



# Chloride removal from reverse osmosis reject water based on *Strychnos Potatorum* seeds by analytical method and Artificial neural network

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## ABSTRACT

In today's world, effective water treatment is necessary for safe and clean drinking water. The chloride can be decreased in water after coagulant treatment. The use of natural coagulants has the upper hand as chemical coagulant has a lot of negative impacts. In the present study aimed to use ANN to model the chloride removal using *Strychnos Potatorum* seeds. The supporting parameters for the model were pH, electrical conductivity (EC), and total dissolved solids (TDS). Using the Jar test and EC measurements, this study assesses using Nirmali seeds (*Strychnos Potatorum*) as a natural coagulant in water treatment. Ionic concentration changes and overall water quality are evaluated by EC measurements, whereas the Jar test establishes the ideal dosage and settling time for efficient turbidity reduction. The outcomes show that Nirmali seeds have the potential to be a more affordable and environmentally responsible coagulant than traditional chemicals. Apart from this, the Non-linear autoregressive neural network with external input (NARX) model that was trained using all three algorithms, i.e., the Levenberg-Marquardt (LM), the Bayesian Regularization (BR), and the Scaled Conjugate Gradient (SCG), was compared, in which the model trained with SCG algorithm showed the most promising test results. Hence, the Non-linear autoregressive neural network with external input (NARX) model trained with the SCG algorithm is the best-suited model for our study. The LOD of 1.28 mg L<sup>-1</sup> and LOQ of 3.87 mg L<sup>-1</sup> were obtained. The removal percentage of chloride content after adding different dosages of SPS, i.e., 0.2 mg, 0.4 mg, and 0.8 mg per liter, was achieved at 21.05%, 29.82%, and 38.59%, respectively.

## 1. Introduction

Growing concern about water treatment methods for consumption has severely impacted numerous communities worldwide. Water contamination as a result of multiple pollutants like mercury [1,2] lead [3], Nickel [4,5], manganese [1,6], and many other

contaminations, including chloride and its ions, is becoming a nightmare and requires urgent action. Numerous cleanup and treatment methods have been employed worldwide, with reverse osmosis (RO) being one of the most popular. However, the amount of wastewater released by such methods as RO is high and alarming. Effective water treatment techniques can be developed by researching the adsorption and desorption capacities of single- and

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multi-walled carbon nanotubes [7,8], air exposure evaluations, and biological monitoring using dispersive ionic liquid-liquid microextraction [9,10]. Furthermore, speciation of heavy metals in water, human blood, and food samples based on pyrrolic and pyridinic nitrogen-doped porous graphene nanostructures [11]. RO reject water is unsuitable for drinking or agricultural use but can be treated for other applications. However, it is essential to properly manage and dispose of RO-rejected water to prevent environmental contamination and ensure compliance with local regulations. Due to the multiple contaminants present, it is impossible to recover water from the rejected bulk water [12]. 15% of the water in the system recovers input; the remaining portion is released as waste. Recovering water from the rejected bulk is unfeasible due to the numerous contaminants. The kernel of *Strychnos Potatorum* and *Moringa oleifera* seeds can remove impurities from the water and make it suitable for secondary purposes. *Strychnos Potatorum* is effective for low, medium, and high turbidity water. Turbidity may be eliminated using the kernels of *Moringa oleifera* and *Strychnos Potatorum* seeds. As experimented by *Strychnos Potatorum*, it is effective for low, medium, and high turbidity water while having a lower removal effectiveness than *Moringa oleifera* for medium and high turbidity water [13]. Defluorination also took place in groundwater within a contact duration of two hours, removing the majority of the high-level fluoride content at a rate of 86% to 81.25%, as concluded. *Strychnos Potatorum* seeds are a natural coagulant to remove turbidity and fluoride. It offers numerous advantages, including no hazardous effects and safety [14]. The Schultz-Hardy rule and particle collision function provide coagulant demand and variations in particle number in the flocculation process [15]. Different models in ANN can be used for modeling, but NARX(non-linear autoregressive models with exogenous inputs) was preferred because of its dynamic neural architecture [16]. Given the system's experimental input and output data, ANN is a sophisticated computational approach that can

accurately and appropriately forecast the performance of a system [17]. In contrast to conventional recurrent neural models, NARX has limited feedback structures from output neurons. At the very least, NARX networks are used for traditional recurrent networks equivalent to Turing machines [18]. Various models can be used for water quality analysis and prediction. A recurrent dynamic neural network called the non-linear autoregressive exogenous (NARX) model has a few network layers surrounded by feedback connections. The NARX model simulates various non-linear processes, including time-series modeling [19]. This model has been widely used in environment-related research, including wastewater treatment. The NARX model was chosen to compare the FANN and NARX models because it performed better and had a better R-squared value. Also, by creating a NARX model, the removal of mercury ions from the water was explored and functionalized multi-walled carbon nanotubes were used as an adsorbent [20]. Mainly based on bench-scale testing, plant-based coagulants derived from *Moringa oleifera*, *Strychnos Potatorum* Linn, *Plantago ovate*, *Trigonella foenum graecum*, and *Opuntia ficus indica* are promising alternatives to chemicals [21]. Natural, water-soluble, organic, ionic, and non-ionic polymers of various molecular weights generated from multiple plant components are called plant-based coagulants [22]. Nano adsorbents and nanocomposite materials like metal-organic frameworks and carbon nanotubes can effectively adsorb specific ions. While electro-spun nanofibers and ion-exchange nanoparticles offer high surface areas and selective ion exchange capabilities for efficient water purification, methods like nano-photocatalysis and magnetic nanoparticles break down pollutants and make separation easier [23]. The method described in [BDMIM][PF6] for USA-DIL-SSPME for CysSB/MetSB@MWCNTs effectively separates and determines nickel and cobalt in human blood samples. This procedure guarantees precise concentration measurements by ET-AAS by eliminating chloride interference and adjusting pH to

extract Co/Ni (II) without requiring extra ligands [24].

This study aims to develop and validate an artificial neural network (ANN) model that uses *Strychnos Potatorum* seeds as a natural adsorbent to predict the efficiency of chloride removal from reverse osmosis (RO) reject water. By optimizing the ANN model, this study aims to provide a reliable predictive tool for enhancing the RO reject water treatment process and to better understand the key parameters influencing chloride adsorption.

## 2. Material and Methods

### 2.1. Study area

The work was conducted in five different locations of Visakhapatnam, a coastal city in India's south-eastern part of Andhra Pradesh. Geographically the city lies between  $17^{\circ} - 41'$  and  $17^{\circ} - 59'$  Northern latitude and  $83^{\circ} - 12'$  and  $83^{\circ} - 27'$  in Eastern longitude. The RO reject water was collected from houses with different reverse osmosis machines from five Visakhapatnam and Andhra Pradesh locations. The locations are marked on the map given in Figure 1.

## 2.2. Experimental procedure

### 2.2.1. Natural Coagulant as Analytical Chemical Procedure

The powder of *Strychnos Potatorum* (SPS) seed, commonly known as "Clearing Nut" or "Nirmali seed," was obtained from Poorna Market, Visakhapatnam, Andhra Pradesh. SEM of *Strychnos Potatorum* seeds and powder were selected, as shown in Figure 2.

To perform this work, we used analytical methods to analyze Nirmali seeds, including the Jar test, pH, and Electrical conductivity before ANN. An analytical technique called the jar test assesses water treatment's flocculation and coagulation processes. It entails treating water samples in several jars with different concentrations of coagulants, mixing, and letting the samples settle. The supernatant water's clarity is evaluated to find the ideal coagulant dose required to eliminate turbidity and suspended particles. This test is essential for optimizing water treatment procedures to ensure effective contaminant removal. Electrical conductivity (EC) measures a solution's ability to conduct electric current, indicating ions' presence.

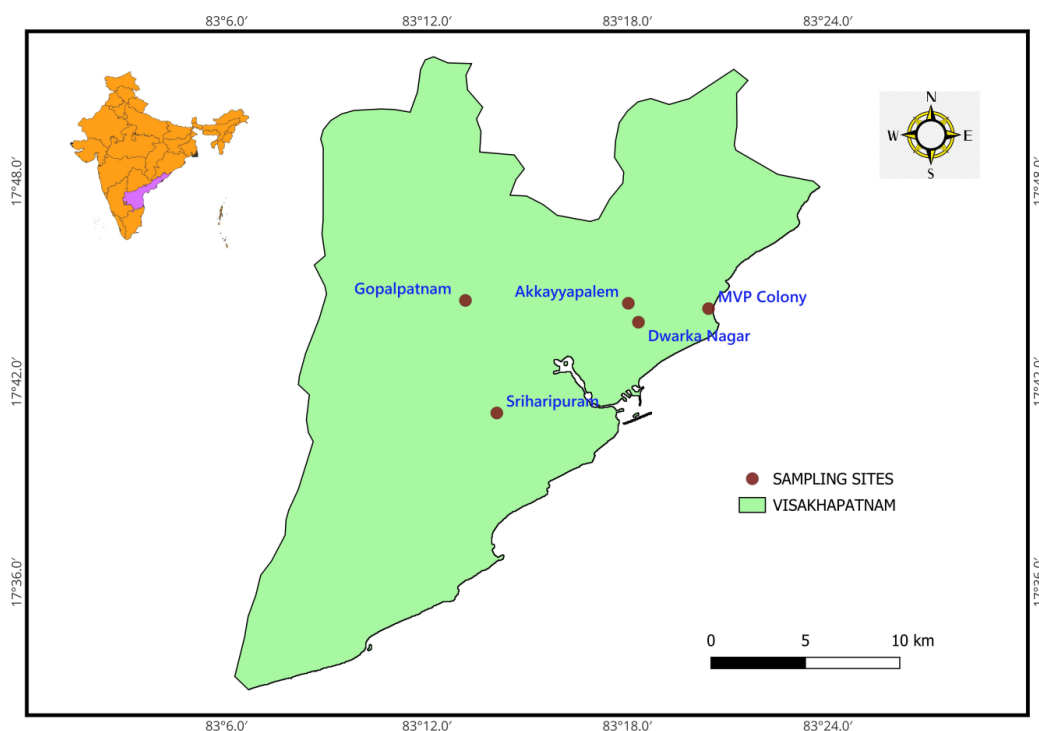
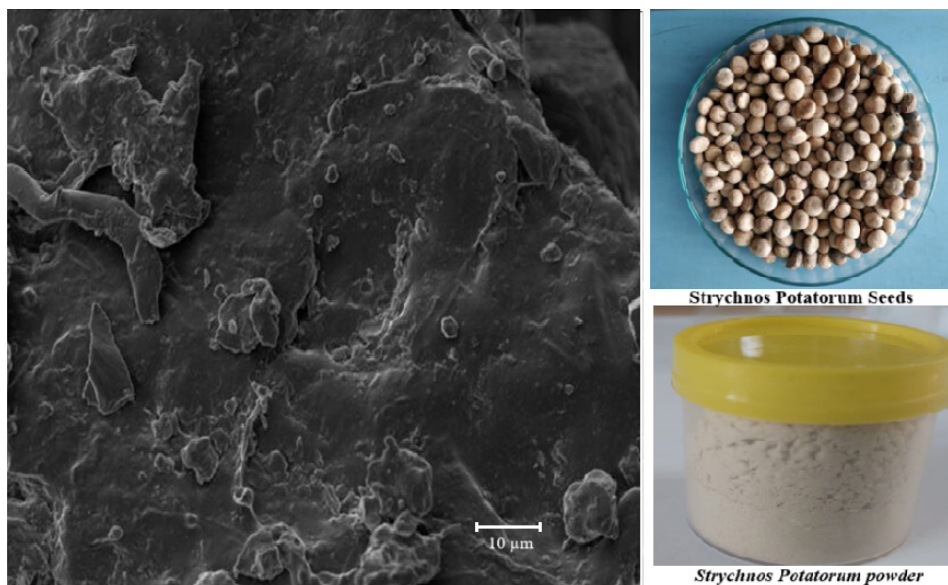


Fig. 1. Sampling sites marked in the map of Visakhapatnam.



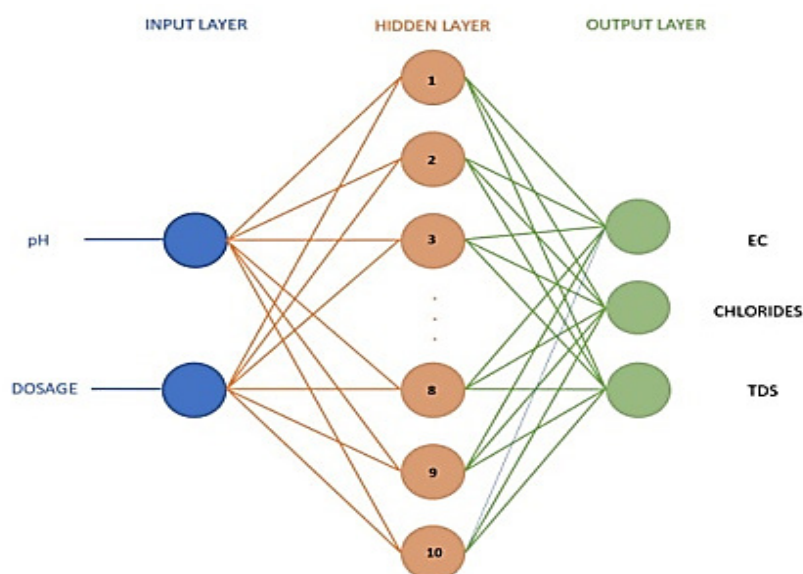
**Fig.2.** SEM of *Strychnos Potatorum* seeds

High EC values suggest elevated dissolved salts and mineral concentrations in water quality assessment, affecting factors like plant growth and soil health. EC is monitored in water treatment to meet quality standards and adjust processes accordingly. Measurements are made using a conductivity meter, providing quick and accurate water quality evaluations.

### 2.2.2. The procedure of Algorithm of Artificial Neural Network

Using MATLAB, the authors selected a non-linear autoregressive network with exogenous inputs

(NARX). A network was created in which we imported the data from the workspace using the diagram shown in Figure 3. Then, the data was imported into the network, input data as responders and output data as predictors from the workspace. 70 % of the data has been taken as training data in both input and output. The model is then trained using all three algorithms, i.e., the Levenberg-Marquardt algorithm, the Bayesian Regularization, and the Scaled Conjugate Gradient. After training the model, it has been tested with new input data. This model is then exported into the workspace.



**Fig. 3.** Diagram of the NARX model

### 3. Results and Discussion

#### 3.1. Physiochemical characteristics of RO reject water

Various physiochemical parameters were determined to assess the effectiveness of *Strychnos Potatorum* (SPS) seeds on RO-reject water. The parameters like pH, EC, turbidity, TDS, and chloride are determined. The results are tabulated in Table 1.

#### 3.2. Removal percentage of chloride using *Strychnos Potatorum* seeds

The highest removal percentage of chloride content after adding different dosages of SPS, i.e., 0.2 mg, 0.4 mg, and 0.8 mg per liter, is 21.05%, 29.82%, and 38.59%, respectively; the values of chloride removal percentage are mentioned in Table 2.

#### 3.3. NARX model generated using MATLAB

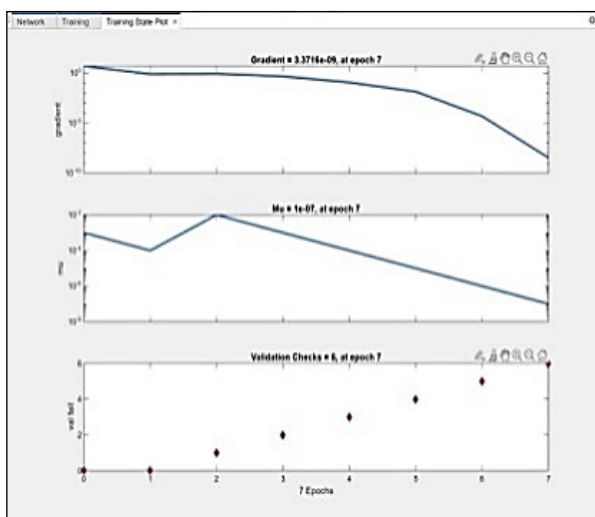
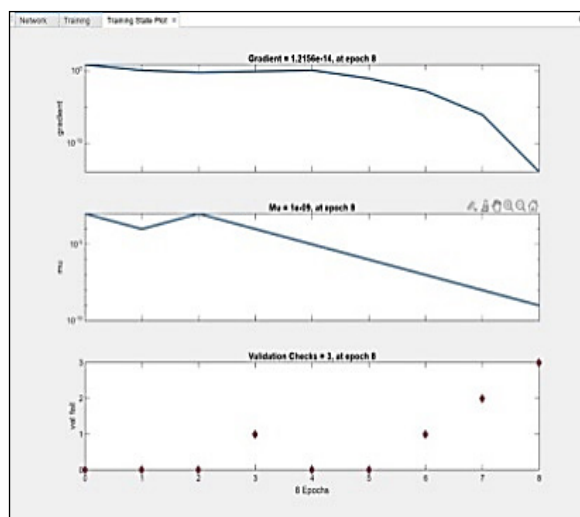
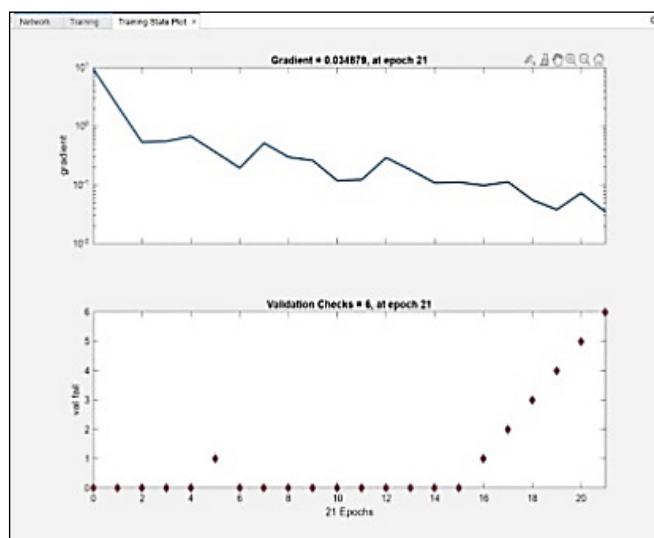
The model was generated using a Non-linear autoregressive neural network with external input (NARX) in MATLAB. The NARX model using the LM training algorithm achieved an overall R-value of more than 0.93 from 10 hidden neurons. Furthermore, the BR and SCG training models achieved an overall R-value of other than 0.92 and 0.98, respectively. The results are shown in Figure 4. For this, the authors generated the Training State Plot, revealing that 7 and 8 epochs are identified, and the Performance Plot means squared error and epochs are generated. Test plot LB and BR, the R-values of 0.97 and 0.96 were observed. The graphs obtained for LB, BR, and SCG are shown in Figures 4a,4b,4c,4d,4e,4f,4g,4h, and 4i.

**Table 1.** The pH, EC, TDS, and chloride of RO water samples from different places and after the addition of different dosages of *Strychnos Potatorum* seeds.

Geographical Location	Dosage (mg L <sup>-1</sup> )	pH	EC	TDS (mg L <sup>-1</sup> )	Chloride (mg L <sup>-1</sup> )
MVP Colony	0.0	7.26	0.61	396.5	76.430
	0.2	7.46	0.64	416.0	69.482
	0.4	7.12	0.62	403.0	59.556
	0.8	6.63	0.63	409.5	64.519
Dwarka Nagar	0.0	7.05	0.67	435.5	97.274
	0.2	7.19	0.69	448.5	94.297
	0.4	7.06	0.72	468.0	84.371
	0.8	6.68	0.79	513.5	79.408
Sriharipuram	0.0	6.95	0.84	546.0	150.875
	0.2	6.72	0.86	559.0	134.001
	0.4	7.64	0.88	572.0	114.149
	0.8	6.45	1.00	650.0	129.038
Akkayypalem	0.0	7.03	0.40	260.0	56.578
	0.2	6.98	0.41	266.5	44.667
	0.4	6.66	0.41	266.5	39.704
	0.8	6.48	0.43	279.5	34.741
Gopalapatnam	0.0	7.13	1.10	715.0	250.135
	0.2	7.11	1.35	877.5	238.224
	0.4	6.63	1.30	845.0	233.261
	0.8	6.53	1.39	903.5	228.298

**Table 2.** The Removal percentage of chloride from RO Reject water samples at different dosages of *Strychnos Potatorum* seeds

Geographical Location	Dosage (mg L <sup>-1</sup> )	Chloride content (mg L <sup>-1</sup> )		Removal %
		Initial	Final	
MVP Colony	0.2	76.430	69.482	9.09
	0.4	76.430	59.556	22.07
	0.8	76.430	64.519	15.58
Dwarka Nagar	0.2	97.275	94.297	3.06
	0.4	97.275	84.371	13.26
	0.8	97.275	79.408	18.36
Sriharipuram	0.2	150.875	134.001	11.18
	0.4	150.875	114.149	24.34
	0.8	150.875	129.038	14.47
Akkayapalem	0.2	56.578	44.667	21.05
	0.4	56.578	39.704	29.82
	0.8	56.578	34.741	38.59
Gopalpatnam	0.2	250.135	238.224	4.76
	0.4	250.135	233.261	6.74
	0.8	250.135	228.298	8.73

**Fig.4a.** Training state plot for LB**Fig.4b.** Training state plot for BR**Fig.4c.** Training state plot for SCG

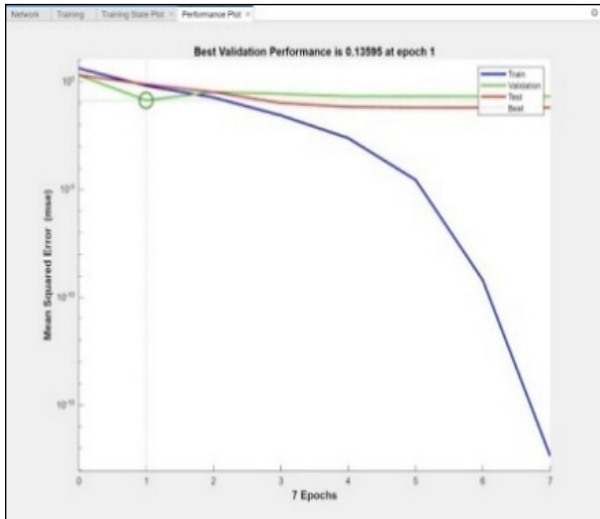


Fig.4d. Performance plot for LB

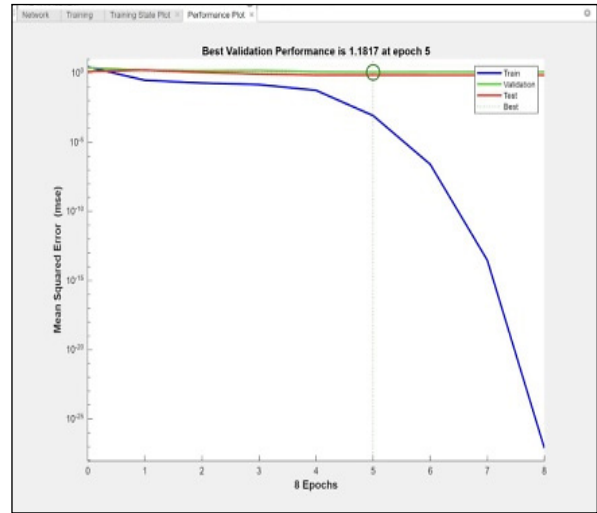


Fig.4e. Performance plot for BR

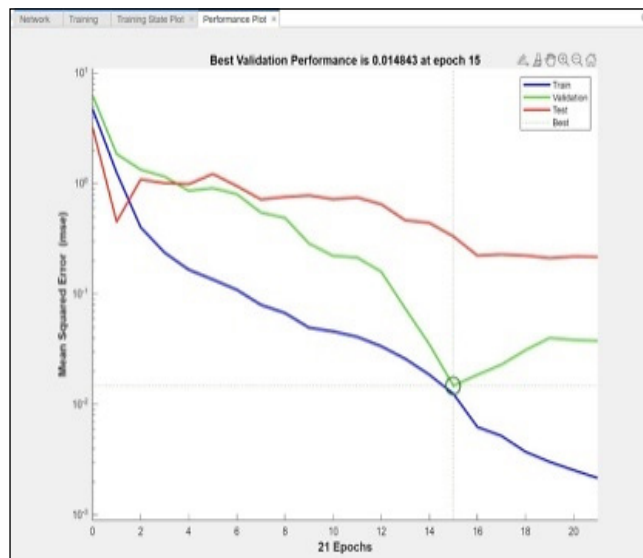


Fig.4f. Performance plot for SCG

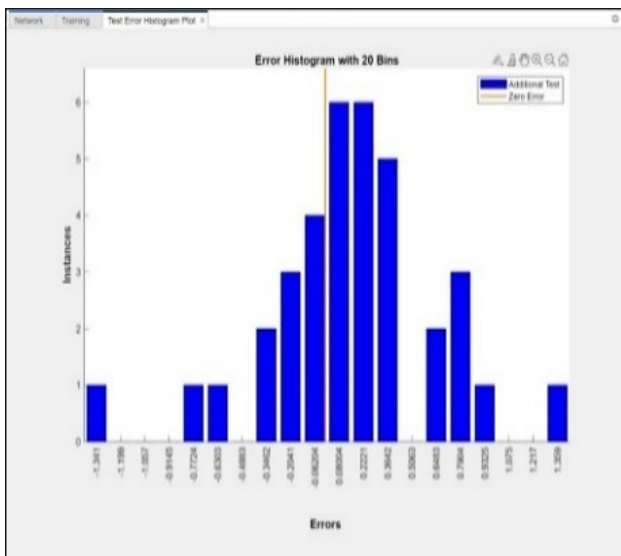


Fig.4g. Test Error histogram for LB

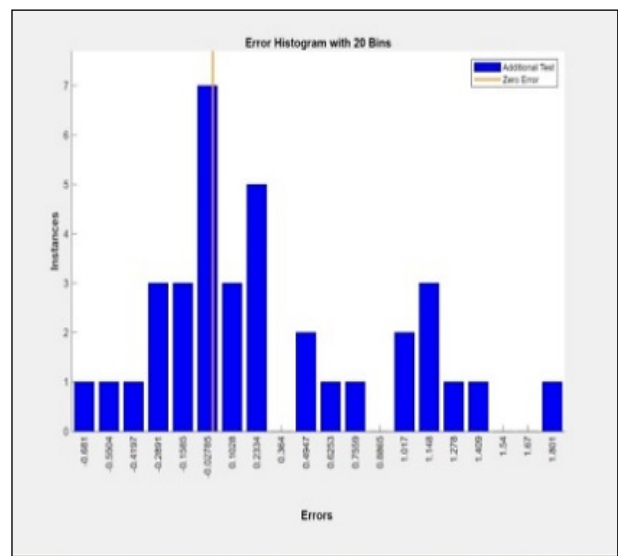
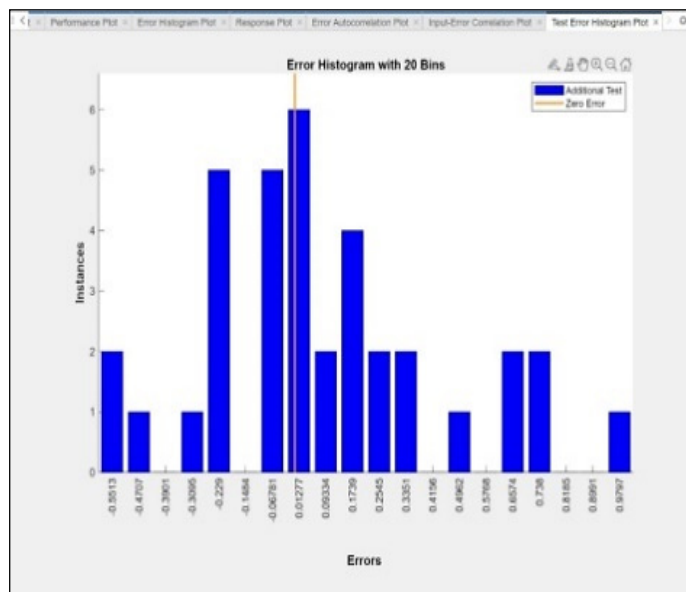


Fig.4h. Test Error histogram for BR



4a-4i Test Error histogram for SCG

### 3.4. Comparison of all the three algorithms

All three algorithms were compared. The overall R-value of Levenberg-Marquardt (LM), the Bayesian Regularization (BR), and the Scaled Conjugate Gradient (SCG) was observed to be more than 0.95, 0.96, and 0.99, respectively. The results are tabulated in Table 4a-4i.

### 3.5. Statistical Results

Limit of Detection (LOD) and Quantification (LOQ) must be analyzed. For this analysis, the chloride concentration is identified using the titrimetric method. Using the given data, a linear regression to find the slope (S) and intercept of the calibration curve is calculated and shown in Figure 5. The standard deviation ( $\sigma$ ) of the blank measurements is 0.0077 mL. The slope (S) of the calibration curve is 0.02. The calculated values are LOD 1.28 mg L<sup>-1</sup> and LOQ 3.87 mg L<sup>-1</sup>.

These values indicate the sensitivity of your titration method for detecting and quantifying chloride concentrations. The results obtained are represented in the Table 5.

### 3.6. Discussion

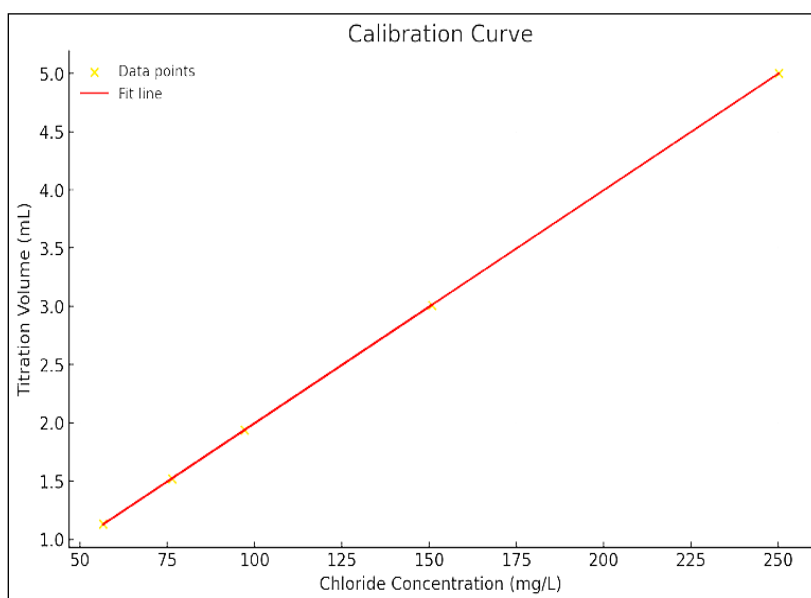
The present study found that the pH of the water sample after adding 0.2 mg L<sup>-1</sup> and 0.4 mg L<sup>-1</sup> of SPS seeds remained almost the same. Still, after adding 0.8 mg L<sup>-1</sup>, the water sample slightly became acidic as the RO water was not acidic. This is likely due to the release of hydrogen ions from the SPS seeds when they come into contact with water. According to the findings, the acidity produced by the SPS seeds is directly proportional to the amount of seed added to the water sample. Adding SPS seeds reduced the chloride content in water samples. The removal percentage of chloride was found to be 9.82%, 19.24%, and

**Table 4.** MSE and R (Regression Coefficient) value of training, validation, and test of all the three algorithms, i.e., the Levenberg-Marquardt (LB) algorithm, the Bayesian Regularization (BR), and the Scaled Conjugate Gradient (SCG).

Algorithm		LB	BR	SCG
Number of hidden neurons		10	10	10
MSE	Training	0.6461	0.1573	0.0125
	Validation	0.1359	0.3997	0.0148
	Test	0.7566	0.205	0.3335
R	Training	0.9365	0.9999	0.9987
	Validation	0.993	0.9349	0.9991
	Test	0.9244	0.9492	0.981
	Overall	0.9513	0.9613	0.9929

**Table 5.** Results of Chloride Concentration

Chloride Concentration (mg L <sup>-1</sup> )	Titration Volume (mL)
76.4	1.52
97.2	1.94
150.8	3.01
56.57	1.13
250.135	5.00

**Fig. 5.** Calibration curve for Titration

19.14% after adding 0.2 mg L<sup>-1</sup>, 0.4 mg L<sup>-1</sup>, and 0.8 mg L<sup>-1</sup> with a contact time of 1 hour. The addition of SPS seeds acted as the de-chlorination substance and helped reduce the overall chloride content in the water sample. This method effectively lowers chloride content in water samples and can be used in various filtration settings. Many complex systems, especially those with non-linear dynamics, are modeled using the NARX (Non-linear Autoregressive with Exogenous Inputs) model. This model combines the strengths of artificial neural networks with time-series analysis to predict the behaviour of the system based on its historical and current inputs. In this instance, the Levenberg-Marquardt (LB), Bayesian Regularization (BR), and Scaled Conjugate Gradient algorithms were used to train the NARX model, which was created based on experimental findings (SCG). The LB algorithm is a prominent optimization approach in training artificial neural networks. By reducing the difference in error between the expected and

actual outputs, this algorithm modifies the network weights at each epoch. The BR algorithm is another optimization method that penalizes the model for having high weights by including a regularisation factor in the loss function. The SCG algorithm is a variation of the conjugate gradient method that scales the search direction to quicken convergence. The overall R (Regression Coefficient) score for the NARX model trained using LB was over 0.95, accounting for 95% of the output's variance. The BR model fared somewhat better with an R-value above 0.96. The most encouraging results, however, came from the SCG algorithm, which had an R-value above 0.99, indicating high output prediction accuracy. Each of the three algorithms utilized in this study had ten hidden layers, although their training data varied regarding the number of epochs. The LB and BR models were trained with 7 and 8 epochs, respectively, while the SCG model attained the best performance with 21 epochs. Comparison studies with other methods are

**Table 6.** Comparison studies with other methods

Method	Percentage degradation (%)	References
DCI-SPS	38.5	Current work
Chemical Precipitation	About 24.35%	[25]
Bentonite Clay Adsorption	15-20%	[26]
Electrocoagulation	Up to 25%	[27]
LDHs Adsorption	11.2% (specific study)	[28]
Anion Exchange Resins (Weak Anion Type)	Potentially below 30%	[29]
Biosorption using Alginate Beads	22.3	[30]
Microwave-Assisted Electrolysis	18.2% (specific study)	[31]
Moringa Oleifera Seed Extract	10-20%	[32]
Cactus (Opuntia spp.) Cladodes Extract	Up to 15%	[33]

DCI-SPS: Degradation of chloride using Strychnos Potatorum seeds

LDHs: Layered Double Hydroxides

represented in Table 6.

#### 4. Conclusion

The present work focuses on using *Strychnos Potatorum* seeds as a natural coagulant for removing chloride in RO reject water and then building a model using an artificial neural network. The use of natural coagulants for water purification is gaining much popularity nowadays. The results of the combined analytical methods show that *Strychnos Potatorum* seeds considerably lower the concentrations of ions and turbidity in treated water. The study's results support the seeds' usefulness as a natural coagulant, providing a cost-effective and environmentally friendly substitute for conventional chemical coagulants. Additional studies and pilot-scale applications are advised to confirm these results in various water treatment scenarios. Hence, integrating artificial neural networks with experimental results can help fill the gap. The present study has used different dosages of *Strychnos Potatorum* seeds to remove chloride in RO reject water. The removal of chloride after using different dosages was significantly high. The removal percentage of chloride content after adding different dosages of SPS, i.e., 0.2 mg, 0.4 mg, and 0.8 mg per liter, is 21.05%, 29.82%, and 38.59%, respectively. Then, these data were fed to the Non-linear autoregressive neural network with external input (NARX) model that was trained using all three algorithms, i.e., the Levenberg-Marquardt (LM), the Bayesian Regularization (BR), and the Scaled Con-

jugate Gradient (SCG) in which it was found that model trained using Scaled Conjugate Gradient has the best R-value. So, the study concludes that using the NARX model trained with the SCG algorithm best optimizes chloride removal.

#### 5. Acknowledgments

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