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ARTIFICIAL NEURAL NETWORK FEEDFORWARD CONTROLLER APPLIED TO A HYBRID SYSTEM FOR TEXTILE EFFLUENT TREATMENT

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Abstract. *Textile industries generate high complex pollutant effluents. A combination of electrocoagulation and organic coagulation can be considered a promising technology for the treatment of this type of wastewater, mainly if the process runs under the supervision of a robust controller. A feedforward controller based on Artificial Neural Networks (ANN) was implemented in a hybrid treatment system for removing Reactive Blue 5G Dye from a synthetic solution. Process was modeled through a Central Composite Rotational Design (CCRD). The ANN was trained by the Levenberg-Marquardt method with Bayesian regularization, using a data bank produced by CCRD model. In order to test controller, step disturbances in the affluent dye load were done. Because of controller action, the controlled variable had its oscillation amplitude reduced, remaining in a region close to the set point. The ANN provided the controller with the capacity to decide between two manipulated variables, whereby following the goal of saving energy upon defining the control action, the ANN opted to reduce the intensity value of the electric current (electrocoagulation) in detriment of natural coagulant concentration.*
Keywords: Electrocoagulation, Natural coagulant, Process control, Artificial intelligence

1. **Introduction.** Textile industries consume huge amount of water [1,2] and synthetic dyes in their production process [3]. As a result, a complex pollutant effluent is generated, which has a high organic load, distinctive colors and chemical compounds that are toxic to the biota [4,5]. Technology developments are demanded to an adequate effluent treatment [6], considering cost, operational time and process efficiency in terms of recycling and toxicity reduction.

Physical-chemical treatments are efficient in the removal of high molecular weight compounds, color, toxicity, suspended solids and organic material [7]. However, many of them are costly and lack efficiency in the removal of low molecular weight compounds. Electrocoagulation, adsorption, advanced oxidation, ozonization, precipitation and membrane filtration have been investigated as important methods for textile effluents treatment [2,8-12].

Electrocoagulation promotes *in situ* generation of coagulants through electrolytic oxidation of a metallic anode, mainly iron or aluminum, which produces insoluble metallic hydroxides, able to remove pollutants through electrostatic attraction [13-15]. This electrochemical technique has emerged as an alternative to chemical coagulation [16], enhancing color removal efficiency in textile effluents treatment [17-19].

Another alternative to chemical coagulants are natural coagulants, such as *Moringa Oleifera* (MO) extract [20,21]. Benefits of MO coagulant in effluent treatment are its biodegradability, coagulation without pH adjustment, low cost and small volume of sludge production [22,23].

A hybrid system application is an alternative to textile effluent treatment, which joins electrocoagulation and a natural coagulant together, such as *Moringa Oleifera* extract [24]. In order to achieve high treatment efficiency with low operational costs, a process optimization is requested [25,26].

In addition to treatment system optimization, it is important to follow and control dye concentration in the effluent outlet stream of effluent treatment. Dye concentration oscillations in the inlet stream often occur, and the controller must manipulate the system operational conditions, such as electrical current and amount of MO extract.

A standard application for process control is a feedback (FB) controller. However, an FB controller can manipulate just one parameter to achieve control goal, and it is also requested on line measurement of controlled variable (dye concentration in outlet stream). The necessity of manipulating two parameters and iron presence in outlet stream, that disturbs dye color measurement, turns FB controller unfeasible. Alternatively, a feedforward (FF) controller can be used; on the other hand, a process model is requested.

Artificial intelligence tools, such as Artificial Neural Networks (ANN), were successfully used to textile effluent treatment system by Fenton process [27]. ANN are computational techniques inspired by the functioning of biological neurons, using mathematical models for pattern classification, simulation of activities, data grouping and temporal forecasts [28-30]. In the literature, there are reports of ANN application in modeling the electrocoagulation process [31,32].

This paper is organized according to the following aspects: (1) A controller was implemented into a hybrid textile effluent system, which is composed by an electrochemical reactor with natural coagulant addition (*Moringa Oleifera* extract); (2) When any disturbance on inlet dye concentration is detected, the controller must manipulate two variables: electric current intensity and natural coagulant dosage, in order to control the outlet dye concentration; (3) The electrocoagulation process has iron electrodes, whose oxidation causes interference in dye concentration measurement by spectroscopy, so a standard feedback controller cannot be implemented. The feedforward controller was considered as an alternative, due to this process limitation; (4) An Artificial Neural Network is supposed to actuate as a feedforward controller. This artificial intelligence tool may evaluate the best configuration among the manipulated variables in order to promote energy savings; (5) The ANN training requires a large data set. Then, an empirical model for the treatment system was obtained by the Central Composite Rotational Design (CCRD) methodology; (6) Many measured process variables (inlet dye concentration, actual values of electric current applied to electrodes and natural coagulant dosage), set point and the estimated outlet dye concentration (empirical model fitted by CCRD) were used as input ANN variables, which was supposed to calculate the new values of manipulated variables.

2. Materials and Methods.

2.1. **Effluent treatment system.** The experimental module of the hybrid system of effluent treatment is illustrated in Figure 1. This module is composed of a reservoir of synthetic solution of Reactive Blue 5G Dye (a), a mixing chamber (b), a dosing system for the *Moringa Oleifera* extract (c), an electrolytic cell (d) and a source of continuous current (e).

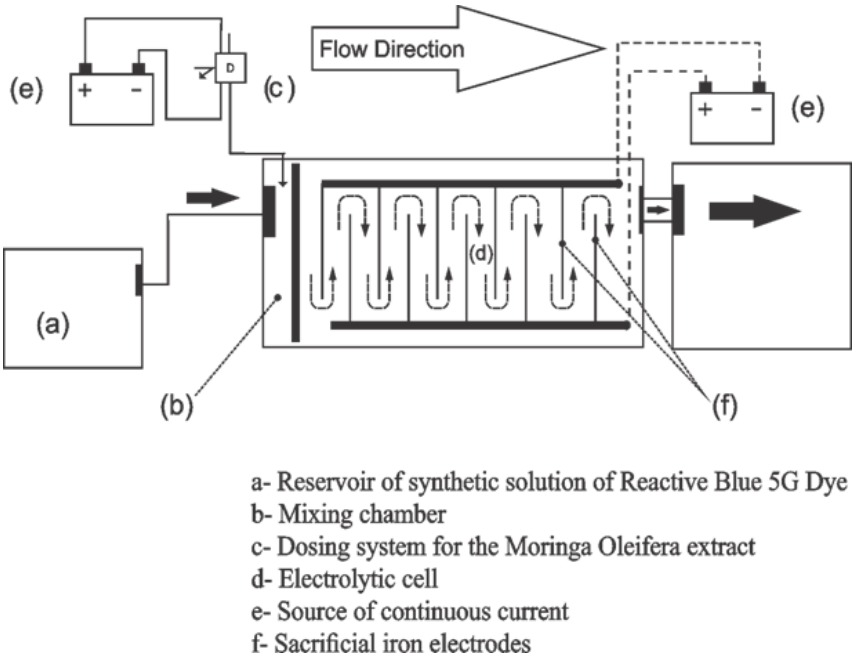

FIGURE 1. Schematic representation of the experimental module of hybrid treatment in continuous flow

The synthetic dye solution is fed into the system through a submersed pump situated in reservoir "a". Dosing of the *Moringa Oleifera* extract is carried out in the mixing chamber (b). This procedure is done with the assistance of a peristaltic pump. Mixing is performed through the injection of compressed air into chamber "b".

After receiving the natural coagulant extract, the synthetic dye solution passes through the electrolytic cell, with dimensions of 65 cm × 12.5 cm × 12 cm (length × width × height). Five pairs of sacrificial iron electrodes were used, and alternately arranged in the baffle plate systems.

The electric current was supplied by a source of continuous current (e), Instrutherm, model FA 3050, which has two outlets, one was used in electrocoagulation process and the other was used for the *Moringa Oleifera* extract dosing pump.

2.2. **Reactive Blue 5G Dye solution.** To perform the assays, aqueous solutions of Reactive Blue 5G Dye were prepared with concentrations defined in an experimental design matrix. In addition, 2 $g.L^{-1}$ of sodium chloride (NaCl) [24] was added to the solution to assure the conductivity required for electrocoagulation.

Analytical determination of the concentration of Blue 5G Dye was given through molecular absorption spectroscopy, at a wavelength of 618 nm [24]. The effluent samples of the treatment module passed through an additional stage to remove the residual iron. As such, the samples were analyzed through spectroscopy only after a settling period of 24 hours.

2.3. **Preparation of Moringa Oleifera Lam extract.** *Moringa Oleifera Lam* seeds were used, which first had their shells removed, and then, manual maceration was performed. In accordance with [24] the resulting cake is used to prepare the coagulant solution at a proportion of 5 g of Moringa to 100 mL of distilled water. NaCl was added into this solution (20% w/v), which was then subjected to 20 seconds of ultrasonic agitation (*Elmasonic*, model P60H) tuned in a frequency of 80 kHz and 580 watts of power. So, natural coagulant from the *Moringa Oleifera Lam* seeds was extracted [24].

After extraction, the solution was submitted to vacuum filtration through a 28-micrometer paper filter. The obtained solution has 50.000 $mg.L^{-1}$ of MO seed (primary solution), which was diluted in water to get solution concentration corresponding to the experimental design matrix (Table 2).

According to the recommendations of [33], the coagulant solution was always prepared at the time of performing the experiments.

2.4. **Control of the treatment system via ANN.** The proposed controller for the hybrid treatment system consists in a feedforward controller based on an inverse model of neural networks.

The input and output variables of the controller are presented in Table 1.

Table 1. Input and output variables of the ANN controller

Input variables	Output variables
C_0|k	
C_0|k+1	
CS.sp|k	I|k+1
CS|k+1	Mo|k+1
I|k	
Mo|k	
CS|k	

In Table 1:

C_0 = Concentration of dye in the input.

I = Intensity of current supplied to the sacrificial electrodes.

Mo = Concentration of *Moringa Oleifera* extract.

CS.sp = Value of the dye concentration at the output of the treatment module utilized as set point for the control system.

CS = Concentration of the dye at the output of the treatment module.

The instant "k" refers to the time referential where there is no disturbance in dye concentration in the affluent, while the time instant "k+1" refers to the future, that is, the moment when the disturbance becomes detected.

Thus, the ANN controller ought to receive current process information (C_0|k, I|k, Mo|k and CS|k), and data on the effects of the disturbance on the dye concentration in the input (C_0|k+1 and CS|k), besides the desired value for the dye concentration in the module output stream, set point (CS.sp|k). As response, the ANN should supply a control action, that is, the updated values of the manipulated variables (I|k+1, Mo|k+1).

Due to the influence of the residual iron concentration, it is not possible to perform on line measurement of the dye concentration by spectroscopy; this measurement is done after sedimentation process that takes 24 hours. However, as the ANN seeks the information of dye output concentration, this data is generated through an empirical model of the treatment system.

2.4.1. *Modeling the treatment system.* For training and database validation of the ANN, in charge for treatment system control, a large quantity of data is necessary in regard to the process dynamic. To avoid an excessive number of assays, an empirical model of the treatment system was produced. The mathematical model generated was used to obtain the data sets required to the ANN training.

Therefore, the effects of the manipulated variables (I and Mo) and disturbance in variable (C_0) were evaluated using a Central Composite Rotational Design, in order to find their effect in the controlled variable (CS).

In accordance with CCRD experimental design, 2^3 factorial assays were executed, adding three repetitions at the central point and six assays on the axial points. The real and coded values, corresponding to variable ranges used in this research, are presented in Table 2.

TABLE 2. Real values corresponding to the coded ones (studied variables)

	−1.68	−1	0	+1	+1.68
C_0 (mg.L^{-1})	10.00	16.07	25.00	33.93	40.00
I (A)	1.00	1.81	3.00	4.19	5.00
Mo (mg.L^{-1})	500.00	601.19	750.00	898.81	1000.00

For each hybrid treatment assay, a dye solution concentration, electrical current and *Moringa Oleifera Lam* extract concentration values are adjusted following the CCRD matrix. The hydraulic retention time used in all the assays was 20 minutes. However, to aggregate dynamism to the control system, the dye concentration in the output stream of the treatment module after 15 minutes was used as response variable.

The adjusted mathematical model is shown in Equation (1).

$$\mathrm{CS} = a_1 + \sum_{i=1}^{3} a_{i+1}(x_i) + \sum_{i=1}^{3} a_{i+4}(x_i)^2 + a_8(x_1)(x_2) + a_9(x_1)(x_3) + a_{10}(x_2)(x_3) \tag{1}$$

in which:

x_1 = Coded variable in reference to the dye concentration in the input stream.

x_2 = Coded variable in reference to the electric current supplied to the pairs of sacrificial electrodes.

x_3 = Coded variable in reference to the concentration of *Moringa Oleifera Lam* extract.

$a_1, a_2, \ldots, a_{10}$ = Regression coefficients of the model.

The codification equations for x_1, x_2 and x_3 variables were obtained from the real values for these factors, which were shown in Table 2. These equations (Equations (2)-(4)) are simple linear relationships between coded and real values for the factors.

$$x_1 = 0.112(\mathrm{C_0}) - 2.8 \tag{2}$$

$$x_2 = 0.84(\mathrm{I}) - 2.52 \tag{3}$$

$$x_3 = 0.00672(\mathrm{Mo}) - 5.04 \tag{4}$$

2.4.2. *Training and validation database of the ANN.* The process model (Equation (1)) was used to produce data required for ANN training and validation. Thus, many combinations of Mo|k, I|k and C_0|k were used in order to calculate respective CS values. The initial conditions of C_0|k, Mo|k and I|k were selected based on this data, which provided values close to the set point.

As the model can provide various combinations of (I) and (Mo) for the same output (CS), it chose values with a lower value of (I). This option was based on the precepts of sustainability, aiming a process with reduced electrical energy consumption.

Of all the data generated, 70% was destined for the training database of the ANN, while the remaining 30% was destined for the validation database. The fraction of data, which is typically employed in the training set, ranges from 60% to 90% [31,32,36-40].

2.4.3. *Details of the ANN.* The ANN used in controlling the hybrid system of effluent treatment was developed on MATLAB®, version R2012a. The details of the ANN used in this application are presented in Table 3.

Table 3. Details of the ANN developed to control the treatment system

ANN type	MLP – Multilayer Perceptron
Training method	Backpropagation: Levenberg-Marquardt with Bayesian regularization
Activation function for hidden layers	Logarithmic
Activation function for last layer	Linear
Objective function for training	Sum of square errors
Convergence tolerance	1E-5
Number of neurons in input layer	7
Number of neurons in output layer	2

In regard to the structure of the ANN, various configurations were tested, with one or two hidden layers, with varying numbers of neurons in each layer, with Mean Percentage Error (MPE) as principal performance criterion, as in Equation (5).

$$\mathrm{MPE} = \left(\frac{1}{N}\right) \sum_{i=1}^{N} \left(\frac{|Y_{\mathrm{ANN}_i} - Y_{\mathrm{EXP}_i}|}{Y_{\mathrm{EXP}_i}}\right) \tag{5}$$

whereby

Y_{ANN_i} = Response value predicted by ANN.
Y_{EXP_i} = Expected response value.
N = Total number of data sets.

2.5. **Application of ANN control in the hybrid system of effluent treatment.** In order to evaluate the performance of the proposed control system, when applied to the hybrid module of textile effluent treatment, 4 assays were carried out with 2 different disturbance configurations (step type) in the affluent dye concentration. An assay was executed for each condition under the action of the ANN controller and another assay was executed without the controller.

Table 4 shows the values of the control assays, as well as their disturbances. The initial values of (Mo) and (I) were determined based on the empirical model so as to provide a predicted value for (CS) equal to the defined set point.

As the HRT was 20 minutes, each disturbance was inserted after double this time had passed, that is, a first disturbance was inserted after 40 minutes, with a second inserted after 80 minutes.

TABLE 4. Assay conditions for evaluation of the action of the ANN controller

Assay	ANN Controller Supervision	C_0 (mg.L^{-1}) (initial)	ΔP1 (%)*	C_0 (mg.L^{-1}) (After disturbance P1)	ΔP2 (%)*	C_0 (mg.L^{-1}) (After disturbance P2)
1	Yes	25.00	14.0	28.50	12.8	32.15
2	No	25.00	14.0	28.50	12.8	32.15
3	Yes	25.00	−14.4	21.4	−16.4	17.89
4	No	25.00	−14.4	21.4	−16.4	17.89

*ΔP1 and ΔP2 correspond, respectively, to the percentage variations imposed on C_0 as a result of the first (P1) and second (P2) step disturbances.

3. Results and Discussion.

3.1. Empirical model of the hybrid system of textile effluent treatment.

The results obtained from the execution of the assays of the experimental design matrix are presented in Table 5. It can be observed that among the many conditions that were tested, the dye concentration in the output of the treatment system varied from 0.94 mg.L^{-1} to 9.81 mg.L^{-1}, with an average value of 3.81 mg.L^{-1}.

TABLE 5. Results of the execution of the experimental design matrix

x_1 (Co [mg.L^{-1}]) Coded (Real)	x_2 (I [A]) Coded (Real)	x_3 (Mo [mg.L^{-1}]) Coded (Real)	CS (mg.L^{-1})
−1 (16.07)	−1 (1.81)	−1 (601.19)	3.01
−1 (16.07)	−1 (1.81)	+1 (898.81)	2.69
−1 (16.07)	+1 (4.19)	−1 (601.19)	3.39
−1 (16.07)	+1 (4.19)	+1 (898.81)	3.33
+1 (33.93)	−1 (1.81)	−1 (601.19)	9.80
+1 (33.93)	−1 (1.81)	+1 (898.81)	9.81
+1 (33.93)	+1 (4.19)	−1 (601.19)	3.35
+1 (33.93)	+1 (4.19)	+1 (898.81)	1.37
0 (25.00)	0 (3.00)	0 (750.00)	2.70
0 (25.00)	0 (3.00)	0 (750.00)	2.53
0 (25.00)	0 (3.00)	0 (750.00)	2.80
−1.68 (10.00)	0 (3.00)	0 (750.00)	0.94
+1.68 (40.00)	0 (3.00)	0 (750.00)	7.21
0 (25.00)	−1.68 (1.00)	0 (750.00)	1.02
0 (25.00)	+1.68 (5.00)	0 (750.00)	1.37
0 (25.00)	0 (3.00)	−1.68 (500.00)	4.65
0 (25.00)	0 (3.00)	+1.68 (1000.00)	4.82

The data presented in Table 5 were analyzed using Statistica software, version 11, resulting in the calculation of factors effect on the response variable (CS), and also in obtaining the coefficients of the empirical model for prediction of the dye concentration in the output of the hybrid system for textile effluent treatment. Results are shown in Table 6.

Table 6. Estimated effects for the dye concentration response at the output of the treatment system and regression coefficients of the empirical model

	Effects	Regression coefficients	p-value
Mean		2.5955	0.0245*
x_1	3.2897	1.6448	0.0063*
$(x_1)^2$	1.5341	0.7671	0.1471
x_2	−1.9468	−0.9734	0.0567
$(x_2)^2$	−0.5067	−0.2534	0.6070
x_3	−0.3026	−0.1513	0.7336
$(x_3)^2$	2.0018	1.0009	0.0710
x_1:x_2	−3.9775	−1.9888	0.0092*
x_1:x_3	−0.3975	−0.1988	0.7321
x_2:x_3	−0.4325	−0.2162	0.7098

* Statistically significant terms at 95% confidence

Besides the mean, only the linear term of x_1, and the interaction of this variable with x_2 show as being significant at 95% confidence. However, all the terms were maintained with the aim of obtaining an empirical model with the largest determination coefficient possible.

Therefore, the empirical model adjusted to show the dye concentration in the output of the hybrid treatment system, as a function of the affluent dye concentration, intensity of electric current used on the electrodes and dosing of *Moringa Oleifera Lam* extract, was previously shown in Equation (1), but with the following coefficients:

$a_1 = 2.5955$, $a_2 = 1.6448$, $a_3 = -0.9734$, $a_4 = -0.1513$, $a_5 = 0.7671$, $a_6 = -0.2534$, $a_7 = 1.0009$, $a_8 = -1.9888$, $a_9 = -0.1988$ and $a_{10} = -0.2162$.

In order to carry out the F test and consequent evaluation of model validity, variance analysis (ANOVA) is necessary. As shown in Table 7, the adjusted empirical model had determination coefficient (R^2) of 0.8542, which indicates that the model explains 85.42% of the total variation in the response. Moreover, as the value of $F_{calculated}$ is greater than $F_{tabulated}$, it can be considered that the model is statistically valid at 95% confidence.

Table 7. ANOVA for output dye concentration response

Source of variation	Sum of squares	Degrees of freedom	Mean squares	$F_{calculated}$	$F_{tabulated}$ $F_{0.05;9;7}$	p-value
Regression	102.111	9	11.346	4.556	3.677	0.029
Residual	17.431	7	2.490			
Total	119.542	16				

Coefficient of determination, $R^2 = 0.8542$

However, according to [34], for the model to be considered predictive, $F_{calculated}$ should be four or five times greater than $F_{tabulated}$. This requirement was not met by the adjusted model, which may demonstrate a certain fragility and chance of error in the forecast of dye concentration in the treated effluent.

[35] concluded that despite electrocoagulation has many advantages, it has few applications in large scale due to difficulties in designing a large-scale reactor. Factors such as the drainage regime, geometry of the electrodes and distribution of the electric current make process modeling a hard task.

3.2. **Implementation and training of the ANN.**

3.2.1. *Training and validation database of the ANN.* After variance analysis, it was concluded that the adjusted empirical model (Equation (3)) has limited forecast capacity. However, it is important to highlight the high complexity of the electrocoagulation process in a continuous flow reactor. In addition, the dye concentration in the output of the treatment system cannot be measured in real time by spectrometry due to the influence of residual iron. Therefore, Equation (3) was used to generate the data destined to training and validation of the ANN in charge for control of the hybrid system of textile effluent treatment.

The control set point was defined as the mean of the results obtained for the dye concentration in the output of the hybrid treatment system (3.81 $mg.L^{-1}$) under the different conditions tested, presented in the experimental design matrix (Table 5).

A total of 411 combinations of ANN input variables were generated, with disturbances varying in the range of $\pm 10\%$ in relation to C_0, which met the defined set point. Of this amount of data, 70% was directed to training of the ANN, while the remaining 30% was reserved for validation.

3.2.2. *Determination of the structure of the ANN.* Table 8 shows the test results carried out to determine the ANN structure destined to control the hybrid system of textile effluent treatment. In accordance with the performance criterion, Mean Percentage Error for both output variables, it is possible to state that structures 6, 10, 11 and 12 had equivalent performances. Therefore, for security, the most robust configuration was chosen, containing 9 and 12 neurons, respectively.

Table 8. Tests to choose the structure of the ANN

	ANN Architecture	Mean Percentage Error [I] (%)	Mean Percentage Error [Mo] (%)
1	7:11:2	4.46	9.81
2	7:13:2	8.58	26.36
3	7:15:2	3.11	9.51
4	7:17:2	1.70	4.51
5	7:21:2	0.31	3.12
6	7:23:2	0.05	1.81
7	7:8:10:2	0.29	2.32
8	7:8:11:2	0.19	4.06
9	7:9:9:2	1.29	3.31
10	7:9:10:2	0.02	1.71
11	7:9:11:2	0.03	1.76
12	7:9:12:2	0.01	1.77

3.3. **Evaluation of ANN controller action on the hybrid reactor for textile effluent treatment.** The values of I and Mo that provided the output value equal to the set point (3.81 $mg.L^{-1}$) were calculated using the empirical model for prediction of the dye concentration in the reactor output stream, considering affluent dye concentration of 25.00 $mg.L^{-1}$. Thus, in all the assays to evaluate the performance of the ANN controller, the I and Mo variables assumed initial values of 2.19 A and 872.00 $mg.L^{-1}$, respectively.

Figure 2 shows a demonstrative graph of CS in a scenario where the treatment system is submitted to two consecutive positive step disturbances, that is, at two moments the affluent dye concentration underwent an increase.

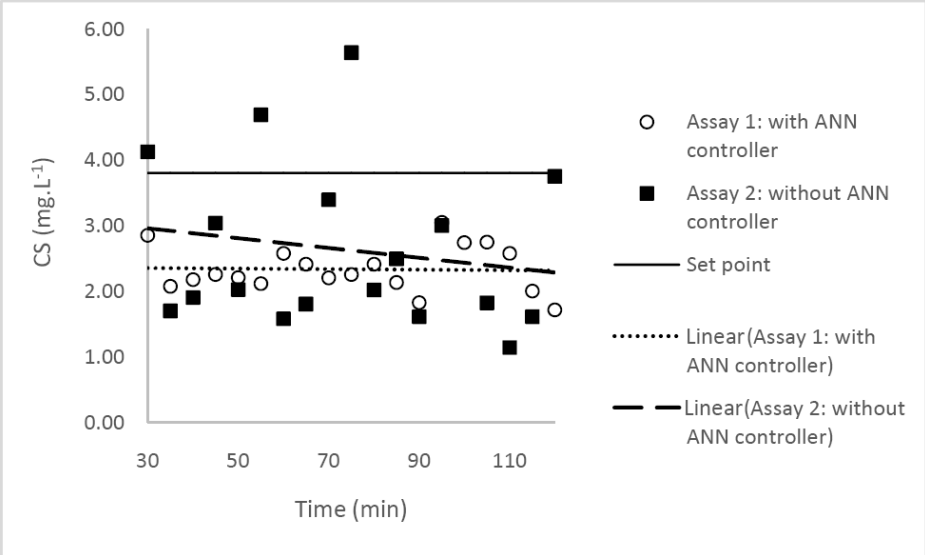

FIGURE 2. Dye concentration in the output of the hybrid treatment reactor given two consecutive positive step disturbances (Assays 1 and 2)

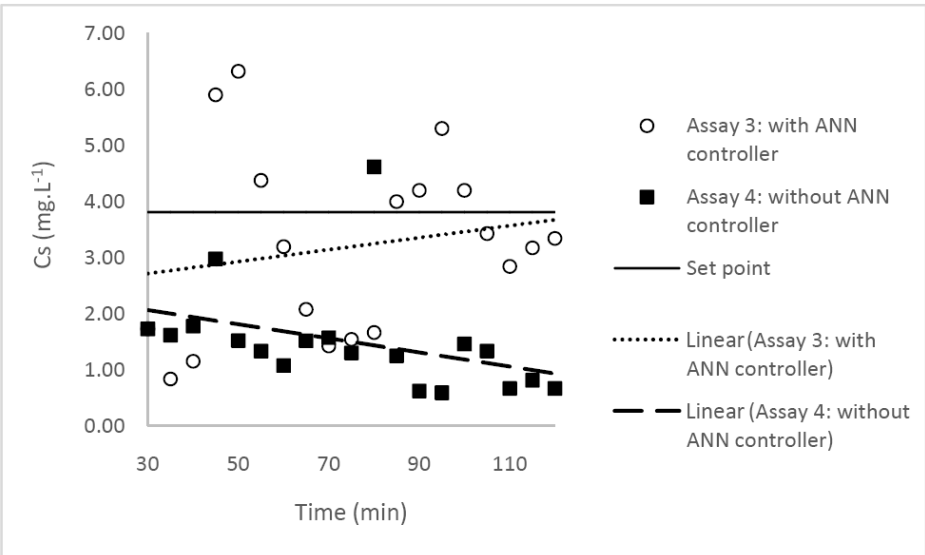

FIGURE 3. Dye concentration in the output from the hybrid treatment reactor given two consecutive negative step disturbances (Assays 3 and 4)

On analyzing Figure 2 it is possible to perceive that from the beginning the treatment system operated far from the set point, which indicates an error in the forecast from the adjusted model.

Considering the data obtained for the system operating under the action of the ANN controller (Assay 1) a lower oscillation can be seen when compared to the results presented by the system without the action of the controller (Assay 2). Moreover, a line of linear tendency can be drawn for the two situations tested; under the controller action, a tendency to stability can be observed, while in the absence of the controller there is a tendency to divergence from the set point.

Corroborating with the performance demonstrated by the ANN controller when the system was submitted to two positive step disturbances, when these disturbances are negative (Figure 3), that is, the affluent dye concentration suffers two successive decreases,

the linear tendency lines demonstrate that the configuration with ANN controller (Assay 3) approximates to the set point, while in the absence of the ANN controller (Assay 4) there is even greater divergence from the set point.

Besides the controlled variable behavior shown in Figure 3, it is important to highlight the controller actions imposed on the manipulated variables of intensity of electric current and concentration of *Moringa Oleifera* extract. After detecting the two disturbances inserted into the system, both reducing the affluent dye concentration, the ANN controller reduced the intensity of electric current from 2.19 A to 1.73 A and then to 1.34 A. However, the ANN controller increased the concentration of *Moringa Oleifera* extract to 974.7 mg.L^{-1}, in order to compensate the drop in electric current, but subsequently reduced the coagulant concentration to 500 mg.L^{-1}. These actions are in accordance with the principle of saving energy.

4. **Conclusions.** In accordance with the results shown in this study, the application of the ANN controller in the hybrid system of textile effluent treatment can be evaluated as satisfactory. For the assays carried out, the performance of the ANN controller in manipulation of the two variables (I and Mo) was important when the system was submitted to step disturbances in the affluent dye load.

Despite the controller not being able to maintain the controlled variable at the set point, the experimental data demonstrates that the action was positive, either diminishing the oscillation or making the controlled variable register in regions closer to the set point when compared to the system without the controller supervision.

It is important to highlight that the ANN provided a controller with capacity of manipulating two variables. At assay where the affluent dye load was reduced twice consecutives (by the insertion of two step disturbances), the controller chose to reduce electric current intensity in detriment of the concentration of the natural coagulant, according to the criterion of saving energy used in the elaboration of the database destined for training of the ANN.

It was also observed that the absence of on line dye concentration measurement in the reactor output stream may have been a limiting factor to the controller not achieving better results. The use of an empirical model to mitigate this difficulty was important; however, the forecast errors (inherent to a complexly modeled system) had possibly affected the controller performance.

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