter, the employed data were not a part of training and validation processes. The optimal NN architecture was obtained as 2-28-18-16-3. The system performance is forecasted based on 10 days data. Concentrations of responses values versus counter of data from experimental results and predicted data by ANN for all data are presented in Figures 6a-c. Visual inspection indicates that the ANN models resulted in a good fit for the measured variables. According to Figure 6a, in some days, the COD removal efficiency was low. These days has coincided with the winter season, so the biological activity of the biomass and their settable-ability were decreased as an effect of cold weather. It was subsequently resulted in high effluent turbidity and COD. In this condition, the F/M ratio varied from 0.0265 to 0.245 kg COD/kg VSS.d. According to the literature, for the activated sludge systems with conventional aeration, the optimal F/M ratio falls between 0.24 and 0.9 kg COD/kg VSS.d [2]. For this system, TSS_{in} varied in the range of 30 to 1648 mg/l. The average of TSS removal efficiency was 85%. According to Figure 6b, in some points, the TSS removal efficiency was found to be low in comparison with other days (lower than 50%). This could be attributed to sludge dispersion caused by the operating conditions applied prior to this event (F/M ratio of 0.105 kg COD/kg VSS.d). Relatively high FSS contents of the influent (FSS/TSS= 0.72) could be another reason for the event [23]. SVI was another measured parameter to evaluate the sludge characteristics. As can be seen in Figure 6c, SVI varied in the range of 40-140 ml/g which matches with the recommended values for the response in activated sludge systems. The quality of match between the ANN-modeled and measured concentrations was determined by regression analysis. Figures 7a-c demonstrate the measured versus ANN-modeled values for the overall data of the COD removal, TSS removal and SVI, respectively. Table 4 presents RMSE and determination coefficient (R^2) values for the responses. The narrow band of error measures for the three modeled parameters is an indication of the ANN's robustness. The model shows enough accuracy for prediction of responses values. From the literature, successful application of ANN has been reported to few research works [24, 25]. For example as industrial applications; an ANN approach with a Feed-Forward Back-Propagation has been employed predicting the performance of a full scale WWTP in terms of COD, BOD and TSS data collected in duration of a research over a 1-year period [26]. A MATLAB script was used to aid in the development of ANN models by screening out the better ANN architectures for a hypothetical and real WWTP [23].

a)



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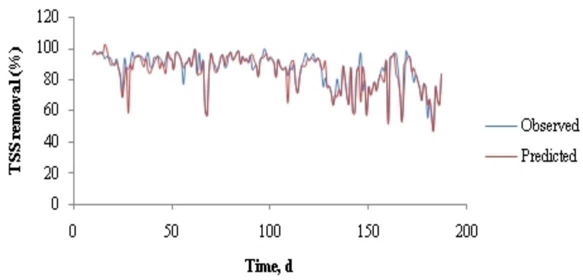

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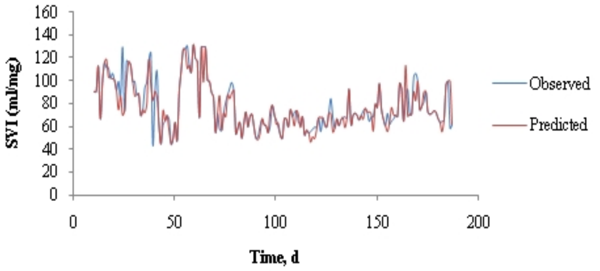
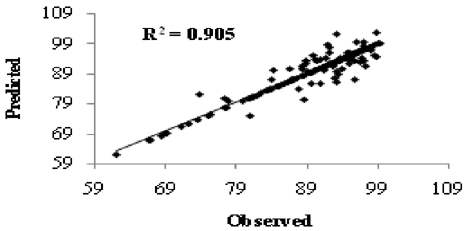


Figure 6. Comparison between all observed and predicted data by ANN for; (a) COD removal, (b) TSS removal and (c) SVI.

a)



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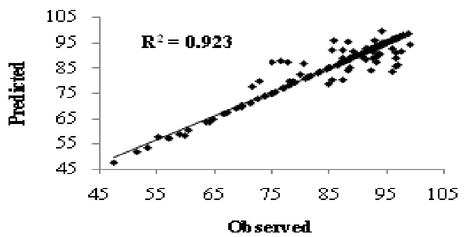

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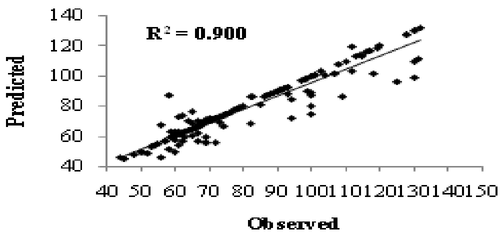


Figure 7. Regression analysis of measured versus ANN-modeled for all data; (a) COD removal efficiency, (b) TSS removal efficiency and (c) SVI

TABLE 4. Performance evaluation of ANN

Parameter	COD removal	TSS removal	SVI
RMSE	2.33	3.08	6.96
R-square	0.905	0.923	0.90

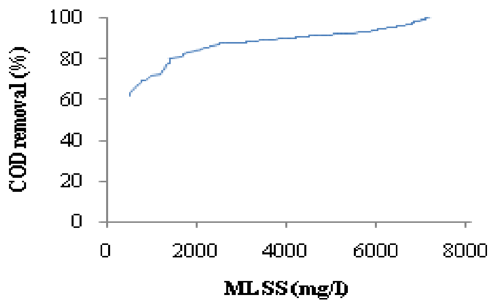
TABLE 5. Average values of the studied variables

Variables	Unit	Average
MLSS	mg/l	4679.9
OLR	Kg COD/ m^3.d	0.387

3. 4. Effect of Input Parameters Variation on the Responses

In this section, the performance of the activated sludge bioreactor was evaluated with varying two selected input variables. In order to study effects of input parameters variation on the responses, first, mean values of input data were evaluated. These values are listed in Table 5. Figures 8a-c show the effect of MLSS on the predicted responses while OLR is constant. It shows an increasing impact of MLSS on the COD and TSS removal at constant OLR, while it showed a deceasing effect on SVI. Figures 9(a) to 9(c) illustrate the effect of OLR values on the predicted responses; while MLSS is constant. As can be seen in Figure 9, inverse trends were obtained; while in COD and TSS removal decreased and also an increase in SVI shows a slightly decrease in COD removal while OLR is increasing. This could be attributed to increasing F/M ratio, sludge dispersion and forming only small clumps or single cells that settle slowly and washed out from the reactor.

a)



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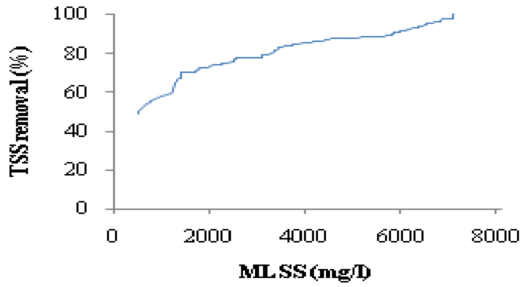

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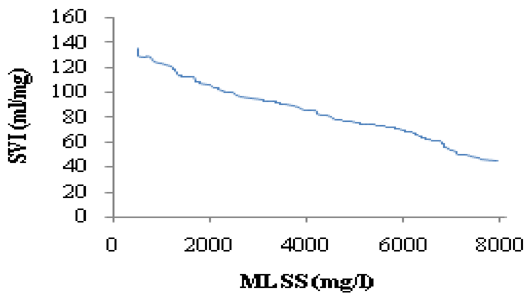

Figure 8. Effects of MLSS values on the (a) COD removal, (b) TSS removal and (c) SVI

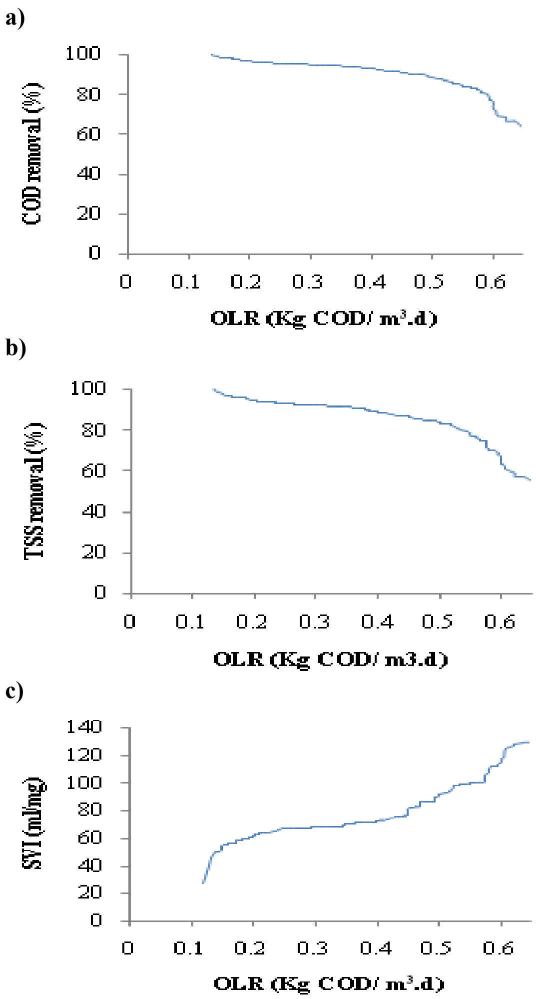

Figure 9. Effects of increasing OLR values on the COD removal, TSS removal and SVI

4. SUMMARY AND CONCLUSION

Process simulation of an industrial scale activated sludge system treating an industrial estate wastewater was successfully performed using ANN. The neural network models provided good estimates for the COD, TSS and SVI data sets, which cover a range of data for training and testing purposes. The ANN models provided a robust tool for predicting the performance of wastewater treatment plants and as a result, the online monitoring parameters could be applied for prediction of effluent characteristics.

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Modeling

چکیده

با توجه به ماهیت متغیر فاضلاب های صنعتی، به منظور حفظ پایداری فرایند در شرایط مطلوب بهره برداری صحیح از تصفیه خانه فاضلاب صنعتی از اهمیت بسزایی برخوردار می باشد. در این راستا، شبکه هوش مصنوعی به منظور شبیه سازی رفتار سیستم تصفیه خانه می تواند بعنوان یک ابزار موثر مورد استفاده واقع گردد. این مطالعه کارکرد طولانی مدت و پایداری فرایندی یک سیستم ترکیبی تصفیه فاضلاب را در مقیاس صنعتی (شهرک صنعتی فرامان، کرمانشاه) طی یک دوره دو ساله مورد ارزیابی قرار می دهد. تصفیه خانه مورد مطالعه متشکل از واحدهای آشغالگیر، تانک متعادلساز، برج بیولوژیکی هوازی (فیلتر چکنده) و تانک هوادهی (لجن فعال) می باشد. از شبکه هوش مصنوعی با ساختار چندلایه ای پیشرو جهت پیش بینی عملکرد واحد سیستم لجن فعال تصفیه خانه استفاده گردید. در این مطالعه، جامدات معلق مایع مخلوط (MLSS) (mg/l) و شدت بارگذاری ماده آلی (OLR) (kg COD/m^3.d) بعنوان پارامترهای ورودی شبکه (متغیر) و راندمان حذف کل جامدات معلق (TSS)، راندمان حذف مواد آلی (COD) و شاخص حجمی لجن (SVI) به عنوان پارامترهای خروجی انتخاب گردیدند. نتایج بدست آمده تطابق خیلی خوبی را بین داده های واقعی و مدلسازی شده با رگرسیونی بالای ۰.۹ نشان می دهد. مدل شبکه هوش مصنوعی یک ابزار قابل اطمینان برای پیش بینی عملکرد سیستم تصفیه خانه فاضلاب ایجاد نمود بطوریکه بر مبنای پارامترهای پایش شده، کیفیت پساب خروجی پیش بینی می شود.

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