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Research Article

Utilizing artificial neural networks (ANN) for predictive modeling of sulfate removal from water

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ABSTRACT

This research centers on developing an artificial neural network (ANN) algorithm to predict the precise removal of sulfate from synthetically prepared water samples. Two distinct resins, sodium-based cationic resin (SBCR) and divinylbenzene styrene (DVBS), were employed to achieve this goal. Additionally, the study investigated the influence of column properties (diameter and height), initial sulfate concentration, and contact time on sulfate removal from synthetically prepared samples. After collecting data from experimental trials, a feed-forward ANN structure was constructed. The selected input parameters for predicting sulfate removal encompassed column properties (diameter and height), contact time, resin type, and initial sulfate concentration. The model's performance was assessed using several statistical criteria, including the correlation coefficient (R), mean absolute percentage error (MAPE, %), root mean square error (RMSE), and mean square error (MSE). The model's training and test performance yielded impressive results: the correlation coefficient (R) was exceptionally high at 1.0000 for training and 0.9999 for test, indicating a strong alignment between predicted and actual values.
Moreover, the mean absolute percentage error (MAPE, %) was 0.5422 for training and 0.9223 for testing, reflecting low average percentage differences between predictions and actual data and indicating high accuracy. The root mean square error (RMSE) values were also 0.0012 for training and 0.0034 for the test, demonstrating minimal average prediction errors. Lastly, the mean square error (MSE) values were notably low, with 1.42×10^{-6} for training and 1.14×10^{-5} for test phase, underscoring the model's ability to provide accurate predictions with minimal deviations from actual values. Based on these comprehensive evaluation criteria, the ANN exhibited strong predictive performance in estimating sulfate removal.

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INTRODUCTION

Water pollution, in terms of anions, is a public health concern with various effects. Sulfate (SO_4^{2-}) is a common pollutant among all anions and can naturally occur in groundwater. High sulfate levels in drinking water are known to cause diarrhea, making removing ions essential. Several methods and technologies are available for removing SO_4^{2-} ions from water sources, including ion exchange, nanofiltration, adsorption, reverse osmosis, and electrodialysis. The choice of method depends on technological development, specific use cases, limitations, and cost [1]. Generally, these methods can be grouped into physical, physicochemical, and biological categories [2]. Physical methods involve adsorption using various adsorbents like activated carbon, biochar, graphene, zeolite, and bentonite [3-6]. Physicochemical methods include ion exchange, precipitation, and electrocoagulation, while biological methods encompass artificial wetlands and bioreactors. Studies on sulfate removal from water resources using these methods are in the literature.

In a study conducted by Darbi et al. [3], bentonite was used to remove sulfate from groundwater, and its performance was compared to ion exchange and nanofiltration processes. Another study on adsorption involved sulfate removal from wastewater using activated carbon [7]. Factors such as adsorbent mass, pH, and contact time were investigated. Hong et al. [4] removed sulfate from acid mine drainage using polypyrrole-tailored activated carbon. Ma et al. [8] used a sol-gel method to create spherical amorphous $ZrO(OH)_2/AlOOH$ composite adsorbent beads for sulfate removal. Spina-christi lotus leaf-derived activated carbon was used to remove sulfate from an aqueous solution, and the study investigated the effects of pH, contact time, temperature, adsorbent concentration, and initial sulfate concentration [9]. Salimi et al. [10] used nanoparticles of natural clinoptilolite to adsorb sulfate ions from Gamasiab River water samples, studying the effects of pH and the adsorbent-to-contaminant ratio (D/C). Ao et al. [11] synthesized low-cost zirconium oxide-modified pomelo peel biochar (ZrBC) for sulfate ion adsorption from an aqueous solution. Sukamto [12] used magnetic silica-chitosan hybrids ($MP@SiO_2/CPTMS/Chi$) to adsorb sulfate ions from an aqueous solution.

Tjeda-Tover et al. [13] synthesized two different adsorbents: these are biochar modified with H_2SO_4 with a mass-to-volume ratio of 1:1 (B 1:1) and cellulose modified with cetyl trimethyl ammonium chloride (CTAC), for adsorbing sulfate in a solution. Obeid et al. [14] removed sulfate from wastewater using a clay-based adsorbent (sludge, waste limestone, bentonite, SBL), investigating different values of pH, contact time, adsorbent dose, and initial SO_4^{2-} concentration. Shahzadi et al. [15] used nickel monometallic and nickel-cobalt bimetallic nanoparticles to remove sulfate and phosphate ions.

Various methods can be employed for sulfate removal, and the choice of method depends not only on experimental procedures and challenges but also on costs. Parameters like maintenance, installation, initial investment, waste management, and operational costs are crucial, especially in pilot-scale research. In recent years, with the advancement of computer technology, modeling studies have gained importance, reducing costs such as experimental workloads for many processes. Artificial neural networks (ANN) are a popular artificial intelligence (AI) technique because they can learn complex and nonlinear systems, making them preferred in many processes [16-23].

To the author's best knowledge, ANN modeling of sulfate removal from drinking water has not been published. Consequently, an ANN model for sulfate removal was developed using experiment data. The experimental system involved two adsorbents (DVBS and SBCR) with varying column diameters and heights, contact times, and initial sulfate concentrations. These parameters were determined as input parameters for predicting sulfate removal.

MATERIALS AND METHODS

Chemicals

- Anhydrous sodium sulfate (Na_2SO_4)
- 0.1 M NaOH solution
- 0.1 M HCl solution
- 0.1 M NH_3 solution

Devices

- Spectrophotometer (Hach-DR 2400)
- Specially designed columns with 3, 3.5, and 4 (R(3), R(3.5), R(4)) cm inner diameters and 7.5, 10, and 15 cm column heights

Adsorbents

- Divinylbenzene styrene (DVBS) anionic resin
- Sodium-based cationic resin (SBCR)

Preparation of Synthetic Sulfate Solutions

This study involved the utilization of three distinct concentrations of sulfate solutions. To prepare these solutions, we initially dried 0.1479 grams of anhydrous sodium sulfate (Na_2SO_4) in an oven at 105°C. It was then dissolved in deionized water and diluted to a final volume of 1 liter, resulting in a sulfate solution with a concentration of 1000 mg/L, referred to as C(1000). From this primary solution, diluted solutions with a concentration of 250 mg/L, denoted as C(250), were subsequently derived. The sulfate content in the solutions intended for analysis was quantified using a Hach-DR2400 spectrophotometer. The sulfate assay kit used was the SulfaVer4 PP 2-70(10 mL) brand.2.3. Experimental System

Within the scope of this investigation, columns possessing internal diameters of 3 cm (R3), 3.5 cm (R3.5), and 4 cm (R4) were employed, each varying in height at 7.5 cm,

Figure 1. Experimental setup.

10 cm, and 15 cm. The standard sulfate removal technique, utilizing the spectrophotometric method, was implemented throughout the study. Furthermore, all experimental procedures were conducted using two distinct types of resins: SBCR and DVBS. A visual representation of the experimental setup is depicted in Figure 1.

During the adsorbent placement within the columns, glass fiber was interposed between the column and the adsorbent material, ensuring a precise balance. A fixed volume of sulfate solution (100 mL) was then passed through the column, and samples collected at designated time intervals (e.g., 1, 3, and 8 minutes) were analyzed using a Hach DR 2400 spectrophotometer. The sulfate concentrations were subsequently determined based on these measurements. The study evaluated sulfate removal efficiencies under these specific conditions, examining variations in sulfate concentration concerning column diameter, column bed height, adsorbent quantity, and contact duration. Furthermore, the study included a comparative analysis of the performance of different adsorbents.

Modeling Studies

In this research segment, we have developed an Artificial Neural Network (ANN) model to forecast the percentage of sulfate removal. To accomplish this, we calculated sulfate removal efficiency employing the adsorption technique with synthetic samples, as detailed in the experimental section of our study, employing DVBS and SBCR as adsorbents. Furthermore, our experimental investigations encompassed a range of column diameters (3, 3.5, and 4 cm), column heights (7.5, 10, 15 cm), and initial sulfate concentrations.

In the ANN modeling phase of the research, we selected input variables consisting of column diameter and height, resin type, contact time, and initial sample concentration. We employed a total of 70 data points for modeling purposes. The most favorable outcomes were achieved by configuring the ANN with three neurons in the hidden layer, employing tangent sigmoid (‘*tansig*’) activation functions for both the hidden and output layers. We randomly partitioned the data into a 70% training set and a 30% testing set to establish the model. We evaluated the model’s performance based on various statistical criteria. A visual representation of the constructed ANN architecture is provided in Figure 2.

The development of the Artificial Neural Network (ANN) model was facilitated using the ANN toolbox within the MATLAB environment. In this process, code was crafted within MATLAB, and the optimal network structure was ascertained through training the network with the provided training dataset. Once the network structure was finalized, the model underwent testing with previously unseen data to assess its overall performance and predictive accuracy.

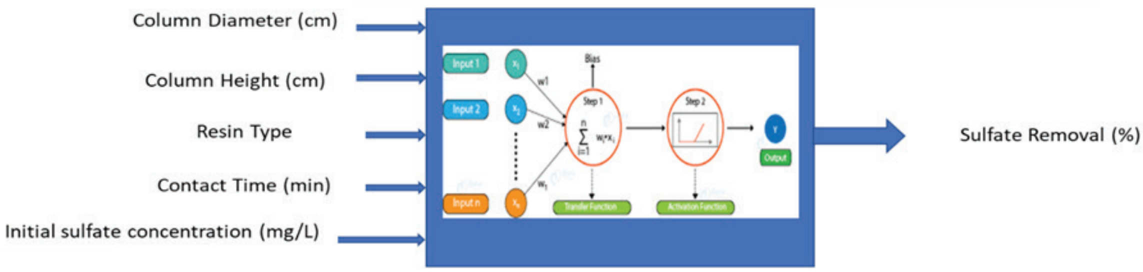

Figure 2. ANN design.

RESULTS AND DISCUSSION

Sodium-Based Cationic Resin (SBCR) Results

The output sulfate concentrations, denoted as C1 (1 minute), C3 (3 minutes), and C8 (8 minutes) for a 3.5 (R(3.5)) cm column diameter and an initial sulfate concentration of 1000 (C(1000)) mg/L, utilizing a sodium-based cationic resin (SBCR), are provided in Table 1 below:

Upon reviewing the results presented in Table 1, it becomes evident that there is a 99.00% reduction in sulfate concentration when employing a column height of 7.5 cm, a 98.00% reduction at a column height of 10 cm, and a remarkable 99.80% reduction at a column height of 15 cm.

Table 2 illustrates the output sulfate concentrations, specifically C1, C3 and C8 for SBCR at a column diameter of 3 cm (R(3)) and an initial sulfate concentration of 1000 ((C(1000)) mg/L:

Upon analyzing the findings in Table 2, it is evident that an impressive 99.90% reduction in sulfate concentration is attained when employing a column height of 10 cm.

Table 3 displays the output sulfate concentrations for SBCR at a column diameter of 3.5 cm [R(3.5)] and an initial sulfate concentration of 250 mg/L [C(250)]:

Upon scrutinizing the data presented in Table 4, it is evident that removal efficiencies of 98.80%, 97.50%, and 94.50% are achieved when utilizing column heights of 7.5 cm, 10 cm, and 15 cm, respectively.

Table 4 provides the output sulfate concentrations, specifically C1, C3 and C8 for SBCR at a column diameter of 4

Table 1. Analysis results for SBCR 1000 mg/L and 3.5cm column diameter

SBCR: C (1000 mg/L), R (3.5 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	30	20	10	99.00
10	50	10	20	98.00
15	25	10	2	99.80

Table 2. Analysis results for SBCR at 1000 mg/L and 3 cm column diameter

SBCR: C (1000 mg/L)¸ R (3 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	10	5	2	99.80
10	3	2	1	99.90
15	5	3	1	99.90

Table 3. Analysis results for SBCR at 250 mg/L and 3.5 cm column diameter

SBCR: C (250 mg/L)¸ R (3.5 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	5	3	2	98.80
10	35	30	25	97.50
15	70	65	55	94.50

Table 4. Analysis results for SBCR at 1000 mg/L and 4 cm column diameter

SBCR: C (250 mg/L)¸ R (3 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	25	20	20	92.00
10	45	35	20	92.00
15	65	55	35	86.00

cm [R(4)] and an initial sulfate concentration of 1000 mg/L [C(1000)]:

As the data in Table 4 indicates, significant removal efficiencies of 99.60%, 99.75%, and 99.90% are attained at column heights of 7.5 cm, 10 cm, and 15 cm, respectively.

Table 5 outlines the output sulfate concentrations for SBCR with a column diameter of 3 cm [R(3)] and an initial sulfate concentration of 250 mg/L [C(250)]:

As per the data presented in Table 5, it is noted that removal efficiencies of 92.00% and 86.00% are attained at column heights of 7.5 cm and 10 cm, respectively, while a removal efficiency of 86.00% is observed at a column height of 15 cm.

The results obtained with the SBCR are detailed below.

The Effect of Initial Sulfate Concentration on Adsorption For SBCR

The influence of the initial sulfate concentration on sulfate removal outcomes is presented in Table 6.

Based on the information provided in Table 6, it is evident that removal efficiencies of 98.00% and 90.00% are achieved for initial sulfate concentrations of 1000 mg/L and 250 mg/L, respectively. This data suggests that as the initial sulfate concentration increases, the removal efficiency also increases. It can be inferred that the adsorbent exhibits higher removal capacity at elevated initial concentrations.

The Effect of Column Fill Height on Adsorption for SBCR

Table 7 summarizes data, including the initial sulfate concentration (C_0), output sulfate concentration (C_e), absorption capacities, and removal percentages for various column heights in an absorption column with a 3.5 cm inner diameter.

Based on the data presented in Table 7, removal percentages of 99.00%, 98.00%, and 99.80% are observed for column heights of 7.5 cm, 10 cm, and 15 cm, respectively.

Table 5. Analysis results for SBCR at 250 mg/L and 3 cm column diameter

SBCR: C (1000 mg/L), R (4 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	20	8	4	99.60
10	8	5	2.5	99.75
15	4	2	1	99.90

Table 6. The effect of initial sulfate concentration on sulfate removal with SBCR

Adsorbent	h (cm)	R (cm)	M (g)	C_0 (mg/L)	C_e (mg/L)	X= C_0-Ce	q_e = (X/M) · V	Removal (%)
SBCR	10	3.5	56.62	1000	20	980	1.73	98.00
SBCR	10	3.5	56.62	250	25	225	0.40	90.00

Table 7. The effect of column height on sulfate removal with SBCR

Adsorbent	h (cm)	R (cm)	M (g)	C_0 (mg/L)	C_e (mg/L)	X= C_0-Ce	q_e = (X/M) · V	Removal (%)
SBCR	7.5	3.5	42.46	1000	10	990	2.33	99.00
SBCR	10	3.5	56.62	1000	20	980	1.73	98.00
SBCR	15	3.5	84.93	1000	2	998	1.17	99.80

Table 8. The effect of column diameter on sulfate removal

Adsorbent	h (cm)	R (cm)	M (g)	C_0 (mg/L)	C_e (mg/L)	X= C_0-Ce	q_e = (X/M) · V	Removal (%)
SBCR	10	3	36.90	1000	1	999	2.71	99.90
SBCR	10	3.5	42.46	1000	20	980	2.31	98.00
SBCR	10	4	74.96	1000	2,5	997.50	1.33	99.75
SBCR	10	3	36.90	250	20	230	0.62	92.00
SBCR	10	3.5	42.46	250	25	225	0.53	90.00

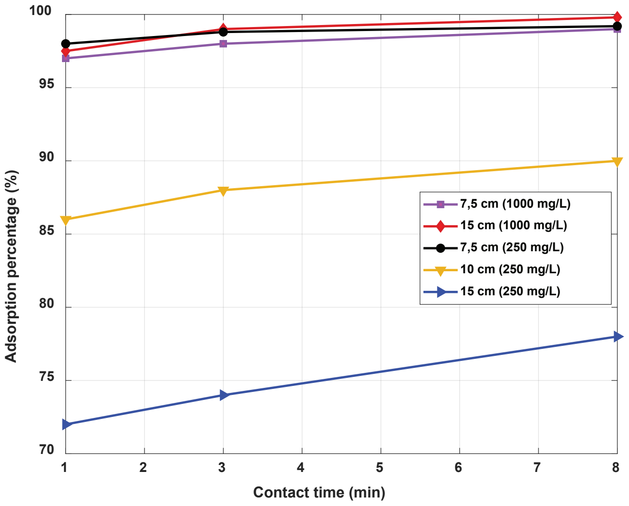

Figure 3. Effect of contact time on adsorption percentage with SBCR.

While the highest removal is attained at a column height of 15 cm, there is no significant variation in removal percentages among the other column heights.

In Table 8, when different column diameters for SBCR are examined at the same column height, it is evident that maximum removal is achieved with a 3 cm column diameter at both 1000 mg/L input concentration (99.9%) and 250 mg/L input concentration (92%). These results indicate higher removal rates are accomplished when the initial concentration is elevated, and the column diameter is smaller due to increased contact.

In investigating the impact of contact time on adsorption using SBCR, Figure 3 illustrates the variations in adsorption percentages across different concentrations and column heights, all within a column with a 3.5 cm internal diameter.

As depicted in Figure 3, when assessing the influence of contact time on adsorption percentage for initial sulfate concentrations of both 1000 mg/L and 250 mg/L, as well as for column fill heights of 7.5 cm, 10 cm, and 15 cm, it becomes apparent that the highest removal rates are achieved with a 15 cm column height and an initial concentration of 1000 mg/L. The trend in removal appears consistently increasing with time.

Optimum Conditions for Sulfate Removal with SBCR

The optimal conditions for maximizing sulfate removal using the sodium-based cationic resin (SBCR) were determined to be a 3 cm column diameter, an initial sulfate concentration of 1000 mg/L, and a column fill height of 10 cm, achieving an impressive 99.90% removal efficiency. Notably, the experimental results consistently indicated that the higher initial concentration of 1000 mg/L yielded superior results to the 250 mg/L concentration.

Subsequently, further experiments were conducted using a different resin, DVBS, at a concentration of 1000 mg/L, confirming the preference for the higher initial concentration in achieving enhanced sulfate removal performance.

Divinylbenzene Styrene (DVBS Anionic Resin)

Table 9 displays the output sulfate concentrations (C1, C3, and C8) for DVBS at a 3 cm column diameter and an initial sulfate concentration of 1000 mg/L [C(1000 mg/L)], measured at 1.3 minutes and 8 minutes, respectively.

Upon examining the data presented in Table 9, it is evident that removal efficiencies of 54% at a column height of 7.5 cm, 92% at a column height of 10 cm, and 98% at a column height of 15 cm have been achieved for DVBS.

Table 9. Analysis results for DVBS at 1000mg/L and 3cm column diameter

DVBS: C (1000 mg/L), R (3 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	620	540	460	54.00
10	140	120	80	92.00
15	60	40	20	98.00

Table 10. Analysis results for DVBS at 1000mg/L and 3.5 cm column diameter

DVBS: C (1000 mg/L), R (3.5 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	580	510	410	59.00
10	140	80	40	96.00
15	30	20	10	99.00

Table 10 provides the output sulfate concentrations (C1, C3, and C8) for DVBS at a 3.5 cm column diameter and an initial sulfate concentration of 1000 mg/L, measured at the 1st, 3rd, and 8th minutes, respectively:

Based on the data presented in Table 10, it is evident that removal efficiencies of 59.00% at a column height of 7.5 cm, 96.00% at a column height of 10 cm, and 99.00% at a column height of 15 cm have been achieved for DVBS.

Table 11 provides the output sulfate concentrations for DVBS at a 4 cm column diameter and an initial sulfate concentration of 1000 mg/L:

Based on the data in Table 11, it is evident that removal efficiencies of 98.00% at a column height of 7.5 cm and 99% at a column height of 10 cm have been achieved for DVBS.

The results obtained with the DVBS anionic are detailed below.

The Effect of Column Fill Height on Adsorption for DVBS

Table 12 summarizes data, including the initial sulfate concentration (C_0), output sulfate concentration (C_e), adsorption capacities, and removal percentages for various fill heights in a 3.5 cm internal diameter absorption column.

Effect of Column Diameter on Adsorption for DVBS

Table 13 presents sulfate removal percentages for DVBS at different column diameters but at a fixed column height. It is evident that when examining removal percentages for various column diameters at the same column height, a notable 99% removal efficiency was achieved with a 4 cm column diameter for DVBS. Moreover, there is a trend of increased removal percentage as the column diameter increases while maintaining the same initial sulfate concentration.

Effect of Contact Time on Adsorption for DVBS

Figure 4 illustrates the variations in adsorption percentage for DVBS across different concentrations and column heights within a 3.5 cm internal diameter column. Notably, the maximum removal is achieved with a 15 cm column height, as observed in Figure 4. Additionally, it's observed that there is a more substantial increase in the adsorption percentage up to 3 minutes for column heights of 7.5 cm and 10 cm. After the 3-minute contact time, the increase in adsorption percentage appears to decrease.

Optimum Conditions for Sulfate Removal with DVBS

The highest efficiency for sulfate removal using the styrene anionic resin DVBS is attained with a 3.5 cm column diameter, an initial sulfate concentration of 1000 mg/L, and a column height of 15 cm, achieving a remarkable 99.00% removal rate.

MODELING RESULTS AND DISCUSSION

The modeling results involve collecting experimental data involving SBCR and DVBS anionic resin, with various input parameters such as different diameters, heights,

Table 11. Analysis results for DVBS at 1000 mg/L and 4 cm column diameter

DVBS: C (1000 mg/L), R (4 cm)				
h (cm)	**C1 (mg/L SO_4)**	**C3 (mg/L SO_4)**	**C8 (mg/L SO_4)**	**Removal (%)**
7.5	280	40	20	98.00
10	220	90	10	99.00
15	NR	NR	NR	NR

Table 12. The effect of column height on sulfate removal with DVBS

Adsorbent	h (cm)	R (cm)	M (g)	C_0 (mg/L)	C_e (mg/L)	X= C_0-Ce	$q_e = (X/M) \cdot V$	Removal (%)
DVBS	7.5	3.5	26.3	1000	410	590	2.24	59.00
DVBS	10	3.5	35	1000	40	960	2.74	96.00
DVBS	15	3.5	52.6	1000	10	990	1.88	99.00

Table 13. The effect of column diameter on sulfate removal

Adsorbent	h (cm)	R (cm)	M (g)	C_0 (mg/L)	C_e (mg/L)	X= C_0-Ce	$q_e = (X/M) \cdot V$	Removal (%)
DVBS	10	3	28,67	1000	80	920	3.21	92.00
DVBS	10	3.5	35.00	1000	40	960	2.74	96.00
DVBS	10	4	43.20	1000	10	990	2.29	99.00

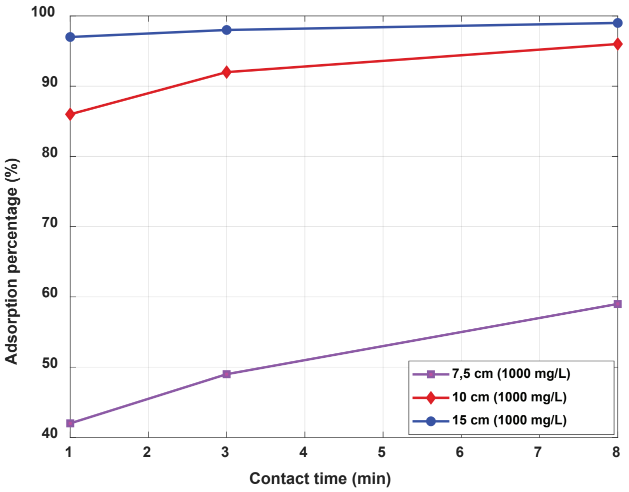

Figure 4. The effect of contact time on adsorption percentage with DVBS.

initial sulfate concentrations, and resin types. The training and testing outcomes are depicted in Figure 5.

The performance criteria for the model are presented in Table 14 for both the training and testing phases. The model's performance is evaluated based on the correlation coefficient (R), mean absolute percentage error (MAPE %), root mean square error (RMSE), and mean square error (MSE).

The results indicate that the model demonstrates strong performance. Low MAPE and RMSE values indicate the model's accuracy in making predictions. Additionally, the model achieves very high R-values in both the training and test phases, further confirming its effectiveness in capturing the underlying patterns and relationships in the data.

COMPARISON OF RESULTS WITH LITERATURE

This study evaluated the sulfate removal capabilities of two distinct resins, SBCR and DVBS, using various experimental designs. The experiments demonstrated high removal rates with SBCR, outperforming DVBS. This disparity can be attributed to the electrostatic interactions between the cationic SBCR and sulfate ions (SO_4^{2-}) compared to the anionic DVBS and sulfate ions, as supported by references [22-25].

Further comparison with the literature reveals that this study has achieved exceptionally high levels of sulfate removal, particularly with SBCR, marking a notable improvement over previously reported results [14, 26-29]. The compatibility of these findings with existing literature underscores the efficacy of both SBCR and DVBS in removing sulfate ions. Additionally, the application of AI modeling in this research contributes new insights and value to the existing body of knowledge.

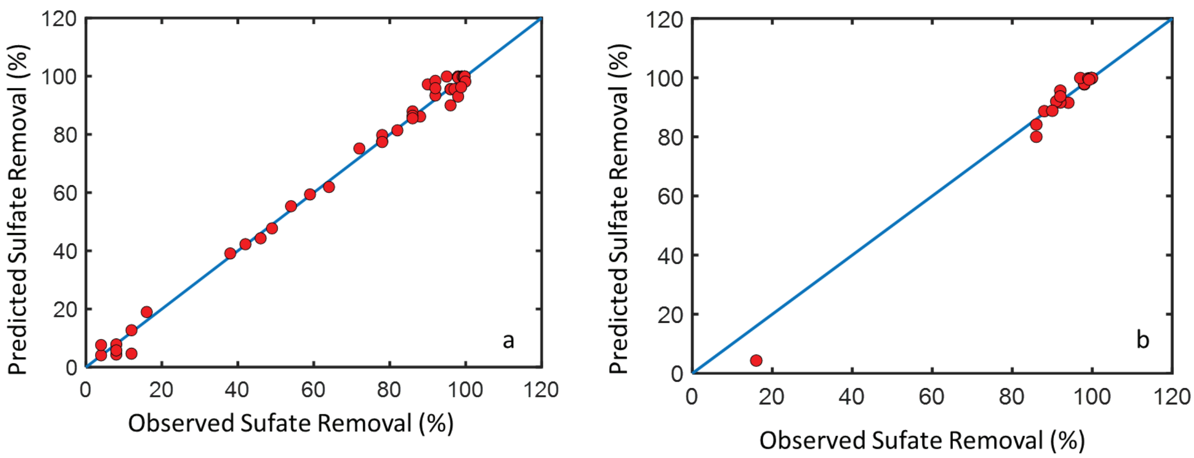

Figure 5. Training (a) and test (b) results.

Table 14. Performance criteria of model

Training Phase				Test Phase			
R	**MAPE %**	**RMSE**	**MSE**	**R**	**MAPE %**	**RMSE**	**MSE**
1.0000	0.5422	0.0012	$1.42x10^{-6}$	0.9999	0.9223	0.0034	$1.14x10^{-5}$

CONCLUSION

In conclusion, this study presents the development of an advanced Artificial Neural Network (ANN) model for predicting sulfate removal efficiency in water, addressing key health concerns related to high sulfate levels. Various factors, including experimental procedures and costs, influence the choice of sulfate removal methods. The ANN model developed here showcases remarkable performance, demonstrated by low error metrics (MAPE %, RMSE, MSE) and high correlation coefficients. These results indicate the model's strong capability in accurately estimating sulfate removal. This model significantly reduces experimental costs and workload, marking it as a practical tool in sulfate removal research. By offering precision and efficiency in predictions, the ANN model represents a shift in research methodologies towards more cost-effective and efficient water treatment and environmental management strategies.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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