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THE USE OF A NEURAL NETWORK TECHNIQUE FOR THE PREDICTION OF SLUDGE VOLUME INDEX IN MUNICIPAL WASTEWATER TREATMENT PLANT

DJEDDOU M. [1, 2]***, ACHOUR B.*** [2]

[1] Research Laboratory in Subterranean and Surface Hydraulics (LARHYSS), University of Biskra, Algeria.
[2] Hydraulic Department, Faculty of Sciences and Applied Sciences, Larbi Ben M'Heidi University of Oum El-Bouaghi, Algeria.

m.djeddou@univ-oeb.dz

ABSTRACT

Modeling Sludge volume index of activated sludge process in municipal WWTP is a difficult task to accomplish due to the high nonlinearity of the plant and the non-uniformity and variability of influent quantity, quality parameters, and operation condition.

ANNs were developed for the prediction of the Sludge Volume Index using influent quality parameters and operating parameters of Batna Wastewater Treatment Plant from 2011 to 2014. The best model given by the neural network for the SVI prediction composed of one input layer with fifteen input variables, one hidden layer with thirteen nodes and one output layer with one output variable with R = 0.8784 and RMSE = 0.443. The results demonstrate the ability of the appropriate Neural Network models for the prediction of SVI. This provides a very useful tool that can be used by WWTP operators in their daily management to increase treatment process performances and WWTP reliability.

RESUME:

La modélisation de l'indice de boues (IB) d'un procédé de boues activées dans une station d'épuration des eaux usées municipales est une tâche difficile à réaliser en raison de la forte non-linéarité des paramètres du process, la non-uniformité, la variabilité de la quantité, de la qualité des eaux usées à l'entrée de la station d'épuration, et de l'état de fonctionnement.

Les réseaux de neurones artificiels (RNA) ont été développés pour la prédiction de l'indice de boues (IB) à l'aide des paramètres de qualité de l'affluent et les paramètres de fonctionnement de la station d'épuration de la ville de Batna durant la période 2011 à 2014. Le meilleur modèle donnée par le réseau de neurones pour la prédiction de l'IB est composé d'une couche d'entrée avec une quinzaine de variables d'entrée, une couche cachée constitué de treize neurones, et une couche de sortie avec une grandeur de sortie. Le modèle proposé à pour indice de performances de la prédiction, un coefficient de correlation (R = 0.8784), et une erreur quadratique moyenne (RMSE = 0.443).

Les résultats démontrent la capacité des modèles de réseaux de neurones artificiels appropriées à prédire l'indice de boue (IB). Cela fournit un outil très utile qui peut être utilisé par les opérateurs dans la gestion quotidienne de la station d'épuration qui pourra contribuer à l'accroissement des performances du process et la fiabilité de la station.

Key words: Sludge Volume Index, prediction, Wastewater treatment, activated, sludge, artificial neural networks

INTRODUCTION

Sludge production in wastewater treatment plant using activated sludge process (ASP), in which the pollutant degradation mainly results from microbial reaction has long been used for municipal and industrial wastewater treatment depends on different factors (Lou and Zhao, 2012 ; Amanatidou, 2015).

Activated sludge plant operators and engineers have traditionally relied almost entirely on formulas and procedures derived from experience to operate the activated sludge system and to try to explain the variable changes that take place (Lacroix and Bloodgood, 1972). The sludge volume index (SVI) introduced by Molman in 1934 has become the standard measure of the physical characteristics of activated sludge solids. It is defined as “the volume in mL occupied by 1 g activated sludge after settling the aerated liquor for 30 min (NF EN 14702, 2006). The SVI commonly used research applications to evaluate the effect of biological variables or physical or chemical treatment on the properties of sludge. Also the SVI has been advocated as mean of establishing the required sludge recirculation rate or for calculating the mixed liquor suspended solids concentration which can be maintained in the aeration tank. The most common use of SVI to monitoring wastewater treatment plant operation and in comparing the settling characteristic of various sludges (Dick and Vesilind, 1969).

Recently many investigations are oriented to reduce the sludge production in WWTP using activated sludge process (ASP), because management and treatment of sludge accumulate more than 50% of the construction and operating cost (Lui and Tay, 2001; Tchobanoglous et al., 2003; Foladori et al., 2010; Guo et al., 2013). Sludge bulking is the most common solid separation problem in activated sludge problem Bulking leads to high level of total suspended solids in effluent that exceeds the discharge permit limitation ans subsequently loses activated sludge in the aeration basin, resulting in the deterioration of wastewater treatment process (Jenkins et al., 2003). Sludge settling and compaction are often quantified using sludge volume index (SVI). When SVI reaches 150 mL/g, bulking can be considered to happen (Lou and Zhao, 2012).

Soft computation techniques, such as artificial neural networks (ANN) can be used for modeling WWTP processes (Cote et al., 1995; Häck and Köhne, 1996; Wena and Vassiliadis, 1998; Plazl et al., 1999; Lee and park, 1999; Hamoda et al., 1999; Holubar et al., 2002; Lee et al., 2002; Baruch et al., 2005; Kathikeyan et al., 2005; Lee et al., 2006; Moral et al., 2008).

The ANN can be used for better prediction of WWTP process performance (Zhua et al., 1998; Belanche et al., 1999; Choi and Park, 2001; Oliveira-Esquerre et al., 2002, Chen et al., 2003; Hamed et al., 2004; Mjalli et al., 2007; Pai et al., 2008; Vyas et al., 2011; Nasr et al., 2012; Djeddou, 2014; Djeddou and Achour, 2015). Developing a model that could predict SVI with reasonable accuracy the potential for bulking is of great practical importance, as it can be used to improve the treatment plant efficiency and cost saving (Capodaglio, 1991). The complexity of the problem can be overcome by applying data-driven model for the whole system, rather than the breaking down of the system into small components described individually, in which only the inputs and outputs of the system are taken into consideration. One major advantage of the data-driven models over mechanistic models is that they require minimal information of the intrinsic processes of the system (Lou and Zhao, 2012).

MATERIALS AND METHODS

Study Area

Batna is an important city in Eastern Algeria. The city has grown very quickly during the last 10 years; localization of Batna WWTP is 35°34'24.41"N latitude and 6°10'34.49"E longitude, Figure 1.

Figure 1: Batna Wastewater Treatment Plant.

A conventional activated sludge process (ASP) is used in Batna wastewater treatment plant, and designed to have a capacity of an average flow rate of 20000 m^3/d and about 230000 EH in carbon, nitrogen, and phosphorus. The process scheme of Batna WWTP is shown in Figure 2.

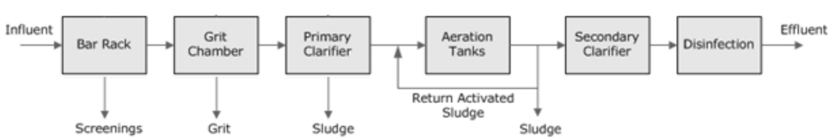

Figure 2: Process scheme of Batna WWTP.

Data Source

Sludge samples were collected daily from the reaction tank. The monitored parameters used in this study include operational conditions temperature, conductivity, and pH. Influent quality characteristics BOD_5, COD, TSS, NH^+_4, NO_3, and Phosphorus concentrations were analyzed using the standard methods of AFNOR (Rodier et al., 1997).

The influent quality parameters variability in time in Batna wastewater treatment plant is observed, with the simple statistical analysis shown in Table 1. It was observed that the pH of the waste water at the inlet of the station varies in the interval of 6.18 to 8.38. The water temperatures matched the atmospheric temperatures that are low in the winter and high in the summer.

Table 1: Variation of influent quality parameters in Batna WWTP from June 15, 2011 to Dec. 31, 2014.

Parameters	**Min.**	**Max.**	**Mean**	**Std. dev.**	**Coef. Of Variation**
TSS (mg/L)	22	1784	337.71	106.78	0.32
COD (mg/L)	67	1996	842.37	200.34	0.24
BOD_5 (mg/L	108	665	337.95	87.60	0.26
N-NH^+_4 (mg/L)	18	48	30.01	5.97	0.20
N-NO^-_3 (mg/L)	0.01	46	0.92	4.55	4.92
P-PO_4 (mg/L)	1.44	5.36	2.88	0.66	0.23
pH	6.18	8.38	7.45	0.21	0.03
Temp. (°C)	10	27.2	19.00	4.00	0.21
Cond. (µS/cm)	1452	2550	2032.35	171.91	0.08
SVI (mL/g)	11	473	196.02	83.84	0.49

The influent quality fluctuated in time, with high standard deviations of 200.34 mg/L for COD, and 87,6 mg/L for BOD_5. However the COD/BOD_5 ratios were within 1.16-2.99 for 90% of data, which were within the normal range of municipal wastewater, indicating that it is readily biodegradable wastewater, the activated sludge process was chosen for pollution removal (Tchobanoglous, 2003; Spellman, 2013).

Similarly, the nitrogen and phosphorus concentrations in the influent fluctuated with 1-2 times higher or lower than the average values, which were believed to be the highly possible reasons that affected the growth of sludge volume index and causing filamentous bacteria in the reaction tank (EPA, 1987; Wilen, 1995; Jenkins et al., 2003; Lou and Zhao, 2012;).

Figure 3 showed the change of SVIs over time, which clearly indicates that high value of Sludge volume index mostly happened winter from October to February, with the SVIs greater than 150 mL/g. We can observe that bulking levels were low in the springs and summers from Mars to September, with the SVI around 65-90 mL/g.

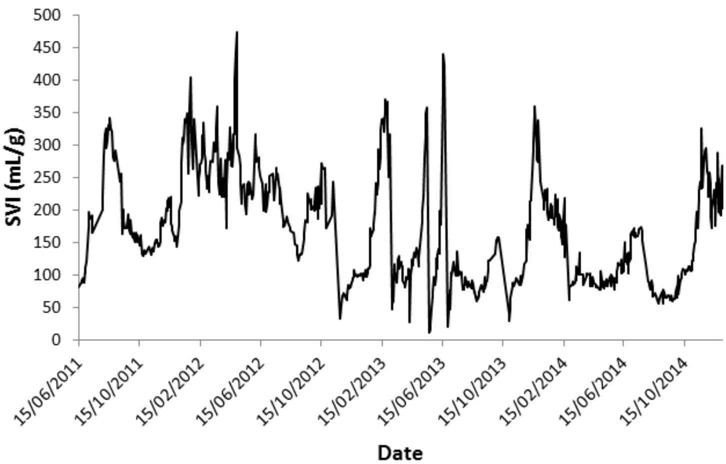

Figure 3: Change of SVI in Batna WWTP from June 15, 2011 to Dec. 31, 2014.

Data preparation and normalization

Operation data was performed on the raw experimental data by excluding all outliers which were unusual points. The existence of these outliers is due to many reasons such as transcription or transposition errors due to improper input of data, errors measurements, and lost data. Neural network training could be made more efficient by performing certain preprocessing steps on the network inputs and targets. Network input processing functions transforms inputs into better form for the network use. The normalization process for the raw inputs has great effect on preparing the data to be suitable for the training. Without this normalization, training the neural networks would have been very slow (Jayalakshmi and Santhakumaran, 2011).

In this study, all variables are normalized between 0 and 1 before and after application in the neural network. Min-Max normalization is described as:

$$x_{norm} = \frac{(x - x_{min})}{(x_{max} - x_{min})}$$

Where:

x_{norm}: normalized value; x_{min} is the minimum value; x_{max}: maximum value of xm.

Artificial Neural Networks Methodology

Artificial Neural Networks (ANNs) present a very flexible, robust and general method of modeling data. An ANN can be trained to model a nonlinear system realized by on experimental data to model a nonlinear mapping realized by some system. One of the advantages of an ANN model over traditional nonlinear regression approaches is that it is not necessary to first find a suitable parametric form of the regression model for the problem at hand. A one hidden layer multilayer perceptron can act as a universal function approximator (Haykin, 1999). ANN's may be defined as structures comprised of densely interconnected adaptive simple processing elements (called artificial neurons or nodes) that are capable of performing massively parallel computations for data processing and knowledge representation (Hecht-Nielsen, 1990; Grubert, 1995).

The attractiveness of ANNs comes from the remarkable information processing characteristics of the biological system such as nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise information, and their capability to generalize (Jain et al., 1996; Tarassenko, 1998; Hajmeer et al., 2000; Hu and Balasubramaniam, 2004).

The basic structure of an artificial neural network (ANN), usually, consists of three distinct layers, the input layer, where data is input to the ANN, the hidden layer or several layers, where data is processed, and the output layer, where the results of ANN are produced. The structure and function of ANN is discussed by a number of authors (Caudill and Butler, 1992; Fausett, 1993; Dowla and Rogers, 1995; Patterson 1996; Haykin, 1999; Gurney, 1997).

ANN's are designed by placing weights between the neurons by using a transfer function which control the generation of the output in a neuron, and using adjustable laws defining the relative importance weight for input to a neuron. In training, the ANN defines the importance of weight and adjusts by an iterative procedure (Diamantopoulou et al., 2006; Demuth et al., 2013)

The Multi-layer perception (MLP) network is the most popular type of feed-forward networks that learn from examples (Diamontopolu et al., 2005; Mjalli, 2007 ; Pai et al., 2009 ;Vyas et al., 2011; Lou and Zhao, 2012 ; Han and Qiao, 2012). The architecture of the proposed artificial neural network is shown in Figure 3. The ANN used in this study was a standard feed-forward back-propagation neural network with three layers: an input layer, one hidden layer and an output layer. The function is the Log-sigmoid transfer function (LOGSIG). This transfer function takes the input (which may have any value between plus and minus infinity) and squashes the output into the range 0 to 1. The log-sigmoid transfer function is commonly used in multilayer networks that are trained using the backpropagation algorithm, in part because this function is differentiable (Dawson and Wilby, 2001; Yonaba et al., 2010; Dorofki et al., 2012). Linear function was used as activation function for output neuron. As shown in Figure 4, by connection strengths named weights, every layer was connected together. Input vectors and the corresponding target vectors were used to train a network till it can approximate a function which associates input vectors with specific output vector.

Fifteen variables were used as input parameters. These variables were TSS_{in} (mg/L), COD_{in} (mg/L), BOD_{in} (mg/L), $temperature_{in}$ (°C), pH_{in}, $conductivity_{in}$ (µS/cm), NH^{+}_{4in} (mg/L), NO_{3in} (mg/L), P_{in} (mg/L), TSS efficiency (%),COD efficiency (%), BOD efficiency (%), N-NH^{+}_{4} efficiency (%), N-NO_3 efficiency (%), P-PO_4 efficiency (%). The output layer consisted of one neuron related to the sludge volume index (SVI).
In most function approximation problems, one hidden layer is sufficient to approximate functions (Basheer, 2000; Hecht-Nielsen, 1990). Generally, two hidden layers may be necessary for learning functions with discontinuities (Masters, 1993). The determination of the appropriate number of hidden layers and number of hidden nodes (NHN) in each layer is one of the most critical tasks in ANN design. Unlike the input and output layers, one starts with no prior knowledge as to the number and size of hidden layers. ANN model with too many hidden nodes will follow the noise in the data due to over parameterization leading to poor generalization for untrained data, and training becomes excessively time-consuming (Basheer and Hajmeer, 2000).
Some general rules for selecting the number of hidden nodes NHN in the ANN model suggest that it should be within N_{INP} and $2N_{INP}+1$ (Hecht-Nielsen , 1987).

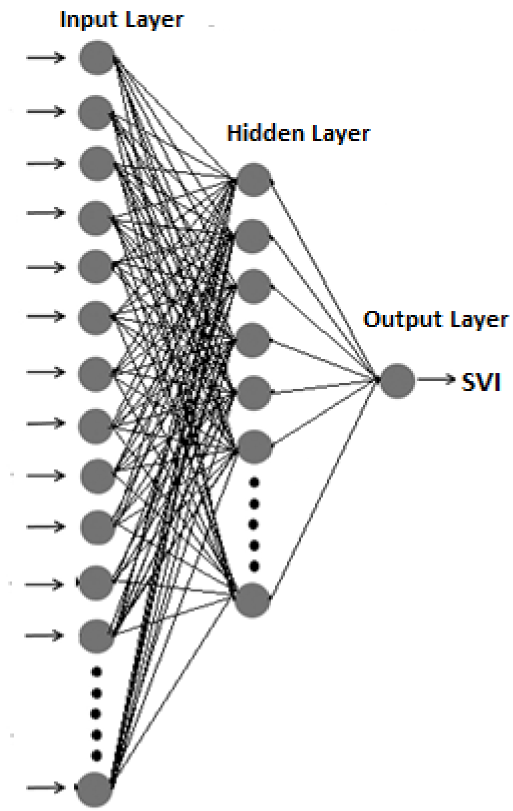

Figure 4: Proposed Multi-Layer Feed Forward Network architecture.

Masters (1993) suggests that the ANN architecture should resemble a pyramid with:

$$NHN \approx \sqrt{N_{INP} x N_{OUT}} \text{ ,}$$

Hecht-Nielsen (1990) used the Kolmogrov theorem to prove that:

$$NHN \leq N_{INP} + 1.$$

Where:

N_{INP} is the number of input, and N_{OUT} is the number of output.

In this study, a trial-and-error approach was carried out to find the optimum number of hidden nodes in the models. The optimal architecture was determined through varying the number of hidden nodes from 5 to 15. In general, a network structure with less hidden nodes is more preferable; this usually gives better generalization capabilities and fewer overfitting problems. To avoid the overfitting problem, which commonly occurs with the application of ANN, cross-validation tests were used. The training process of the ANN model was stopped when the minimum value of MSE for the cross-validation data set is reached (Sousa et al., 2007), and the best architecture was selected.

Evaluation of predicting performance

In order to evaluate the predicting performance of different ANN models, the correlation coefficient (R) for training set, and all dataset, mean absolute error, root mean square error (RMSE), and the mean absolute percentage error (MAPE) were employed and described as:

$$R = \frac{\sum_{i=1}^{n}\left(x_{o,i} - \bar{x}_{o,i}\right) \times \left(x_{p,i} - \bar{x}_{p,i}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_{o,i} - \bar{x}_{o,i}\right)^2 x \sum_{i=1}^{n}\left(x_{p,i} - \bar{x}_{p,i}\right)^2}}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_{p,i} - x_{o,i}\right|$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{p,i} - x_{o,i}\right)^2}{n}}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_{o,i} - x_{p,i}}{x_{o,i}}\right|$$

Where : $x_{p,i}$: correlated value; $x_{o,i}$: observed value; n: number of observation; x_{max}: maximum observed value; x_{min}: minimum observed value; and $\bar{x}_o$: average of observed values.

RESULTS AND DISCUSSION

The data used in this study include operational conditions temperature, conductivity, and pH. Influent quality characteristics BOD_5, COD, TSS, NH^+_4, NO_3, and Phosphorus concentrations at Batna WWTP, were selected for this application. The statistical measures of operational conditions, influent quality and efficiencies used for modeling are given in Table 2.

For neural network models construction, the entire data set was randomized. They were divided as follows: (70%) of this data was used for training, (15%) was used for testing and (15%) was used for validation. Levenberg-Marquardt algorithm achieved the training of neural networks. The networks are designed by putting weights between neurons, by using the log-sig function of training. The number of nodes in the hidden layer was determined based on the maximum value of coefficient of correlation. Different networks structures tested in order to determine the optimum number of hidden layers and the number of nodes in each.

The statistical performance of the ANN models for predicting SVI with various hidden neuron numbers for the training process is presented in Table 3. Initially with 5 neurons and log-sig transfer function in the hidden layer, statistical parameter values were as follows 0.9490, 0.8091, 0.364, 0.548, 18.76 for $R_{TRAINING}$, R_{ALL}, MAE, RMSE and MAPE respectively. It was found that increasing the number of neurons in the hidden layer, the values of statistical parameters previously mentioned is improved, which reflects on the performance. This is illustrated by that when the number of neurons in hidden layer was 10, it found that the statistical parameter values were 0.9775, 0.8476, 0.268, 0.446 and 18,76 for $R_{TRAINING}$, R_{ALL}, MAE, RMSE and MAPE respectively. With arrival the number of neurons to 13, it was obtained the best results (in bold in Table 3). With increasing the number of neurons in hidden layer at 15, the performance indexes of ANN's model decreases. The best model given by the neural network for the SVI prediction composed of one input layer with fifteen input variables, one hidden layer with thirteen nodes and one output layer with one output variable with 0.9993, 0.8784, 0.186, 0.443 and 10.98 for $R_{TRAINING}$, R_{ALL}l, MAE, RMSE and MAPE respectively.

The ANN model has the best performance, with R_{ALL} (0.8164-0.9993) , MAE (0.186-1.141), RMSE (0.393-1.346), and MAPE (10.98-28.43) for accuracy and generalization performance, indicating that using ANN model can handle well the nonlinear relationship between SVIs, operation parameters, influent quality parameters and performances of activated sludge process (ASP).

Table 2 : Descriptive statistics for the fifteen inputs used for training, testing and validation.

Parameters	Min.	Max.	Mean	Std. dev.	Coef. Variation
TSS_{in} (mg/L)	202	614	340.56	92.74	0.27
CODin (mg/L)	480	1484	843.38	192.48	0.23
$BOD_{5\ in}$ (mg/L)	108	606	343.78	86.71	0.25
$NH^{+}_{4\ in}$ (mg/L)	19	48	29.99	6.11	0.20
$NO_{3\ in}$ (mg/L)	0.01	46	1.12	5.41	4.83
P_{in} (mg/L)	1.44	5.08	2.91	0.64	0.22
pH_{in}	7	8.18	7.55	0.23	0.03
T_{in} (°C)	10	25.2	18.30	3.84	0.21
$Cond_{in}$ (µS/cm)	1628	2370	2019.18	158.62	0.08
TSS effeciency (%)	81.12	96.44	90.02	3.92	0.04
COD effeciency (%)	68.67	94.16	88.22	3.36	0.04
BOD_5 effeciency (%)	79.83	99.81	92.72	4.26	0.05
N-NH^{+}_{4} effeciency (%)	1.64	38.37	14.39	8.98	0.62
P-PO_4 effeciency (%)	3.39	96.15	48.32	24.09	0.50
N-NO_3 effeciency (%)	42.85	99.55	75.46	29.41	0.39

Table 3: Performance indexes of the ANN prediction models.

ANN model	R		MAE	RMSE	MAPE (%)
	$R_{TRAINING}$.	R_{ALL}			
ANN 15-5-1	0.9490	0.8091	0.364	0.548	18.76
ANN 15-6-1	0.9705	0.9126	1.141	1.346	14.79
ANN 15-7-1	0.8164	0.7565	0.394	0.484	28.43
ANN 15-9-1	0.9922	0.8246	0.292	0.479	21.35
ANN 15-10-1	0.9775	0.8476	0.268	0.446	18.67
ANN 15-11-1	0.9131	0.8217	0.347	0.454	22.82
ANN 15-13-1	**0.9993**	**0.8432**	**0.186**	**0.443**	**10.98**
ANN 15-15-1	0.983	0.8784	0.254	0.393	17.12

The prediction of all data set showed in Figure 5 exhibit over estimation in the low SVI level region and underestimation in extreme value of SVI. In general that ANN model was able to predict the SVI with a reasonable degree of accuracy.

The study of the evolution of MAE and RMSE shows that, in general $RMSE > MAE$ for the range of most values. The degree to which RMSE exceeds MA is an indicator of the extent to which outliers (or variance in the differences between the predicted and observed values) exist in the data (Legates and McCabe Jr., 1999).

The modeling SVIs using ANN versus measured SVI in Batna WWTP showed in Figure 6 clearly demonstrate the ability of the Neural network model to predict very well the Sludge Volume Index at Batna WWTP.

From modeling point view, a disadvantage of ANN modeling is that the mechanisms of inner signal processing are unknow (Lou and Zhao, 2012), this is why we called the ANN Black-box modeling. However, it be used as a tool to prevent sludge bulking problems (Belanch et al., 2000; Lou and Zhao, 2012; Han and Qiao, 2013; Han and Qiao, 2015). The operators can control the predicted SVI and adjust activated sludge process parameters to increase efficiencies. In the future other parameters, such MLSS, SRT and DO will be added to the ANN model for more understanding the complete mechanisms and the relationships among the variables in activated sludge process.

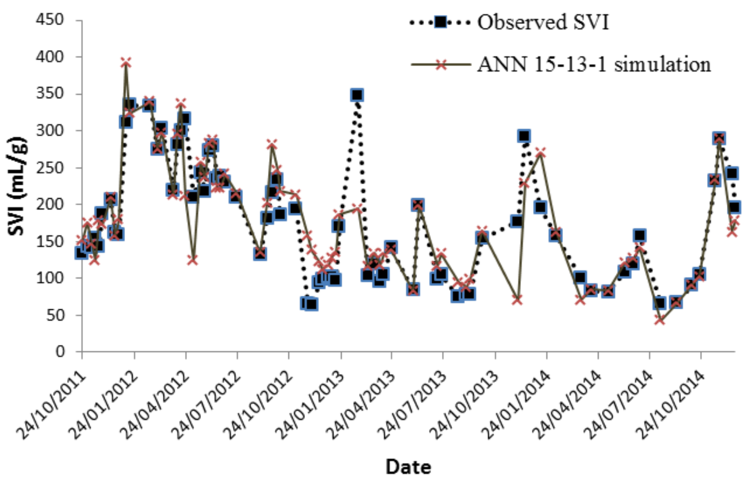

Figure 5: Observed and predicted sludge volume index in Batna wastewater treatment plant (2011-2014).

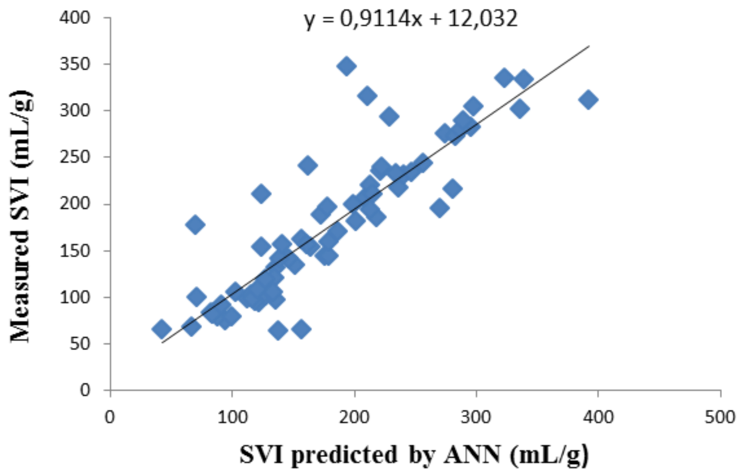

Figure 6: SVI estimated by the Neural Networks versus corresponding values of SVI for all data set.

CONCLUSION

Modeling Sludge volume index of activated sludge process in WWTP is difficult to accomplish due to the high nonlinearity of the plant and the non-uniformity and variability of influent quality parameters, and operation.

In this paper, ANNs were developed for the prediction of the sludge volume index using influent quality parameters (TSS (mg/L), COD_i (mg/L), BOD (mg/L), temperature (°C), pH, conductivity (µS/cm), NH^+_4 (mg/L), NO_3 (mg/L), P (mg/L), and operating parameters, TSS efficiency (%), COD efficiency (%), BOD efficiency (%), Ammonia efficiency (N-NH^+_4) (%), Nitrate efficiency (N-NO_3) (%), Phosphorus efficiency (P-PO_4) Batna wastewater treatment plant, for the time period 2011-2014 were selected for this analysis. The training of neural networks was achieved by Levenberg-Marquardt algorithm. The networks are designed by putting weights between neurons, by using log-sig function transfer and linear function activation. The number of nodes in the hidden layer was determined based on the maximum value of coefficient of correlation. The results for the training and the test data sets were satisfactory. Consequently, the Neural Network models can be used for the prediction of SVI.

The best model given by the neural network for the SVI prediction composed of one input layer with fifteen input variables, one hidden layer with thirteen nodes and one output layer with one output variable with R= 0.8784, MAE = 0.186, RMSE = 0.443 and MAPE = 10.98%.

The plant input data were used to predict the SVI without using mechanistic bio-modeling which involves a great degree of complexity and uncertainty. The modeling approaches used in this study had better prediction power. The ANN modeling technique has many favorable features such as efficiency, generalization and simplicity, which makes it an attractive and useful tool for modeling activated sludge process, and can be used by WWTP operators in their daily management to increase treatment process performances and WWTP reliability.

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