Analyzing Multi-stage Reverse Osmosis Desalination Using Artificial Intelligence

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***Abstract*—Population growth has resulted in a decrease in readily available sources of potable water. Desalination is one of many approaches that has been studied and proposed as a way out of this predicament. In this study, multistage Reverse Osmosis desalination process is used in the model, since it has the potential to achieve a higher purity percentage than the single-stage RO desalination process. Some researchers have studied the distinctive tools of AI, specifically Artificial Neural Network as regression model and the genetic Algorithms as an optimization technique in the process of desalination and water treatments. This paper aims to examine multistage RO desalination by employing various artificial intelligence (AI) techniques, including Artificial Neural Network (ANN) and Support Vector Machine (SVM). Both training methods used for this research come under the category of regression algorithms, which are used to establish a predictive link between variables and labels. The main finding of this study was the noticeable decrease of Mean Square Error (MSE) in second stage when data was trained using the ANN. While on the other hand the MSE increased in second stage when the data was trained using the SVM. It can be concluded that the results of this research indicate that applying ANN and SVM to RO desalination process modelling would yield substantial improvements. Future work will be focusing on predicting and improving the performance of ANN and SVM prediction with other function variables.**

Keywords*—*Artificial intelligence; artificial neural network; desalination; regression; reverse osmosis; support vector machine

I. Introduction

The problems of water scarcity, which have plagued our world since ancient times, persist today. Clean water is becoming increasingly difficult to come by, and its quality is deteriorating to the point where it is being blamed for the deaths of people in some countries. The demand for and consumption of clean water would rise as a result of the fact that not only humans but also animals and plants require it [1]. The concern is also rising around the world because the current supply of fresh water is insufficient to meet the needs of the global population [2]. We live in a world that is 71% water, with almost 97% of that water held by oceans, yet we have a water shortage [3]. Through a variety of processes that scientists have tried to solve, desalination is one of the most common methods for converting salt water into potable water. Reverse osmosis (RO), which employs a specialized membrane, is a frequently employed desalination method.

Reverse osmosis desalination is a rapidly expanding and popular method used to produce water, and it now accounts for around 70% of the world's water supply.

Reverse Osmosis desalination is a method of separating brackish water from dissolved salts by pumping it under high pressure through a water-permeable membrane. Initially, seawater (brackish water) flows into a primary settling tank. This brackish water is then pumped into the reverse osmosis feed tank. Part of the permeate (clean) water and the strong concentrated brine solution is recycled into the water storage tank with the proper pressure, temperature, and feed [4].

Despite the outstanding performance, the application of RO has some limitations. Those limitations include high pressure required, high cost of membrane replacement, low permeation flux, low membrane durability, high equipment and operating cost that affects the process economically[3]. Therefore, ongoing efforts and studies are needed to be carried out to increase pure water recovery by developing new process configurations that use multi-stage RO and optimization processes (see Fig. 1).

According to studies [5][6] AI has proven to be a versatile tool for learning complex patterns. As explained in that paper, to learn those complex patterns it employs two methods, namely: supervised and unsupervised learning. The supervised learning algorithm is the most commonly used machine learning algorithm, in which a dataset trains an algorithm with known input and responses to make the desired predictions.

This supervised learning algorithm is further classified as Classification and Regression, with Classification being used when categorical response values are separated into specific classes. When you have numerical continuous-response values, you use Regression. According to [7] and [8] research papers, RO dataset responses which had numerical values were implemented, where the Regression algorithm was used for AI techniques. To train the data, they used the Artificial Neural Network (ANN) and the Support Vector Machine (SVM) as Regression algorithms [7]. Both of the techniques were implemented to analyze and compare the performance of the RO desalination process [9].

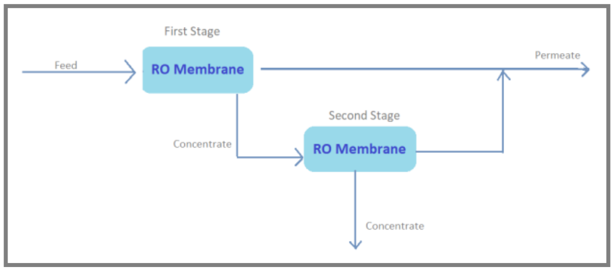

Fig. 1. Multi-Stage RO.

The RO process is used in this paper to convert brackish water to fresh water via a selected membrane. It also investigates how AI can be used to control the factors that contribute to this process. To achieve the best possible result, the various factors that affect these processes were managed using Artificial Intelligence technology.

In this study, a multi-stage RO process is used to achieve permeate water by inhibiting multiple RO membrane stages. This improves water recovery and reduces RO rejection. The concentrate water is collected in a brackish tank obtained from previous cycles, whereas the permeate water is collected in a water storage tank after passing through the multistage membranes.

II. Materials and Method

In this research, a multi-stage RO process is proposed as a means to produce potable water. This research into its acquisition will consist of three stages. First, the study goes over the steps that are taken to collect information for the RO procedure.

For both steps of the RO procedure, the efficacy of data that has been trained using an ANN is discussed. Both sets of simulated data are used to train a Support Vector Machine (SVM) MATLAB will be used by these two AI methods to analyze the water quality that is achieved after several steps have been taken.

A. Acquiring Data from Simulating Reverse Osmosis

Starting with a good simulator, the Reverse Osmosis process is run to get a feel for how it works. The ASPEN Plus platform was suitable for modeling the entire procedure because it provides a realistic insight by allowing the model to be fed brackish water and subsequently yielding clean water.

The information obtained from ASPEN Plus was useful because it mimics the physical RO process, as discussed in the prior study "Using Artificial Intelligence for Reverse Osmosis Desalination." In order to plan for and acquire the data, the actual effect of temperature, pressure, salt concentration, and feed flow rate would be studied and monitored [10].

While holding all other variables constant, a simulation in ASPEN Plus was run to determine the impact of each individual variable on the operation (see Fig. 2). For instance, in Table I, the effect of changing the pressure while holding the other parameters constant was examined in order to better understand the RO.

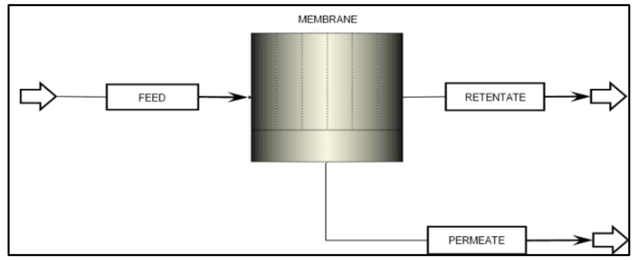

Fig. 2. Schematic Diagram of RO Membrane using ASPEN Plus.

Water flux and salt rejection are both influenced by the pressure that is applied, as shown in Fig.3 and Fig. 4, which depict the performance of stream pressure and the permeate flux, respectively. As can be seen in the graphs, there is a direct correlation between the water flux and the operating pressure. In order to verify the accuracy of the ASPEN Plus experiment and develop an algorithm to aid in the prediction of the parameters in the future, it can be fed into AI training tools. In addition, the AI tools investigate and make predictions about how various elements influence the quality of the membrane's output water (permeate).

A data set of inputs (temperature, pressure, and salt concentration) and outputs (percentage of pure water) is used to train, validate, and test the ANN and SVM tools.

B. Maintaining the Integrity of the Specifications

In this part, an Artificial Intelligence method commonly referred to as an ANN is used to train the data that had been collected so far. An artificial neural network (also known as a neural network) is a type of adaptive system that acquires knowledge through the use of interconnected nodes or neurons arranged in a hierarchical framework similar to the human brain. Because neural networks are data-driven, they can be taught to perform a wide range of tasks, including pattern recognition, data classification, and event prediction [5].

TABLE I. RO Modelling Condition for Altered Pressure

Parameters	**Feed Water Temperature, 0C**	**Flow rate, m3/h**	**Feed Water Salt Concentration, g/l**
	20	8	30

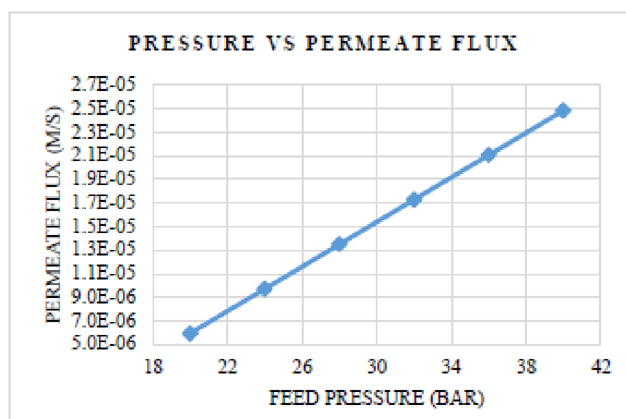

Fig. 3. Effect of Operating Pressure on Water Flux.

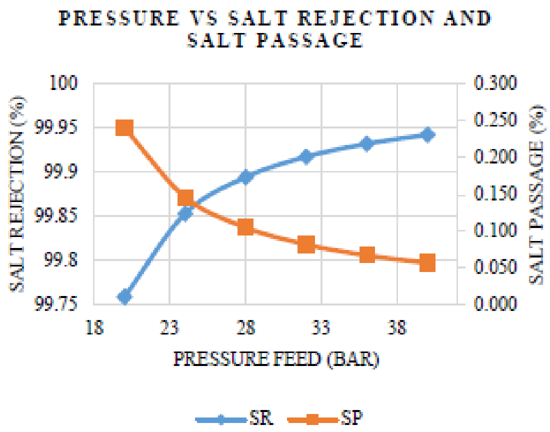

Fig. 4. Effect of Feed Pressure on Salt Rejection and Salt Passage.

In order to better process the input, a neural network can abstract it in layers. Similar to how the human brain learns, it can be trained with lots of examples to recognize patterns in things like speech or images. How its parts are linked together, and how strongly they are linked together (the weights), determine its behavior. During training, these weights are continuously fine-tuned in accordance with some predetermined learning rule until the artificial neural network achieves the desired performance level.

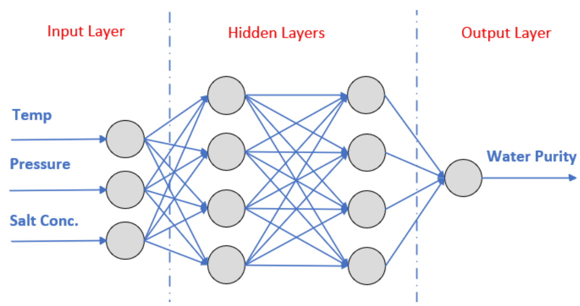

Fig. 5. Architecture of Artificial Neural Network.

The data collected by the ASPEN Plus is used for neural training. The learning technique is then used to train the data in two stages. This promotes to analyze and compare data in order to obtain clean water from the process and predict (Fig. 5).

1) First stage data training: In the first phase, the neural network is fed the three variables that together define the RO (see Table II). Those factors are heat, moisture, and saltiness. Training results can be obtained by treating the percentage of pure water as a response and the aforementioned variables as predictors. The initial stage included the implementation of a three-layer hidden layer. 70% was used as the training set, 15% as the validation set, and 15% as the test set. While the Levenberg-Marquardt training algorithm does require more memory than some other methods, it is typically the fastest training algorithm available. The weight and bias values are recalculated using the Levenberg-Marquardt algorithm. (Table III).

2) Second stage training: In this project, the Multistage Reverse Osmosis uses a two-stage RO process to obtain clean water. Following the completion of the first stage RO process, the permeate received is subjected to a second stage RO process (Table IV). This improves clean water recovery while decreasing rejections from the second RO stage (Table V).

C. *Training With Support Vector Machine*

In this section, the data acquired is going to use SVM to train and predict the purity of water using the RO process. Support Vector Machine (SVM) is one of the supervised learning algorithms that solves regression problems by learning objects and assigning labels.

As it is noted in [1] and [11], SVM's big data environment can be used to help applications with multidomain. Additionally, [12] has been popular as it is simple and flexible to address various classification problems, where SVM specifically affords balanced predictive performance [5]. The objective of this algorithm is to find a plane that maximize the margin between the training data, where to be optimized the hyperplane must yield a maximum margin. According to Fig. 6, the SVM selects the maximum-margin hyperplane which gives the highest accuracy of prediction [13] and [14].

TABLE II. FIRST STAGE TRAINING PROGRESS

Training Progress			
Unit	***Initial Value***	***Stopped Value***	***Target Value***
Epoch	0	40	1000
Elapsed time	-	00:00:3	-
Performance	3.43e+03	13	0
Gradient	5.64e+03	0.601	1e-07
Mu	0.001	1e-06	1e+10
Validation Checks	0	6	6

TABLE III. MODEL SUMMARY AFTER FIRST STAGE RO PROCESS

	Observations	**MSE**	**R**
Training	700	13.2622	0.9543
Validation	150	15.6231	0.9468
Test	150	17.2769	0.9498

TABLE IV. SECOND STAGE TRAINING PROGRESS

Training Progress			
Unit	***Initial Value***	***Stopped Value***	***Target Value***
Epoch	0	35	1000
Elapsed time	-	00:00:02	-
Performance	1.34e+03	5.69	0
Gradient	3.56e+03	1.04	1e-07
Mu	0.001	0.01	1e+10
Validation Checks	0	6	6

TABLE V. SECOND STAGE TRAINING RESULT

	Observations	**MSE**	**R**
Training	700	5.9063	0.9811
Validation	150	5.8044	0.9778
Test	150	6.0216	0.9808

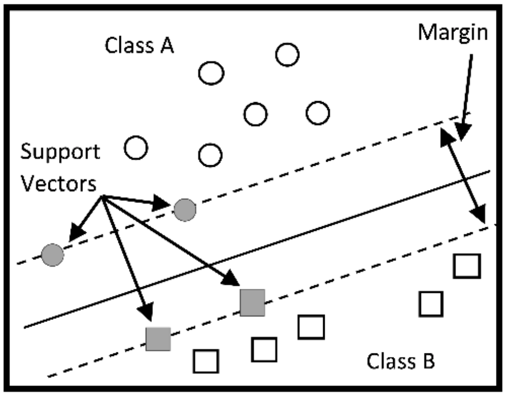

Fig. 6. Hyperplane Margin Selection.

The aim of this research is to predict the purity of water from the three features that determine the RO process. The 'fitrsvm' function is used to fit an SVM regression model. It is used to cross-validate or train the data set on a low-through moderate dimensional predictor. This function uses kernel function to map predictor data.

The MATLAB R2021b version was used to train the SVR model as it offers a built-in function 'fitrsvm' to train the given data sets. To get the SVR model, the right input parameters should be provided, such as the training set, kernel function, epsilon, and penalty coefficient. Similarly, the input for this RO desalination process temperature, pressure and salt concentration were given to yield the purity of water in percentage. Using the same 'fitrsvm' built-function, MATLAB was able to generate the model for the first and second processes. The same data obtained from the ASPEN Plus simulation were used for the training process using the SVM algorithm.

III. Result and Discussion

Two types of Artificial Intelligence techniques were used to analyze the performance of Reverse Osmosis desalination in this research. The ANN and SVM algorithms were used to compare the performance of the desalination process. The aim is to have an efficient prediction learning algorithm from both of the techniques [15]. The results obtained are viewed in two categories for the multistage RO desalination.

A. *Analyzing Performance of Multistage RO using ANN*

The results from the first stage RO of the variables for temperature, pressure and salt concentration is given in the ASPEN Plus simulation model again for the second RO stage to obtain data on the purity of water in percentage.

This result data is then taken and fed to the neural network software to be trained for prediction. In the second stage of the RO, three layers were implemented for the hidden layer. The data was divided into 70% training data, 15% validation data and 15% test data selected randomly. They were trained in the neural network to give out these results (Table VI).

The graph from Fig. 8 represents the performance of the Mean Square Error (MSE) with respect to each epoch the training of ANN undergoes in the first stage RO process. The MSE is achieved by calculating the mean of the square of the difference between the actual and the ANN output for all the data points. It can be seen the best validation performance of this RO desalination process was achieved at the 35th epoch(iteration). In the model summary for the first stage (Fig. 7), information about the training algorithm and the result for each data set is presented for the inputs and outputs of the RO desalination process.

The second stage RO dataset of the variables for temperature, pressure and salt concentration is given to the ASPEN Plus simulation model again for the second RO stage to obtain data on the purity of water in percentage.

This result data is then taken and fed to the neural network software to be trained for prediction. In the second stage of the RO, three layers were implemented for the hidden layer. The data was divided into 70% training data, 15% validation data and 15% test data selected randomly. They were trained in the neural network to give out these results. The same Levenberg-Marquardt training algorithm was used in the second stage of training to receive the following results (Table VII).

TABLE VI. Model Summary for Stage 1 Training

Model Summary	
Predictors	[Temperature Pressure Salt Concentration]
Responses	[Purity]
Data division	Random
Training Algorithm	Levenberg-Marquardt
Performance	Mean squared error

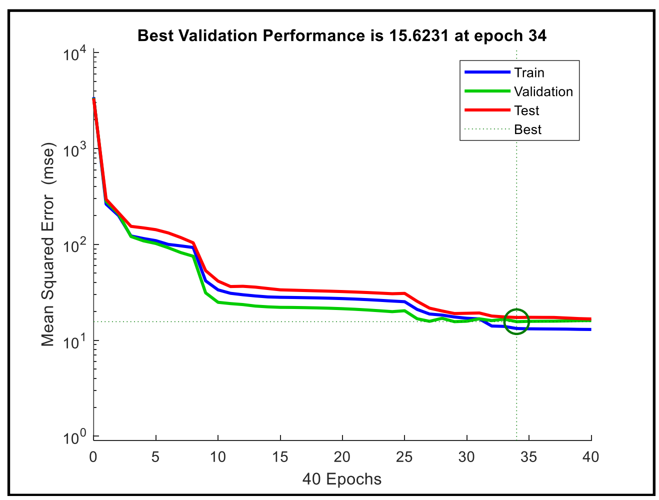

Fig. 7. First Stage Best Validation Performance.

TABLE VII. Model Summary for Stage 2 Training

Model Summary	
Predictors	[Temperature2 Pressure2 Salt Concentration2]
Responses	[Purity2]
Data division	Random
Training Algorithm	Levenberg-Marquardt
Performance	Mean squared error

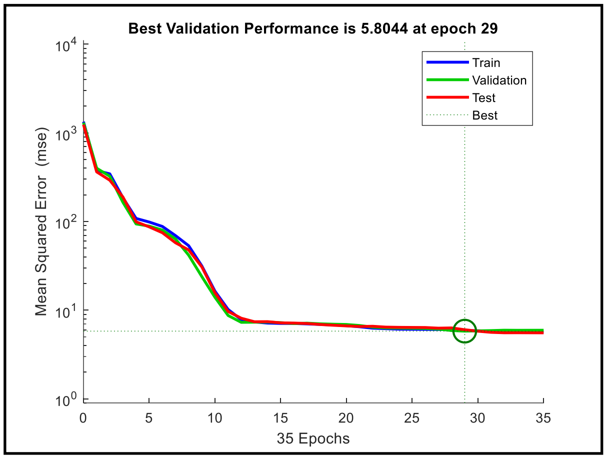

Fig. 8. Second Stage Best Validation Performance.

On the other hand, when referred to Fig. 10, it could be seen a graph plot of MSE vs epochs run to train the second stage RO desalination process using the ANN. As a result, the best validation performance of the second stage training was achieved at 29th epoch which was much better validation performance that the first stage training. The same data division and training algorithm was used to help in comparing both stages of the RO process which can be seen in Fig. 9.

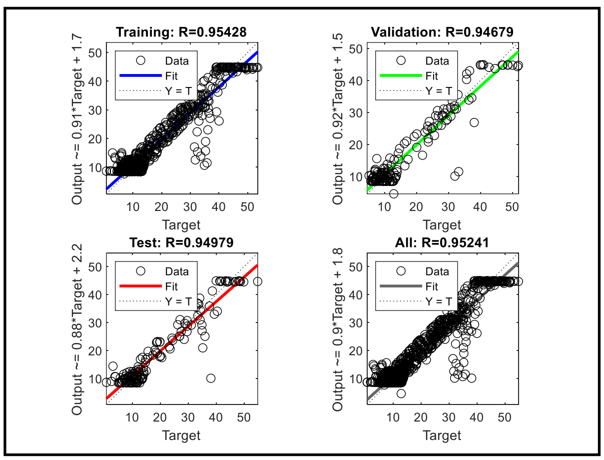

Fig. 9. First Stage RO Training Regression Plot.

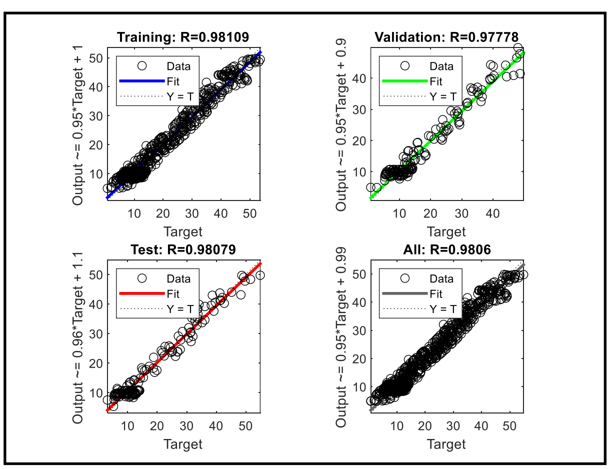

Fig. 10. Second Stage RO Training Regression Plot.

In Fig. 9 and 10, the regression plots can be seen to show the network prediction with respect to responses. Both these graphs test the relation between the actual output with respect to the target for training, validation, and test sets. In these graphs, it can be seen the output (from ANN) is very close to the target (actual purity of water from the process). It can be concluded that the close relationship between ANN output and target can be from the high correlation reflected in the R-value. Moreover, when the graphs are compared for the first stage and second stage, it could be seen that the correlation of the second stage RO process has good performance and would aid better in predicting more accurately.

B. *Analyzing Performance of Multistage RO using SVM*

The data from the first stage was loaded to MATLAB workspace to go on with the training process. It was trained using a standardized data. This means the software centers and scales each column of predictor data(X) by the weighted column mean and standard deviation. This trains the model by a standardized predictor matrix, while storing the unstandardized data in the model property X. Moreover, the convergence information of the model was set to 'Converged'. When computed the optimizing routine of the Solver was found to be 'SMO' (Sequential Minimal Optimization) and the mean-square error of the model was 0.2630. Each element of the initial estimates of alpha coefficients corresponds to an observation in X. As the Alpha cannot contain any NaNS, it can be observed the model had run properly as it listed all elements (Table VIII).

The data from the second stage RO process was also loaded into MATLAB and trained using the same SVM (Table IX). Temperature, pressure, and salt concentration were all grouped together and trained to produce water purity. This dataset was trained with the 'fitrsvm' function and the 'Standardized' model training method [16]. The computed mean square error of the second stage was 1.0451. The resulting epsilon, known as half the width of the epsilon-insensitive band, stores a nonnegative scalar value of 1.2149. Because the Standardize option was set to true during training, the Mu value is also be provided, with the length equal to the number of predictors.

TABLE VIII. FIRST STAGE SVM TRAINING

Property	**Value**
Epsilon	0.9032
Solver	'SMO'
Bias	17.9891
Kernel Parameter	Linear function, scale 1
Alpha	[1;1;0.572330238305089;-0.275138601731484;-0.297191636573605;-1;-1]
Beta	[-0.001485696802116;9.495296357877216;-3.931750668547228]
Mu	[23.555762711655710,23.548202705561412,28.190442046205046]
Sigma	[5.977559943498434,5.982586319655137,5.794770001389037]

TABLE IX. SECOND STAGE SVM TRAINING

Property	Value
Epsilon	1.2149
Solver	'SMO'
Bias	17.74008
Kernel Parameter	Linear function, scale 1
Alpha	105 x 1 double
Beta	[-0.013834278784691; 0.362070130142010;11.741070351439940]
Mu	[24.765164217883978,28.057443299385262,37.792550502075830]
Sigma	[6.400203608352864,2.922463103239594,5.838943078299873]

After training the first and second stages of RO desalination with cross-validation SVM, the results for both sets were displayed in Tables VI and VII. When trained with the 'fitrsvm' function, the Mean-Squared Error of the loss function was measured for both stages to evaluate the performance of the training. The MSE for the first trained model was 0.2360 and for the second trained model it was 1.0452. This indicates that the output obtained from the first stage of RO desalination training is more similar to the actual output, as it has a lower MSE than the output obtained from the second stage of training. Although the MSE of the second stage was found to be slightly higher, it could be trained to predict the actual water purity when given the correct RO desalination process parameters.

IV. CONCLUSION

This paper used Artificial Neural Network and Support Vector Machine algorithms to train multi-stage Reverse Osmosis desalination data. Both techniques used ASPEN Plus simulation data to predict the entire RO process. ANN trained RO's first and second desalination stages. Training resulted in a high correlation between actual and obtained output and increased water purity.

The trained ANN predicted multistage RO desalination well given the inputs. The SVM can train and predict multistage RO desalination. It used ASPEN Plus simulation data. ANN had a higher classification and prediction rate than SVM despite its shorter execution time. ANN outperformed SVM with multistage RO alignment based on AI function implementations.

This study signifies that the use of Artificial Intelligence techniques could bring ease of processes if implemented well. In this case, the multi-stage RO process was made to be trained both using the ANN and SVM to determine the prediction of water purity. Both techniques would yield an accurate prediction rate based on the data fed previously but exhibit slight differences on their output. This research aimed to study what the differences are amongst both techniques and help determine which to implement on the research. MSE, regression correlation, and other functions can be used to compare the two stages of RO desalination. These findings from training the collected data using ANN and SVM could lead the research to further use other training models on future work to find the best training model that would align with the multi-stage RO process. Future research could focus on predicting multistage RO desalination properties and factors using ANN and improving SVM prediction performance. Moreover, the exploration and validation of new prediction techniques for different applications could be of great importance for future research.

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