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PERFORMANCE PREDICTING OF CATALYTIC REFORMING PLANT USING ARTIFICIAL NEURAL NETWORKS

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Abstract- The predictive model of the catalytic reforming plant has been applied by using an artificial neural network model for finding the weights of operating conditions which effect on the quality of gasoline. Operating conditions of catalytic reforming plant of Basrah refinery is used as data for simulating the predictive model. An artificial neural network model is trained and tested by using available data set (4213). The input variables of ANN model are inlet temperature of reactors, operating pressure, feed flowrate, liquid hour space velocity, and hydrogen to hydrocarbon molar ratio, while the output of ANN model is research octane number (*RON*) of gasoline produced. This study has used neural networks with multilayers of feed-forward and feedback propagation. Six training methods are tested to determine which one is the best performance. Levenberg-Marquardt Algorithm has shown to be the best algorithm for predicting the performance of the catalytic reforming model. Neural network activity is studied with various factors, including the number of hidden layers, nodes in the hidden layers, and transfer functions. The results show that the neural network with 17 hidden neurons and (tansig, tansig) as transfer function is the best model for representing the data collection from Basrah refinery. This is due to the model has given lower *MSE* and higher regression value 0.0494,0.9736 respectively compared with other models. Also, the results of ANN model have shown the weight of pressure, temperature, *LHSV*, and H_2/HC are (10%), (55.4%), (15.10%), and (9.10%) respectively. The results indicate that the predictive model of the catalytic reforming plant can predicted the *RON* of the gasoline in training sets.

Keywords: Catalytic Reforming Process, Artificial Neural Network, Simulation and Modelling.

1. INTRODUCTION

The catalytic reforming process is one of the essential processes in petroleum refining for producing high-octane gasoline. Naphtha or cracking oil is used as a feedstock in several chemical processes such as aromatization, dehydrocyclization, and hydrocracking to produce aromatics and high-octane liquids. As byproducts, it simultaneously creates hydrogen (H2) and liquified petroleum gas (LPG) [1].

An artificial neural network is a mathematical tool for analyzing the data and improving the performance of computing [2]. An artificial neural network uses a connectionist method of computing to process the information and is consisted of a network of artificial neurons that are linked to one another [3]. Typically, an extensive and complicated configurations are needed to estimate and obtain highly non-linear models. Neural networks can be processing the information in a way comparable to the brain functioning. Also, it has consisted from several linked components called neurons or nodes make up the ANN [4].

In the Naphtha catalytic reforming, Manamalli, et al. [5] introduced model of catalytic reformation plant by using ANN for predicting operating conditions and optimized aromatics production. Two neural networks have been trained to provide the optimal temperature, one in the forward and another in the feedback. The predicted model showed that aromatic production was increased by increasing the operating temperature. The predicted model showed that increased in aromatic production to 14%.

Zahedi, et al. [6] introduced a model for Naphtha catalytic reforming plant by using ANN. The model could be predicting the flow rates, outlet temperatures, gasoline specific gravities, vapor pressure, and the *RON* of gasoline. There were 90 of data set collected from Tabriz Refinery unit provided 90 data sets for this model. The results showed that mean square error was 1.07%. The model could be determining a set of optimal operating conditions that increased production yield 80% to 82.38%.

Alves, et al. [7] presented a model to explain the performance of catalytic reforming plant by using ANN. The ANN model was trained the industrial data from actual plant for predicting and enhancing the operating conditions of process. The predicted and actual results showed a good agreement with deviation less than 1%. Sepehr and Mohaddecy [8] presented a model for Naphtha catalytic reformation by using ANN. There were 97 of data set collected from actual industrial plant and used in this model. The ANN model was used to predict the volume flow rate and RON of gasoline over time with deviation 0.238% and 0.833% respectively. The predicted and actual results showed a good agreement with deviation less than 1.447%.

Butheana, et al. [9] presented an ANN model for the Naphtha catalytic plant. ANN model is tested using all 504 test cases including reactor temperature, operating pressure, weight-hour-space velocity, and the molar ratio of hydrogen to hydrocarbons. The model could be predicting the *RON* of gasoline. The predicted and actual results showed a good agreement with mean square error and regression were 0.000413 and 0.99935, respectively.

2. SUMMARY OF THE NAPHTHA CATALYTIC REFORMING PLANT

As a sequence of reaction units, the Naphtha catalytic reforming plant is laid up so that the smallest reformer contains the slightest catalyst and the most significant reformer has the most. The reaction's pace is slowed in the early stages because of the endothermic reactions. Reheating reactor effluent is thus accomplished using heaters [10]. The initial reactor's reaction temperature is typically about 500 °C. The dehydrogenation of Naphthenes to aromatics causes this temperature to fall quickly. Heating and isomerization occur in the second reactor using the first reactor's output. Dehydrocyclization and cracking are then carried out in the third reactor, which receives the heated product from the second reactor. Because of the exothermic cracking process, the temperature decrease in this reactor is minimal [11].

Basrah catalytic reforming plants are the most critical units. Feedstock with a low octane number about (65) is transformed into a high-octane number product with about (98) by this process. About 10000 barrels of reformate can be produced each day with this technique. Every one of the three semi-regenerative reactors has been equipped with Pt-Re/Al_2O^3 as a catalyst. Naphtha catalytic reforming plant can be operating under high operating conditions of temperatures ranging from (460-513 °C), operating pressures ranging from (1.5-2.5 MPa), molar ratio of hydrogen to hydrocarbons around of 5.5, and the feedstock density ranges from (728.8 to 743.7 kg/m^3) [12].

3. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial neural networks (ANN) have received a lot of attention recently. It can be used in many different applications in real-world such as engineering, industrial processes, mathematical models, mathematical equations, medical procedures, and oil drilling. An artificial neural network is a way to improve the performance of computing. Typically, an extensive and complicated configurations are needed to estimate and obtain highly non-linear models. Therefore, the performance of the Naphtha catalytic reforming plant can be predicted using ANN [13].

An artificial neural network model of the Naphtha catalytic reforming plant has consisted from three layers: an input layer, output layer, and hidden layer. Neurons at the input Layer are responsible for receiving information from outside the network and passing it on to the network's processors for analysis. The hidden layer is receiving data from the input layer, and the last layer is a neuron that collects and analyses information before sending out responses [14]. The essential parts of neural network are inputs and outputs, weighting variables, bias, and activation function are shown in Figure 1 [15].

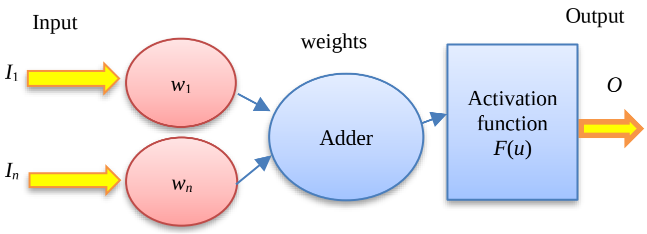

Figure 1. Essential parts of artificial neural network [16][17]

4. ARTIFICIAL NEURAL NETWORK MODEL ANALYSES

In this part, artificial neural networks have been applied for finding the weights of operating conditions which effect on the quality of light gasoline such as, (Temperature, Pressure, space velocity, Feed Flow rate, and H_2/HC molar ratio). For constructing the artificial neural network model, a data collection of Basrah refinery is collected, utilized and divided into two sets of experimental data: a training set and a testing set. There are (4213) data set of catalytic reforming plant of actual operating conditions collection from Basrah refinery summarized in the Table 1. The operating conditions of catalytic reforming plant represented the inputs to the ANN model, while the RON of gasoline represented the output of the ANN model of the catalytic reforming plant, as seen in Table 2 and Figure 2.

Table 1. Experimental data of catalytic reforming plant of Basrah refinery have used in the ANN model

LHSV (hr^{-1})	Temperature (°C)	Pressure (Bar)	H_2/HC	Feed (Kg/hr)	RON
1.082	485	18.7	5.875	43300	90
1.082	485	18.7	5.850	43300	90
1.082	485	18.7	6.083	43300	90
1.082	485	18.7	5.875	43300	90
1.022	480	18.7	6.005	40900	90
0.782	470	18.7	7.862	31300	87
0.782	470	18.7	8.452	31300	87
1.024	480	18.7	7.135	41000	88
1.024	480	18.7	6.833	41000	88
0.782	470	18.7	8.237	31300	88

Table 2. Input and output variables of the ANN model

Items	Parameter	Symbol	Unit
Input Variables	Temperature	*T*	°C
	Pressure	*P*	Bar
	Ratio of hydrogen to hydrocarbon	H_2/HC	-
	Liquid hour space velocity	*LHSV*	hr^{-1}
		F	Kmol/ hr
Output variables	Research octane number	*RON*	-

Figure 3 shows steps of computer program written in MATLAB 18 to implement training and testing procedures of several Naphtha catalytic reforming training methods.

5. RESULTS AND DISCUSSION

In this section, the catalytic reforming system has modelled using neural networks with one hidden layer. Six training algorithms (traingdx, trianscg, trainoss, trainrp, traingda, and trainlm) have been analyzed and tested also, different numbers of nodes for various algorithms are studied to predict the optimum method for the Naphtha catalytic reforming network.

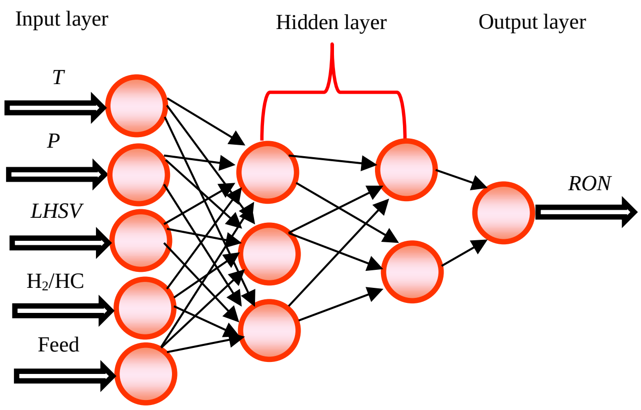

Figure 2. Proposed network for Naphtha catalytic reforming plant

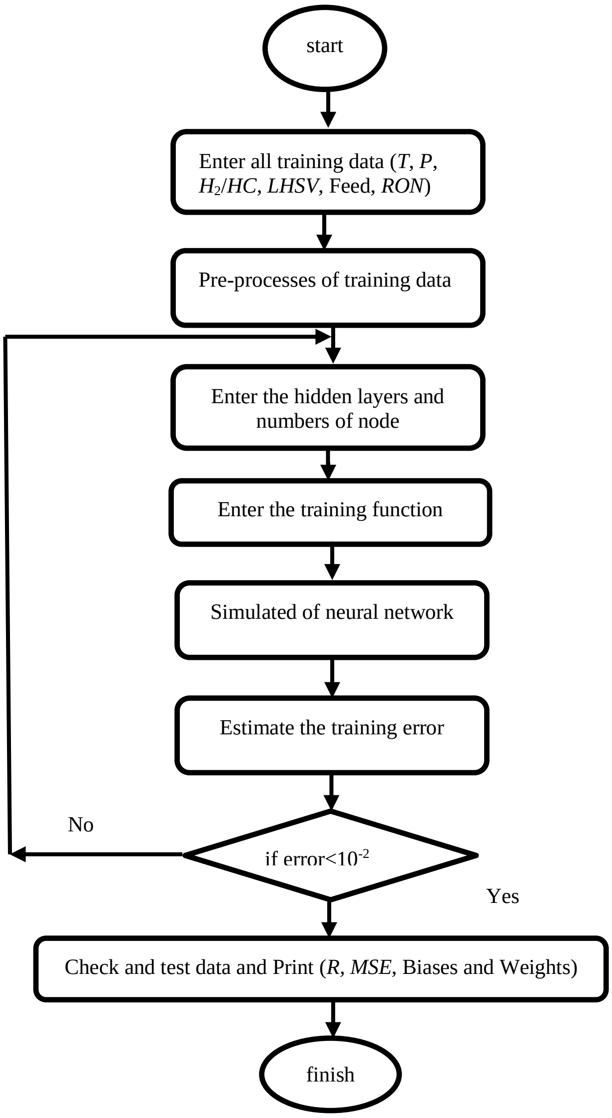

Figure 3. Steps of ANN model

Additionally, different numbers of nodes for various algorithms are studied to predict the optimum method for the Naphtha catalytic reforming network. The linear (purelin) and hyperbolic tangent (tansig) function served as the activation functions for the hidden and output layers, respectively.

The performance of artificial neural network is being examined by increasing the hidden nodes in a neural as shown in Table 3. The Levenberg-Marquardt algorithm gives the best results and performance compared to networks with different numbers of nodes in the hidden layer. The comparisons of the several algorithms utilized in ANN mode, where the Levenberg-Marquardt algorithm (trainlm) gives the highest regression value and lowest *MSE* between the predicted and the actual value of *RON* in the training data set. It can also be shown that the (trainrp) method gives good results.

Table 3. *MSE* and *R* for the one hidden layer of different ANN training algorithms

No. of nodes	Items	trianlm	trainrp	traingdx	triangda
11	*R*	0.9671	0.965	0.9642	0.9629
	MSE	0.0561	0.064	0.0665	0.0691
13	*R*	0.9634	0.9594	0.9596	0.9581
	MSE	0.0506	0.0619	0.0656	0.0692
15	*R*	0.97	0.9704	0.9662	0.9652
	MSE	0.0546	0.0623	0.0698	0.0725
17	*R*	0.9736	0.9634	0.9612	0.9606
	MSE	0.0494	0.0619	0.0684	0.0693
19	*R*	0.9608	0.9613	0.9595	0.9588
	MSE	0.0519	0.0611	0.067	0.069

Furthermore, the various types of activation functions effects on the results of the neural network model of Naphtha catalytic reforming since some of activation functions unable to be given the optimum *MSE* and regression. Therefore, several activation functions for the hidden layer and output layer are examined. Table 4 shows the values of *MSE*, and *R* by using various transfer functions.

Tables 4. Training of ANN models with various neurons and transfer functions

No. of nodes	Items	(tansig, tansig)	(tansig, purelin)
11	*R*	0.9671	0.965
	MSE	0.0561	0.0641
13	*R*	0.9634	0.9597
	MSE	0.0506	0.0606
15	*R*	0.97	0.9695
	MSE	0.0546	0.0616
17	*R*	0.9736	0.9616
	MSE	0.0494	0.0557
19	*R*	0.9608	0.9631
	MSE	0.0519	0.0559
21	*R*	0.9717	0.9704
	MSE	0.0494	0.055

The arrangements of activation function have involved (tansig, tansig) and (tansig, purelin). It can be seen from the shaded cell in Table 4 has stated that networks with (tansig, tansig) layout can be able to provide the optimum performance and regression when utilizing one hidden layer in an artificial neural network. The results show that the neural network with 17 hidden neurons and (tansig, tansig) as transfer function is the best model for representing the data collection from Basrah refinery plant. This is due to the model has given lower *MSE* and higher regression value 0.0494, 0.9736 respectively compared with other models.

Finally, Table 5 shows the comparison between the results of neural network prediction model and industrial data of RON of gasoline. The results show a good agreement where *MSE* and regression value is 0.0494, 0.9736 respectively. Also, the results show the weight percentages of operating conditions (temperature of reactors, pressure of reactors, ratio of hydrogen to hydrocarbon, liquid hour space velocity, and feed) are 55.40%, 10%, 15.10%, 9.10%, and 10.40%, respectively. The results illustrate the reactor inlet temperature of has the greatest influence on the performance of the catalytic reforming system and quality of *RON* of gasoline in comparison with other variables.

Table 3. Comparison between the predicted and industrial data of *RON*

Industrial data of *RON*	Predicted data of *RON*
87	85.77
88	86.3
87	85.32
88	88.8
91	90.09
88	86.97
90	89.18

6. CONCLUSIONS

In this study, the operating conditions of Naphtha catalytic reforming plant of Basrah refinery is used as data for simulating the predictive model. The input variables of ANN model are inlet temperature of reactors, operating pressure, feed flowrate, liquid hour space velocity, and hydrogen to hydrocarbon molar ratio, while the output of ANN model is research octane number (*RON*) of gasoline produced. This study has used neural networks with multilayers of feed-forward and feedback propagation. Six training algorithms are examined to determine which one is the best performance.

The results show that Levenberg-Marquardt algorithm has shown to be the best algorithm for predicting the performance of the Naphtha catalytic reforming model. Also, by using various factors, including the number of hidden layers, nodes in the hidden layers, and transfer functions. It can be seen that Levenberg-Marquardt algorithm (trainlm) and (tansig, tansig) as training and activation functions respectively for the hidden layer and output layer gives the best mean square error and regression for testing and training.

The results show that the neural network with 17 hidden neurons and (tansig, tansig) as transfer function is the best model for representing the data collection from Basrah refinery. The values of *MSE* and higher regression are 0.0494, 0.9736 respectively compared with other models. Also, the results of ANN model have shown the weight of pressure, temperature, *LHSV*, and H2/HC are (10%), (55.4%), (15.10%), and (9.10%) respectively. The lower *MSE* and higher regression values show that the data used to train and test the ANN model is very acceptable.

NOMENCLATURES

1. Acronyms

ANN	Artificial Neural Network
RON	Research Octane Number
LHSV	Liquid Hour Space Velocity
LPG	Liquefied Petroleum Gas
Trainlm	Levenberg - Marquardt Algorithm
Trainrp	Resilient algorithm
Traingda	Gradient Descent Algorithm
Traingdx	Gradient Descent with Momentum and Adaptability
Trainoss	Algorithm for one-step backpropagation
Trainscg	Backpropagation Technique with A Scaled Conjugate Gradient
Purelin	Linear Function
Tang-sig	Tangent Hyperbolic Function

2. Symbols / Parameters

T: Temperature of reactors
P: Pressure of reactors
H_2/HC: Ratio of hydrogen to hydrocarbon
F: Feed Flowrate
R: Regression
MSE: Mean Square Error

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