ARTIFICIAL NEURAL NETWORKS TO PREDICT WASTEWATER TREATMENT IN DIFFERENT MEDIA HSSF CONSTRUCTED WETLANDS

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ABSTRACT

Artificial neural networks, ANNs were developed to model the biological oxygen demand (BOD), biochemical oxygen demand (COD), and total suspended solids (TSS) treatment in 3 horizontal subsurface flow (HSSF) constructed wetlands (CWs) located in Samaha village, Nile Delta, Egypt. Gravel, hollow plastic bits and shredded tires pieces were used as different wetland treatment media. Three hundred data sets were used, of which 240 and 60 for ANNs calibration and validation respectively. Input variables for the models are influent concentration (C_i), loading rate (q), media surface area (A_s), and actual velocity (v). Performance of the models in calibration and validation processes was evaluated using the error and the percentage error between experimental and model values. Output result is the effluent concentration (C_o). Training procedure for effluent concentrations was quite successful; as perfect matches were obtained between measured and calculated concentrations. The ANN that showed best BOD modeling has a structure of 4-5-4-1 (4 input variables, 5 neurons in the first hidden layer, 4 neurons in the second hidden layer, and 1 output variable). As for COD and TSS simulation; the ANN structures were 4-7-5-1 and 4-6-5-1 respectively. Modeling results displayed very good behavior of the ANN with reliable and accurate simulation. Plastic media gave the best treatment performance than both gravel and rubber media by percentages varied between 6.75 and 10.84% (more than gravel) and between 10.87 and 13.95% (more than rubber) which coped with the measured field results.

Keywords: Constructed wetland, Horizontal subsurface flow, Artificial neural network, shredded tires, hollow plastic bits.
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1 INTRODUCTION

Wastewater treatment is a problem that has faced man ever since he discovered that discharging his wastes into surface water can lead to many additional environmental problems. Constructed wetlands (CWs) are techniques aim to improve water quality and reduce the harmful effect of effluent (Sarafraz et al.,). Horizontal subsurface flow constructed wetlands have a variety of complicated and interrelated physical, chemical, and biological processes, so the mathematical representation for these processes is a complex task.

Constructed wetlands are definitely more complex than conventional treatment processes because the diffusive flow and the large number of processes involved in pollution reduction. For these reasons, many authors have pointed out that the removal efficiency of constructed wetlands is not easily predictable, and being highly influenced by the hydraulic or environmental conditions (Marsili-Libelli and Checchi). For this reason it was obvious to use artificial neural networks (ANNs) to simulate treatment of municipal wastewater through HSSF wetlands.

An Artificial Neural Network (ANN), is a mathematical model that attempts to simulate the functional aspects of biological, physical or chemical processes in CWs. The neural networks composed of many simple neurons like processing units. These networks have the ability to recognize patterns of input and output information and making a group of complex relationships linking these input variables with each other and with the output values. Models based on ANN have been successfully used in wastewater treatment systems and are very effective at capturing the non-linear relationships between variables (multi-input) in complex systems (Çinar et al). Also, these ANNs have the potential ability to predict the value of a new output if they are fed with the corresponding input variables (Hu and Hwang).

Nayak et al. , reported that; ANN managed for forecasting/predicting, pattern recognition and process control in most of the areas in science and technology including driving a design equation for the total nitrogen treatment in CWs (Akratos et al.). ANN was used to compare the performance of both surface and subsurface flow CWs using an ANN–back propagation algorithm. The ANN prediction of COD and BOD were of better results in subsurface wetlands than the surface wetlands (Naz et al.). Tomenko et al. compared multiple regression analysis (MRA) with two ANNs; to predict BOD concentration at effluent and intermediate points of HSSF wetlands in India. Both MRA and ANNs provided an efficient and robust tool in predicting CW performance. Yalcuk , developed an ANN model to represent phenol removal in vertical and horizontal planted and unplanted CWs. Calculated results through the training procedure for different wetlands was quite successful matching the measured effluent phenol concentrations.

Wetland beds can contain more than one type of media in different sequences. Gravel and soil are the widely media used in subsurface CWs (Zidan et al.). Collaço and Roston, successfully used shredded tires as a medium for HSSF wetlands for treating domestic wastewater planted with typha species aquatic macrophytes. Cordesius and Hedström, investigated the use gravel and plastic pieces on treating domestic waste-water. In Samaha village, Dakahliya governorate, Egypt, 3 pilot scale HSSF CW cells using gravel, hollow plastic pipes and shredded tiers slices as different media were investigated for treating primary treated municipal wastewater. The plastic media which has the maximum media surface area showed better treatment performance followed by gravel then rubber media (Zidan et al.). The aim of this study was to develop ANN modules to evaluate the performance of 3 different media types HSSF CWs in BOD, COD, and TSS removal from municipal wastewater.

2 METHODOLOGY

2.1. Study Area

Samaha HSSF wetlands plant that located in Dakahlia governorate, about 100 km northeast of Cairo (30° 52' 09.81" N and 31° 16' 55.28" E) was built in 1995 for treating 1000 m^3 d^{-1} of primary treated domestic wastewater. The HSSF consists of 8 gravel bed cells (33 m long, 7 m wide, and 0.7 m deep each) that suffer from over loading and inefficient treatment performance. One cell was chosen to examine using different materials as CW bed media . The cell was divided into three parallel micro cells (10 m long, 2 m wide, and 0.65 m deep each) (Figure 1). Three types of treatment media were used ; (a) rubber made from shredded tires (average dimensions are 50 mm length, 40 mm width, and 10 mm thickness), (b) hollow corrugated pieces of plastic pipes 50 mm length and 19 mm diameter, and (c) natural washed gravel in 3 layers (50 mm at bottom, 30 mm at middle , and less than 20 mm size at top). To prevent rubber and plastic media from floating, a plastic screen was placed on the top surface and covered by 10 cm coarse gravel layer.

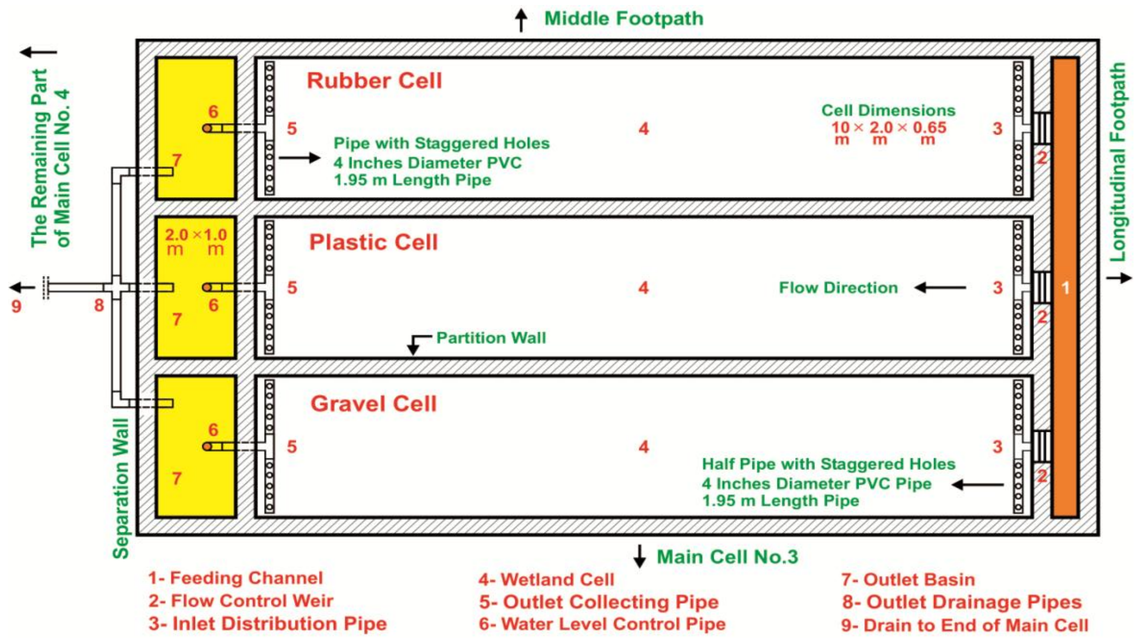

Figure. 1 Experimental setup for wetland cells.

2.2. Field water sampling and analysis

Water samples were collected manually in 500 ml sterile bottles from each cell inlet, outlet and every 2 meters in between along the 10 m wetland length. Water samples were stored in ice tanks, sent to laboratory and analyzed for BOD, COD, and TSS. Five water samples were collected during each sampling cycle. Sampling cycles were repeated 5 times during the period from mid-April until mid-October, 2010. The influent and effluent pollutants concentrations were analyzed according to Standard Methods (5530D) (APHA)

2.3. Modeling with ANN

In this study, Various different networks with different number of neurons in their hidden layers were studied and tested for each pollutant with input layer and one or more hidden layers to find out the output layer. These layers could be arranged as a general neural network. The feed-forward network is used in this study as the information moves only in the forward direction (Abdel-Hady).

The experimental data (influent and effluent concentrations) for steady stage are 25 runs where 5 cycles was performed through the steady stage as each cycle represents a specific discharge and water samples were repeated five times during each cycle, so the total number of input sample was 25.The input variables for the models are influent concentration (C_i – mg l^{-1}), the hydraulic loading rate (q – m d^{-1}), media surface area (A_s - m^2), and the actual velocity (v – m d^{-1}). To increase the input data, every influent concentration gave four intermediate outlet concentrations, loading rate, surface area, and actual velocity at lengths 2, 5, 8, and 10 m from cell inlet for each media which means 100 data patterns/media for BOD, COD, and TSS pollutants. Hence, 300 data patterns (25 run × 4 lengths × 3 media) were available from the experimental work to train and test the proposed ANN.

Many different neural networks structure having 4-input variables (C_i, q, A_s, and v) and one output value (C_o) for steady operating stage were designed. These multi-feed forward neural networks (MFFNNs) have one and two hidden layers with different number of neurons in these layers. These MFFNNs were trained and tested. The weight matrixes and biases vectors for the selected networks are presented. The program used for implementing the MFFNNs is developed by applying the MATLAB neural network toolbox.

2.4. Calibration & Validation Processes for ANN models

The training algorithm of ANN will be used in this study where a target output (effluent concentration, C_o) is available. The ANN learns during training by adapting to a dataset of inputs and the desired output corresponding to them. The network parameters such as the weights and biases are adjusted according to the error between the desired and obtained outputs in a closed-loop feedback type system, Dreyfus,. Sixty random samples were chosen from the total 300 data of each BOD, COD, and TSS pollutants concentration samples, to validate the obtained models, these random samples represent 20% of the total data and the remaining part of data were used for modeling construction and calibration process (Abdel-Hady, 2014).

After the models have been constructed, they were graphically analyzed for goodness of fit by plotting the actual results against the predicted results. The training performance (the relationship between the measured concentrations and corresponding model ones); and the error values and the percentage errors for these outputs will be discussed. The points that give percentage error (difference between measured concentration and model outputs) less than 5% will be considered as a good output result for the model, between 5 and 10% "acceptable", and more than 10% will be described as "not good representation". The error and the percentage error between experimental and model outputs are computed using the following formulae:

$$Error = C_{Exp} - C_{ANN} \tag{1}$$

$$E_n = \left(\frac{C_{Exp} - C_{ANN}}{C_{Exp}} \right) \times 100 \tag{2}$$

Where: E_n = artificial neural network percentage error, % , C_{Exp}=experimental measured output concentration, (mg l^{-1}), and C_{ANN}= artificial neural network output concentration, (mg l^{-1}).

2.5. Comparison between HSSF CW treatment media

Equations 3 and 4 give the average removal difference, (ARD) of ANN modeled pollutant removal efficiency, through 5 discharge cycles (300 data sets) between plastic cell and both gravel and rubber cells, whereas equation 5 gives this average difference between gravel and rubber (Abdel-Hady,). Discharges of influent wastewater were changed from a maximum values to smaller values for the purpose of estimating the optimum treatment efficiency. Discharges gradually reduced from 5.12 to 1.19 m^3 d^{-1}.

$$ARD_{(\text{Plastic}\,\&\,\text{Gravel})} = \frac{\sum \left(RE_p - RE_g \right)}{No.\,\text{of Cycles}} \tag{3}$$

$$ARD_{(\text{Plastic}\,\&\,\text{Rubber})} = \frac{\sum \left(RE_p - RE_r \right)}{No.\,\text{of Cycles}} \tag{4}$$

$$ARD_{(\text{Gravel \& Rubber})} = \frac{\sum\left(RE_g - RE_r\right)}{No.\text{ of Cycles}} \quad (5)$$

where: RE_p= removal efficiency of plastic cell outlet, %, RE_g= removal efficiency of gravel cell outlet, %, and RE_r= removal efficiency of rubber cell outlet, %.

3 RSULTS AND DISCUSSIONS

3.1. Structure of ANNs for BOD, COD, and TSS

Different networks with one and two hidden layers were considered and their performance was evaluated. It was found that the networks with reasonable number of neurons in one hidden layer cannot cover all used data. Also, networks with two hidden layers provided better results without having large number of neurons in their hidden layers. The number of neurons in hidden layers was taken as two or three and was increased till desired results were obtained by testing the neural network. Many different neural networks structure having 4-input variables (C_i, q, A_s, and v) and one output value (C_o) for steady stage were designed. Two hidden layers with different number of neurons were considered and trained. Some of the MFFNNs were tested, and the comparison between these different networks is listed in Table 1.

Table 1. Comparison between different tested networks for BOD, COD and TSS

Network Structure	**Number of Epoch**			**Mean Square Error**			**Gradient**			**Mu**		
Pollutant	BOD	COD	TSS	BOD	COD	TSS	BOD	COD	TSS	BOD	COD	TSS
4-3-3-1	236	53	222	2.99	7.96	4.60	26.2	≈0	0.09	0.160	≈0	≈0
4-4-3-1	320	89	47	2.07	4.76	2.19	23.4	8.68	54.0	≈0	20.9	2.39
4-4-4-1	53		121	3.09		1.28	209		61.0	13.0		2.05
4-5-3-1	119		102	0.880		1.76	38.1		158	0.445		0.981
4-5-4-1	**77**	147	546	**0.582**	2.99	0.96	**10.70**	216	1.29	**0.145**	0.08	0.233
4-5-5-1	42			3.03			60.4			8.74		
4-6-5-1		54	**60**		0.879	**0.347**		96.4	**0.75**		1.78	**2.01**
4-7-5-1		**103**	52		**0.590**	1.18		**78.8**	130		**0.226**	0.502
4-7-6-1		61			1.89			221			2.91	

Structures of the chosen ANN for BOD, COD, and TSS are (4-5-4-1), (4-7-5-1), and (4-6-5-1) respectively. Epoch: Determines when training will stop once the number of iterations exceeds epochs. When training by minimum error, this represents maximum number of iterations. Epoch range = (1, ∞) .

The MFFNNs for BOD, COD, and TSS pollutants which show satisfactory results while not having a big size with minimum mean square error have a structure of (4-5-4-1), (4-7-5-1), and (4-6-5-1), respectively. These best networks which give both minimum mean square error, (MSE) and minimum percentage error between experimental and ANNs outputs is presented in figures 2 to 4. Table (1) present ANN networks features of BOD, COD and TSS. The developed ANNs models are capable to minimize to least values of 0.582, 0.590, and 0.347, for BOD, COD, and TSS, respectively. The training stops when the validation error increases by additional twenty iterations, for the studied pollutants and the ANN structure proved to have the minimum MSE value of all networks. The best validation performance occurs by 77, 103, and 60 iterations number for BOD, COD, and TSS respectively. The correspondence MSE values were 0.582, 0.590, and 0.347 respectively which is the minimum of all tested networks.

3.2. Calibration Process for Networks

A number of 240 patterns for input variables were randomly selected from the available 300 data sets and used to calibrate the designed networks for the studied pollutants. The training performance and error values for BOD, COD, and TSS output pollutants are illustrated in Figures 5 to 7, respectively. The computed values of BOD, COD and TSS by ANN model were in close agreement with their respective measured values. It is found that, the error between the experimental effluent concentration and the ANNs model outputs varies between -0.85 and +0.66 mg l^{-1} for BOD pollutant. For COD this error ranges from -1.08 to +1.06 mg l^{-1}, whereas, for TSS the error varies between -0.63 and +0.84 mg l^{-1}. Results of calibration process are very encouraging and match accurately with the target values. For BOD outlet concentration, 236 points give percentage error (E_n) less than ±5% and 4 points gave E_n between ±5 and ±10%. For COD, 238 points give E_n less than ±5% and 2 points give E_n between ±5 and ±10%. For TSS effluent, 227 points give E_n less than ±5% and 11 points give E_n between ±5 and ±10%, and 2 points give E_n more than ±10%.

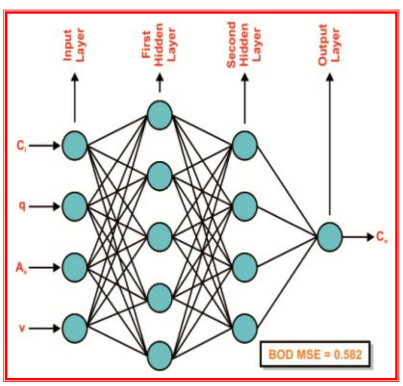

Figure 2. Optimum structure of ANN for BOD.

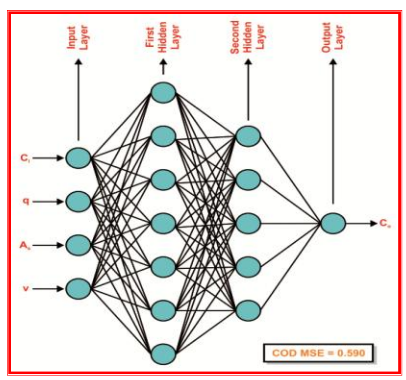

Figure 3. Optimum structure of ANN for COD.

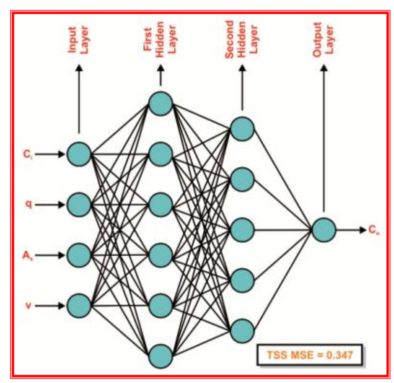

Figure 4. Optimum structure of ANN for TSS.

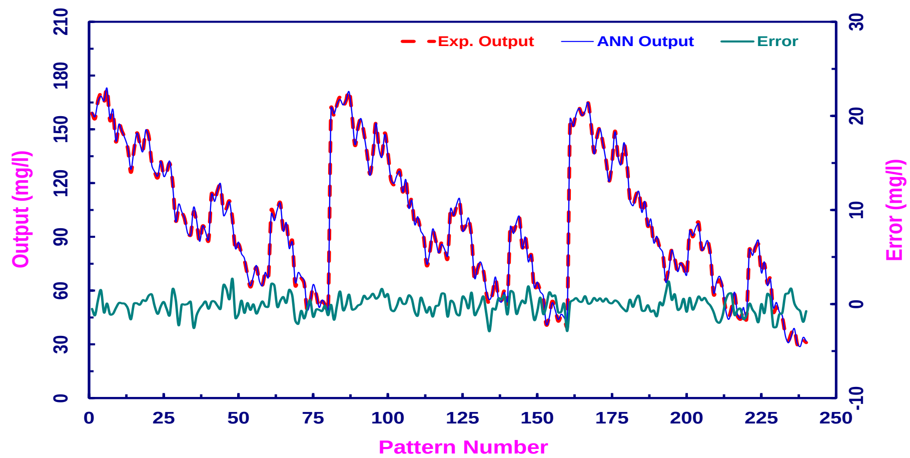

Figure 5. Training performance and error values of 240 patterns for BOD outputs.

3.3. Validation Process for ANNs

The validation performance and error values for the proposed ANNs models for 60 patterns left from the available 300 data sets are presented in Figures 8 to 10 for BOD, COD, and TSS pollutants, respectively. The average error between the experimental and the ANN model output concentrations varies between; -0.81 and +0.80 mg l^{-1} for BOD, -1.60 and +1.61 mg l^{-1} for COD, and -0.70 and +0.99 mg l^{-1} for TSS pollutant. The model results are very close to the experimental output concentration for BOD and COD pollutants. For BOD effluent, all points (60) give percentage error (En) less than ±5%. As for COD, 59 points give En less than ±5% and one point give En between ±5 and ±10%. For TSS, the model results are matching with the experimental effluent value except few peculiar points. Fifty five points give En less than ±5% and 4 points gave En between ±5 and ±10%, and one point give En more than ±10%.

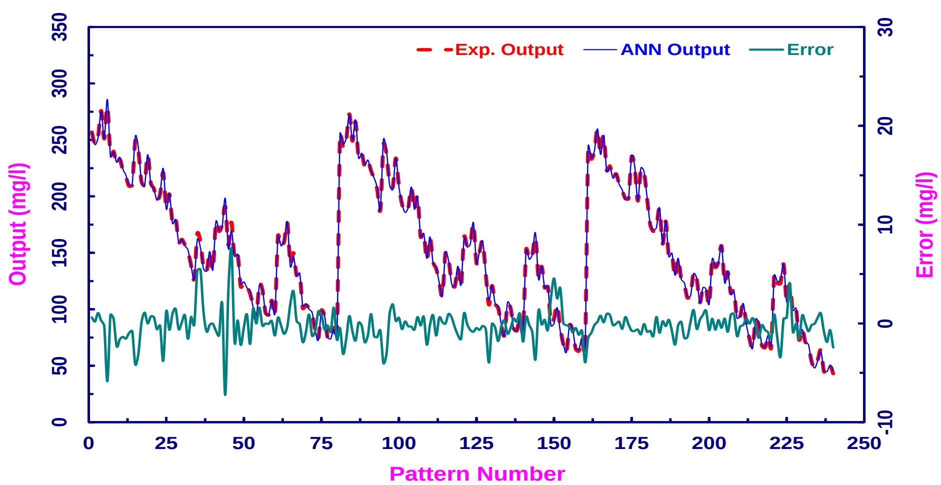

Figure 6. Training performance and error values of 240 patterns for COD outputs.

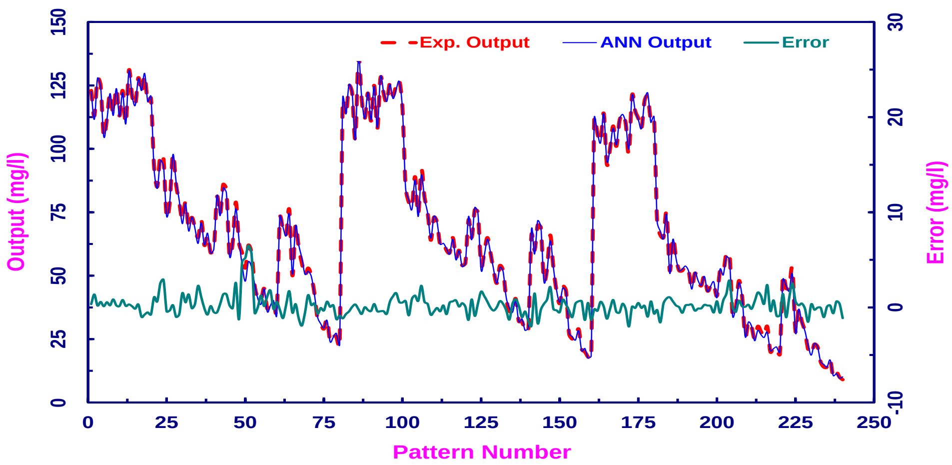

Figure 7. Training performance and error values of 240 patterns for TSS outputs.

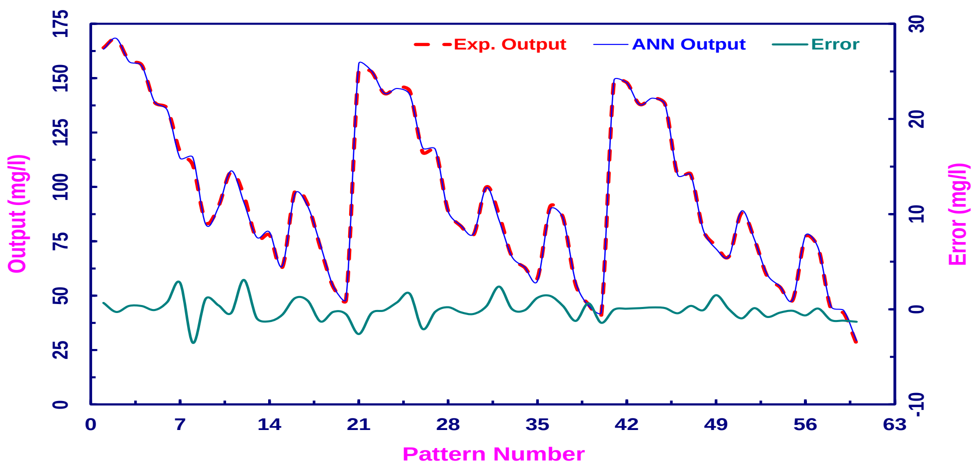

Figure 8. Validation performance and error values of 60 patterns for BOD outputs.

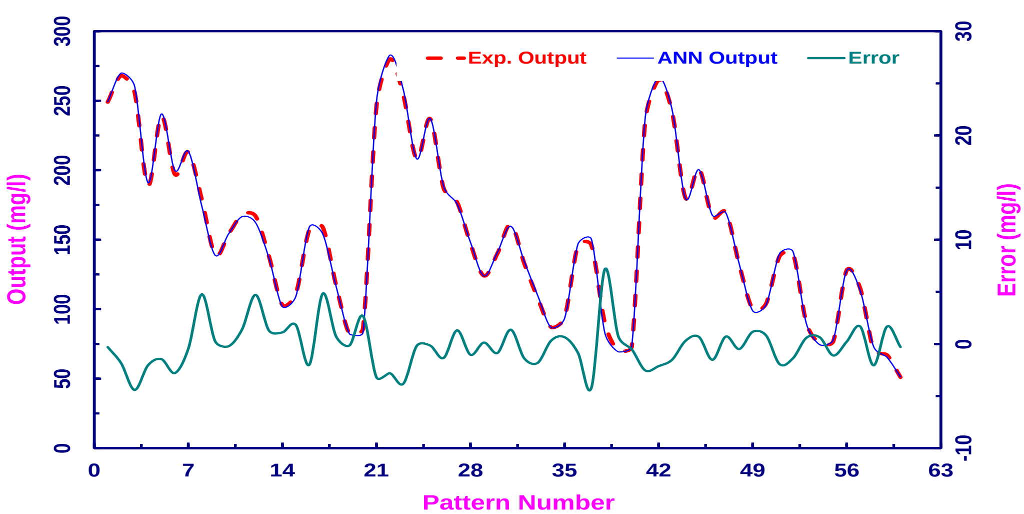

Figure 9. Validation performance and error values of 60 patterns for COD outputs.

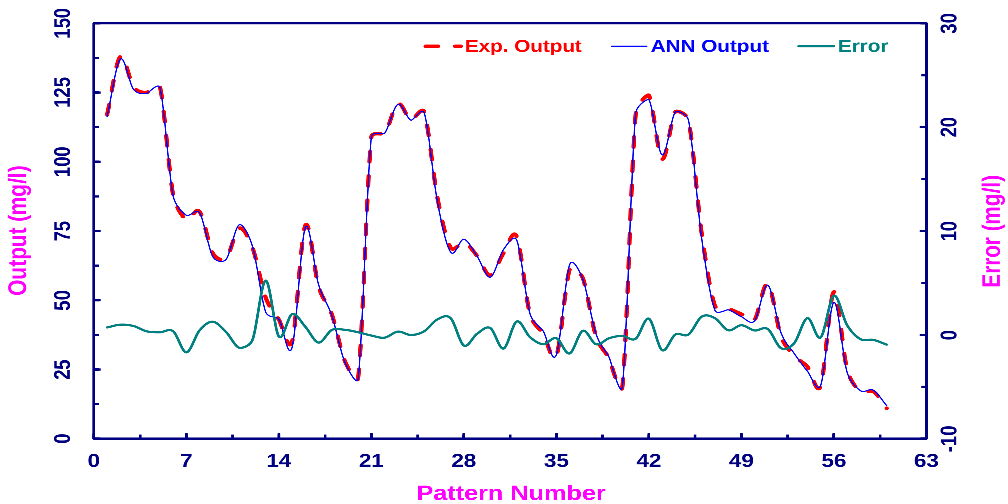

Figure 10. Validation performance and error values of 60 patterns for TSS outputs.

A summary of E_n for both calibration and validation processes are presented in Table (2). These results show the stability of the ANN outputs under all conditions including a wide pollutants load (discharge range = 1.19 - 5.12 m^3 d^{-1}) and rapid convergence of the output variables to the expected values. This clearly confirms the effectiveness of the proposed ANN modules.

Table 2. Average percentage errors between Experimental and ANN results

Parameter	Average E_n (%) (ANNs)	
	Calibration process (240 Patterns)	Validation process (60 Patterns)
BOD	-0.85 : +0.66	-0.81 : +0.81
COD	-1.08 : +1.06	-1.60 : +1.60
TSS	-0.63 : +0.84	-0.70 : +0.99

3.4. Effects of HSSF CW media on Pollutant treatment

The ANNs simulated effluent concentrations of BOD, COD, and TSS were evaluated to determine the optimum wetland media in pollutants treatment through different flow discharges. Table (3) presents average removal differences, (ARD) between HSSF media types for BOD, COD, and TSS. As the discharge decreases, the effluent removal efficiency of BOD increases for plastic, gravel, and rubber media. The plastic media cell has highest removal efficiency followed by the gravel and then the rubber cells essentially due to the higher surface area (high amount of attached biofilm bacteria) of the plastic media comparing with the other used media (Zidan et al.). At CWs outlets, plastic cell gives average BOD removal difference higher than both gravel and rubber cells by about 6.75 and 10.88%, respectively. Gravel cell gives average removal difference higher than rubber cell by about 4.13%. As for COD, plastic cell gives average removal difference higher than both gravel and rubber cells by about 6.77 and 10.87%, respectively. Gravel cell gives average removal difference higher than rubber cells by about 4.10%. However for TSS, plastic cell gives average removal difference higher than both gravel and rubber cells by about 10.84 and 13.95%, respectively. Gravel cell gives average removal difference higher than rubber cell by about 3.12%. The removal differences are quite higher in case of TSS comparing with BOD and COD due to the treatment mechanism of TSS which mostly depends on sedimentation at treatment media pores.

Table 3: Average removal differences between HSSF media types for BOD, COD, and TSS

Cycle No.	Discharge range (m^3d^{-1})	ARD BOD (%)			ARD COD (%)			ARD TSS (%)		
		P - G	P - R	G - R	P - G	P - R	G - R	P - G	P - R	G - R
1	4.81-5.12	7.40	11.52	4.12	7.43	11.48	4.05	11.05	15.75	4.70
2	3.28-3.48	7.04	10.96	3.92	7.03	10.94	3.91	17.51	19.26	1.75
3	2.25-2.40	6.39	10.54	4.15	6.35	10.57	4.22	13.86	17.84	3.98
4	1.60-1.70	5.75	10.19	4.44	5.73	10.20	4.47	6.77	9.02	3.25
5	1.19-1.26	5.18	9.21	4.03	5.31	9.18	3.87	5.00	7.90	2.90
Mean	1.19-5.12	6.75	10.88	4.13	6.77	10.87	4.10	10.84	13.95	3.12

P=plastic media, R=rubber media, and G=gravel media.

CONCLUSIONS

The ANNs managed to mimic the HSSF wetlands for BOD, COD and TSS treatment with an acceptable accuracy. The ANNs models represent the experimental data in calibration and validation processes proving its ability to simulate a variety of complex relationships between variables precisely. The ANN networks that show the best fit results having a structure of 4-5-4-1, 4-7-5-1, and 4-6-5-1, (input variables - 1st hidden layer neurons layer - 2nd hidden layer neurons - output variable) for BOD, COD, and TSS respectively. The ANNs used 4 input variables (influent concentration, loading rate, media surface area, and actual velocity to model the effluent pollutants concentrations. Results of calibration and validation processes are very encouraging and match accurately with the field measured values. Comparisons between the ANNs simulated results proved that plastic media had the best treatment performance for BOD, COD, and TSS followed by gravel then rubber. The ANN modeling technique can be an easy speed design tool to forecast the HSSF CW effluent concentrations when assuming the CW influent concentration, loading rate, flow discharge and media type.

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