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Artificial Neural Network (ANN) Modelling of Purity of Hydrogen Gas using Palm Kernel Shell Activated Carbon (PKS-AC) adsorbent

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ABSTRACT

Hydrogen is a promising clean energy source, but impurities like carbon dioxide can negatively impact its fuel quality and performance. This problem also has gained attention due to the global concern over rising carbon dioxide emissions contributing to global warming. Consequently, purifying hydrogen through pressure swing adsorption has become crucial. However, a significant challenge in hydrogen purification is the trade-off between purity and recovery. To address this challenge, an artificial neural network (ANN) is used to optimize the hydrogen purification process, balancing the compromise between purity and recovery. A feedforward ANN (FANN) model was developed with one hidden layer containing 14 neurons. The model included three input factors and two output responses. The model successfully identified adsorption pressure and blowdown time as the key operating conditions affecting hydrogen purity with a very low mean square error (MSE) of 0.00109. The regression coefficients (R) for training, validation, and testing were exceptionally high at 0.99998, 0.99996, and 0.99996, respectively. Optimal operating parameters were found to be 2 bar pressure, 5 minutes of adsorption time, and 5 minutes of blowdown time, resulting in 99.99% hydrogen purity. This approach offers a renewable and efficient solution with significant potential for the energy sector, supporting efforts to achieve a cleaner and more sustainable future.

Keywords: Artificial neural network; hydrogen gas; pressure swing adsorption; PKS-AC

INTRODUCTION

In recent years, hydrogen gas has emerged as a promising and environmentally friendly energy source, providing a viable substitute for conventional fossil fuels and addressing the urgent need to combat global warming and reduce carbon emissions (Azni et al. 2023; Shabbani et al. 2022). Ensuring high purity levels in hydrogen gas is crucial for optimal performance and safety across various applications. Impurities in the gas stream can negatively impact the efficiency of hydrogen-based systems and pose potential hazards, making the achievement of high purity levels a critical research focus (Idris et al. 2019). Consequently, the achievement of high purity levels has become a crucial area of research focus (Ahad et al. 2023; Du et al. 2021). Therefore, it is essential to purify hydrogen gas before its use in human consumption for health or as a fuel for electricity generation. Adsorption purification technologies, particularly pressure swing adsorption (PSA), are widely employed for this purpose, making the optimization of hydrogen gas purity increasingly important (Song 2024; Santana et al. 2023). Hence, the optimization of hydrogen gas purity has gained significant prominence in recent times.

This study employs two adsorbent beds to enhance the adsorption performance of hydrogen purification and recovery. PSA is widely used for separating gas species from a mixed gas because different gases are attracted to solid surfaces with varying degrees of force (Kottititum et al. 2020; Ye et al. 2019).

Activated carbons are gaining popularity due to their thermal and chemical inertness, outstanding thermal conductivity, and meso/microporous structures. The low-cost biomass precursor provides activated carbon from many resources, making it more viable. Palm kernel shells (PKS), like other renewable biomasses, are plentiful in Malaysia and are used in adsorption processes. Similar to other sustainable biomasses, PKS is widely available in Malaysia (Abdul Rahim et al. 2024) and is frequently employed in adsorption procedures (Sabri et al. 2023). In 2019, Malaysia exported 18.47 million metric tonnes of palm oil (Kaniapan et al. 2021). Shabbani et al. (2021) noted that PKS have a porous surface, chemical stability, mechanical strength, water insolubility, and low moisture content, making it useful as gas adsorbent.

The literature cites Abdelkareem et al. (2022) as saying that ANN have attracted a lot of interest in a number of scientific fields, including the optimization of hydrogen production. Artificial neural networks (ANNs) have gained significant attention in various scientific domains, including hydrogen production optimization. ANNs simulate the human brain's learning process by modeling the network structure of interconnected nerve cells (Di Franco & Santurro, 2021). ANNs are preferred for solving difficult engineering problems because they learn from examples and recognize patterns in input and output data without assumptions about their nature or interrelationships (Paul et al. 2022). Chen et al. (2020) demonstrated the application of ANN models in predicting and optimizing hydrogen production processes, providing a versatile and efficient tool to analyze complex relationships between input parameters and output hydrogen purity. The ANN model is the chosen technique. The key benefit of ANN is that it never needs any mathematical model because it learns from examples and recognizes patterns in a series of input and output data without making any assumptions about their nature or interrelationships (Abdolrasol et al. 2021).

The experimental results obtained from PSA serve as a crucial component in the development and validation of the ANN model (Pai et al. 2022; Khoshraftar et al. 2024). Anna et al. (2017) built a surrogate model, a multi-layered feed-forward artificial neural network to predict and optimise PSA performance. Overall, the information gathered from the sources was divided into three data sets: 70% for training, 15% for validation, and 15% for ANN testing (Tong et al. 2021).

This study's main goal is to create an Artificial Neural Network (ANN) model that uses palm kernel shell activated carbon (PKS-AC) as the adsorbent to forecast the purity of hydrogen gas. In order to attain the highest level of hydrogen purity, the study attempts to optimize the pressure, adsorption time, and blowdown time parameters. This will offer a thorough comprehension of PKS-AC's efficacy in purifying hydrogen gas.

By leveraging the capabilities of the ANN model, this research paper contributes to the development of sustainable and clean energy solutions for the future.

METHODOLOGY

DATA RESOURCE

A dataset was gathered from USM. The training data served to generate the network parameters (weights and biases), while the validation data were used to confirm the network parameters' flexibility. The parameters of interest were adsorption pressure at 1, 2, and 3 bar, adsorption and blowdown times at intervals of 0.5, 1, 3, and 5 minutes, respectively.

SOFTWARE

MATLAB R2021a was used to create and implement the ANN. The ANN was first trained to ensure optimal performance.

PSA OPERATION

A straightforward PSA unit method is shown in Figure 1. Adsorbent bed, purging valve, and valves are the main pieces of equipment that regulate the cycle process, as seen in Figure 1. The procedure makes use of three distinct pressure settings. The PSA unit was studied at 1,2 and 3 bar. Based on the limitations of the adsorption column design, the adsorption and blowdown times ranged from 0.5, 1, 3 and 5 minutes. Pressure is applied to the first bed at 3 bar to allow the pressurisation phase to take place. During the first step of pressurisation, the product valve was closed to pressurise the bed to the specified pressure (3 bar). CO_2 was captured during both the pressurisation and adsorption steps. After 30 minutes, the product valve of bed 1 is opened to collect the released hydrogen gas, and 10 minutes later, the final product valve is opened to check the purity of then collected hydrogen gas. There is still carbon dioxide present in the final product stream, but it is in a tiny percentage, perhaps 0.2% - 0.4%. At the top, highly pure hydrogen exits the adsorber vessel.

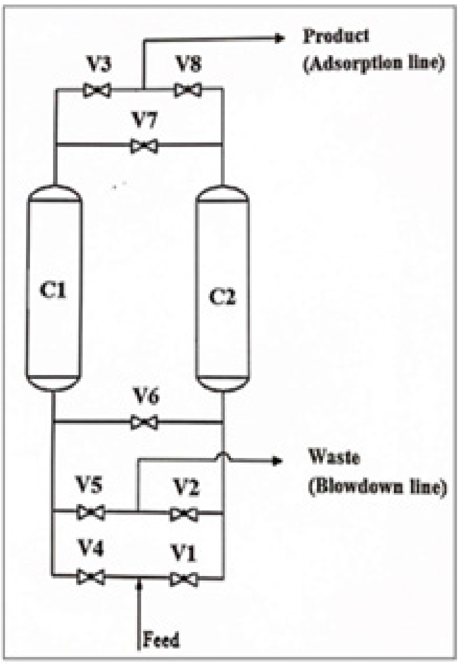

FIGURE 1. A schematic diagram of the two column PSA unit valves in the cycle involving pressure equalization mode (Idris et al. 2019).

ARTIFICIAL NEURAL NETWORK (ANN)

A multilayer feedforward Artificial Neural Network (ANN) model was used, consisting of an input layer, two hidden layers, and an output layer. Data on several process parameters, including pressure, adsorption time, and blowdown time, are fed into the input layer. The hidden layers contain neurons with sigmoid activation functions to capture non-linear relationships in the data. The output layer forecasts the purity of hydrogen. Data preprocessing involved normalization of the input data to a range between 0 and 1 to improve the convergence speed during training. Outliers were identified and removed, and missing values were imputed using mean and median values.

The dataset was divided into three subsets: training (70%), validation (15%), and testing (15%). The network weights were optimized using gradient descent and backpropagation methods on the training set. The validation set was used to monitor performance during training, allowing adjustments to the model parameters to avoid overfitting. The testing set evaluated the generalization capability of the trained model. Cross-validation techniques ensured the results' reliability and robustness. A dataset from Universiti Sains Malaysia (USM) was used to optimize hydrogen purity. Input parameters included adsorption pressure at 1, 2, and 3 bar, and adsorption and blowdown times at 0.5 min, 1 min, 3 min, and 5 min. Experimental results from Pressure Swing Adsorption (PSA) provided valuable data for training, validating, and testing the ANN model.

The ANN model was developed and implemented using MATLAB R2021a's Neural Network Toolbox, which provided functions for creating, training, and evaluating the neural network. Statistical analyses and graphical representations were performed using MATLAB's built-in functions and custom scripts. Statistical evaluations included calculating R-squared (R^2) values, mean squared error (MSE), and root mean squared error (RMSE) to assess the model's performance.

As seen in Figure 2, there were seven main processes involved in developing the artificial neural network: (1) Gathering and preparing data: Gather and prepare the input data, then separate it into test, validation, and training sets; (2) Selection of Input Data: Temperatures at feed pressure, adsorption time, and blowdown time were selected as input data, while experimental studies' hydrogen purity data was chosen as the output data for ANN modelling; (3) ANN Training: Make use of the training set to train the ANN model; (4) Validation: To correct parameters and avoid overfitting, validate the model using the validation set; (5) Testing: Make use of the testing set to evaluate the model's performance; (6) Performance Analysis: Use regression (R) and mean square error (MSE) figures to examine the expected output performance; and (7) Optimization: For the training, validation, and testing datasets, use a trial-and-error approach to find the optimal network topology based on the lowest MSE and R values closest to 1.

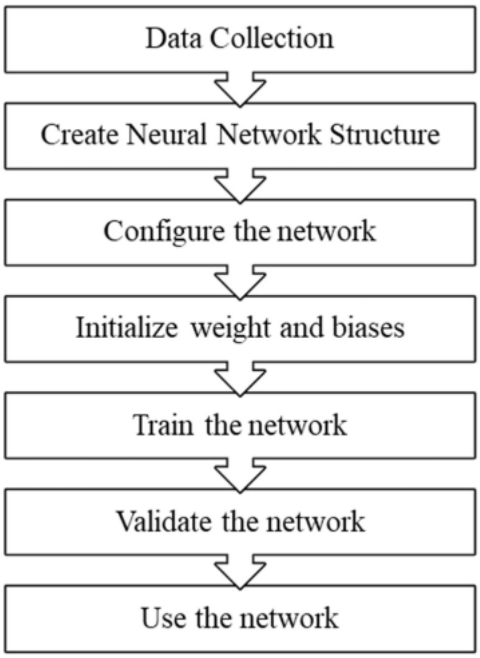

FIGURE 2. Workflow for a general neural network design process

Currently, there are no mathematical rules that can be used as a guidance to divide the data into the required sizes for the three previously mentioned subsets. In this study, input data were divided randomly into three data sets which are 70% for training (42 samples), 15% for validation (9 samples) and 15% for training (9 samples).

Another step is to construct the network structure and assign the network model, number of hidden layers, number of neurons in the hidden layer, type of training algorithm (trainlm), and type of transfer function for the hidden layer (tansig) and output layer (purelin) (Beale et al. 2012). For the forward propagation, the weight values were randomized. For this study, the trainlm training function with the Levenberg-Marquardt (LM-BP) backpropagation algorithm was used since it is fastest way in the toolbox. After the weight and biases were initialized, the network would be ready for training.

ANN MODEL DEVELOPMENT

FEEDFORWARD ANN IN MATLAB

The FANN model development was initiated using the "nntool" command in the Matlab command window. Input data, including feed pressure, adsorption time, and blowdown time, along with target data such as gas purity, were saved in the workspace, as depicted in Figure 3. These three input parameters and the output purity data were then imported from the workspace into the neural network/data manager. To optimize the neural network architecture, computations began with an initial setup using one neuron in the hidden layer. Subsequently, the number of neurons was systematically increased, and metrics such as MSE and R^2 values were computed to evaluate performance. Once the input data was selected, it was assigned as a variable. This was followed by importing the target data using the "import" icon. Specifically, the "Purity" parameter was selected, and the "Import" button was activated once more to finalize the data importation process.

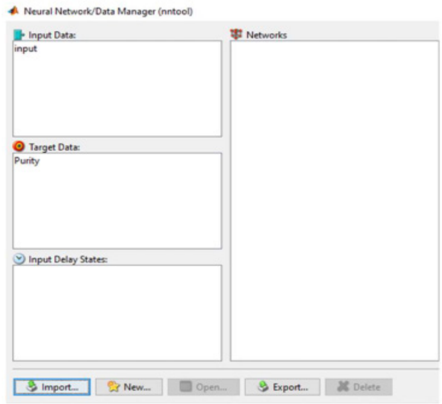

FIGURE 3. ANN setup windows

RESULTS AND DISCUSSION

ARTIFICIAL NEURAL NETWORK (ANN) MODELLING

This model will help other researchers to predict hydrogen gas purity using the PSA systems, equipped with the ANN tool, with the specified range of feed pressure 1 bar, 2 bar and 3 bar. The feed inlet adsorption time and blowdown time were varied between 0.5, 1, 3 and 5 min. In this study, a multilayered feedforward back propagation neural network was used. Feed inlet pressure, adsorption time and blowdown time were set as the input data, and hydrogen purity from the experimental data was set as the output or target data. 45 data samples were used in this modelling study. The optimal ratio for training, validation and testing which were 70:15:15, depicted from the default value of ANN tool in MATLAB R2021a.

DATASET

The training data served to generate the network parameters (weights and biases), while the validation data was used to confirm the network parameters' flexibility. The actual data used in this ANN modelling experiment is shown in Table 1.

EFFECT OF ADSORPTION PRESSURE

TABLE 1. Experimental data of hydrogen purity

Input			Output	
Pressure (bar)	Adsorption time (min)	Blowdown time (min)	P1	P2
Training Set				
1.00	0.50	0.50	0.50	1.00
1.00	0.50	0.50	0.78	0.71

continue...

...cont.

1.00	0.50	0.50	0.91	0.92
1.00	0.50	0.50	0.92	0.93
1.00	0.50	0.50	0.89	0.88
1.00	0.50	0.50	0.72	0.90
1.00	0.50	0.50	0.83	0.93
1.00	0.50	0.50	0.91	0.87
1.00	0.50	0.50	0.94	0.87
1.00	0.50	0.50	0.89	0.87
1.00	0.50	0.50	0.84	0.87
1.00	0.50	0.50	0.81	0.87
1.00	0.50	0.50	0.88	0.93
1.00	0.50	0.50	0.93	0.89
1.00	0.50	0.50	0.94	0.90
2.00	0.50	0.50	0.24	0.90
2.00	0.50	0.50	0.71	0.88
2.00	0.50	0.50	0.65	0.92
2.00	0.50	0.50	0.87	0.88
2.00	0.50	0.50	0.91	0.88
2.00	0.50	0.50	0.11	0.42
2.00	0.50	0.50	0.59	0.88
2.00	0.50	0.50	0.83	0.87
2.00	0.50	0.50	0.90	0.87
2.00	0.50	0.50	0.86	0.86
2.00	0.50	0.50	0.20	0.85
2.00	0.50	0.50	0.86	0.86
2.00	0.50	0.50	0.83	0.85
2.00	0.50	0.50	0.81	0.81
2.00	0.50	0.50	0.88	0.86
3.00	0.50	0.50	0.09	0.84
Validation Set				
3.00	0.50	0.50	0.63	0.87
3.00	0.50	0.50	0.65	0.86
3.00	0.50	0.50	0.87	0.85
3.00	0.50	0.50	0.86	0.85
3.00	0.50	0.50	0.86	0.85
3.00	0.50	0.50	0.86	0.84
3.00	0.50	0.50	0.88	0.84
Testing Set				
3.00	0.50	0.50	0.86	0.83
3.00	0.50	0.50	0.85	0.85
3.00	0.50	0.50	0.79	0.84
3.00	0.50	0.50	0.81	0.84
3.00	0.50	0.50	0.88	0.86
3.00	0.50	0.50	0.87	0.85
3.00	0.50	0.50	0.86	0.85

NETWORK OPTIMIZATION OF ANN MODEL

The previously suggested neural network in this study was FANN using the Levenberg-Marquardt (LM) back-propagation training algorithm. Tan sigmoidal (tansig) worked as an activation function in the hidden layer, while purelin was used at the output layer, and the number of hidden layers was specified as one. Tansig is a popular choice for the nonlinear activation function for neural networks. One reason it is popular is that it has output values between 0 to 1, which mimic probability values (Chng, 2022). The hidden nodes in the hidden layer were changed between 3 and 15 to define the neural network's architecture. The MSE was then calculated in each concealed node a, as shown in Table 2. Figure 4 depicts the plot of the MSE versus the number of hidden neurons. As illustrated in Figure 4, the determination to use 14 hidden neuron units in the hidden layers was based on the training data sets minimum MSE (0.00109). Overfitting will occur if there are a large number of hidden neurons (Heaton, 2018). Conversely inadequate number of hidden neurons will result in the ANN being too rigid to reflect the experimental signal.

TABLE 2. MSE value form training data set for various numbers of hidden neurons

No of Hidden Neuron	Model Error (MSE)
3	0.02300
4	0.02820
5	0.02649
6	0.02907
7	0.01586
8	0.00236
9	0.01599
10	0.01323
11	0.01811
12	0.01458
13	0.02197
14	0.00109
15	0.01306

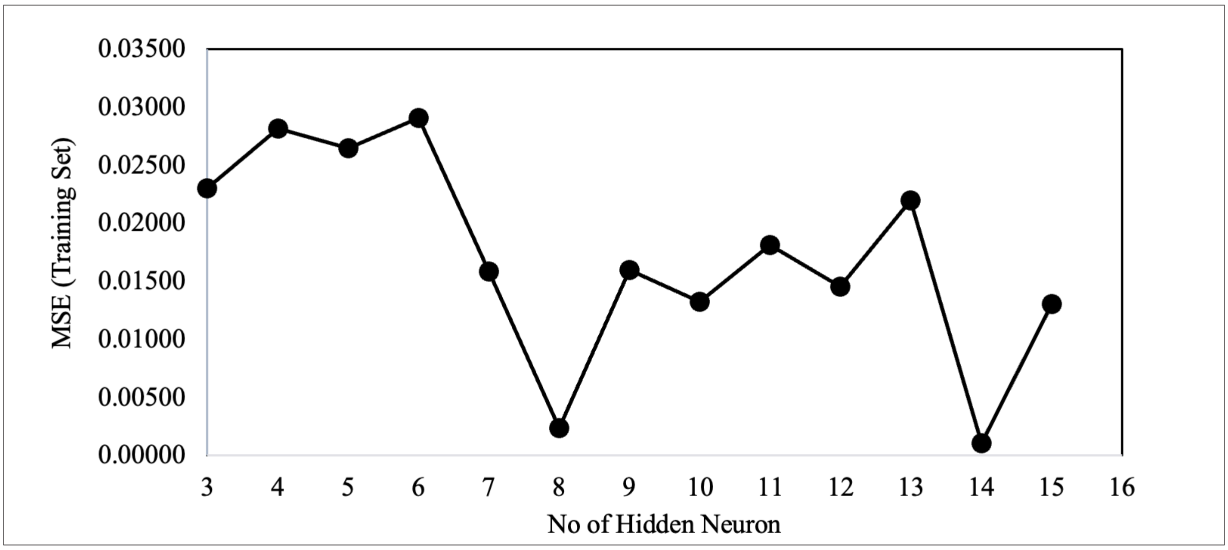

FIGURE 4. The effect of the number of the neurons in the hidden layer for MSE on the performance of the network

The training error would reduce during the training and testing process until the 'over fitting' phenomena occurred, at which point the error would begin to grow in this study, the strategy known as early stopping is frequently employed to prevent overfitting when the error value of the validation data has increased. The MSE values had changed as the number of neurons increased. The optimum value of the error function MSE for a network design with 14 neurons in the hidden layer is clearly highlighted. Considering the MSE and regression (R) values in the training data set, the best number of neurons was chosen.

PERFORMANCE OF THE DEVELOP ANN MODEL

A feedforward back propagation, multi-layer neural network with Levenberg-Marquardt (LM) training method can yield the lowest MSE and highest correlation coefficient R for the data set among the known ANN kinds.

The number of active neurons in the hidden layer was chosen by minimising the MSE function. Table 3 shows the properties of the model generated in this study. This table summarises the details of the ANN application as implemented in the MATLAB.

Figure 5 (i) illustrates the scatter regression (R) plot, depicting the actual values obtained from experimental data and the predicted hydrogen purity values derived from the advanced ANN model developed for the training data set. The solid linear line represents the optimal fit between the output of the network (predicted hydrogen gas purity from the ANN model) and the desired output. An excellent correlation coefficient (R) of 0.99998 was achieved between the predicted values of the ANN model and the experimental values, indicating a strong correlation in the prediction. The mean square error (MSE) value of 0.00109 further confirms the accuracy of the prediction. A similar study by Cao et al. (2020) utilized an ANN model for hydrogen production through biomass gasification and reported an MSE of 0.0001 and an R value of 0.9998. This study corroborates that the MSE and R values obtained here accurately reflect the precision of the hydrogen gas purity prediction. R values above 0.9 indicate excellent model performance, while values between 0.8 and 0.9 signify a good performance. Conversely, R values below 0.8 suggest an unsatisfactory model performance (Azmi et al. 2020). The closer the R value is to 1, the better the model aligns with the actual data. For this study, the ANN architecture with the minimum MSE and the maximum R value was considered the best. Consequently, the ANN utilized three input neurons, 14 hidden neurons in a single hidden layer, and one output neuron to achieve optimal performance.

TABLE 3. Characteristics of the develop ANN model

Characteristic	Commentary
Algorithm	Feed forward back propagation
Minimize error function	MSE
Learning type	Supervised training
Training algorithm	Levenberg-Marquardt (LM)
Hidden layer	Hyperbolic tangent transfer function
Output layer	Pure linear transfer function
Number of hidden layer	1
Number of neuron in input layer	3
Number of neuron in hidden layer	14
Number of neuron in output layer	1

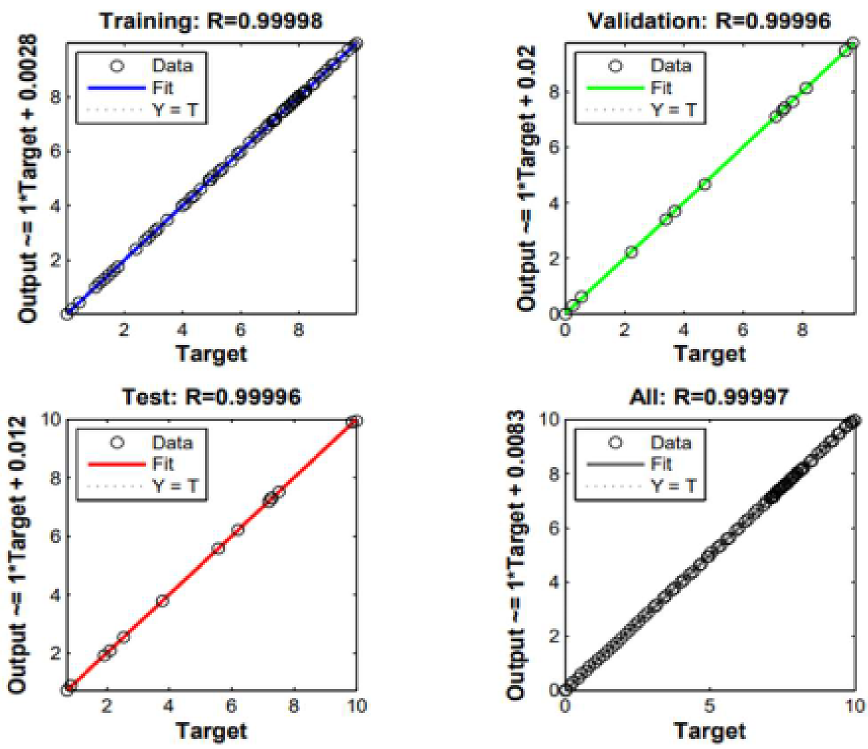

FIGURE 5. Scatter regression plot of actual and ANN model/s predicted hydrogen purity for (i) training data (ii) validation data (iii) testing data (iv) overall data correlations at inlet pressure 1 bar, 2 bar and 3 bar

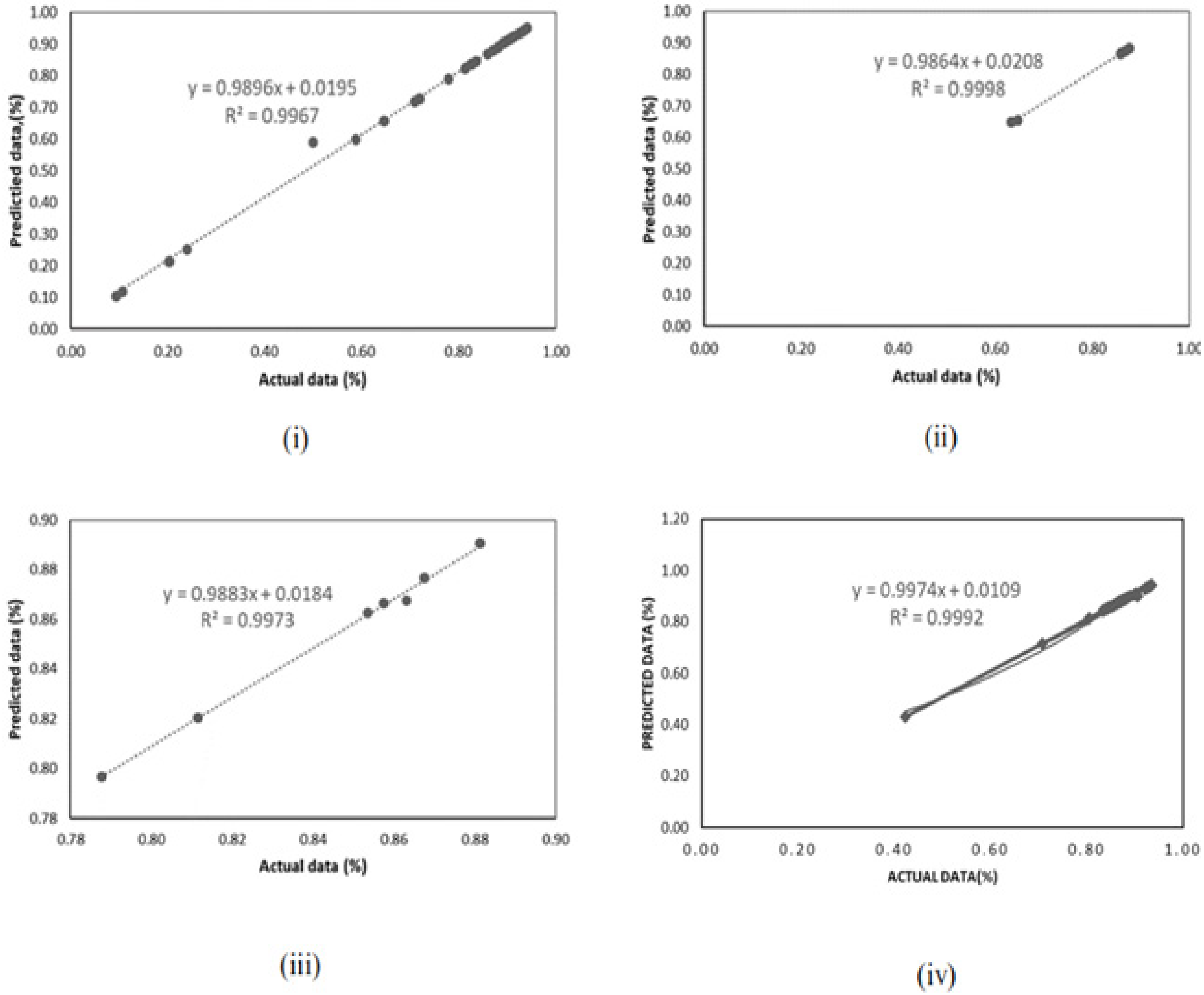

FIGURE 6. Comparison between predicted hydrogen purity and the actual data hydrogen gas purity for (i) training data (ii) validation data (iii) testing data (iv) overall data correlations at the inlet pressure 1 bar, 2 bar, and 3 bar

Figure 6 (i) presents a comparison between the experimental values and the predicted values of hydrogen gas purity using the developed ANN model for the training set. The ANN model exhibited a strong correlation with the experimental results, as indicated by an R value of 0.9967. To validate the performance of the optimal ANN, a separate validation data set consisting of 7 data points, which were not used during the training process, was employed. Figure 5 (ii) displays a scatter plot depicting the actual values and predicted values of hydrogen purity for the validation data set. The ANN analysis yielded an impressive R value of 0.99996, demonstrating the model's high predictive ability and quality. In Figure 6 (ii), the comparison between experimental and predicted hydrogen purity values for the validation data set further reinforces the strong correlation, with an R value of 0.9998. To assess the accuracy of the developed ANN model, testing data was employed, and Figure 5 (iii) presents a scatter plot of the experimental data versus the predicted particle size data. The results obtained from the testing data set were deemed acceptable, as evidenced by the R value of 0.99996. Figure 6 (iii) compares the hydrogen purity values between the experimental and predicted values from the ANN model for the testing data set, revealing a satisfactory correlation with an R value of 0.9973. Furthermore, Figure 5 (iv) illustrates a scatter regression plot that combines the actual and predicted particle size values for all 45 data points used in the study, yielding an R value of 0.99997, indicating an exceptionally satisfactory model performance. Lastly, Figure 6 (iv) showcases the comparison between experimental and predicted hydrogen purity values for the entire data set, resulting in a highly satisfactory R value of 0.9992.

EFFECT OF ADSORPTION TIME

Figure 7 (i) presents a scatter regression plot comparing the actual values with the predicted values generated by the developed ANN model for the training set. The ANN model demonstrates a strong correlation with the experimental results, as depicted in Figure 8 (i) with an R value of 0.9867. To validate the performance of the optimized ANN, a separate validation data set comprising 9 data points, which were not utilized during the training process, was employed. Figure 7 (ii) displays a scatter plot illustrating the actual values and predicted values of hydrogen purity for the validation data set. The validation process resulted in an impressive R value of 0.99996. Figure 8 (ii) compares the hydrogen purity values obtained from the experimental study with those predicted by the ANN model for the validation data set, with a correlation coefficient (R value) of 0.9456.

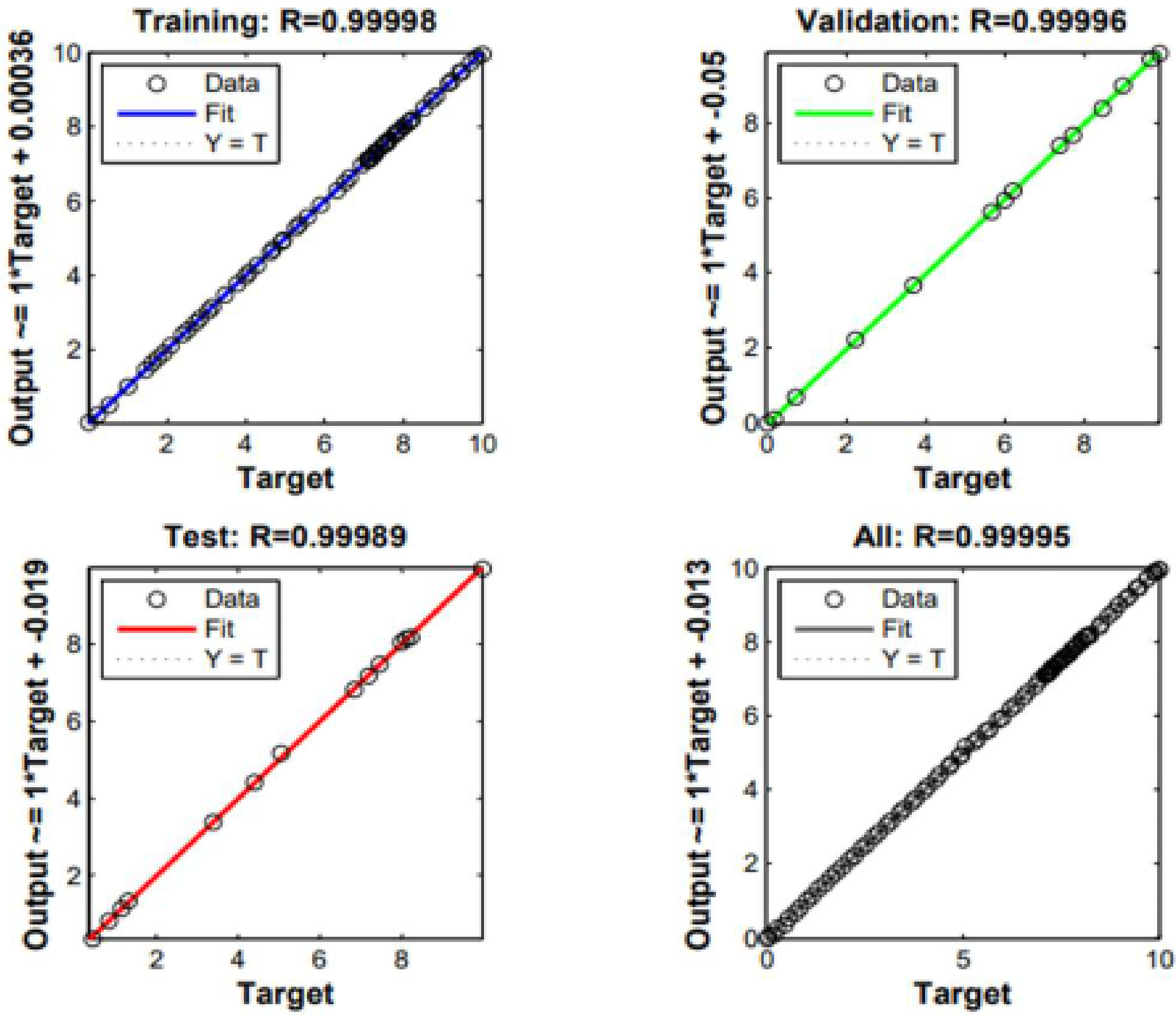

FIGURE 7. Scatter regression plot of actual and ANN model/s predicted hydrogen gas purity for (i) training data (ii) validation data (iii) testing data (iv) overall data correlations at adsorption time 0.5, 1, 3 and 5 minutes

In order to assess the accuracy of the developed ANN model, a scatter plot of the experimental data versus the predicted particle size data is presented in Figure 7 (iii). The results obtained from the testing data set were deemed acceptable, as indicated by an R value of 0.99989. Figure 8 (iii) demonstrates the comparison of hydrogen purity values between the experimental and predicted values derived from the ANN model for the testing data set. The correlation coefficient between the predicted hydrogen purity and the actual data from the testing data set is a satisfactory R value of 0.998.

Figure 7 (iv) presents a scatter regression plot combining the actual and predicted particle size values for all 45 data points used in the study. The model performance is considered highly satisfactory, with an R value of 0.99995. Finally, Figure 8 (iv) showcases the comparison between the experimental and predicted values of hydrogen purity from the ANN model for the entire data set, resulting in a satisfactory R value of 0.9816.

Figure 9 (i) displays a scatter regression plot comparing the actual values with the predicted values generated by the developed ANN model for the training set. The ANN model exhibits the strongest correlation with the experimental results, as shown in Figure 10 (i) with an R value of 0.9989. To validate the performance of the optimized ANN, a separate validation data set consisting of 9 data points, which were not used during the training process, was employed. Figure 9 (ii) presents a scatter plot illustrating the actual values and predicted values of hydrogen purity for the validation data set. The validation process yielded an impressive R value of 0.99996. In Figure 10 (ii), a comparison is made between the hydrogen purity values obtained from the experimental study and those predicted by the ANN model for the validation data set, resulting in a correlation coefficient (R value) of 0.9970. To assess the accuracy of the developed ANN model, a scatter plot of the experimental data versus the predicted particle size data is presented in Figure 9 (iii). The results obtained from the testing data set were deemed acceptable, as indicated by an R value of 0.9996. Figure 10 (iii) illustrates the comparison of hydrogen purity values between the experimental and predicted values derived from the ANN model for the testing data set. The correlation coefficient between the predicted hydrogen purity and the actual data from the testing data set is a satisfactory R value of 0.9988.

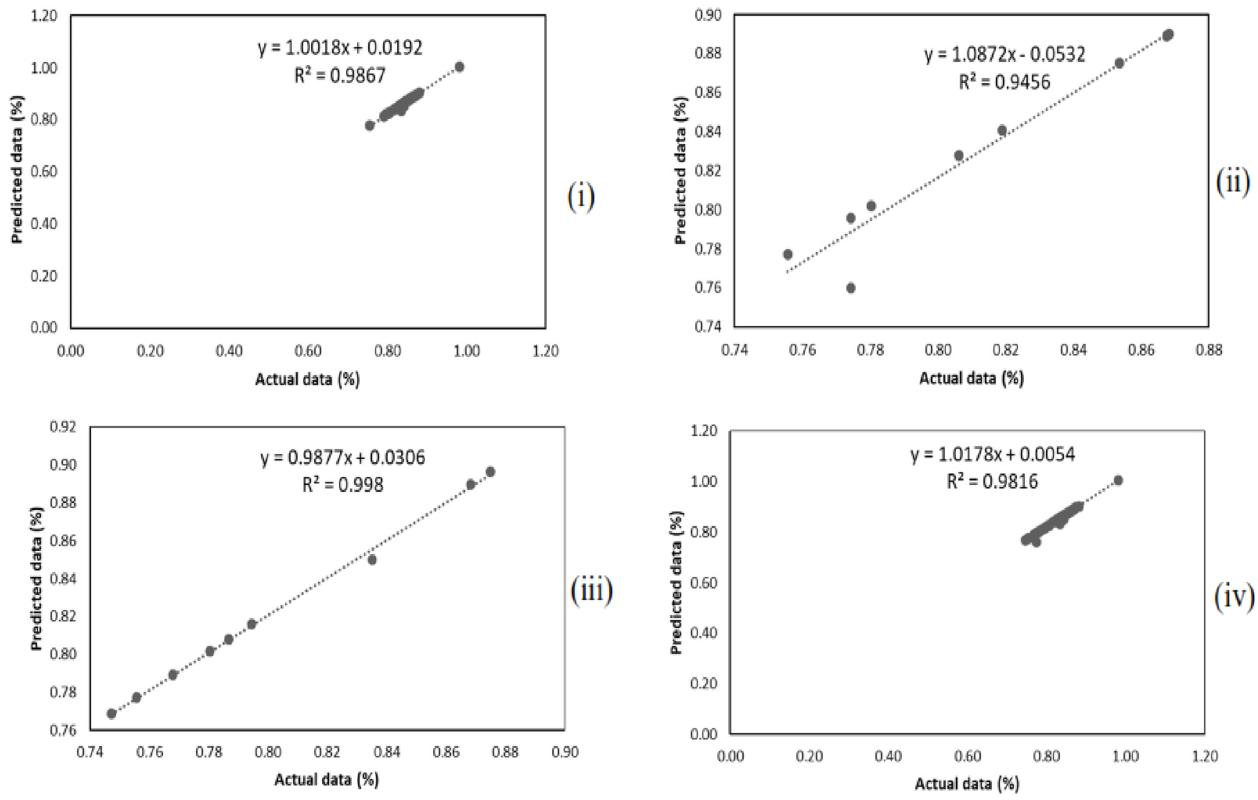

FIGURE 8. Comparison between predicted hydrogen purity and the actual data hydrogen purity for (i) training data (ii) validation data (iii) testing data (iv) overall data correlations at adsorption time 0.5,1 3 and 5 minutes

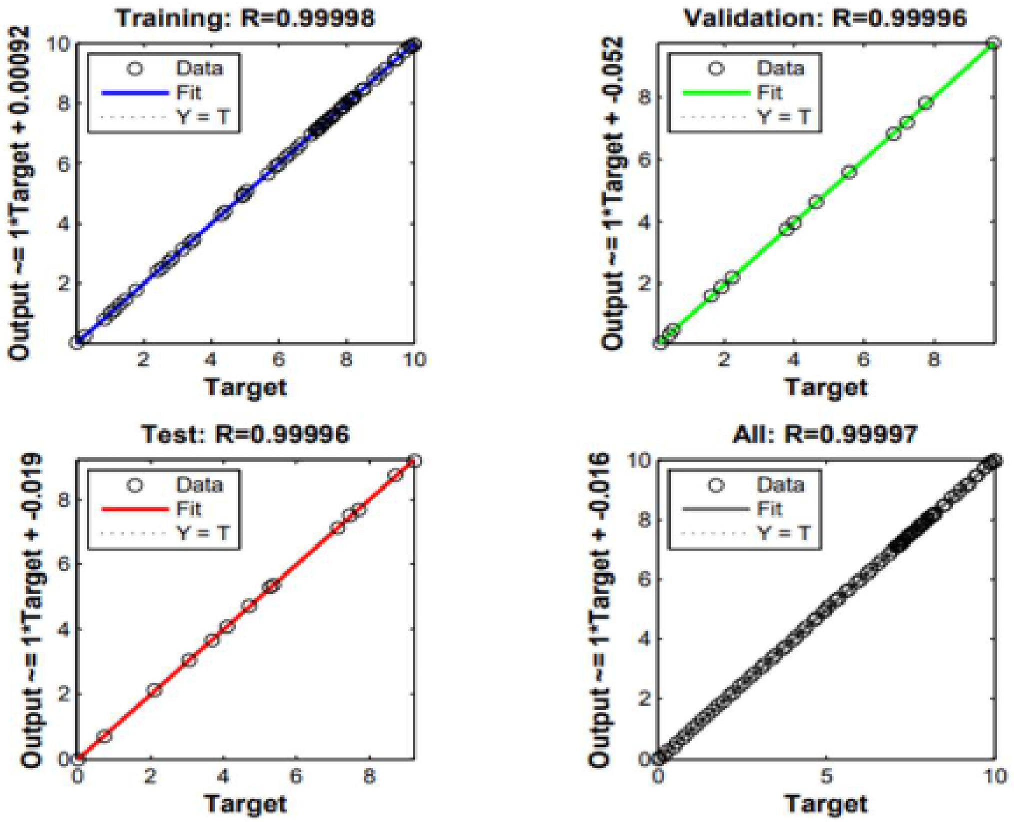

FIGURE 9. Scatter regression plot of actual and ANN model/s predicted hydrogen gas purity for (i) training data (ii) validation data (iii) testing data (iv) overall data correlations at blowdown time 0.5, 1,3 and 5 minutes

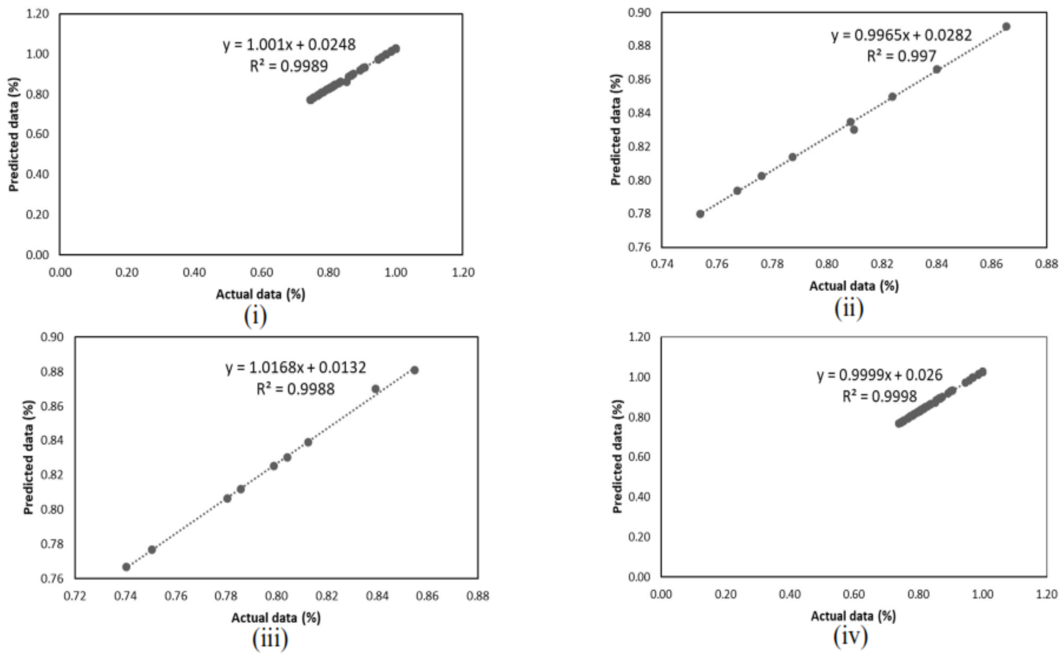

FIGURE 10. Comparison between predicted hydrogen purity and the actual data hydrogen gas purity for (i) training data (ii) validation data (iii) testing data (iv) overall data correlations at blowdown time 0.5,1, 3 and 5 minutes

Figure 9 (iv) showcases a scatter regression plot combining the actual and predicted particle size values for all 45 data points used in the study. The model's performance is considered highly satisfactory, with an R value of 0.99997. Lastly, Figure 10 (iv) displays the comparison between the experimental and predicted values of hydrogen purity from the ANN model for the entire data set, resulting in a satisfied R value of 0.9998. Table 4 represents a summary for MSE and R value of training, validation and testing data set that was found in this study.

TABLE 4. The Mean Square Error (MSE) and Regression (R) values for the training, validation and testing

Description	MSE value	R-value
Training	0.0013	0.99998
Validation	0.0563	0.99996
Testing	0.0521	0.99996

CONCLUSION

Feed forward artificial neural network (FANN) is a simple simulation that uses the MATLAB command. In this study, FANN was able to predict hydrogen gas purity through the command window. A three layers FANN with three input and two output with 45 experimental data was used for modelling purposes. Different networks were trained and tested by changing the number of neurons in the hidden layer. The developed FANN showed a precise and effective prediction of the experimental data with a good overall correlation coefficient of 0.99997 for three input variables. In addition, selectivity analysis was studied by manipulating feed pressure, adsorption time and blowdown time values. The ideal parameters for hydrogen purity, as determined by the ANN model, were 2 bars of pressure, 5 minutes for adsorption, and 5 minutes for blowdown. By comparing these predictions with the outcomes of the experiments, the high degree of accuracy and predictive power of the model were confirmed. The R-values for training, validation and testing data set were 0.99998, 0.99996 and 0.99996 respectively with the mean square error (MSE) was 0.00109. All the manipulated parameters had affected the hydrogen purity. Analysis showed that hydrogen purity was sensitive to the pressure, adsorption time compared to compared to the other parameters which can impact the purity of the hydrogen stream. Our findings supported that FANN model can serve as a useful tool to identify the effective parameters for the PSA process. Further research and development in this field will contribute to the advancement of sustainable energy solutions.

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DECLARATION OF COMPETING INTEREST

None.

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