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Predicting Density, Viscosity,Volume and Temperature for Kerosene and Gas Oil Suplied by Doura Refinery From a Measured Experimental Result as Input Variables to Artificial Neural Network (ANN)

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Abstract: This study shows the possibility of predicting specific characteristicsof kerosene and gas oil using experimental measurements as inputs. Variables for programming (ANN) of artificial neuron networks. This study examines fuels from Dora refinery and investigates the relationship between fuel density and various properties such as volume, viscosity, and temperature. The correlation equation was determined by several linear regression analyses, and the coefficient (R2) showed some measurements in a strong achieved:R = 0.99986 for keosene, R= 0.99886 for gas oil.

Keywords: Fuels, Kerosene; Gas oil; Fuel properties; Artificial Neural Network(ANN).

1- Introduction

Evaluating fuel functions is an expensive and long process primarily based on specific operating conditions. High quality testing has a major impact on the price of oil quality. The experimental method predicts the physical properties of kerosene and gas oil, but is time-consuming and expensive. However, without reprocessing, the kerosene and gas oil industry will need a more efficient way to complete it at a cheaper price in a practical and shorter period. Xiao-Yu Wang & et al. [1], their study summarized the effects of fuel composition and hydrocarbon molecular structure on the physicochemical properties of fuels, including fluidity, flash point, and thermal oxidation stability at low temperatures (NHOC), low temperatures (viscosity and freezing). Several correlations and predictions of fuel properties from chemical composition were checked. Furthermore, fuel properties were correlated with hydrogen/carbon moles (N H/C) and molecular weight (M).The results of the minimal square method suggest that the H/C-MOL ratio and M bonding are suitable for estimating the density, NHOC, viscosity, and evaluation of hydrocarbon fuels

David J. Cookson & et al. [2], investigated the correlation between the fuel composition of kerose ne and diesel fuels and several fuel properties. Equestrian values and compositional data were e valuated with a simple linear relationship. Multiple linear regression analyses were used to derive correlation equations and coefficients of multiple measurements R2 were used to display the quality of adaptation between observed and computational properties (Rusinoff, 2000).

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Narges Zohari & et al. [3], presented two new reliable simple correlations for predicting the flash point of kerosene hydrocarbons using multiple linear regression methods, and they found that th e flash point of kerosene fuels can be expressed as a function of elemental composition and sev eral structural parameters.

Attempts to predict the CFPP in fuels has been done by Al-Shanableh et al.who developed models for predicting CFPP in bio-diesel from its fatty acid composition using both artificial neural network (ANN) and Fuzzy logic. Both methods showed promising results with R2 values of 0.96 and 0.98 [4, 5].

Chuanjie Wu et al. (2006), ANN was applied using factors such as viscosity, density, refractive sect ion, CFPP of current components, and proportion of individual components. They also modeled ca ses with a certain amount of additives, but did not use additives as parameters.The model was test ed at a refinery and the results were accepted [6].

Li Weimin & et al., explore the use of artificial neural networks (ANNs), specifically for predicting properties such as pour point (PP) and cold filter plugging point (CFPP) of diesel oil, as well as the octane number of gasoline. They suggest an application of ANNs in the petroleum industry for predicting fuel characteristics [7]. Semwal and et al. were worked to develop new correlations. Three low-temperature properties correlations, the Pour point, Cloud point, and Cold filter plugging point were established to predict accurately of up to 30% with the new point equatio .[8],

While other researchers report models for prediction of CFPP based on spectroscopy [9,10].This m ethod is slow and makes it difficult to improve the process. Additionally, in addition to high capital investment costs and high operating costs, it may need to purchase individual machines for the property you want to test.

We use a variety of tests to assess the quality of oils for different uses. Prediction of the physical properties of kerosene and gas oil using experimental methods has a high level of accuracy. Howe ver, it takes time and cost. The kerosene and gas oil industry requires more efficient and functional methods, which can be performed in less costly and in less time than experimental methods. Therefore, artificial neural networks (ANNs) are considered the best alternative to predict the phy-sical properties of kerosene and gas oil.

2. Experimental work

Two samples studied. One was kerosene and another gas oil. Several physical properties were measured such as viscosity (ASTM D-445), volume and density (ASTM D1480-21). At different temperatures, 19 measurements were obtained for each property (Tables 1 and 2).

2.1 Kerosene

Kerosene, also known as paraffin or paraffin oil, is a flammable, pale yellow or colorless peetroleum product with a distinctive odor associated with the volatility between gasoline and diesel oil. This is produced by atmospheric distillation of crude oils in the 150°C and 280°C range and is further processed in downstream units to improve product quality. There are many kerosene classes. Therefore, the property is specified as a range value. Standard quality parameters and experimental methods used for measuring properties..

Table 1: Some physical properties for kerosene

Item No.	Temperature, oC	Viscosity, cst	Density, g/m^3	Volume , mL
1	25	5.12	0.7612	15.0
2	27.5	4.98	0.7598	15.05
3	30	4.84	0.7584	15.1
4	32.5	4.68	0.7567	15.13
5	35	4.52	0.755	15.15
6	37.5	4.39	0.7533	15.18
7	40	4.25	0.7516	15.2
8	42.5	4.08	0.7499	15.22
9	45	3.92	0.7499	15.25
10	47.5	3.81	0.7463	15.27
11	50	3.71	0.744	15.3
12	52.5	3.51	0.7426	15.35
13	55	3.33	0.7406	15.4
14	57.5	3.31	0.7386	15.42
15	60	3.3	0.7366	15.45
16	62.5	3.22	0.735	15.47
17	65	3.14	0.7334	15.5
18	67.5	3.04	0.7318	15.52
19	70	2.94	0.7301	15.55

2.2 Gas oil

Gas oil is a crude oil fraction distilled in the 300-550°C range and produced by a traditional (atmospheric or vacuum) distillation process. It is dark and viscous, and remains as a result of the refined distillation of crude oil or as a mixture with light components, and is used in steamers and various industrial processes, and steam generation,

Table 2: Some physical properties for gas oil

Item No.	Temperature °C	Viscosity, cst	Density, g/m^3	Volume, mL
1	25	11.64	0.7864	15.0
2	27.5	10.92	0.784	15.05
3	30	10.2	0.7795	15.1
4	32.5	9.78	0.7965	15.13
5	35	9.37	0.7746	15.15
6	37.5	8.96	0.7728	15.18
7	40	8.49	0.7709	15.2
8	42.5	8.02	0.7685	15.22
9	45	7.55	0.7662	15.25
10	47.5	7.08	0.7638	15.27
11	50	7.01	0.7614	15.3
12	52.5	6.73	0.7602	15.35
13	55	6.45	0.7589	15.4
14	57.5	6.2	0.7571	15.42
15	60	5.95	0.7552	15.45
16	62.5	5.74	0.7528	15.47
17	65	5.53	0.7503	15.5
18	67.5	5.35	0.7475	15.52
19	70	5.17	0.7447	15.55

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3- Model evaluation - Neural Net Fitting

During the project, modeling was performed in a neuron network tuning app to create, visualize and train a two-tier feedforward network to solve the MATLAB data tuning problem. I used this app, which imported data by Excel files into the MATLAB R2022B work area and split into training, validation, testing, and updating selected weight and preload values according to Levenberg Marquardt optimization. The fastest training algorithm is Levenberg-Marquardt training, but it requires more memory than other techniques. Results were analyzed using visualization diagrams such as regression adjustments and error histograms.

4- Results

Kerosene or gas oil, predictors and reactions are given, and observations are in the row. Information about the imported data records contains 19 observations each with four characteristics:Temperature, viscosity, and volume are displayed in the model overview. The data is divided into 70% of the training to verify that the network is generalized and to verify that the pre-adjusted training is tested by 15% for generalization of the network [11]. For network creation, the created network was a two-layer forward network with sigmoid transmission functions in the hidden layer and linear transmission functions in the output layer. The shift size value defined the number of hidden neurons and was retained as standard layer size 10. The network plot was updated to reflect the input data. The data had 4 inputs (features) and one output as shown in Figs. 1a, 1b .

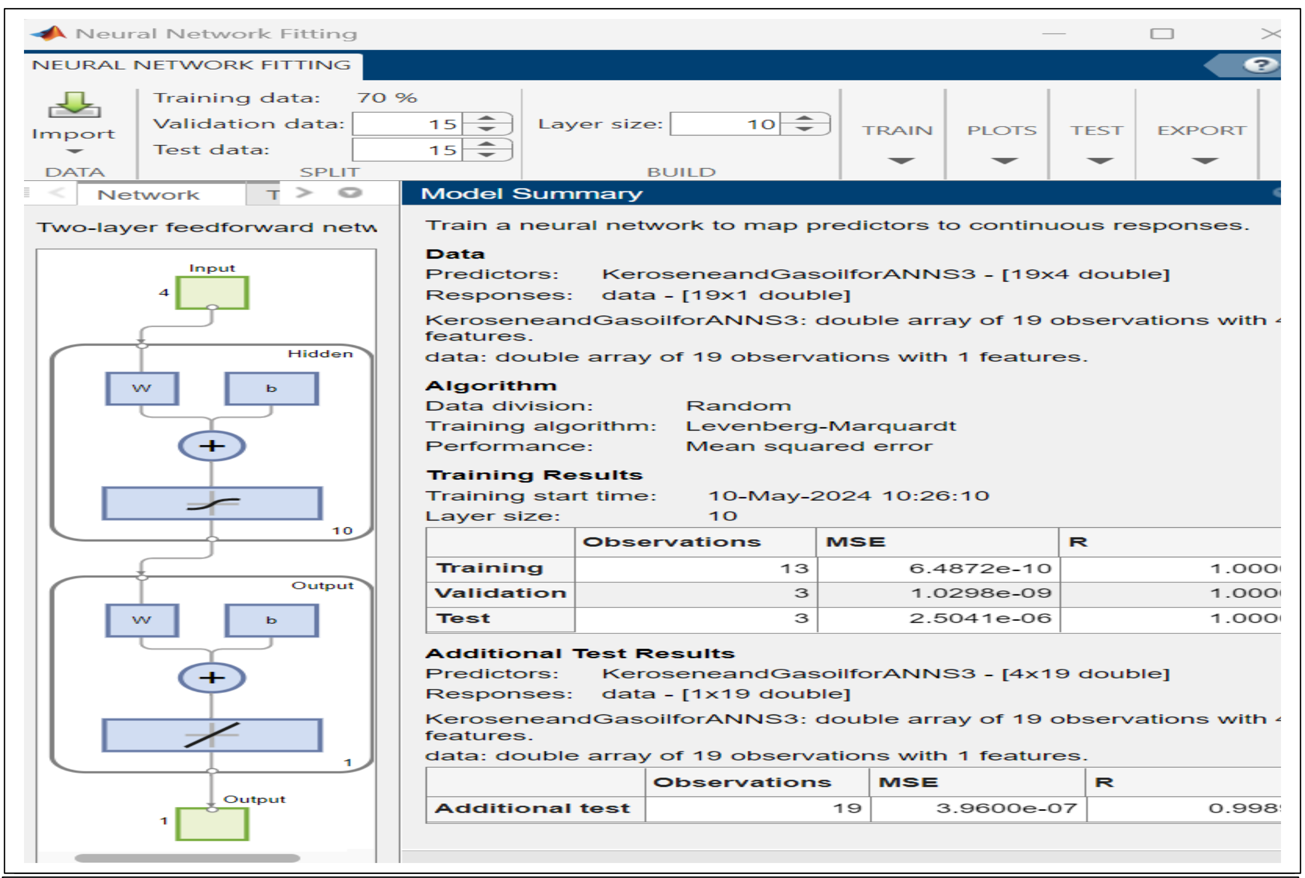

Fig.1a: Kerosene feed forward network with sigmoid hidden neurons and linear output neurons suitable for regression

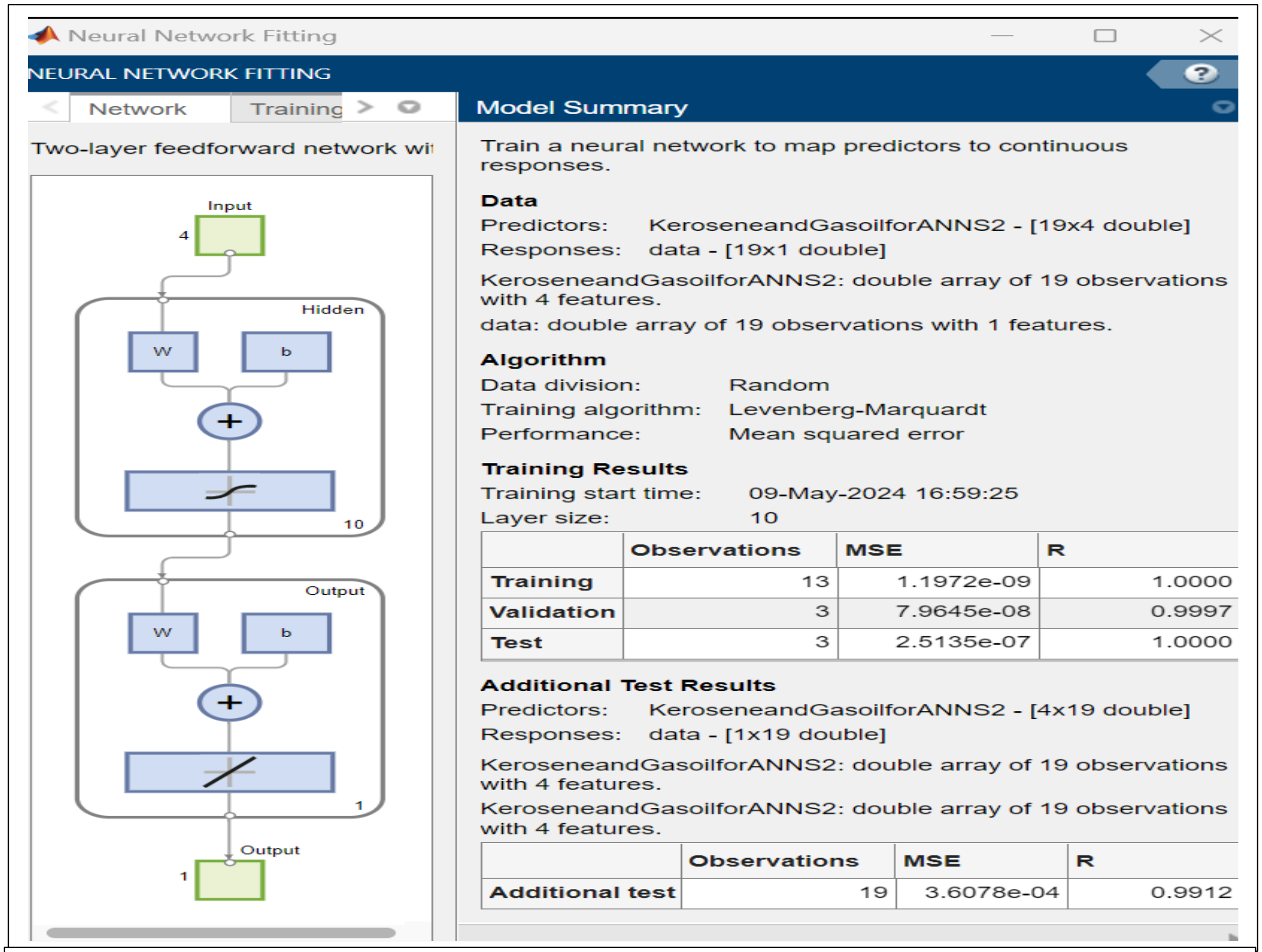

Fig.1a: Gas oil feed forward network with sigmoid hidden neurons and linear output neurons suitable for regression

4.1 Network Training

Training progress continues until three iterations of kerosene and two iterations of gas oil (" etverification criteria") increase one after another. See, :Tables 3 , 4 , and traioning plot,":. 2a, 2b", and performance plots" Figs. 3a, 3b".

Table 3: Kerosene training results

Training Results

Training finished: Reached minimum gradient

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	22	1000
Elapsed Time	-	00:00:01	-
Performance	0.00102	8.93e-17	0
Gradient	0.00281	7.53e-10	1e-07
Mu	0.001	1e-11	1e+10
Validation Checks	0	3	6

Table 4: Gas oil training results

Training Results

Training finished: Reached minimum gradient

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	18	1000
Elapsed Time	-	00:00:01	-
Performance	0.000579	3.9e-10	0
Gradient	0.00242	9.23e-08	1e-07
Mu	0.001	1e-08	1e+10

Network Training

In the **Training** pane, the training progress, training continues until the validation error increases consecutively for three iterations for kerosene and two iterations for gasoil ("Met validation criterion") as in Tables 3,4 , kerosene and gasoil training state plots Figs. 2a, 2b ,and performance plots Figs.3a,3b.

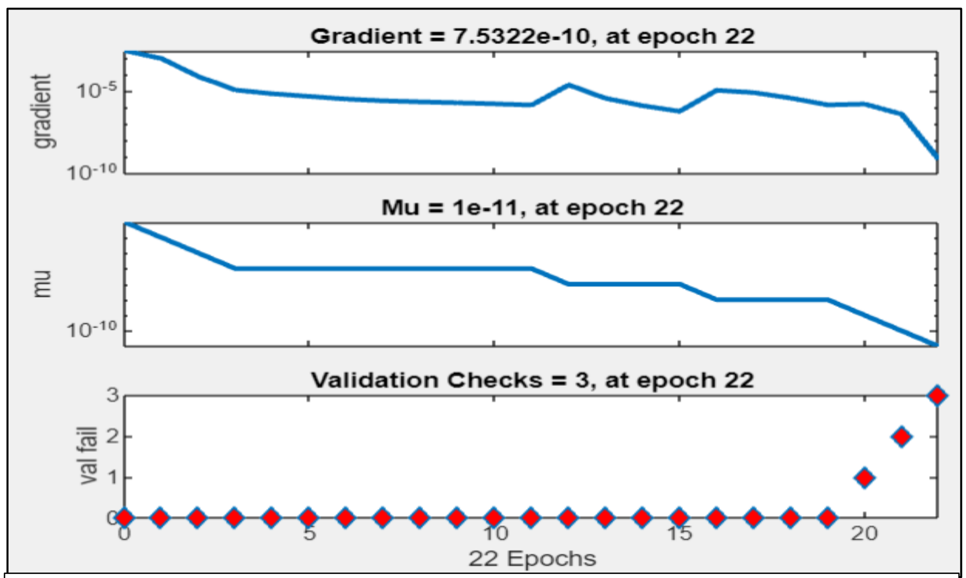

Fig. .2a: Kerosene training state plots

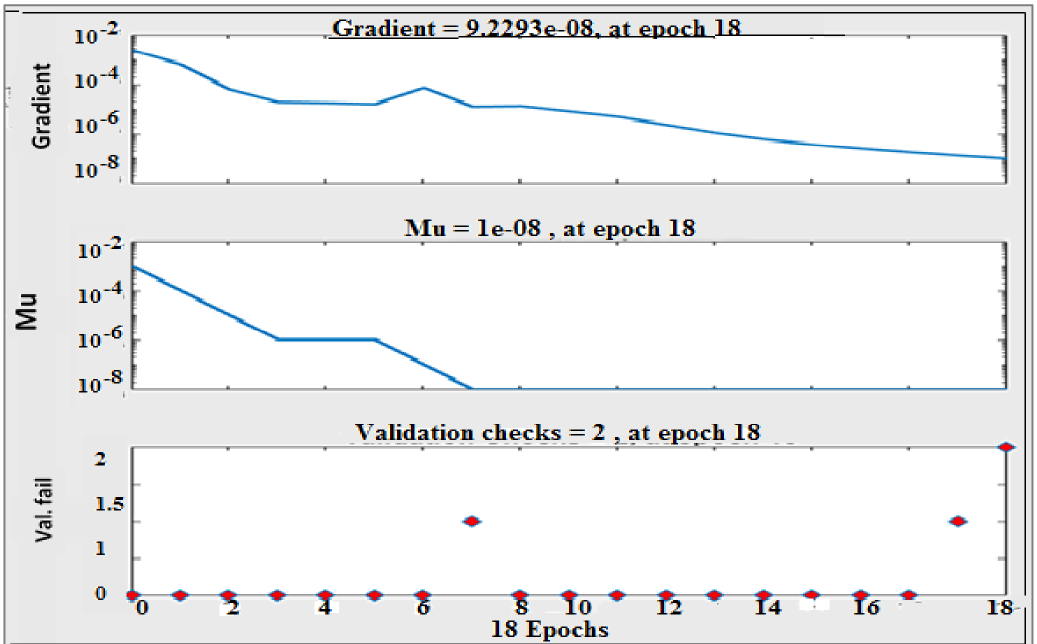

Fig.2b :Gas oil training state plot

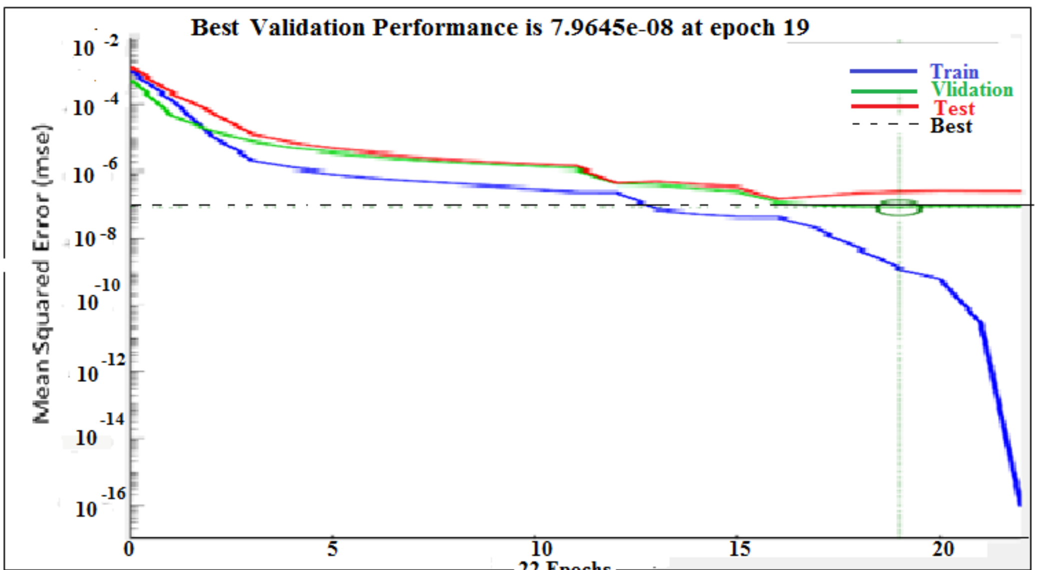

Fig. 3a : Kerosene performance plot

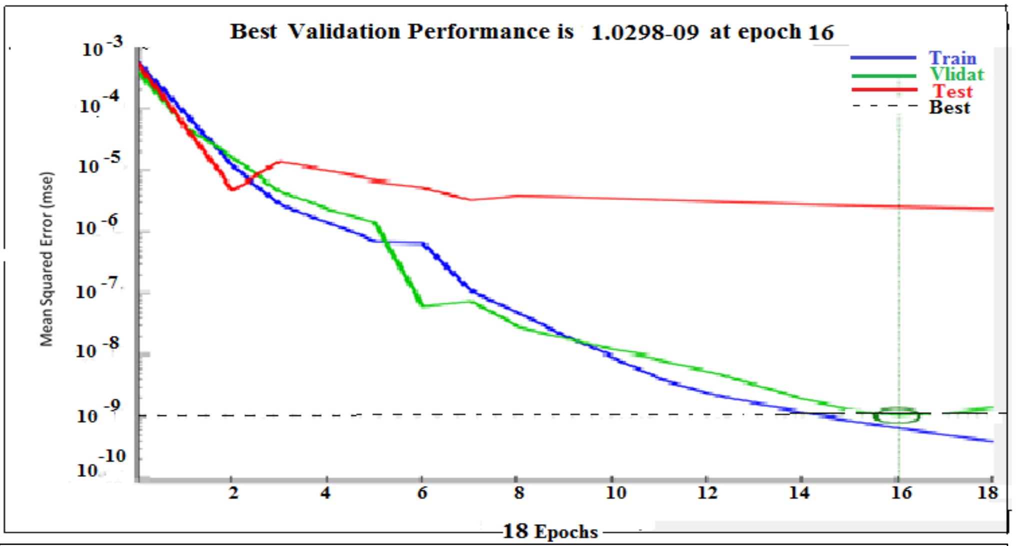

Fig.3b : Gas oil performance plot

4.2 Result analysis

The model summary contains information about the training algorithms and the training results for all data records for kerosene and gas oil are shown in Tables 3 and 4. The regression graphs and diagrams in Figs. 4a, 4b show network predictions (editions) for training, validation, and test set responses (goals). . For kerosene and gas oil, the adjustment R= 0.99986 for all data records, 0.99986 for kerosene, and R = 0.9886 for gas oil is pretty good and doesn't require more accurate results. However, if the network is more accurate, all new training is up to different initials and network.

In the error histogram, for additional checks to add network performance, the blue bar represents training data, the green bar represents validation data, and the red beam represents test data. The The histogram Figs. 5a, 5b provide an indication of outliers, which are data points where the fit is significantly worse than most of the data. The results are very good. The error-free points are 0.00000866 for kerosene and 0.000019 for gas oil.

Future work

More detail results can be using experimental physical properties of kerosene as well as experimental physical properties such as flash point, auto-ignition temperature, melting/freezing point, color, pH, initial boiling point and boiling area, vapor pressure, auto-ignition, specific gravity. Comparisons can then be estimated to determine which of the admission predictors dominate.

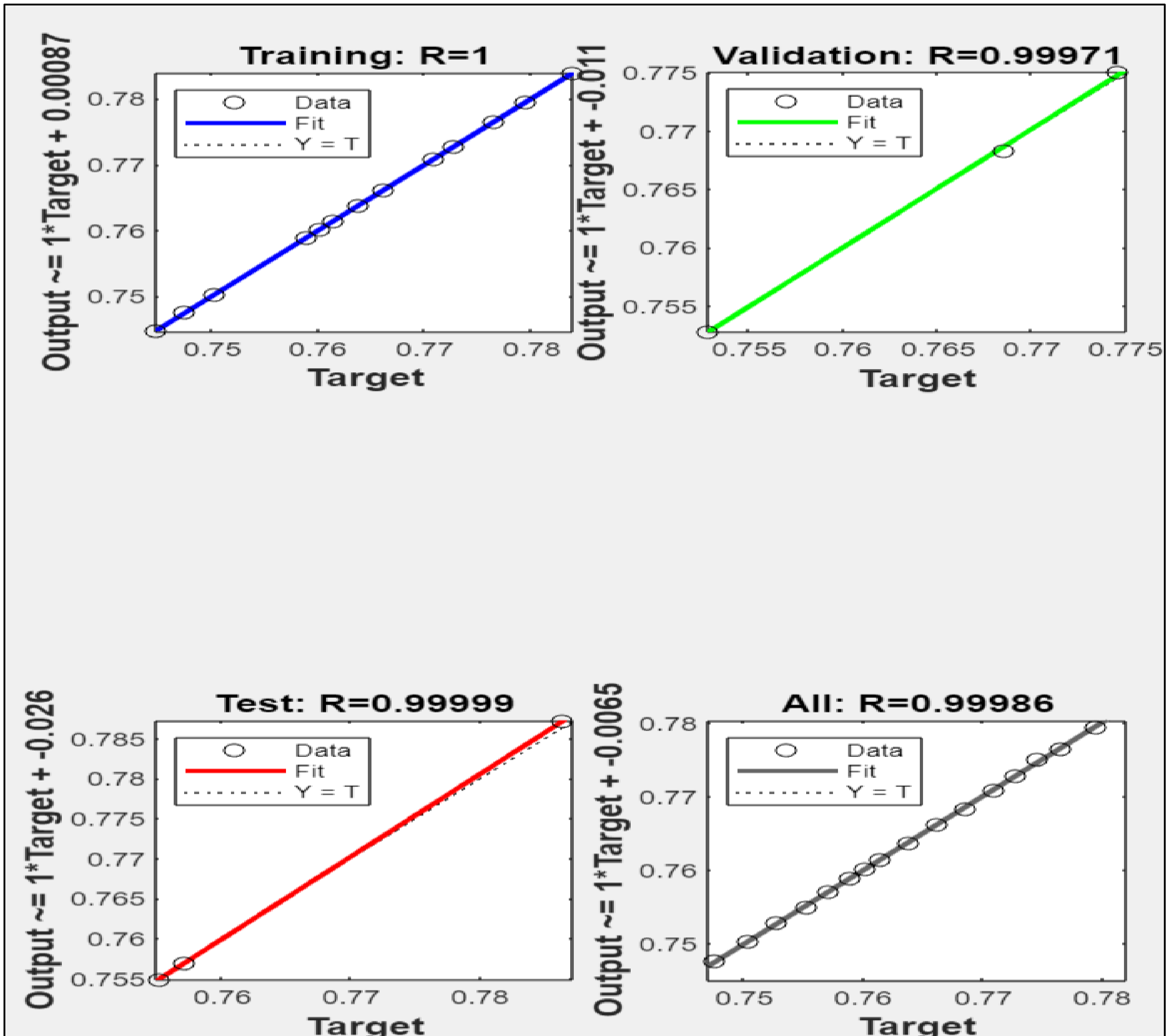

Fig. 4a: Kerosene regression plot

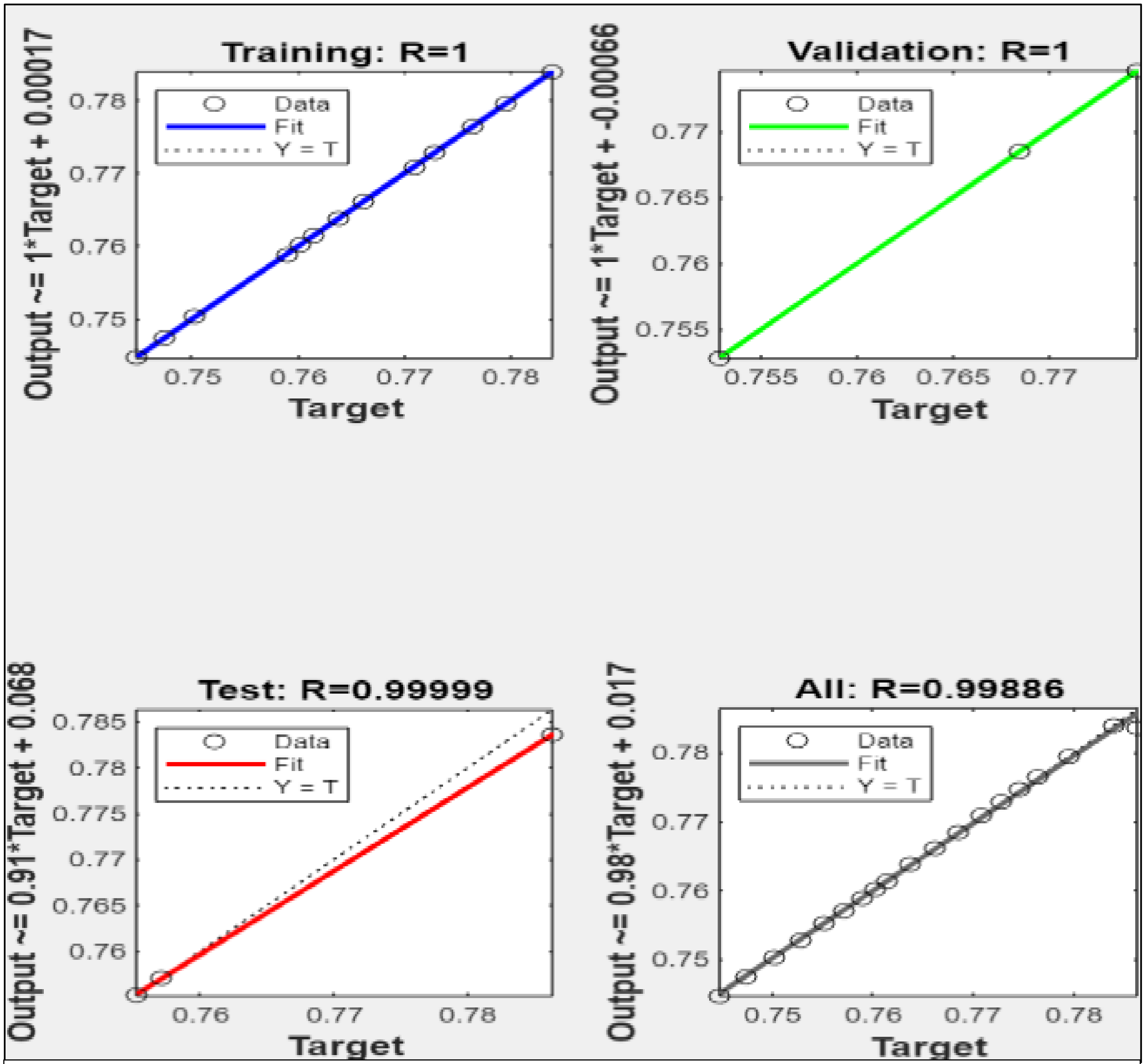

Fig.4b: Gasoil regression plot

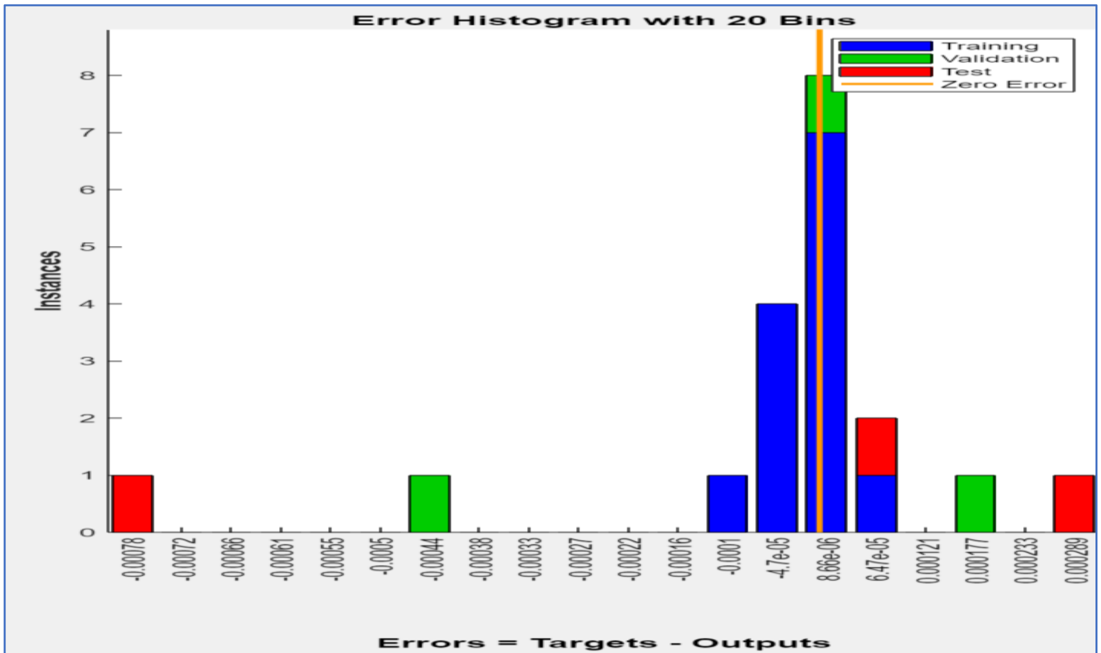

Fig.5a: Kerosene error histogram

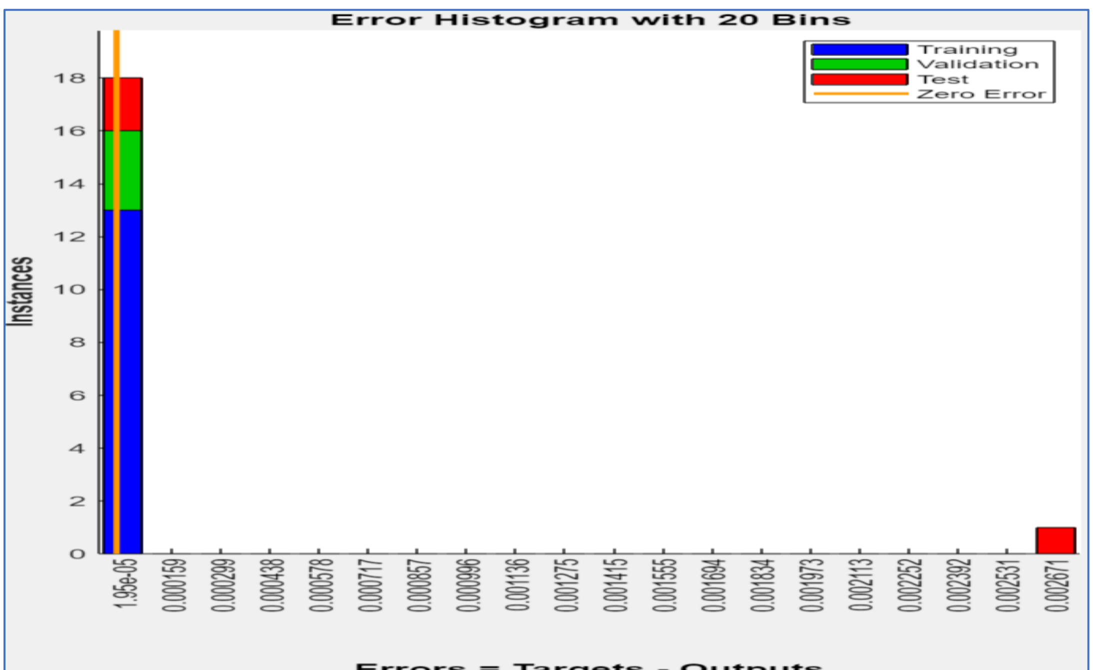

Fig.5a: Gas oil error histogram

Abbreviation

ANN	Artificial Neural Network
CFPP	Cold Filter Plugging Point
ASTM -455	Standard Test Method for Kinematic Viscosity of Transparent and Opaque Liquid (and Calculation of Dynamic Viscosity).
ASTM D1480-21	Standard Test Method for Density and Relative Density (Specific Gravity) of Viscous Materials by Bingham Pycnometer
Cst	Centistock (Knematic viscosity unit)

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