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Prediction of cadmium removal efficiency by emulsion liquid membrane using an artificial neural network

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Abstract

This study presented Intelligent Network's proposed methodology for forecasting the effectiveness of cadmium removal from wastewater using emulsion liquid membrane (ELM). The research examined the removal of cadmium from an aqueous solution in the internal phase of water-in-oil emulsions. ELM was composed of kerosene as the membrane phase, Span 80 as the surfactant, di-2-ethylhexyl phosphoric acid (D_2EHPA) as the extracting agent, and hydrochloric acid (HCl) as the stripping solution. Experiments were conducted to investigate the effects of five parameters: surfactant concentration, feed-phase agitation speed, internal-to-membrane phase volume ratio, emulsion-to-feed volume ratio, and stripping-phase concentration in the internal phase. More than 97.4% of cadmium can be extracted in less than 15 minutes. This study evaluates the effectiveness of various learning algorithms, including gradient descent (GD), resilient back propagation (RB), gradient descent with momentum (GDM), gradient descent with learning momentum and adaptive rate (GDX), polak-ribiére conjugate gradient (CG), and levenberg marquardt (LM), in predicting the efficiency of cadmium elimination from wastewater using liquid emulsion membrane technology. The researchers developed a neural network model with 8 input neurons, 10 hidden neurons, and 1 output neuron. This feed-forward artificial neural network (ANN) incorporated various back-propagation training algorithms to simulate the cadmium removal process using ELM. The neural network model's predictions closely aligned with results from batch experiments, as demonstrated by a correlation coefficient (R2) of 0.9723 and a Mean Squared Error (MSE) of 0.0041, calculated in MATLAB. In conclusion, the ANN models demonstrated high accuracy and reliability in predicting cadmium removal efficiency, confirming their potential as practical tools for process optimization.

Keywords: emulsification; surfactant; cadmium removal; emulsion; artificial neural network.

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1- Introduction

Cadmium is one of the most common inorganic water contaminants [1]. The World Health Organization (WHO) and the US Environmental Protection Agency (EPA) have set stringent allowable limits for cadmium in drinking water at 0.003 mg/L and 0.005 mg/L, respectively, due to its high toxicity and serious long-term health effects [2]. It mostly comes from industrial operations, including mining, metal smelting, battery manufacturing, the application of phosphate fertilizers, and the manufacturing of plastics and colors [3]. Classed as a Group 1 carcinogen by the International Agency for Research on Cancer (IARC), this very poisonous heavy metal is even at trace levels quite toxic. Mainly in the kidneys and bones, cadmium bioaccumulates, causing nephrotoxicity and skeletal damage, including bone demineralization.

Moreover, its persistence in aquatic environments poses long-term ecological hazards, and its interactions with water treatment processes can produce secondary carcinogenic compounds, thereby aggravating risks to both human health and the environment [4]. Over time, a variety of treatment methods have been created to extract cadmium (Cd) from industrial wastewater. For that, a variety of methods have been employed, including solvent extraction, adsorption, coagulation, softening, membrane separation, and ion exchange [5]. ELM is a way to remove contaminants from wastewater and recover them. Scientists are very interested in it because it has many great qualities, such as the ability to remove pollutants and recover materials simultaneously within a single system, including unsteady-state mass transfer, elevated selectivity, increased flux rates, potential for reuse, and reduced energy demand [6].

Due to its exceptional benefits, the ELM technique is considered an effective method for removing cadmium from wastewater. This approach reduces the use of chemical reagents by combining the stripping and extraction phases into a single stage [7]. The method forms a stable water-in-oil emulsion, in which an organic membrane, including a surfactant and a carrier, captures the internal aqueous phase. The large interfacial area that this structure offers greatly improves mass transfer rates. The technique, however, also presents difficulties,

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including emulsion swelling due to water migration from the external to the internal phase, which might lower system efficiency. Furthermore, the whole performance of the ELM process depends on the emulsion remaining stable [8].

Artificial neural networks (ANNs) give computers and information systems classification and approximation capabilities that are comparable to those of humans [9]. This capability is further enhanced by developments in networking and computing technology, leading to increasingly sophisticated ANNs that are growing larger and more complex. This article focuses on key details of the design and training of intricate ANNs. Researchers in the domains of information management, soft computing, artificial intelligence, and informatics, as well as practitioners, will find these descriptions very interesting [10, 11]. Typically, an ANN consists of multiple layers. The input layer, one or more hidden layers, and one output layer are these layers. The number of parameters that are offered to the network as inputs typically correlates with the number of input neurons; the same is true for the output layer. The number of neurons and hidden layers is unknown and may be infinite. Depending on the kind of network, the neurons are grouped and structured differently.

The ANN is composed of layers of neurons connected by weights. The feed-forward with back-propagation ANN architecture is the most widely used. In this network, information moves from input to output in a single direction [12]. The efficiencies of cadmium removal were estimated using a three-layer neural network with a backpropagation algorithm in MATLAB. A three-part ANN design was employed in this study to assess the simultaneous efficiency of cadmium removal, based on EML removal. The outcomes of the models and the experiments are compared.

In 1986, the Back Propagation (BP) algorithm was introduced by Hinton, Williams, and Rumelhart to establish weights and train Multilayer Perceptron (MLPs) [13]. The error is propagated from the goal signal to the network's output using the BP technique. Upon receiving the input pattern, the error for each output unit is determined by contrasting the network output with a designated target pattern. The propagation of this error signal backwards creates a closed-loop control system. A continuous, nonlinear, monotonically increasing, differentiable activation function is necessary for the BP algorithm to be implemented. The logistic role, Eq. 1, and the hyperbolic role, Eq. 2, are the two most often utilized activation functions [14].

$$\mathrm{F(net)} = \frac{1}{1+e^{-\mathrm{net}}} \tag{1}$$

$$\mathrm{F(net)} = \frac{e^{\mathrm{net}}-e^{-\mathrm{net}}}{e^{\mathrm{net}}+e^{-\mathrm{net}}} \tag{2}$$

The actual output is represented by F (net). The BP algorithm for determining neuronal weights may appear precarious under specific operating conditions. To lessen the tendency to instability, in 1986, scientist David E. Rumelhart proposed the addition of a term (a) Variable, the Variable known as momentum in the $0< a <1$ scope, usually approximately 0.9. Although using the (a) parameter will appear to prevent swift variation, it is not invariably effective and may even undermine convergence [15]. A learning rate is another metric that indicates a more extensive learning process. In BP, weight alterations are directly related to negative error gradients. Although this guideline does not specify the precise magnitudes of the intended weight changes, it does specify the relative changes that will occur upon introducing a training pattern. The learning rate is affected by those magnitude differences. While weights can vary, a high learning rate leads to quick learning, while a low learning rate results in slower learning [16, 17].

In this context, the present study aims to examine the effectiveness of removing cadmium from industrial wastewater using the emulsion liquid membrane (ELM) technique. To achieve this, an artificial neural network (ANN) model was developed, and its predictive accuracy was evaluated using the mean squared error (MSE) and correlation coefficient (R^2). The efficiencies of cadmium removal were estimated using a three-layer feed-forward neural network with a backpropagation (BP) algorithm implemented in MATLAB. Although several studies have reported cadmium removal using ELM, few have integrated this process with intelligent modeling approaches. In particular, the comparative performance of multiple BP algorithms in predicting removal efficiency remains underexplored. Therefore, this study fills that gap by developing and validating an ANN-based model trained with various BP algorithms to forecast cadmium removal efficiency based on experimental ELM data.

2- Experimental work

2.1. Emulsion preparation

For this project, purified kerosene with a boiling point between 175 and 325 °C from Al-Dora Refinery, high-purity, refined D_2EHPA (di-2-ethylhexyl phosphoric acid) from Sigma Chemicals, span 80 (sorbitan monooleate), hydrochloric acid, and cadmium from Thomas Baker. To create the necessary concentration (8.4, 21.1, 84.6) M for hydrochloric acid and 100 ppm for cadmium, the proper volume and weight of hydrochloric acid (24, 42, 86) ml and cadmium (0.195) g were added to distilled water (1) liter.

2.2. Extraction process

To produce a water-in-oil emulsion, the internal stripping component (HCl) was added to a blend of kerosene and a surfactant. This mixture contained Span 80 at 2-5% (w/v) and a carrier containing 5% (w/v) D_2EHPA. The mixture was vigorously homogenized using a high-speed homogenizer (Ultra Turrax IKA-T45 (Germany)) set to 10,000 rpm for 10 minutes to produce a thin layer of milky white liquid. This thin layer needs to be made fresh before the extraction process. Different ratios (V_I/V_M) of the internal stripping phase to membrane phase (kerosene) of (1/2,1/4,1/6) were made. Then, using an OS20-S Overhead LED Digital stirrer (CHINA), water and emulsion were mixed with a cadmium feed phase containing an initial concentration of 1000 parts per million, in a ratio of milky white liquid to external phase (VE/VF) of (1/3, 1/5, 1/7) by volume. The stirrer rotated at (250, 350, 450, 650 rpm). Fig. 1 presents a schematic representation of the ELM process.

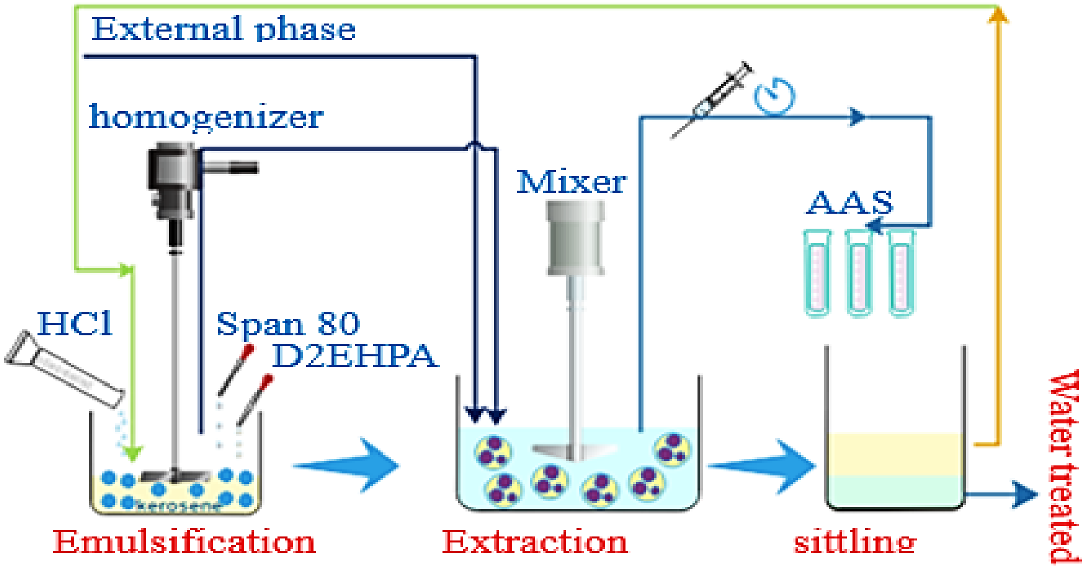


Fig. 1. Diagrammatic representation of cadmium removal from wastewater via ELM

A 5-milliliter nylon syringe was used to draw samples from the disturbed solution at different intervals. (A circular, 125 mm Ø, medium speed, Type 001) Filter paper from Thomas Baker was then used to filter the samples. The Atomic Absorption Spectrophotometer (AAS) SHIMADZU AA-7000 (Japan) at the Ministry of Science and Technology was used to determine that the cadmium level in the external phase decreases over time during ELM removal at 228.85 nm. The procedure was adapted and modified from previous works on ELM preparation [3].

2.3. Exploring various methods in BP neural networks

These techniques adjust the network's weights and biases to minimize the performance function along its steepest descent, i.e., the negative gradient direction. The updated weight vector W_{k+1} is modified according to the descriptions of the BP techniques employed in this study, as illustrated in Table 1. The weight adjustment process is determined by the derivative symbol alone. This method follows a straightforward principle for updating weights: when the derivative is positive, indicating an increase in error, the weight is reduced by its update value. Conversely, when the derivative is negative, the update value is added to the weight [18,19].

2.4. The suggested (ANN) model design

At the moment, ANN methods are becoming powerful tools for modeling various engineering applications. Neural networks' capacity to learn from prior information and generalize to new information is the fundamental concept behind their use in modeling correlations. The model used in this work analyzes the removal of cadmium from wastewater using an ELM. After the learning file was created, ANN correlation modeling began by selecting a large data bank. Approximately 80% of the database was randomly selected to train the network. The generalization ability of the model is then tested using the remaining 20% of the data [21]. The steps involved in neural network modeling are as follows:

2.5. Collection of data

Data collection is the first stage of neural network modeling. To train the network and gauge its generalization capacity, data is required. Numerous researchers looked into the use of emulsion liquid membranes to remove cadmium from wastewater. As indicated in Table 2, approximately 207 experimental points have been gathered for this model.

2.6. The structure of the proposed ANN

The feed forward model of a 3-layer neural network is selected as the correlation model. MATLAB programming is used to determine the weighting coefficients for neural networks. The structure of an ANN was created as:

1. Layer of input: This can include signals from structures outside the model or sensory inputs. This study utilizes eight neurons for this part and has 164 data points in the training set.
2. Layer of Hidden: A part that secretly takes in and interprets data from the previous layer. Its inputs and

outputs are not directly related to the external environment. The hidden layer is where all connections to other system layers originate. Therefore, keeping ten neurons in this layer is the optimal value can yield satisfactory results.

3. Layer of output: It is single-neuron part that leads output signs from the process after receiving processed data. Here, the result is the cadmium removal efficiency from the wastewater using an ELM.
4. Bias: It a function sets a level at which neurons are activated. Every hidden neuron in the network is connected to the bias input. Fig. 2 shows the framework for multilayer ANN modeling for effectively extracting cadmium from wastewater via an ELM.

In this instance, the same variables were chosen to be the input layer neurons: V_I / V_M, V_E / V_F, C_{i0}, span 80, D_2EHPA, t, Ci, and rpm (feed phase agitation speed). Table 1 contains the information gathered in this instance. Eight neurons make up the input layer of the chosen ANN structure, ten neurons make up the hidden layer, and singly neuron makes up the output layer. Fig. 2 illustrates this framework.

Table 1. The different methods of BP neural networks [20]

Type of Training Algorithm	Abbreviation	Network weights	MATLA B Code
Gradient Descent	GD	$W_{k+1} = W_k - \alpha_{gk}$	traingd
Resilient BP	RB	$\Delta w_{ij}(t) = \begin{cases} -\Delta_{ij(t), \ if \frac{\partial E}{\partial w_{ij}}(t)} > 0 \\ -\Delta_{ij(t), \ if \frac{\partial E}{\partial w_{ij}}(t)} < 0 \\ 0 \quad \text{else} \end{cases}$ $w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t)$	trainrp
Gradient Descent with Momentum	GDM	$w_{k+1} = w_k - \alpha_{gk} + \mu w_{k-1}$	traingdm
Gradient Descent with Learning momentum and adaptive rate	GDX	$w_{k+1} = w_k - a_{k+1}\, g_k + \mu w_{k-1}$ $a_{k+1} = \beta_{ak}$	traingdx
Polak-Ribiére Conjugate Gradient	CG	$\beta_k = \frac{\Delta g_{k-1} T g_k}{g_{k-1} T g_{k-1}}$	traincgp
Levenberg-Marquardt	LM	$X_{k+1} = x_k - [\, J^T J + \mu I \,]^{-1} J^T e$	trainlm

Table 2. Review of earlier research on using emulsion liquid membranes to remove cadmium from wastewater

Set-Data number	**Author**
<1…93>	[22]
<94…109>	[23]
<110…142>	[24]
<143…207>	Experimental work

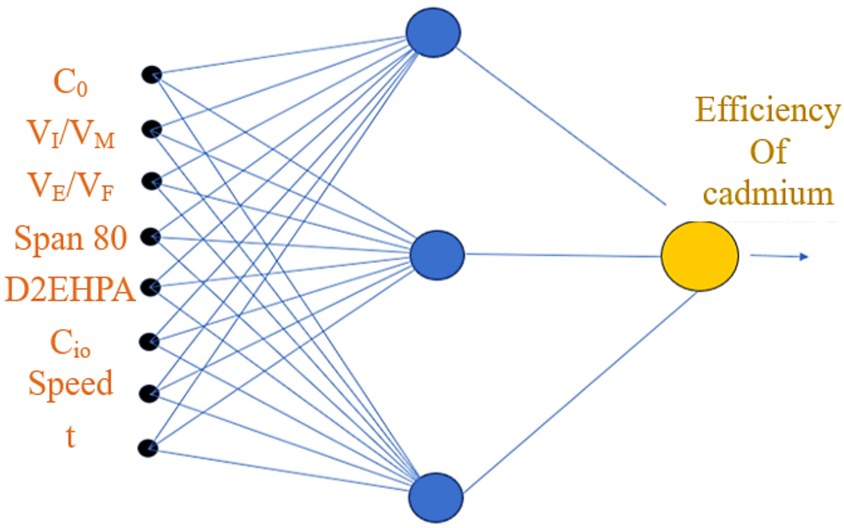


Fig. 2. Emulsion liquid membrane-based layer neural network structure for removing cadmium from wastewater. The input layer's neurons are represented by black dots, the hidden layers by blue dots, and the output layers by yellow dots

3- Result and discussion

3.1. The impact of surfactant concentration

The influence of surfactant concentration, emulsion stability, and integration into the emulsion-based liquid-liquid (ELM) system depends much on the surfactant (Span 80). Different concentrations of Span 80 (2%,3%, 4%, and 5%) were investigated in this work; a significant cadmium removal effect of 4% was obtained, and 92.6% cadmium removal, as depicted in Fig. 3.

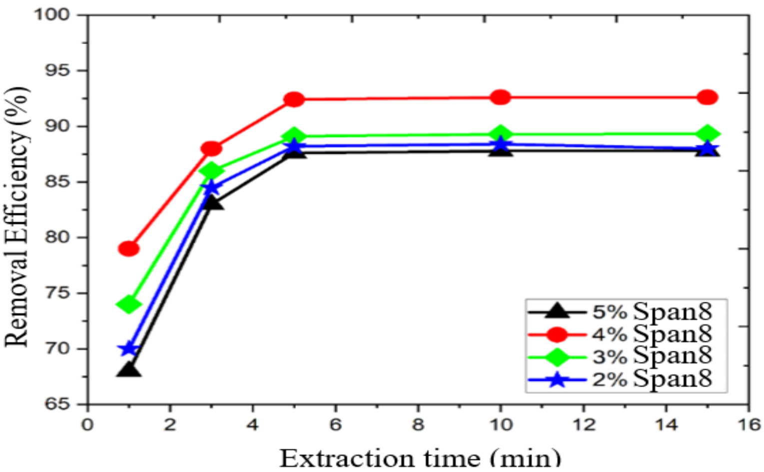


Fig. 3. Impact of surfactant concentration on cadmium removal efficiency in the ELM process. (Experimental conditions: agitation speed = 350 rpm, V_I:V_M = 1:4, V_E: V_F= 1:5, C_{i0}= 0.25 M, rapidity of homogenizer =ten thousand rpm, initial cadmium concentration: 100 ppm)

Previous research confirms that raising the surfactant concentration to a specific threshold increases emulsion stability and reduces the breaking rate, thereby improving cadmium transport across the membrane [25]. One study, for instance, indicated that raising the Span 80 concentration from 1% to 4% (v/v) reduced the membrane breakdown rate, thereby improving the removal efficiency [24]. This outcome is in line with our findings, in which the removal efficiency was much raised by using 4% Span 80. As seen with 5%, when the efficiency dropped to 87.8% compared to 4%, raising the Span 80 concentration above the optimal range may thus result in decreased removal efficiency. The fact that a high surfactant concentration increases the mass transfer resistance at the interface between the internal and external phases limits the transport of cadmium ions [26], thereby explaining this drop. Furthermore, very high surfactant concentrations lead to greater osmotic swelling, resulting in emulsion breakdown and reduced removal efficiency [27]. Consequently, the experimental results align with the scientific literature, verifying that there is an ideal surfactant concentration that balances emulsion stability with ion transport efficiency; in this case, it was 4% Span 80.

3.2. Impact of agitation speed

This parameter was tested at various speeds (250, 350, 450, and 650 rpm). Fig. 4 shows the effect of agitation speed on cadmium removal efficiency. The results indicated that increasing the agitation speed improved the removal efficiency, rising from 86.8% at 250 rpm to 92.6% at 350 rpm, and then to 94.6% at 450 rpm, indicating the part shear force in lowering the emulsion volume and increasing the contact area between the phases, so improving mass transfer [28]. The efficiency rose to 95% when the speed was raised to 650 rpm, but a slow decline was noted over time, most likely due to emulsion breakage resulting from the significant increase in shear force and osmotic swelling, losing the capacity to contain cadmium ions [22, 24].

These findings led to 450 rpm being regarded as the ideal speed, as it maximized efficiency and stability over time without causing emulsion collapse, unlike 650 rpm. This is in line with research showing that, above a maximum agitation speed, emulsion breakdown rates rise, lowering removal efficiency.

3.3. Impact of internal-to-membrane phase ratio (V_I/V_M)

The results of this work show an apparent influence on cadmium removal effectiveness through the inner-to-membrane phase ratio (Vi/Vm). Three various ratios 1:2, 1:4, and 1:6 were investigated. At a 1:4 ratio, the best cadmium removal efficiency was 94.6%. As seen in Fig. 5, an efficiency of 93.8% was attained at a ratio of 1:2; at a ratio of 1:6 the removal efficiency attained 91%. These findings are in line with earlier studies showing that the lower the ratio is to 1:6, the lower the removal efficiency.

This is due to the emulsion's higher viscosity, which causes the inner droplets to coalesce and large bubbles to form. This lessens contact between the inner and outer phases, thus compromising the removal process. These big bubbles also lower the effective contact area with the outer phase, therefore lowering the removal efficiency [29]. Conversely, raising the ratio to 1:2 reduces removal efficiency and increases membrane breakage, as the insufficient available membrane fails to shield the inner droplets, leading to emulsion rupture. Membrane breaking was shown to be higher at a ratio of 2:1 than at a ratio of 4:1, therefore significantly affecting the removal efficiency [3]. Significant emulsion breakage occurs when the inner droplets swell at ratios above 1:4, further reducing the removal and stripping efficiency. Consequently, the results show that the ideal ratio is 1:4 for achieving the best cadmium removal efficiency; hence, it is necessary to maintain this ratio to ensure emulsion stability and process efficiency.

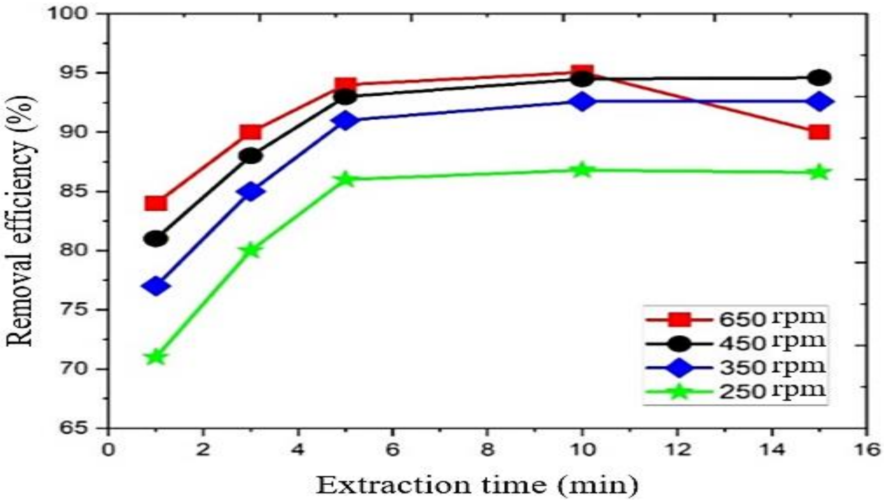


Fig. 4. Impact of agitation speed on cadmium removal efficiency in the ELM process. (Experimental conditions: span 80 concentration = 4%, V_I:V_M = 1:4, V_E: V_F = 1:5, C_{i0}= 0.25 M, rapidity of homogenizer =ten thousand rpm, initial cadmium concentration: 100 ppm)

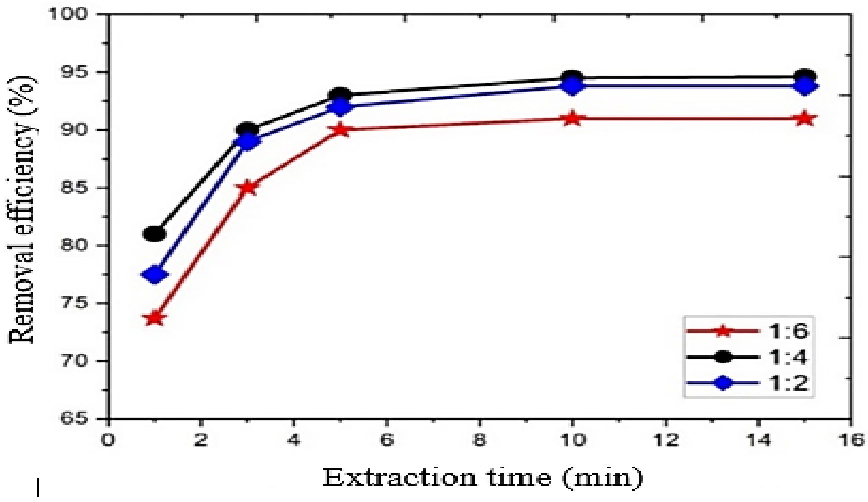


Fig. 5. Impact of the internal to membrane phase ratio on cadmium removal efficiency in the ELM process. (Experimental conditions: agitation speed = 450 rpm, surfactant concentration = 4%, V_E: V_F = 1:5, C_{i0}= 0.25 M, rapidity of homogenizer =ten thousand rpm, initial cadmium concentration: 100 ppm)

3.4. Impact of emulsion-to-feed phase ratio (V_E/V_F)

Cadmium removal effectiveness was investigated with relation to the emulsion-to-external solution ratio. Using several ratios—one 1:3, one 1:5, and one 1:7 the outcomes were as follows: At a ratio of 1:3, one attained the best cadmium removal efficiency, 97.4%. Fig. 6 shows that the cadmium removal effectiveness declined to 85.4% at a 1:7 ratio, whereas at a 1:5 ratio it was almost 94.5%. In this work, the results showed that higher removal efficiency occurs from changing the treatment ratio from 1:7 to 1:3. The higher number of emulsion droplets and the contact surface area between the membrane phase and the internal phase could be the reasons behind this, so improving the transport process and thereby helping to raise efficiency. This is in line with the findings of Ghorbanpour, where the 1:3 ratio, which has the highest emulsion volume, improves cadmium transport efficiency through a larger surface area and thus explains the high removal efficiency of 97.4% [30-33]. Laki underlined that raising the treatment ratio (V_E/V_F) results in higher removal efficiency.

The decrease in effective transport area due to membrane density may cause efficiency to drop as the emulsion volume increases. Higher treatment ratios could lead to greater emulsion breakup and lower transport efficiency, as confirmed. Thus, the results obtained at the ratio of 1:7, where the efficiency is lower than that of 1:5 and 1:3, may be attributable to this similar occurrence, as raising the volume beyond an optimum value may lead to emulsion rupture and decreased process efficiency [26]. These conversations lead us to believe that the best ratio of 1:3 may be related to achieving a balance between increasing the emulsion volume and maximizing the effective surface area for transportation. Effects such as higher viscosity, emulsion breakup, and reduced transport area reduce efficiency when the volume is increased beyond a given limit.

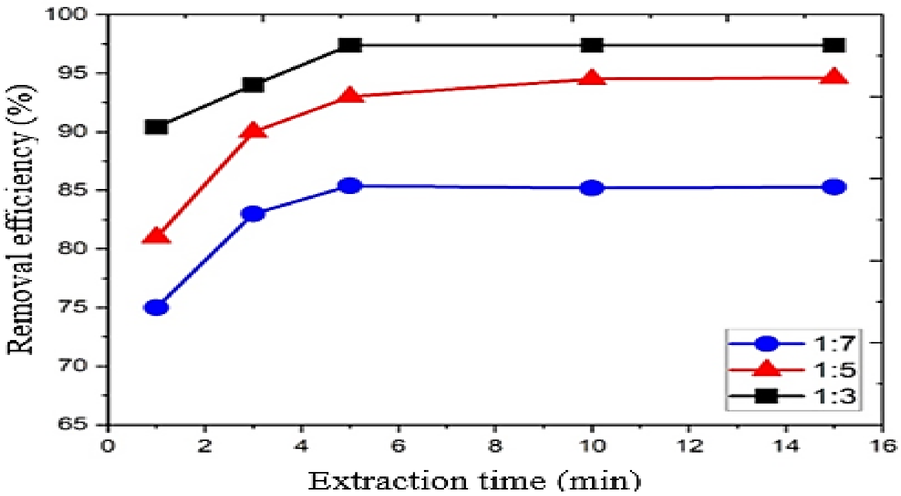


Fig. 6. Impact of the emulsion to feed phase ratio V_E/V_F on cadmium removal efficiency in the ELM process. (Experimental conditions: agitation speed = 450 rpm, surfactant concentration = 4%, V_I:V_M = 1:4, C_{i0}= 0.25 M, rapidity of homogenizer =ten thousand rpm, initial cadmium concentration: 100 ppm)

3.5. Impact of HCl concentration

Three concentrations, 0.1, 0.25, and 1.0 M, were investigated to show that HCl concentration affected cadmium removal. As seen in Fig. 7, the highest efficiency, 97.4% was achieved at 0.25 M; the efficiency was 57% at 0.1 M and 95.7% at 1.0 M. The improvement in efficiency when the concentration was raised from 0.1 to 0.25 M is ascribed to the increase in the ionic driving force between the two phases, thus improving the cadmium transfer, which is in line with the findings of past research confirming that the main driver of the removal process is the difference in the chemical potential of H^+ ions [33]. The effect of the high acid concentration on membrane stability explains the declining efficiency at 1.0 M, since it may interact with the surfactant Span 80, therefore compromising its efficiency and impairing emulsion stability [34].

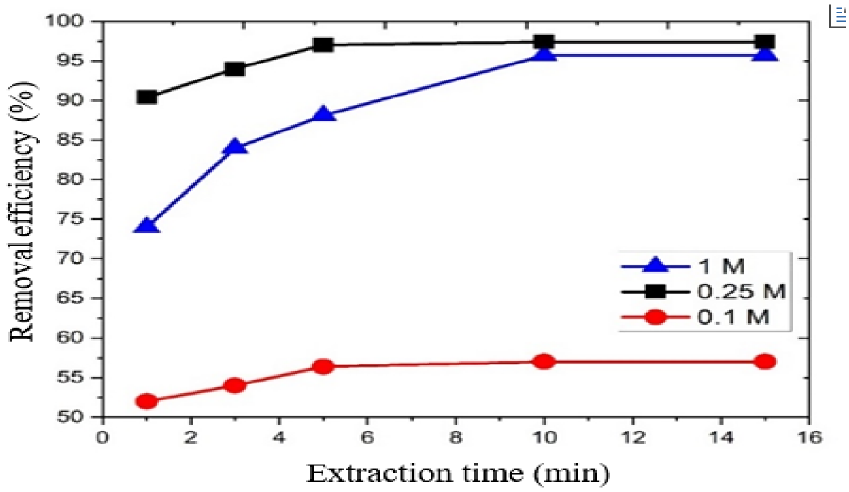


Fig. 7. Impact of HCl concentration on cadmium removal efficiency in the ELM process. (Experimental conditions: surfactant concentration = 4%, V_I:V_M = 1:4, V_E: V_F= 1:3, agitation speed = 450 rpm, rapidity of homogenizer =ten thousand rpm, initial cadmium concentration: 100 ppm)

Moreover, raising the acid concentration results in a significant variation in ionic strength between the two phases, which causes osmosis to swell the emulsion, therefore diluting the internal phase and lowering the removal efficiency [35]. Thus, as it offers the optimum balance between ion transport efficiency, membrane stability, and removal efficiency, 0.25 M is the ideal concentration for cadmium removal.

3.6. The various approaches to BP in neural networks

The dataset comprises 164 experimental data points utilized for network training, along with 60 points reserved for testing. Various feed-forward BP network algorithms were trained using MATLAB 2019a software. The objective of training various algorithms is to achieve optimal results, which involves minimizing the Mean Squared Error (MSE) while using fewer neurons, as illustrated in Fig. 8. The iterative approach of evaluating different algorithms and adjusting their parameters, such as the quantity of neurons, through a trial-and-error methodology ultimately yields the optimal outcome, as demonstrated in Table 3. This selection process involves testing various options to identify the most effective solution. The Levenberg-Marquardt algorithm yielded the best training results, achieving a Mean Squared Error (MSE) of 0.0041 after 22 epochs with 10 neurons. This result is considered exceptional, as the network performance function's MSE approaching zero indicates high decision-making accuracy. The outcomes of training various BP neural network techniques are illustrated in Fig. 8, which shows the most effective results.

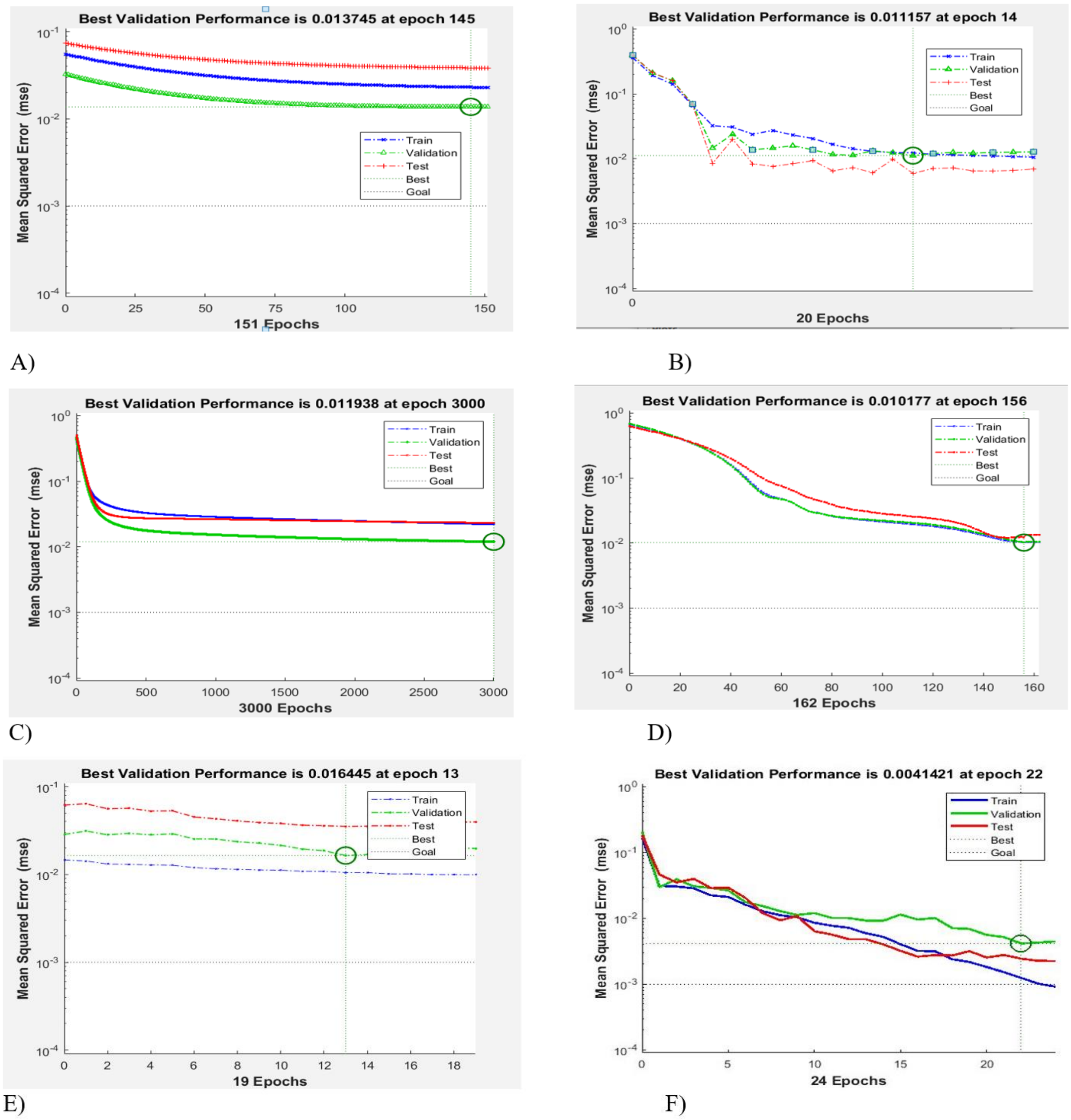


Fig. 8. The various Approaches to BP in Neural Networks. (A) Resilient BP (RB) (B) gradient descent BP (GD) (C) gradient descent enhanced with momentum (GDM) (D) gradient descent with momentum and adaptive learning rate BP (GDX) (E) conjugate gradient BP with Polak-Ribiere (CG) (F) Levenberg–Marquardt (LM) optimization method

For the network to adjust the weight of every neuron and repeat the process until the intended Mean Squared Error (MSE), as illustrated in Fig. 8, is reached, the MSE is computed as a consequence of the training network. Table 4 displays the weights assigned to the input and hidden layers. Table 5 summarizes ANN correlation for the cadmium removal from wastewater case utilizing an ELM process with a range of changes in the removal process variable quantity. Fig. 9 uses MATLAB 2019a to train an ANN with 10 hidden neurons using the BP algorithm.

Table 3. Results of the training of the gradient descent algorithm

Type of training algorithm	Performance (MSE)	Std deviation	No. of neurons in hidden layer	epoch
GD	0.011157	0.3250	10	14
RB	0.013745	0.1980	10	145
GDM	0.01193	0.1079	10	3000
GDX	0.01017	0.2877	10	156
CG	0.016445	0.4331	10	13
LM	0.004142	0.0507	10	22

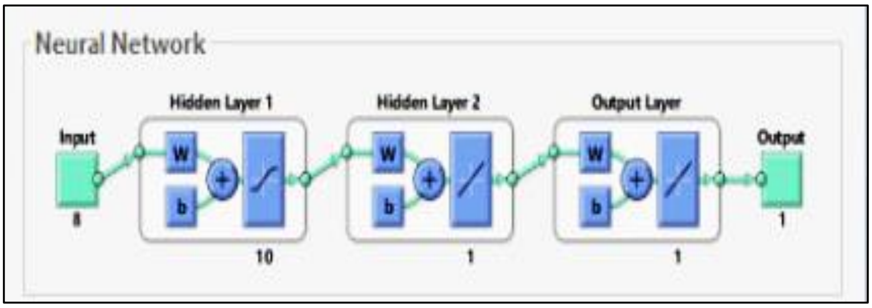


Fig. 9. ANN model training performed with the Levenberg–Marquardt approach

Table 4. Final optimized weights and biases of the implemented ANN model

Input weights (w) / no of neurons	C_0	V_I/V_M	V_E/V_F	span 80	D_2EHPA	C_{io}	rpm	T	Bias (b)	layer weights (w)
1	-1.268	0.1628	-0.3718	0.0341	-0.8891	0.8779	-0.2171	-0.1128	2.2475	1.1153
2	0.4963	-0.9951	0.524	-0.8534	0.8687	-0.4796	0.7974	0.2841	-1.3228	0.1199
3	-0.6404	-0.7287	-1.5377	0.6574	-0.5179	1.6268	0.0047	0.8102	1.2408	1.4227
4	-0.2688	0.8262	0.695	-0.9039	1.4435	-0.7624	-0.2725	-4.2636	-3.9834	1.4629
5	-0.6812	-1.2278	-2.2632	2.0054	2.4918	4.2757	0.9176	-1.9509	3.2101	-1.986
6	-1.4526	0.067	-1.3809	2.2132	-0.0964	1.1628	0.551	-0.5893	0.4753	1.5923
7	-2.5346	-0.579	0.919	-0.8891	-0.2227	-1.282	3.9478	-0.5275	0.059	-0.5778
8	0.1359	-2.999	0.2894	-0.0563	-0.3896	-2.4625	0.1372	-3.2048	-1.2207	1.3134
9	-0.7839	0.6661	-1.6542	0.4725	2.2829	-2.7932	-2.341	0.4103	2.2265	-0.6737
10	-1.9049	-0.9679	1.3786	0.2714	0.4796	-1.8228	0.9531	-1.9574	-0.107	-0.6183

The results obtained in this study confirm the effectiveness of the Levenberg–Marquardt (LM) training algorithm in achieving the lowest Mean Square Error (MSE = 0.0041) and high prediction accuracy. Similar findings were reported by Esfandyari [36], who compared several back-propagation algorithms (SCG, GDX, GDA, GDM, and GD) for modeling the removal of heavy metals and found that LM provided the best performance with the smallest MSE and highest R^2 values. Therefore, the present results are in strong agreement with the literature, confirming that the LM algorithm offers superior convergence and accuracy for nonlinear environmental process modeling.

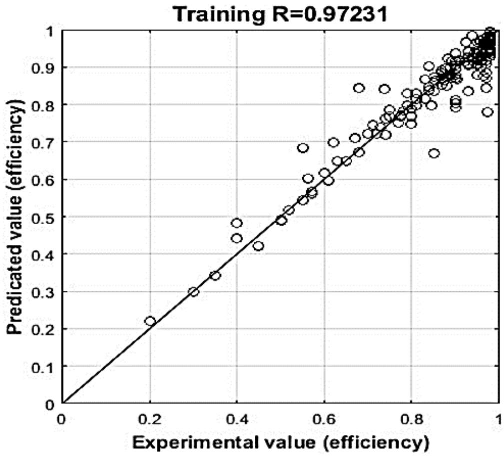
3.7. Training results

(BP) Neural network methods were trained using MATLAB 2019a. The code (newff) was employed to create the network, and tansig was used as the activation function. ANN exhibits superior precision in result identification, including in the evaluation of untrained data, as illustrated in Fig. 10. This figure demonstrates the optimal performance of the Levenberg–Marquardt algorithm, with (a) achieving R=0.9723 for training and (b) attaining R^2=0.9672 for testing. The obtained correlation values (R = 0.9723 for training and R^2 = 0.9672 for testing) demonstrate high prediction accuracy of the developed ANN model.

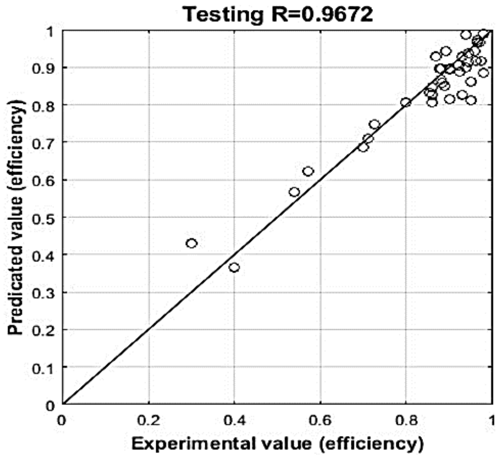
Kabuba reported comparable findings [37], who applied the Levenberg–Marquardt (LM) algorithm for heavy-metal removal modeling and achieved $R^2 \approx 0.9998$, confirming its superior convergence and precision. Therefore, the present results are in close agreement with recent literature, validating the reliability of the LM algorithm for accurate environmental process prediction.

Table 5. Range of experimental variables applied in the modeling process

Input parameters	Smallest	Largest
Initial Cd concentration (C_0) ppm	33	1000
Internal to membrane phase(V_I/V_M)	1:6	1:2
Emulsion to external phase (V_E/V_F)	1:10	1:3
surfactant concentration (Span 80)	1%	5%
Carrier concentration (D_2EHPA)	0%	20%
HCl concentration	0.1	3
Agitation speed (rpm)	100	650
Time (t) min	1	90



(a)



(b)

Fig. 10. The optimal training outcome of the gradient descent BP algorithm: (a) train system, (b) test system

4- Conclusions

This study demonstrated the effectiveness of the emulsion liquid membrane (ELM) technique for removing cadmium from industrial wastewater and confirmed that process optimization significantly enhanced extraction efficiency. The results showed that optimal cadmium removal (97.4%) was achieved under specific operating conditions—particularly 4% Span 80, 0.25 M HCl, 450 rpm, and an internal-to-membrane phase ratio of 1:4. Furthermore, the developed artificial neural network (ANN) model accurately predicted the removal efficiency, with a correlation coefficient (R^2) of 0.9723 and a mean squared error (MSE) of 0.0041. Among the examined backpropagation algorithms, the Levenberg–Marquardt (LM) method yielded the most reliable training performance. These findings confirm the potential of ANN-assisted ELM systems as efficient and intelligent tools for optimizing heavy-metal removal processes.

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التنبؤ بكفاءة إزالة الكادميوم باستخدام الغشاء السائل المستحلب بالاعتماد على الشبكات العصبية الاصطناعية (ANN)

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الخلاصة

تقدم هذه الدراسة المنهجية المقترحة من الشبكات الذكية للتنبؤ بفعالية إزالة الكادميوم من مياه الصرف باستخدام تقنية الغشاء السائل المستحلب إذ تناول البحث إزالة الكادميوم من محلول مائي في الطور الداخلي لمستحلبات من نوع ماء في زيت وتكون الغشاء السائل المستحلب من الكيروسين كطور غشائي و Span 80 كمادة خافضة للتوتر السطحي و D2EHPA(حمض ثنائي-٢-إيثيل هكسيل الفوسفوريك) كعامل استخلاص وحمض الهيدروكلوريك (HCl) كمحلول تجريد وقد أُجريت التجارب لدراسة تأثير خمسة متغيرات وهي تركيز المادة الخافضة للتوتر السطحي وسرعة تحريك الطور المغذي ونسبة حجم الطور الداخلي إلى الطور الغشائي (VI/VM)ونسبة حجم المستحلب إلى الطور المغذي (VE/VF) وتركيز الطور المجرّد في الطور الداخلي وأظهرت النتائج أن أكثر من ٩٧,٤% من الكادميوم يمكن استخلاصه في أقل من خمس عشرة دقيقة وقد قيّمت هذه الدراسة فعالية عدة خوارزميات تعلم تشمل Gradient Descent (GD) و Resilient Back Propagation (RB) وGradient Descent with Momentum (GDM) وGradient Descent with Learning Momentum and Adaptive Rate (GDX) وPolak–Ribiére Conjugate Gradient (CG) وLevenberg–Marquardt (LM) في التنبؤ بكفاءة إزالة الكادميوم من مياه الصرف باستخدام تقنية الغشاء السائل المستحلب وقد طوّر الباحثون نموذج شبكة عصبية اصطناعية مكوّناً من ثماني عقد إدخال وعشر عقد في الطبقة الخفية وعقدة إخراج واحدة واعتمدت هذه الشبكة العصبية ذات التغذية الأمامية على خوارزميات تدريب مختلفة للانتشار العكسي لمحاكاة عملية إزالة الكادميوم عبر الغشاء السائل المستحلب وقد أظهرت تنبؤات النموذج العصبي توافقاً وثيقاً مع النتائج المستخلصة من التجارب الدفعيّة حيث بلغ معامل الارتباط $R^2 = 0.9723$ ومتوسط مربع الخطأ $MSE = 0.0041$ وذلك باستخدام برنامج MATLAB وفي الختام أثبتت نماذج الشبكات العصبية الاصطناعية دقة وموثوقية عالية في التنبؤ بكفاءة إزالة الكادميوم مؤكدةً إمكان اعتمادها كأدوات فعالة لتحسين العمليات.

الكلمات الدالة: الاستحلاب، المستحلبات (المواد الخافضة للتوتر السطحي)، إزالة الكادميوم، الشبكات العصبية الاصطناعية.