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Optimization of the artificial neuronal network for the degradation and mineralization of amoxicillin photoinduced by the complex ferrioxalate with a gradual and progressive approach of the ligand

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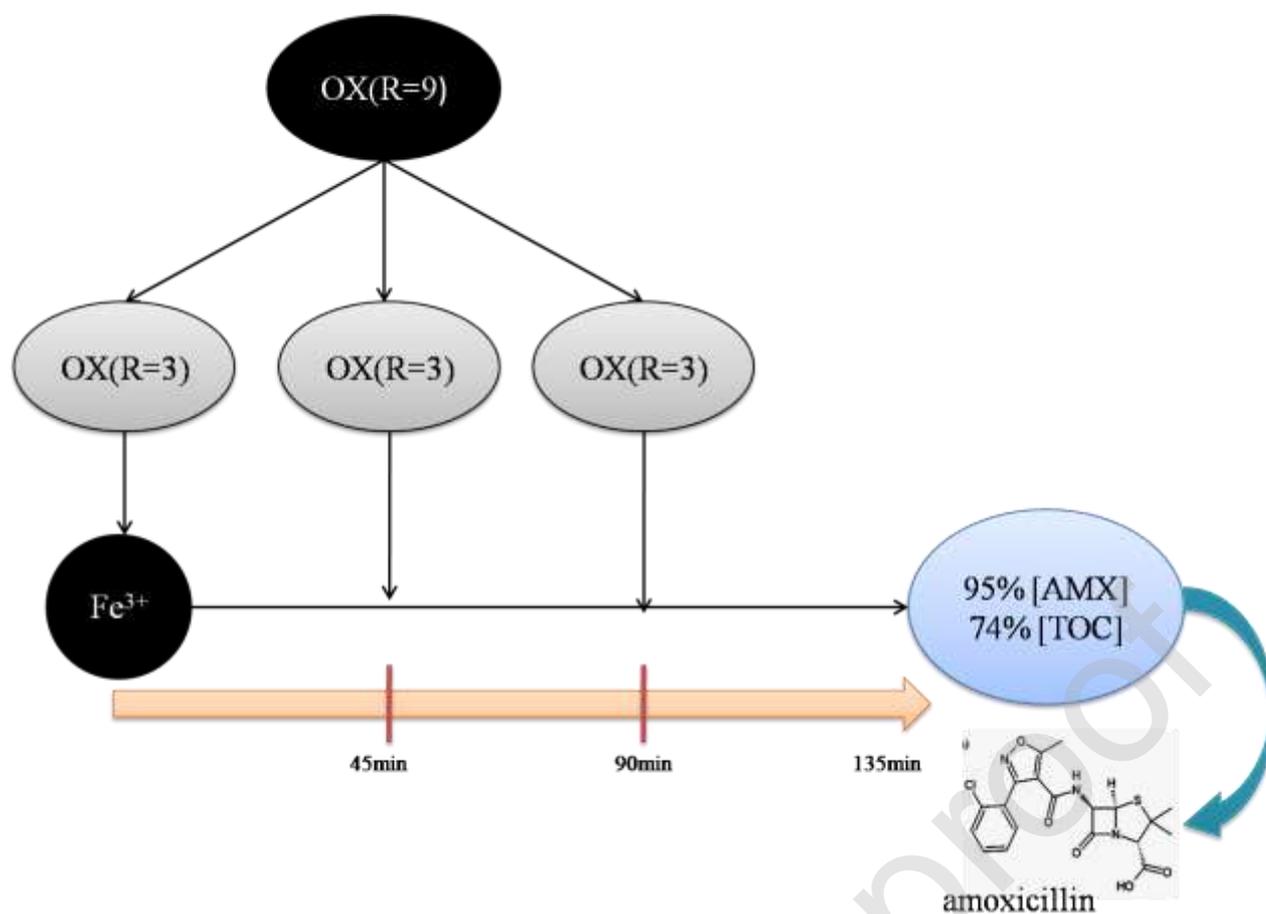
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Graphical abstract



Highlights

- The use of the Fe^{3+} -Oxalate complex under UV light was studied
- This study is done with an unadjusted pH, with a result, in the end, of a pH final to neutrality.
- The using an approach progressive and gradual of the oxalate
- An artificial neural network optimized and modeled is used to simulate the degradation and mineralization of amoxicillin.

Abstract

In this work, the Ferrioxalate complex was used to mineralize the widely used antibiotic amoxicillin (AMX). The effect of operational parameters such as Fe^{3+} concentration, the molar ratio (Oxalate/ Fe^{3+}), and initial pH was studied for achieving high efficiency of degradation and mineralization. The effect of inorganic ions in the degradation of AMX was also investigated. Optimization of an Artificial Neural Network (ANN) to predict the performance of the process

was realized. Neural networks were applied to model AMX degradation using 75 experimental data. Analysis of the results shows that the oxalate: iron ratio is limited to 3 with a Fe^{3+} concentration of 0.35 mM. In order to avoid this limitation, an alternative solution was adopted to increase the molar ratio with the gradual and progressive use of oxalic acid ligand. Almost total degradation and mineralization of AMX was achieved at the free initial pH of 2.8 and final pH of 6. The study of the effect of inorganic ions showed that bicarbonate and sulfate ions play an important role in contrast to Cl^- ions with no noticeable influence. Neural network application resulted in a MSE of 1.1543×10^{-5} and a correlation coefficient r of 0.99 for AMX degradation and MSE of 1.12162×10^{-5} with r of 0.99 for mineralization. The model can describe successfully the percentage of degradation and mineralization of AMX under various conditions. ANN and NSGA-II (Non-dominant Sorting Genetic Algorithm -II) hybrid method to solve a multi-objective problem was proposed to determine the optimal ($\text{Fe}^{3+}/\text{Ox}/\text{UVA}$) operating and process parameters.

Keywords: Complex, Degradation, Mineralization, Artificial Neural Network, Injection method, Genetic algorithm.

1. Introduction

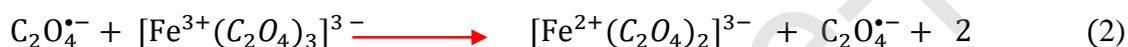
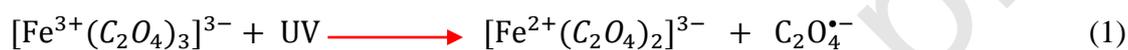
Pharmaceuticals are a class of health and care products widely used to promote human, animal, and plant health [1-3]. Among them, antibiotics are the most used drugs for the prevention or treatment of bacterial infections [3]. Antibiotics are subsequently discharged into various waters, mainly by municipalities and pharmaceutical laboratories. They are increasingly recognized as contaminants, bio-accumulative in the recipient environment (aquatic and terrestrial), and dangerous chemicals [4-5]. Effluents containing antibiotics must be treated chemically or physically to reduce the adverse effects of contaminated water [6-7]. Medicine comprises a wide range of various chemical structures (compounds of excreted metabolites) including AMX, which is a β -lactam antibiotic used as a broad-spectrum first-line anti-infectious treatment [8-10]. The study of AMX harmful environmental impact in aquatic environments is of utmost importance.

The photo-Fenton process is an advanced oxidation process (AOP) generating hydroxyl radicals, when hydrogen peroxide reacts with an iron solute under UV radiation. The complex $[\text{Fe}(\text{H}_2\text{O})_5\text{OH}]^{2+}$ hydroxo formed at pH ~ 3 is photoactive generating Fe^{2+} ions [11-13].

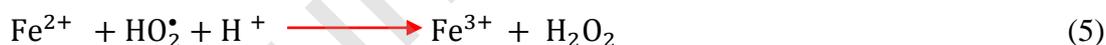
The photo-Fenton process is very effective in the pH range ($2 < \text{pH} < 4$). The inefficiency of the process found at higher pH values is generally attributed to the precipitation of ferric oxyhydroxide [14].

Fe^{2+} ions can be better regenerated by the addition of chelates of organic acids such as carboxylates, hydroxyl-carboxylates of amino-polycarboxylates, and natural organic acids. These chelates coordinate with Fe^{3+} , thus inducing a photochemical reduction of Fe^{3+} to Fe^{2+} via a ligand-to-metal charge-transfer (LMCT) to generate Fe^{2+} [15-17].

The photo-decomposition reaction (charge transfer from the ligand to the metal) of the Fe^{3+} /oxalate complexes is written as follows [17-18]:



According to the above reactions, photolysis of the Fe^{3+} complex is followed by dissociation of the oxalate radical $\text{C}_2\text{O}_4^{\bullet-}$, the latter reacts with molecular oxygen to give $\text{O}_2^{\bullet-}$ or is in equilibrium with $\text{HO}_2^{\bullet-}$ ($\text{pK}_a = 4.8$). The disproportionation product of $\text{HO}_2^{\bullet-} / \text{O}_2^{\bullet-}$ and H_2O_2 according to the following reactions [19]:



The hydrogen peroxide formed from $\text{HO}_2^{\bullet-} / \text{O}_2^{\bullet-}$ reacts with Fe^{2+} giving rise to the Fenton reaction [18].



Besides, chelates increase the solubility of iron and allow the photo-Fenton process to operate in a wider pH range instead of a specific pH around 3 [20- 21]. The significant effect of chelates on the degradation of organic pollutants has been attracting considerable attention over the last decades [22].

The lack of selectivity of $\bullet\text{OH}$ radicals in AOP reaction mechanisms makes it difficult to use phenomenological kinetic models and simple description models [23]. Thus, an artificial neural network (ANN) has been used as an alternative tool for modeling complex industrial processes [24]. ANN is of great interest in chemical engineering, including the AOP study [25]. However, it must be trained with a relevant set of data to model the neural network and to address the inaccessible complexity to the phenomenology. Thus, it must adjust to generate responses from a set of entries [26]. ANN is a modern modeling tool consisting of input, output, and hidden layers whose outputs are sums of weighted inputs. It is a technique, which allows better treatment of quantitative variables with exceptional learning from experience and estimation of uncertain systems with reliable results [23-24]. In addition, finding optimal conditions of the operating parameters to achieve the best AMX degradation and mineralization with the ($\text{Fe}^{3+}/\text{Ox}/\text{UVA}$) process is a complex task. In this respect, a computer-based artificial intelligence technique, such as the genetic algorithm (GA), is a very helpful tool for solving nonlinear stochastic optimization problems [27].

The objective of this paper is to work with solutions at unadjusted (initial) pH to obtain a final pH close to 7. A thorough investigation of the effect of influential parameters is undertaken as well as that of inorganic ions, with the aim of achieving degradation and mineralization of potential pharmaceutical pollutant Amoxicillin. For this purpose, several artificial neural network (ANN) models were developed to simulate the degradation and mineralization of AMX using the ferrioxalate complex under UVA light. The performance of the network was optimized by changing the network type, the training function, the adaptation learning function, and the transfer function for each input and output layer to obtain the best fit between the experimental and modeling data. Also, the non-dominated sorting genetic algorithm (NSGA-II) was employed to optimize AMX degradation and mineralization design.

2. Materials and methods

2.1. Chemicals and reagents

Analytical grade amoxicillin (AMX, $\text{C}_{16}\text{H}_{19}\text{N}_3\text{O}_5\text{S}$), FeCl_3 (97% purity), $\text{Fe}(\text{SO}_4)_2 \cdot 6\text{H}_2\text{O}$ (99%), H_2O_2 50% (w/v), NaOH (98%), Na_2SO_4 (> 99%), KSCN (99%) were supplied by Sigma-

Aldrich, HCl (37% v/v), NaHCO₃ (99%), NaCl (99.5%), by Across Organics, hydrated oxalic acid (C₂H₂O₄, 2H₂O) by Merck. All solutions were prepared with high-purity water obtained from a Millipore Milli-Q system.

2.2. Analysis method

The experiments were performed in a double-walled photoreactor with a laboratory-scale cooling circuit equipped with a 24 W UV_A light simulator (Philips PL/L).

Typically, an AMX solution of 100 mg/L initial concentration with a known initial pH at room temperature was first introduced into the photoreactor. The solution was constantly stirred magnetically at 200 rpm to ensure a good homogenization. Before irradiation, a volume of oxalic acid of known concentration was introduced to first acidify the reaction mixture and then the iron solution was added, the total reaction volume was kept at 900 mL throughout the experiments.

The residual concentration of AMX was analyzed by a Waters 996 Photodiode Array Detector HPLC system, which includes a Waters 600 LCD Pump. The column used type C-The mobile phase was a mixture of acetonitrile/ultrapure water (05/95, v/v) and 0.1% of formic acid with a flow rate of 1 mL/min and a sample injection volume of 20 µL. The retention time was about 6 min with a wavelength of 228 nm. Total organic carbon (TOC) analysis was carried out using a TOC-VCPH/CPG Shimadzu total organic analyzer. Since the use of oxalic acid as a ligand influences the TOC results, all manipulations were replicated with the same operating conditions but without AMX, a subtraction of the two results was presented in all results of the follow-up mineralization. A Thermo Scientific DIONEX DX120 ion chromatography system with a stationary phase consisting of an AS19 anion exchange column (4 × 250 mm) and a mobile phase of KOH solution (12 M) was used for the determination of oxalic acid. A gradient elution mode was used for analysis. The flow rate was set at 1 mL/min [27]. A retention time of 19 min was taken for oxalic acid. Fe³⁺ was analyzed performed by spectrophotometry; the technique is based on the use of a complexing agent between Fe³⁺ and SCN⁻ [26].

3. Results and discussion

3.1. Effect of Fe³⁺

Before starting this study, we carried out a comparison between the Photo-Fenton process ($\text{Fe}^{2+}/\text{H}_2\text{O}_2/\text{UV}$) and the modified Photo-Fenton ($\text{Fe}^{3+}/\text{Ox}/\text{UV}$) process using an equal concentration of 0.05 mM for Fe^{3+} , Fe^{2+} , Ox, H_2O_2 and an AMX concentration of 100 mg/L. According to (**Fig. 1**), a slight difference between the two processes can be observed, where the percent decrease in AMX is larger for the modified photo-Fenton process than the initial photo-Fenton process.

It can also be noted that the degradation kinetics of AMX is faster for the photo-Fenton process. This is a significant advantage as the production of hydroxide radicals is imminent for the photo Fenton process while for the modified photo-Fenton process, it takes longer to produce H_2O_2 in the solution (reaction.5). Then, reaction with Fe^{2+} to produce in turn hydroxide radicals via the reaction .6. Also, in this study, a variation of the concentration of Fe^{3+} keeping the molar ratio $R = (\text{Ox} / \text{Fe}^{3+})$ constant was realized in the beginning. The best result was obtained for a concentration of 0.35 mM (**Fig.2**). Beyond this value, the rate of degradation and mineralization decreased. Other results Fig S1 were obtained for higher concentrations of Fe^{3+} up to 0.65 mM. According to this data, It has also been observed that the rates of degradation and mineralization decreasing with an increasing Fe^{3+} concentration beyond 0.35 mM.

This means that one of the reagents is problematic. And it is due to the increase in the concentration of oxalic acid, that it subsequently inhibits the mechanism.

The solution becomes more acidic at high oxalic acid concentration, which slows down the production of $\bullet\text{OH}$ radicals, due to the non-complexation of Fe^{3+} with $\text{C}_2\text{O}_4^{2-}$ (**Fig. 2 a and b**). Also, as shown in (**Fig.2c and d**) for Fe^{3+} concentrations less than 0.45 mM, Fe^{3+} and $\text{C}_2\text{O}_4^{2-}$ are completely regenerated and consumed respectively, thus proving that complexation between the metal and ion occurs [27- 28].

3.2. Effect of molar ratio

Since the Ferrioxalate complex reaches saturation with 3 moles of the oxalate $\text{Fe}(\text{C}_2\text{O}_4)_3^{-3}$, an optimal molar ratio of 3 was used [29].

Beyond the molar ratio of 3, the increase in oxalic acid concentration led to the same problems already encountered in section 3.1. The diagram of the distribution of ferric hydroxyl species (**Fig. 3**) helps to clarify that with the present conditions and for an initial strong acidic pH value (pH), complexation does not occur, thus limiting the amount of ligands.

For a ratio greater than 3, there is an excess of oxalate, the time that Fe^{3+} regenerates, the oxalate ion acts as an organic compound and would therefore compete with AMX and the intermediates react with free radicals, thus reducing the degradation and mineralization process efficiency [29-30]. As shown in (**Fig. 4**), the target was not reached with a molar ratio of 3. The fact that a molar ratio of 3 is the maximum ratio to be used, requires the use of an alternative solution. Knowing that under favorable conditions, the final pH value increases and it is possible to use another approach to add, after the final pH stabilization, a similar and progressive amount of the ligand. The amount injected each time (1.05 mM) is equivalent to a molar ratio of 3 for a gradual moment of 45 min until the desired quantity to inject is exhausted (**Fig. 5c**). This allowed us to reach a molar ratio of 9, where a total degradation and partial mineralization of AMX are observed in (**Fig. 5a and b**).

3.3. Effect of pH

Working with an unadjusted pH and having a neutral final pH close to 7 is one of the targeted objectives. pH is an important parameter in the POAs processes where Fe^{3+} is used as a catalyst because it affects and controls both the production rate of $\bullet\text{OH}$ radicals and the nature of iron species in solution. The initial pH of the solution was adjusted by HCl (0.01 N) and NaOH (0.01 N) solutions accordingly.

Several pH values were used (2, 4, 6 and 8), the unadjusted pH of 2.8. According to other studies, at high pH values, other ferric species are formed, leading to the total precipitation of $\text{Fe}(\text{OH})_{3(s)}$ in its amorphous form [30], because of its low solubility product ($K_s = 4 \times 10^{-38}$). Below pH of 5, other ferric ions such as Fe^{3+} , $\text{Fe}(\text{OH})^{2+}$, $\text{Fe}(\text{OH})_2^{2+}$ [31-32], exist in the aqueous solution.

It is noted that at too acidic a pH, the degradation and mineralization of AMX decrease by 40 and 50% respectively, compared to initial results (**Fig. 6.a**). However, a high concentration of

oxalate remains in the solution (**Fig. 6. b**) with an observed consumption yield of only 25% at pH 2.

At the small initial pH, weak degradation and mineralization rates were observed with respective yields of 60 and 65%, lower than the corresponding initial results. In addition, a significant amount of $\text{H}_2\text{C}_2\text{O}_4$ remains in solution, with consumption efficiency not exceeding 20%. The remaining $\text{H}_2\text{C}_2\text{O}_4$ in solution at high pH is due to the conversion of Fe^{3+} to other ferric species, which do not form a complex with the ligand. Therefore, the most favorable pH is the initial unadjusted pH of 2.8. The final pH of 6 will be measured.

3.4. ANN modeling

An Artificial Neural Network (ANN) simulates the operating principle of the human brain that manages a flow of information from a database. It is a powerful model for calculating and establishing the complexity of the input-output relationships of a system [30-32]. The artificial neuron receives digital input information from neurons upstream through their weighted connections (each connection has a numeric value: the weight) [33-36].

The first layer receives the input variables ($X_i = \text{Fe}^{3+}$ and $R (\text{Ox}/\text{Fe}^{3+})$) through the input neurons (i), transforms them with the activation function on the input neuron, and sends them to the neurons of the first hidden layer (j). The hidden layer consists of the neurons processing that receives the S-weighted sum (Eq. 7) from the input layer, transforming them using the activation function and finally transferring them to the next layer [37]:

$$S_{ij} = W_0 + \left[\sum_n^i w_{ij} * X_i \right] \quad (7)$$

where n is the number of input elements, X_i the value of the neuron output of the previous layer, W_{ij} the weight value between neurons i and j , and W_0 the added bias.

The production equation in a three-layer network (n neurons in the input layer, m neurons in the hidden layer and p neurons in the output layer) is as follows [38]:

$$Y_k = f_k \left(\sum_{j=1}^m w_{jk} \times f_i \left(\sum_{i=1}^n x_i \times w_{ij} \right) \right) + w_o \quad (8)$$

Y_k is one of the system outputs, f_k and f_j are successively the activation functions of the neuron k of the output layer and the neuron j of the hidden layer; W_{jk} and W_{ij} are successively the weights between the same neuron and the k^{th} exit neuron and the weight between the i^{th} and j^{th} neurons.

Output 1 of the network relates to AMX degradation (concentration of AMX) while Output 2 relates to AMX mineralization (TOC concentration).

Two types of ANN have used the present work, **Feed Forward Back Propagation** and **Cascade Forward Back Spread** [39]. The former, related to the propagation artificial neural network model, consists of input, hidden and output layers. The backpropagation learning algorithm was used to train these networks [40]. The cascade forward back propagation model is similar to the former network, but includes a weight transfer from the input to each layer and from each layer to successive ones [40-41].

Trainlm (Levenberg-Marquard BP), Trainscg (Scaled conjugate gradient BP) training algorithms, Learngd (Gradient descent weight/bias learning) and **Learngdm (Gradient descent with momentum weight bias learning)** learning functions were used in this work. For the hidden layer, two transfer functions were used, Tansig (Hyperbolic tangent sigmoid) and Logsig (Log sigmoid) and for the output layer, the transfer function is perlin and logsin making a total application of 32 models with different algorithms and functions. For all models, the number of neurons of the hidden layer was 10 to achieve the best simulation [35]. **(Fig. 7)** groups all the models. MATLAB software (version 2015a) was used to execute these operations.

The performance of the Feed Forward Back Propagation and Cascade Forward Back Propagation was evaluated using the mean squared error (MSE) and / or correlation coefficient (r) [42-44].

$$\text{MSE} = \frac{1}{Q} \sum_{i=1}^{i=Q} (y_{i,\text{pred}} - y_{i,\text{exp}})^2 \quad (9)$$

$$r = \sqrt{1 - \frac{\sum_{i=1}^{i=Q} (y_{p,i} - y_{\text{exp},i})^2}{\sum_{i=1}^{i=Q} (y_{p,i} - y_m)^2}} \quad (10)$$

Where Q is the number of data points, $y_{p,i}$, the network prediction, $y_{exp,i}$, the experimental response, y_m , the mean of the experimental value and I , a data index.

Table 1 shows the MSE objective for the rest of the work. After optimization, a neuron number ranging from 1 to 8 was chosen.

As shown in **Table.2**, a neuron number of 2 in the hidden layer was chosen based on the low MSE value (1.1534×10^{-5}), the high r -value (0.99) for degradation and to the corresponding values of 1.1216×10^{-5} with r 0.99 regarding the mineralization. (**Fig.8**) represents the optimal neural network scheme used.

(**Fig.9**) shows a comparison between the experimental results with those calculated via neural network modeling. A correlation coefficient of 0.99 for both outputs was obtained; which confirms the fitting of the model to the experimental results and the successful results reproduction by the adjusted model.

3.5. Genetic Algorithm

Genetic algorithms (GA) are stochastic optimization algorithms based on the mechanisms of natural selection and genetics. They were originally developed by John Holland (1975) [45-46]. Any genetic algorithm with a common structure operates in the same way and follows the same methodology. First, a set of solutions or individuals is generated to train the initial population. Subsequently, individuals in the population are assessed and classified into the population. Then, a subset of parents is created to favor the best solutions and from this set, a group of children is generated by reproduction mechanisms (crossover and mutation). After creating the set of children, their performance is evaluated in order to compare their level of performance with the rest of the population and thus guide the construction of the new generation. Then, the process is repeated from this new generation until the stop criterion defined at the start is reached [47-49].

The NSGA-II proposed by Deb *et al.* [50] is a fast and elitist version of the genetic unordered sorting algorithm, which is an evolutionary approach to find an optimal solutions to complex multi-criteria optimization problems [51-52].

In this study, the degradation and mineralization of AMX were taken as objective functions. Decision variables include the two process parameters, the concentration of Fe^{3+} and Oxalate. The computer codes for the optimization of genetic algorithms were developed using MATLAB whose parameter values are given in **Table.3** below. The ANN model formed was integrated into the NSGA-II algorithm in serving as an objective function.

The purpose of applying NSGAI is to optimize the proposed treatment process involving the (Fe^{3+} / Oxalate) complex under UVA light was to maximize the degradation and mineralization of AMX. The results of optimization using GA have shown that the best results were obtained when Fe^{3+} concentration is 0.39 mM and molar ratio (Ox/Fe^{3+}) ranges from 9.4 to 10.2. The results are grouped in **Table.4**.

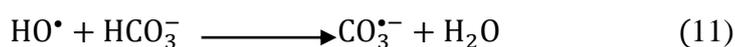
Finally, the performance of the (Fe^{3+} /Ox/UVA) process under the optimal conditions predicted by GA analysis was tested experimentally. Degradation and mineralization values were found to be in good agreement between the predicted values. The ANN coupled with AG (NSGAI) proved the robustness of the proposed model to degrade and mineralize the AMX.

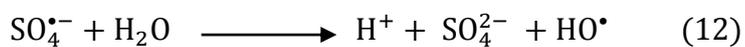
3.6. Effects of the solution matrix on AMX degradation

In this section, different concentrations of some inorganic salts (NaCl , Na_2SO_4 and NaHCO_3) were added to the system to evaluate their effect on AMX removal. The operating conditions were a Fe^{3+} concentration of 0.35 mM and a molar ratio of 9.

From (**Fig.10**), it can be observed that SO_4^{2-} ions influence significantly the progress of the reaction, by increasing their concentration, AMX degradation decreased from 31% and 12% for SO_4^{2-} and HCO_3^- respectively for 100 mg/L concentration of AMX. However, for Cl^- ion, no decrease was noticed.

AMX degradation was considerably reduced with the addition of bicarbonate HCO_3^- ions. Two mechanisms might be involved: either the bicarbonate and sulfate ions play the role of an inhibitor for $\bullet\text{OH}$ radicals or they are complexed with Fe^{3+} (next reaction) [53-55]





The addition of Cl^- up to 100 mM tends generally to affect the reaction mechanism. In such cases, generally, when Cl^- is added to the solution, it acts as a scavenger by trapping the hydroxyl radicals as follows:



The lack of inhibition by Cl^- ions was observed for the AMX oxidation, the reaction of free radicals with AMX is faster than that of Cl^- . The reaction rate of AMX with $\bullet\text{OH}$ is $10^{10} \text{ M}^{-1} \text{ S}^{-1}$ while that of Cl^- with $\bullet\text{OH}$ is $4.3 \times 10^9 \text{ M}^{-1} \text{ S}^{-1}$. [56-57]

4. Conclusion

The Fe^{3+} /oxalate complex under UVA light was used to degrade and mineralize the antibiotic amoxicillin. The study of the operating parameters effect showed that the best AMX degradation and mineralization conditions were obtained for an unadjusted pH of 2.8, a Fe^{3+} concentration of 0.35 mM and a molar ratio of 9 with a gradual and progressive introduction of the ligand and a final pH of 6. Bicarbonate and sulfate ions were found to have an inhibitory effect on the mechanism as the conversion yields decreased down to 31 and 12%, respectively. However, no yield decrease was observed with Cl^- ions. The cascade-type neural network, the Trainl training function and the learning function Learngdm were successfully used for the optimization. The transfer function for the hidden layer used was Logsig while for the output layer Perline was used with a MSE of 1.1957×10^{-5} for degradation and 1.1948×10^{-5} for mineralization. However, an optimization of the hidden layer neuron was carried out for the optimized model. The results showed that the best MSE and correlation coefficient were obtained for a number of neurons of 2 with a MSE of 1.1534×10^{-5} and a correlation coefficient of 0.99 for the degradation. For

mineralization, the respective values were 1.12162×10^{-5} and 0.99. This confirms that the adjusted model can reproduce the results of process with great accuracy. A multi-objective optimization model was also proposed to determine the optimal experimental parameters, where the efficiency of degradation and mineralization of AMX were taken as an objectives. The problem was resolved successfully using the NSGA-II algorithm to obtain the optimal conditions for the ($\text{Fe}^{3+}/\text{Ox}/\text{UVA}$) system under customized conditions.

Author Statement

- **Imene Kahina Benramdane** : Conceptualization- Methodology – Software -Data curation- (Writing - original draft).
- **Nourddine Nasrallah**: Supervision- Visualization.
- **Abdeltif Amrane** : Project administration
- **Mohammed Kebir**: Investigation- Formal analysis- Visualization- review and editing.
- **Mohamed Trari** : Review and editing.
- **Florence Fourcade** : Supervision.
- **Aymen Amine Assadi** : Supervision.
- **Rachida Maachi** : Project administration - Visualization.

Note :

The present work has not been published before in any form whatsoever, that it is not envisaged to publish it elsewhere.

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Figure caption

Fig.1 Comparison between the Photo Fenton process, \blacklozenge -($\text{Fe}^{2+}/\text{H}_2\text{O}_2/\text{UVA}$) and the modified Photo Fenton \blacklozenge -($\text{Fe}^{3+}/\text{oxalate}/\text{UVA}$). Parameters: $[\text{AMX}]_0 = 100 \text{ mg.L}^{-1}$, $[\text{Fe}^{3+}]_0 = [\text{Fe}^{2+}]_0 = [\text{Ox}]_0 = [\text{H}_2\text{O}_2]_0 = 0.05 \text{ mM}$ and $\text{pHi} = 3$, mixed for 45 min.

Fig.2 Effect of the initial concentration of Fe^{3+} , (\blacklozenge - 0.15 mM; \blacklozenge - 0.25 mM; \blacklozenge - 0.35 mM; \blacklozenge - 0.45 mM) on the degradation and mineralization of AMX, (a). Degradation yields of AMX; (b). Mineralization yields of AMX; (c). Consumption yields of oxalic acid; (d). Fe^{3+} oxidation yields. Process parameters: $[\text{AMX}]_0 = 100 \text{ mg.L}^{-1}$, $R=1$ and initial pH unadjusted, mixed for 45 min.

Fig.3 distribution diagram of ferric hydroxyl species as a function of pH for a solution containing 0.35 mM Fe^{3+} and 0.35 mM oxalate. The distribution diagram was obtained by VISUAL MINTEQ Software.

Fig.4 Effect of the molar ratio, (\blacklozenge - $R = 1$; \blacklozenge - $R = 2$; \blacklozenge - $R = 3$) on the degradation and mineralization of AMX, (a). Degradation yields of AMX; (b). Mineralization yields of AMX; (c). Consumption yields of oxalic acid; (d). Fe^{3+} oxidation yields. Process parameters: $[\text{AMX}]_0 = 100 \text{ mg.L}^{-1}$, $[\text{Fe}^{3+}]_0 = 0.35 \text{ mM}$ and initial pH unadjusted, mixed for 45 min.

Fig.5 Influence of the molar ratio with an increase of oxalic acid by an injection method. (a). Degradation yields of AMX; (b). Mineralization yields of AMX; (c). Consumption yields of oxalic acid; Process parameters: $[\text{AMX}]_0 = 100 \text{ mg.L}^{-1}$, $[\text{Fe}^{3+}]_0 = 0.35 \text{ mM}$, $[\text{OX}]_0 = 3.15 \text{ mM}$ ($1.05 \text{ mM} \times 3$) and initial pH unadjusted, mixed for 135 min ($45 \text{ min} \times 3$).

Fig.6 Effect of initial pH on the degradation and mineralization of AMX, (a). \blacksquare -Degradation yields of AMX, \blacksquare -Mineralization yields of AMX and \blacklozenge -pH final; (b). Consumption yields of oxalic acid. Process parameters: $[\text{AMX}]_0 = 100 \text{ mg.L}^{-1}$, $[\text{Fe}^{3+}]_0 = 0.35 \text{ mM}$ and $[\text{OX}]_0 = 3.15 \text{ mM}$, mixed for 135 min.

Fig.7 Schema of the different type, algorithm and function for the modeling and optimization of the ANN.

Fig.8 The ANN optimized structure.

Fig.9 Comparison of the experimental results with those calculated via neural network modeling for outputs 1 (% AMX) and 2 (% TOC). (a). Comparison of the experimental results with those calculated via neural network modeling for outputs 1 (% AMX). (b). Comparison of the experimental results with those calculated via neural network modeling for outputs 2 (% AMX)

Fig.10 Effect of inorganic ions (\blacksquare O_4^{2-} , \blacksquare Cl^- , \blacksquare HCO_3^-) on the degradation of AMX (\blacksquare - AMX), Process parameters: $[\text{AMX}]_0 = 100 \text{ mg.L}^{-1}$, $[\text{Fe}^{3+}]_0 = 0.35 \text{ mM}$, $[\text{OX}]_0 = 3.15 \text{ mM}$ and initial pH unadjusted, mixed for 135 min.

Fig.1

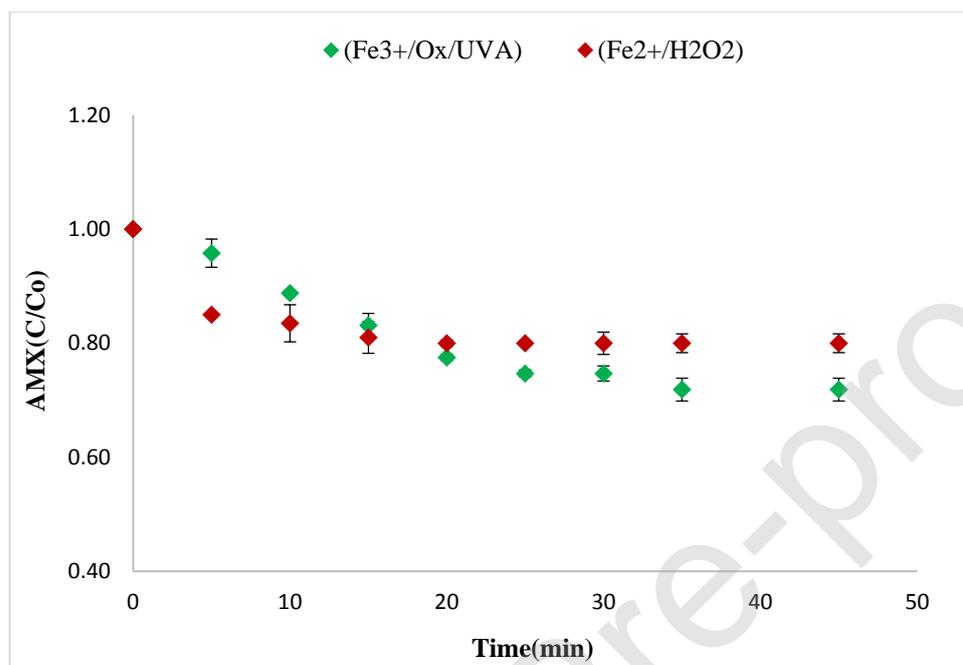


Fig.2

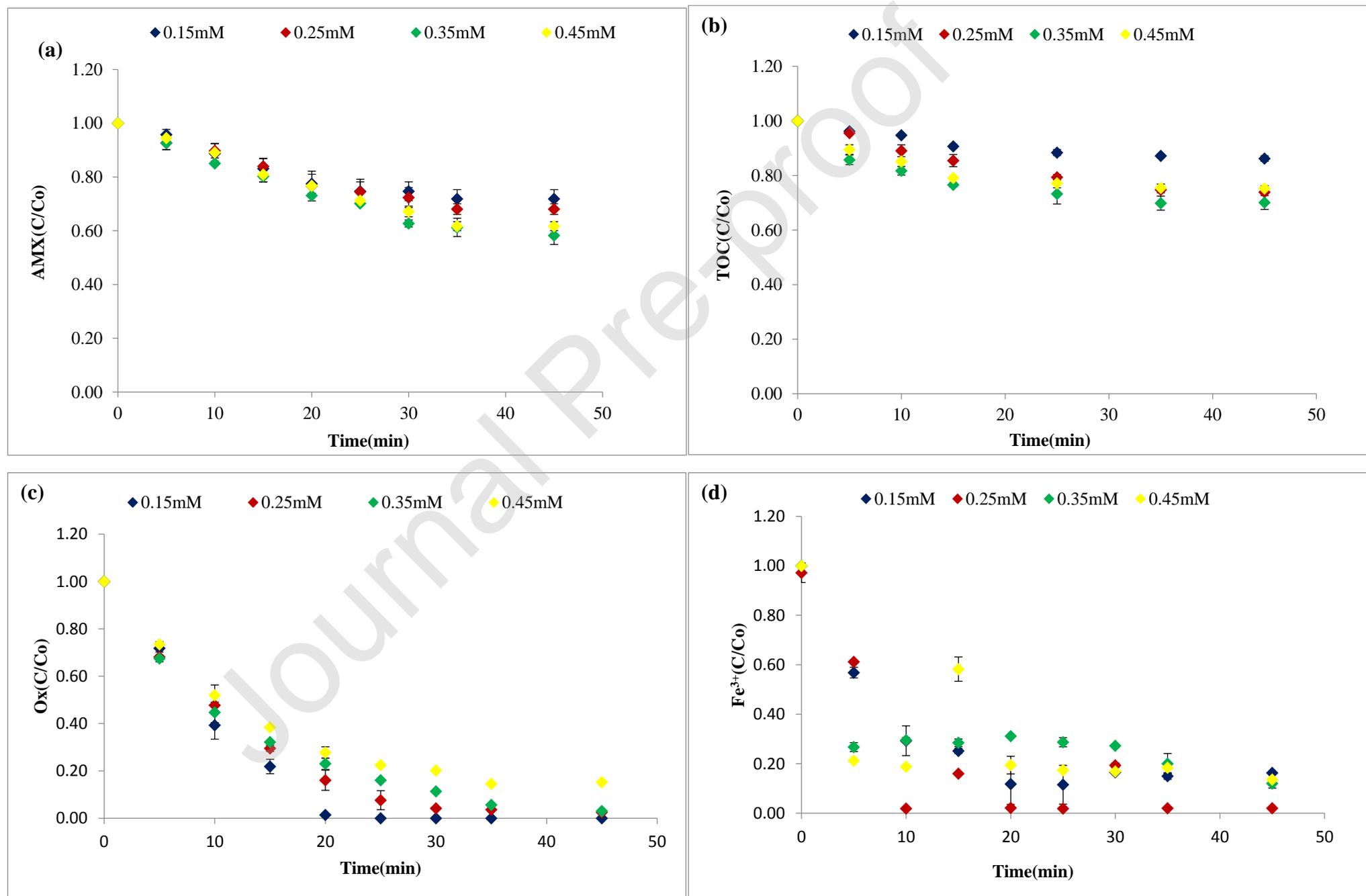


Fig.3

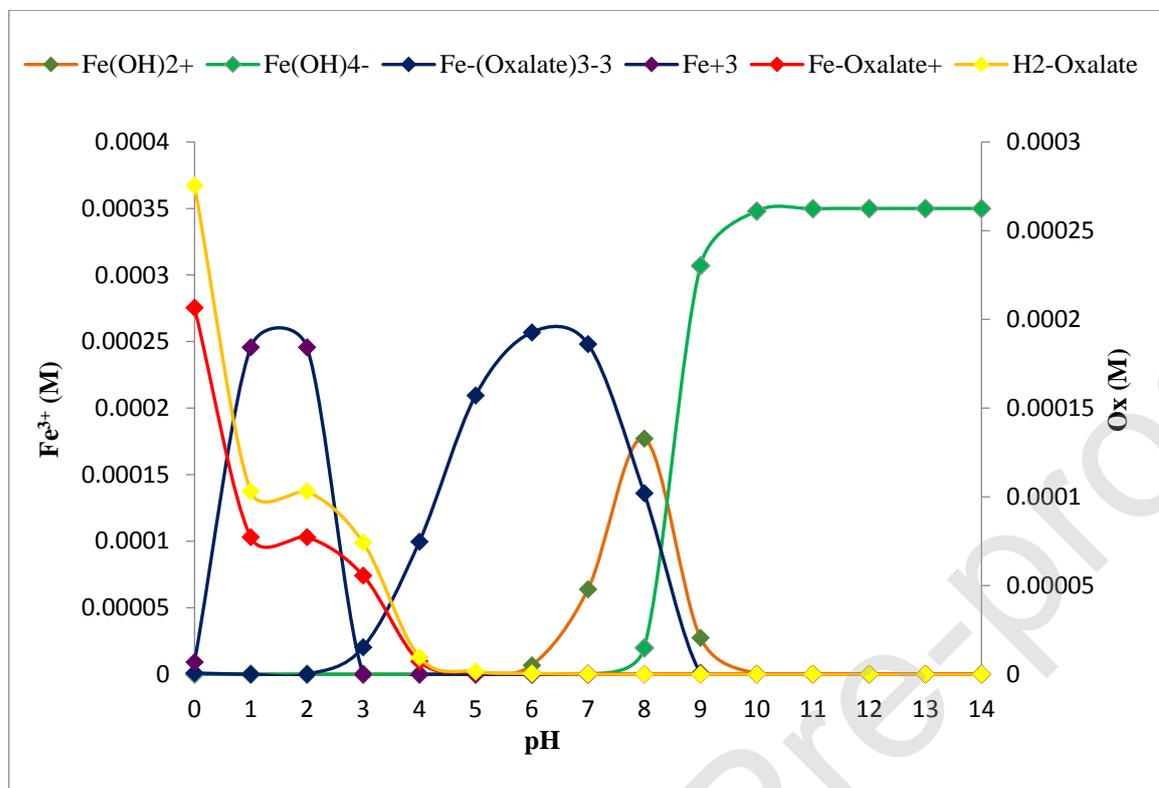


Fig.4

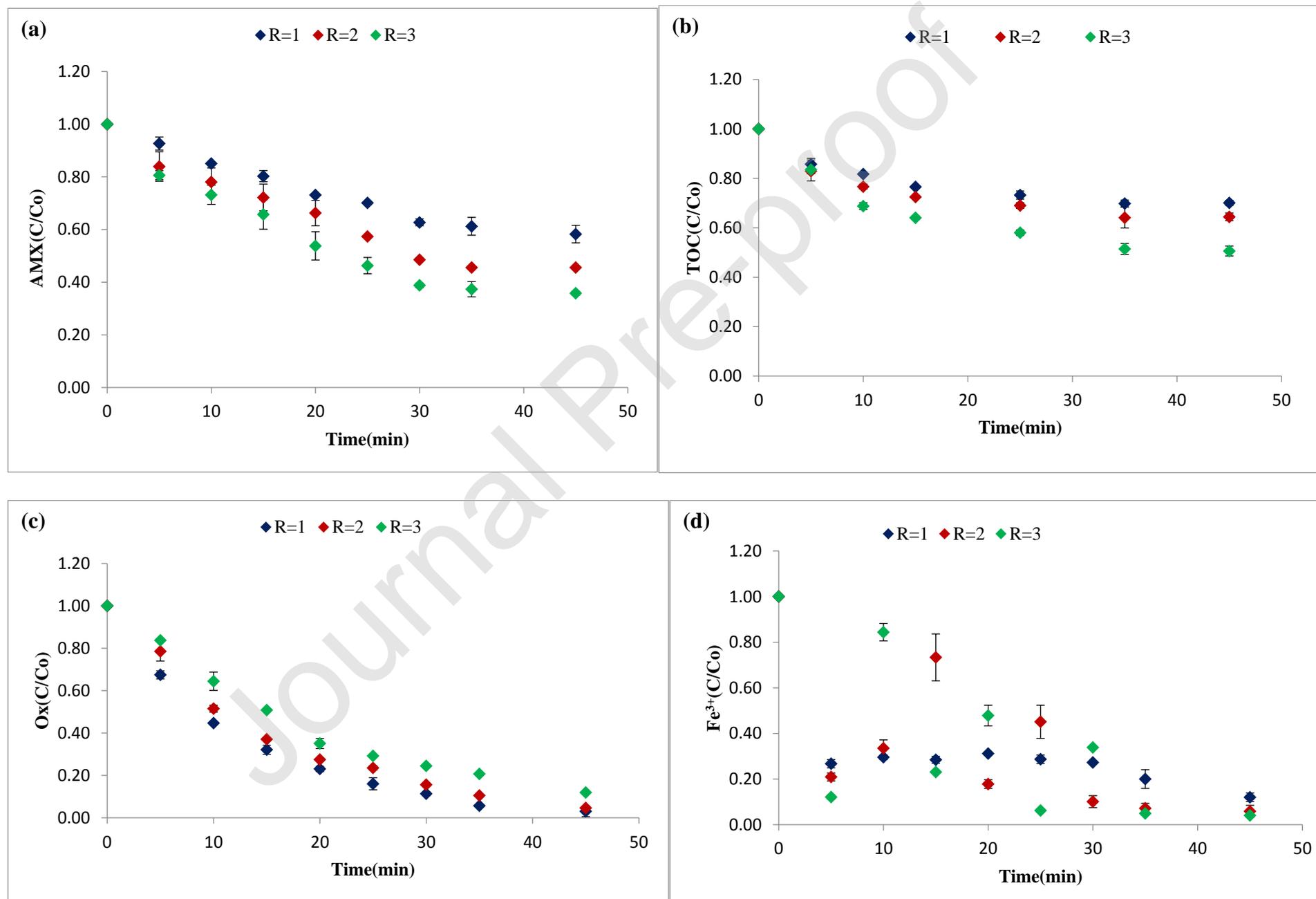


Fig.5

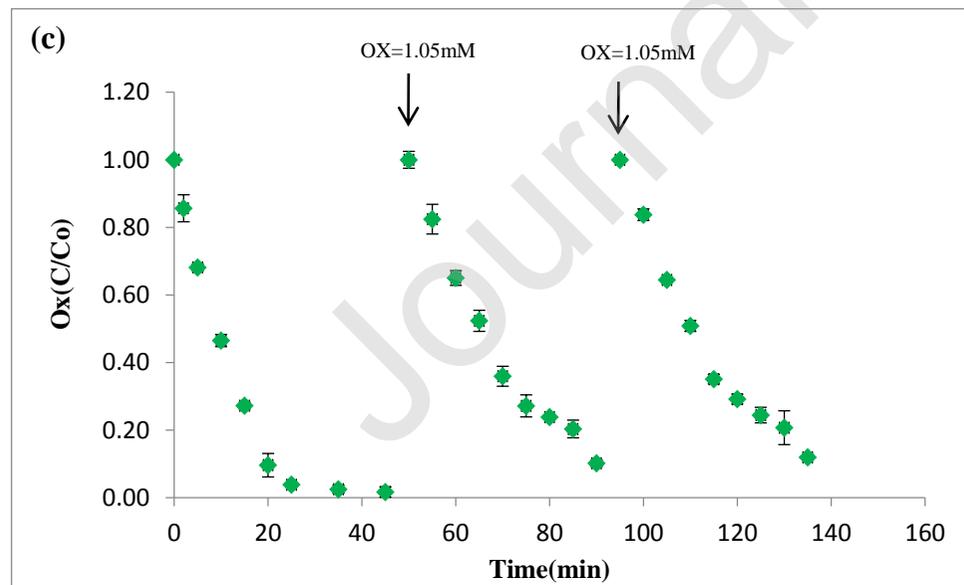
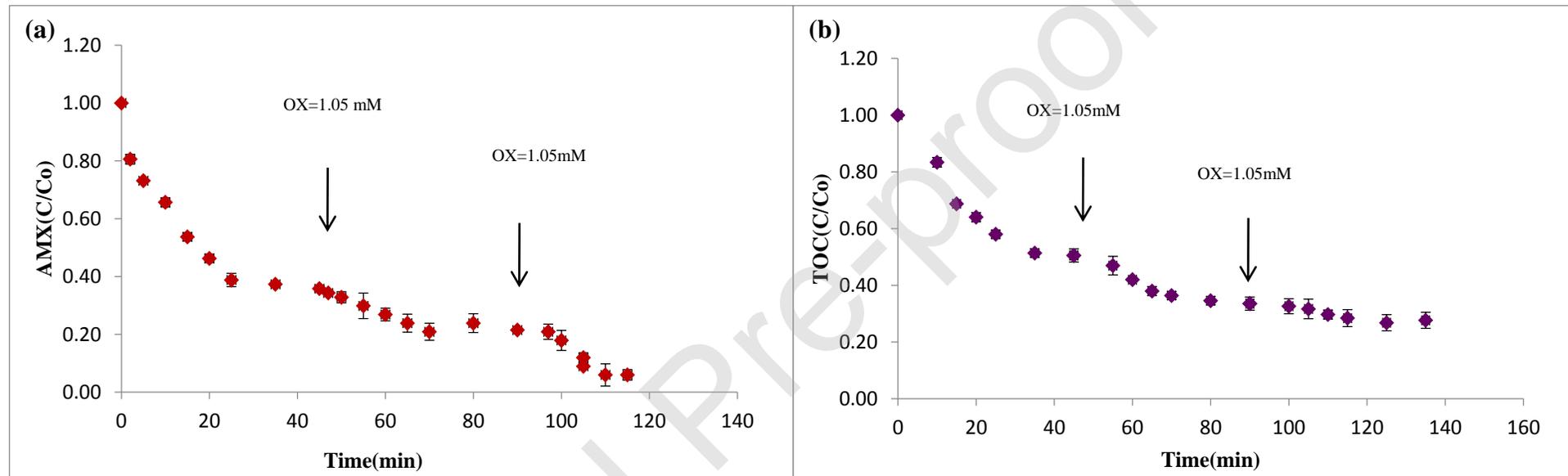


Fig.6

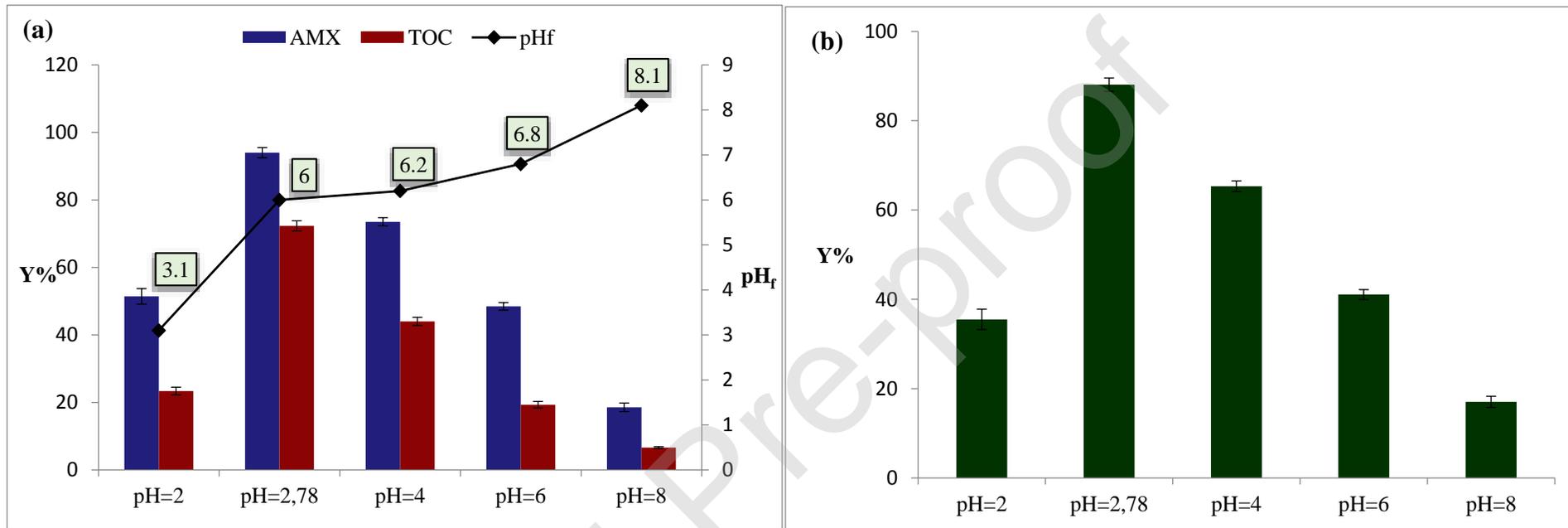


Fig.7

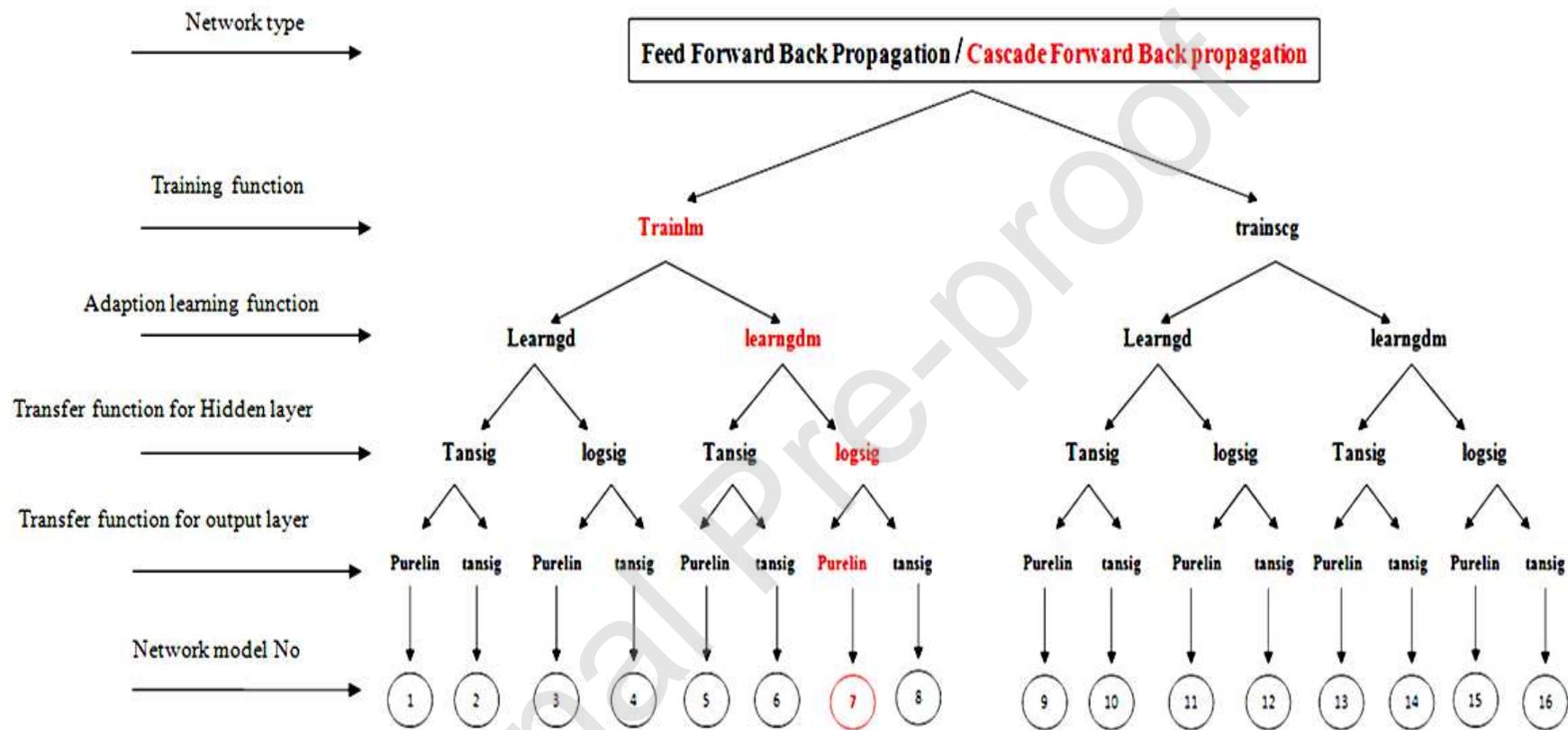


Fig.8

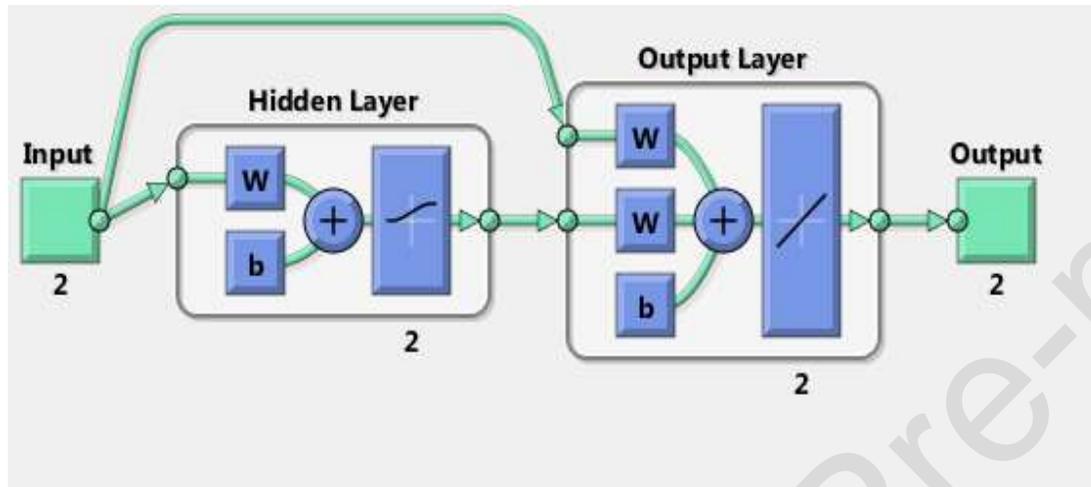


Fig.9

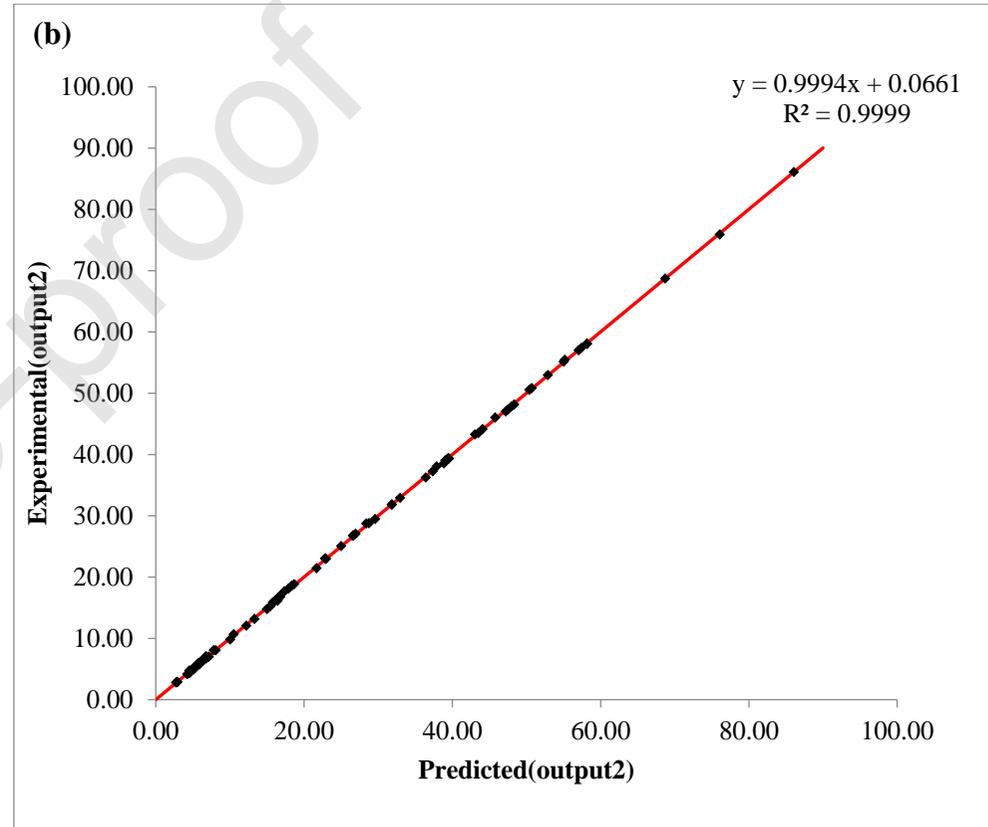
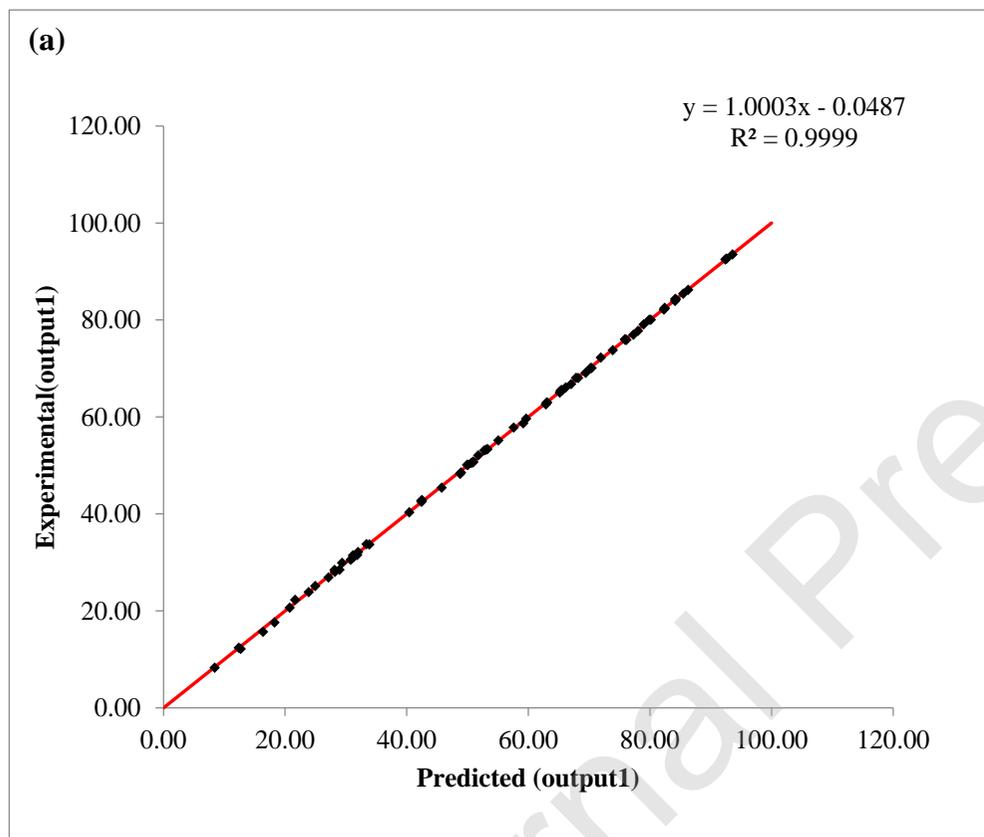


Fig.10

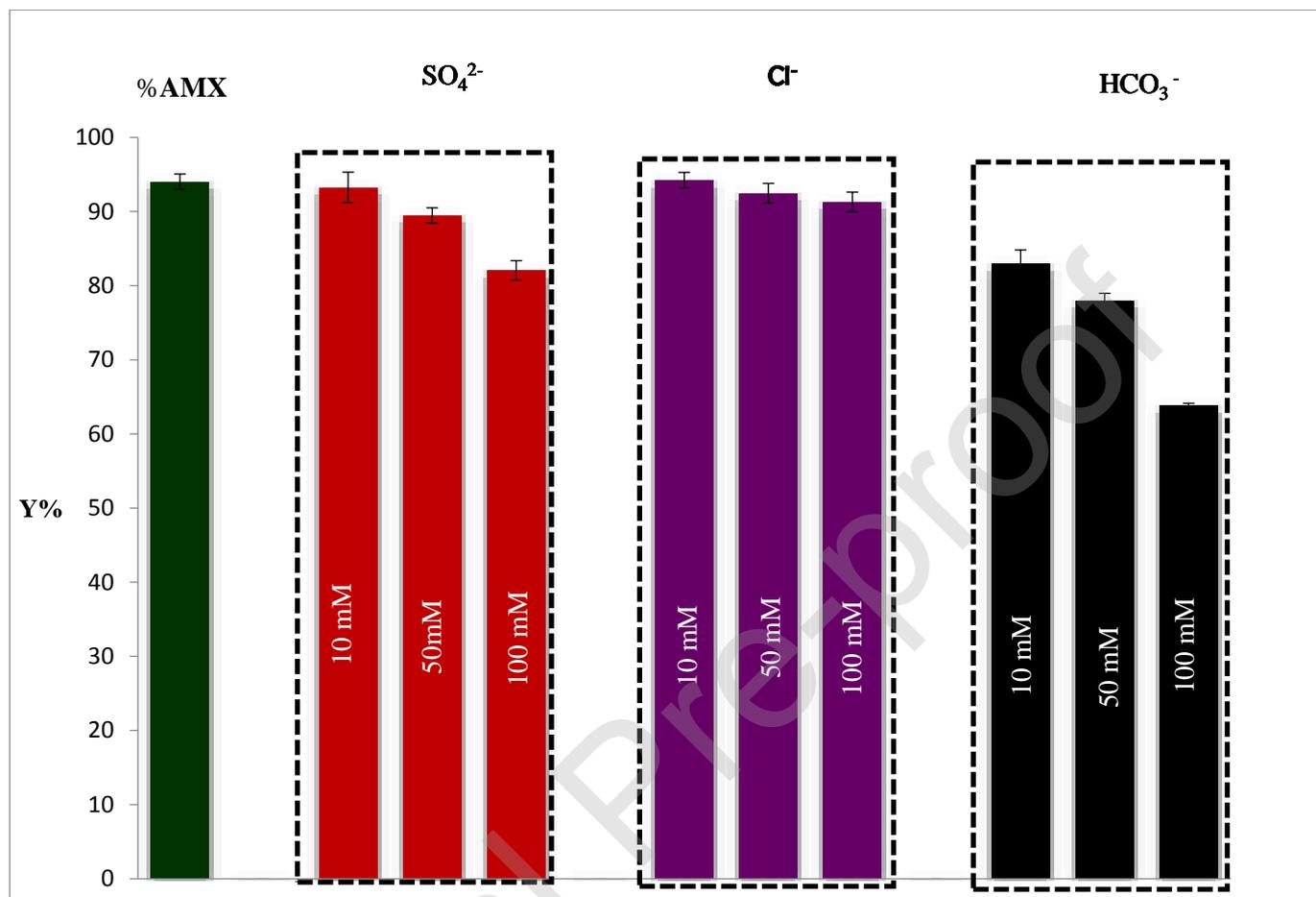


Table.1 The MSE of the ANN Models for both types of networks.

Numbre of neurons	Feed Forward Back Propagation		Cascade Forward Back propagation	
	output 1([AMX])	output 2 ([COT])	output 1([AMX])	output 2 ([COT])
1	0.00014522	1.65143E-05	1.56926E-05	1.28163E-05
2	0.000599189	0.000647383	0.000102425	0.000158567
3	1.52171E-05	2.73573E-05	0.001899822	0.001961148
4	0.02826941	0.086593115	0.030507007	0.086824817
5	8.47637E-05	0.000139967	0.000260609	3.71719E-05
6	3.70679E-05	0.000127639	2.97214E-05	2.92166E-05
7	6.64265E-05	7.03378E-05	1.1957E-05	1.19482E-05
8	0.028293735	0.086733243	0.028273919	0.08671381
9	0.000469778	0.000227214	0.000278718	0.000129881
10	0.001316821	0.001576089	8.0757E-05	0.000439247
11	0.0018198	0.000824118	0.000397543	0.000340885
12	0.028380543	0.086706329	0.028325797	0.094981329
13	0.000118855	0.000145659	0.001045723	0.001878532
14	0.001199719	0.001188769	0.000376937	0.000865203
15	0.001568241	0.002990617	0.000581513	0.000835322
16	0.028626286	0.094980263	0.086789387	0.086789387

Table.2 Effect of the number of hidden neurons on the ANN model performance for both outputs.

Number of neurons	Output 1(%AMX)		Output 2 (COT%)	
	MSE	r	MSE	r
1	0.00036	0.99856	0.00109	0.99012
2	1.15434E-05	0.999954148	1.12162E-05	0.99989
3	1.18874E-05	0.99995	1.14733E-05	0.99989
4	1.15743E-05	0.99995	1.20176E-05	0.99989
5	1.39195E-05	0.99994	1.13726E-05	0.99989
6	1.9235E-05	0.99992	1.63017E-05	0.99985
7	1.23978E-05	0.99995	1.21522E-05	0.99989
8	1.89431E-05	0.99992	1.45052E-05	0.99987

Table.3 Parameter values of the NSGA-II algorithm.

Population size	50
Number of generation	100
Crossover rate	0.8
Mutation rate	0.01

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Table.4 Optimal conditions proposed by GA with their predicted and experimental values.

R	Fe³⁺	Predicted		Experimental	
		[AMX]	[COT]	[AMX]	[COT]
9.4	0.39	94.061	73.78	93.78	73.64
9.5	0.39	94.04	73.87	94.71	73.45
9.7	0.39	93.98	73.08	93.01	73.15
9.8	0.39	93.93	72.86	93.99	73.27
9.9	0.39	93.86	73.60	93.12	74.21
10	0.39	93.78	74.29	94.68	74.88
10.1	0.39	93.65	75.21	94.17	74.91
10.2	0.39	93.51	75.10	94.58	75.9