Utilization of Response Surface Methodology (RSM) in the Optimization of Crude Oil Refinery Process, New Port-Harcourt Refinery, Nigeria

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***Abstract*—Design expert version (7.1.6) was used for response surface methodology analysis. The correlation coefficients of determination (R^2) for the developed models show that the actual data fitted well with the predicted data calculated from the models. The optimal values of the process variables were found to be combinations of AB and AC. For AB: liquid inlet pressure of 595.5 kPa and liquid inlet temperature of 586.1°K gave the best optimum exergy efficiency of 69.5%. For AC: liquid inlet temperature of 586.1 °K and condenser pressure of 133 kPa gave exergy efficiency of 68%. The base case design of the Atmospheric Distillation Unit (ADU) of the New Port-Harcourt refinery has exergy efficiency of 52.4%. These result shows that the optimal cases from the response surface methodology (RSM) above achieved an increase in exergy efficiency by 32.8% for the AB combination and 30.0% for the AC combination.**

Keywords—Response Surface Methodology, Exergy, Refinery

Introduction Statistical optimization is the use of statistical methods to determine the most cost-effective and efficient solution to a problem or process design. It is concerned with selecting the best operating conditions among the entire set by efficient quantitative methods like response surface method. This technique is one of the major quantitative tools in industrial decision making. Statistical optimization has many advantages, it gives better understanding of the process, it helps the process engineer to see the effect of the control variables and the interactions among all the variables.

Response surface methodology (RSM) is a collection of mathematical and statistical technique used for modeling and analyzing a process in which a response of interest is influenced by several variables and the objective is to optimize this response [1]. RSM can either be linear model or non-linear model. Linear models are generally used in most studies to assess the dependent and independent factors. In linear model, the behavior of the dependent variable (response) can be expressed as equation 1 [2].

$$Y_i = b_o + \sum_{i=1}^{n} b_i x_{ii} + \varepsilon_i \quad (1)$$

Where ε_i is independent random variables, b_o is the mean of observations, and b_i is unknown constant, i is the factor and n is the number of observations.

The non-linear models are important and necessary to consider an experimental design, which would allow one to fit the experimental data to a quadratic model [3]. The factorial design allows for experimentation of all main effects of the factors at any level and interactions between each pair of factor as well as all three ways interactions between each triplet of factors. Equation 2 is used to describe the non-linear model [1].

$$Y = b_o + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} {x_i}^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} b_{ij} x_i x_j + e_i \quad (2)$$

Where, Y is the predicted response; n is the number of factors; x_i and x_j are the coded variables; b_o is the offset term; b_i, b_{ii}, and b_{ij} are the first-order, quadratic, and interaction effects, respectively; i and j are the index numbers for factor; and e_i is the residual error.

In the last decade, RSM has been extensively utilized for modeling and optimization of several chemical engineering processes. Such processes include: catalytic conversion of methane and ethylene into liquid fuel products [4], ethanol dehydration process [5], production of citric acid [6], nickel electroplating process [7]. Others are tartaric acid reactive extraction [8], transesterification of moringa oleifera oil [9] and ethanol fermentation from sweet sorghum [10]. In the petroleum industry, RSM has been used to optimize thermal cracking of petroleum residue oil and it was found out that the predicted conversion and yields of total distillate fuels, gasoline, kerosene and diesel agreed satisfactorily with the experimental values [11]. Similarly, RSM was used to optimize removal of nickel and lead from petroleum wastewater and was discovered that petroleum wastewater treated at these optimized conditions compared to the raw sample showed a marked decrease in the concentration of the specified metals far below the standard limits set by National Environmental Standards and Regulations Enforcement Agency (NESREA) and Federal Environmental Protection Agency (FEPA) [12].

Literature search did not reveal any study on modeling and optimizing refinery operations using Response Surface Methodology (RSM). This study will no doubt serve as a baseline study in which further research into the use of RSM in modeling and optimizing refinery operations can be based.

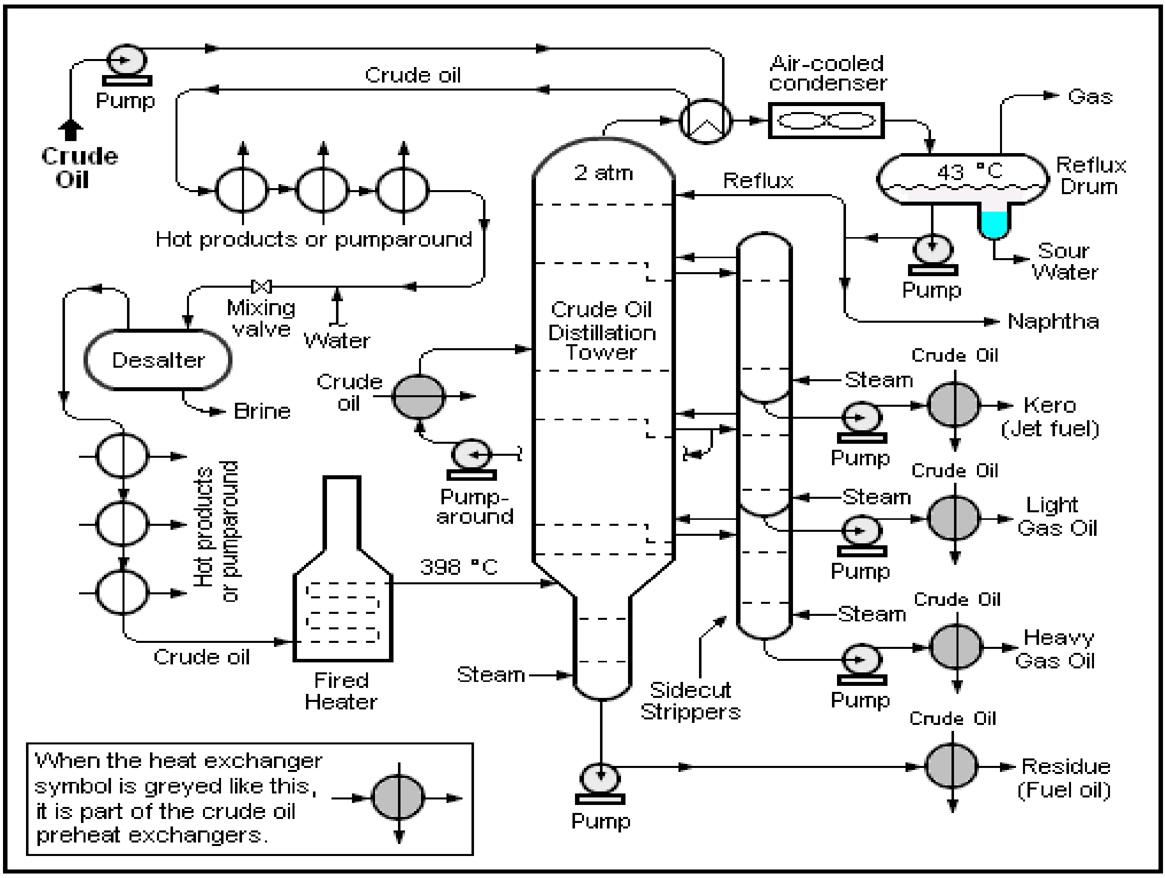
The Process Units

The processing of crude oil is done in two stages in the distillation units of a refinery. We have the atmospheric distillation unit (ADU) and the vacuum distillation unit (VDU). The former is used for light fractions of the crude oil while the latter is employed in the heavier fractions of the crude oil. The products from these distillation units can either be the final or intermediate products. This research focused on the ADU of crude distillation unit of the New Port Harcourt Refinery. The crude distillation unit is made up of the pre-flash unit which increases the temperature of the crude oil so as to separate into different fractions mainly liquid and vapour phase after it has passed through cleaning process and desalination process. The vapour phase is sent straight to the refluxed absorber while the liquid phase is sent to heater then to a furnace before entering the refluxed absorber which then separates it into different products.

A. Figures and Tables

1) Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation "Fig. 1," even at the beginning of a sentence.

TABLE I. SCHEMATIC FLOW DIAGRAM OF A TYPICAL CRUDE OIL DISTILLATION UNIT AS USED IN PETROLEUM CRUDE OIL REFINERIES [13]



Methodology

Materials for the Study

The research was carried out using the design flowchart and the operating data of the crude distillation unit of the New Port Harcourt refinery. Simulation of the plant was carried out using simulation software (HYSYS 2006.5). Parametric studies was performed by changing the operating variables (liquid nlet temperature, liquid inlet pressure, condenser temperature, condenser pressure, pump around flow rates 1, 2 and 3) to determine their effect on energy and exergy efficiencies. Data from the three most sensitive operating variables in the parametric analysis was extracted and exported to Design Expert Software to improve the performance of the Atmospheric Distillation Unit (ADU). Design Expert (7.1.6) was used for statistical analysis.

Optimizing the ADU using Statistical Analysis

The response surface methodology (RSM) was used to evaluate the effects of sensitive operating variables from the parametric analysis in the ADU of the New Port-Harcourt refinery. The Box-Behnken design was used to screen significant factors among the three operating variables with respect to their effects on the operating condition of the atmospheric distillation unit of the New

Port-Harcourt refinery. The three factors are liquid inlet temperature (A), liquid inlet pressure (B) and condenser pressure. Each variable was represented at three levels i.e. low level (-1), medium level (0) and high level (+1). According to the Box-Behnken design developed by Design Expert Software (Version 7.1.6, Stat-Ease Inc, Minneapolis, MN, USA), seventeen runs of data was predicted by the software. A general second-order model that was employed is defined in Equation 3

$$Y = b_o + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} {x_i}^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} b_{ij} x_i x_j + e_i \qquad 3$$

Where, Y is the predicted response; n is the number of factors; x_i and x_j are the coded variables; b_o is the offset term; b_i, b_{ii}, and b_{ij} are the first-order, quadratic, and interaction effects, respectively; i and j are the index numbers for factor; and e_i is the residual error [1]. The RS-model was tested for statistical significance using the analysis of variance (ANOVA) which includes Fischer's test (F-test) (overall model significance), its associated

probability (p-value), correlation coefficient (R), coefficient of determination (R^2), sum of squares of residuals and regression together with the corresponding degree of freedom.

Results and discussion

Simulation result diagrams of the Crude Distillation Unit (CDU) and Atmospheric Distillation Unit (ADU) of new Port-Harcourt refinery are as shown in Figures 2 and 3 respectively [14].

Figure 2: Simulation Diagram of the CDU for New Port Harcourt Refinery

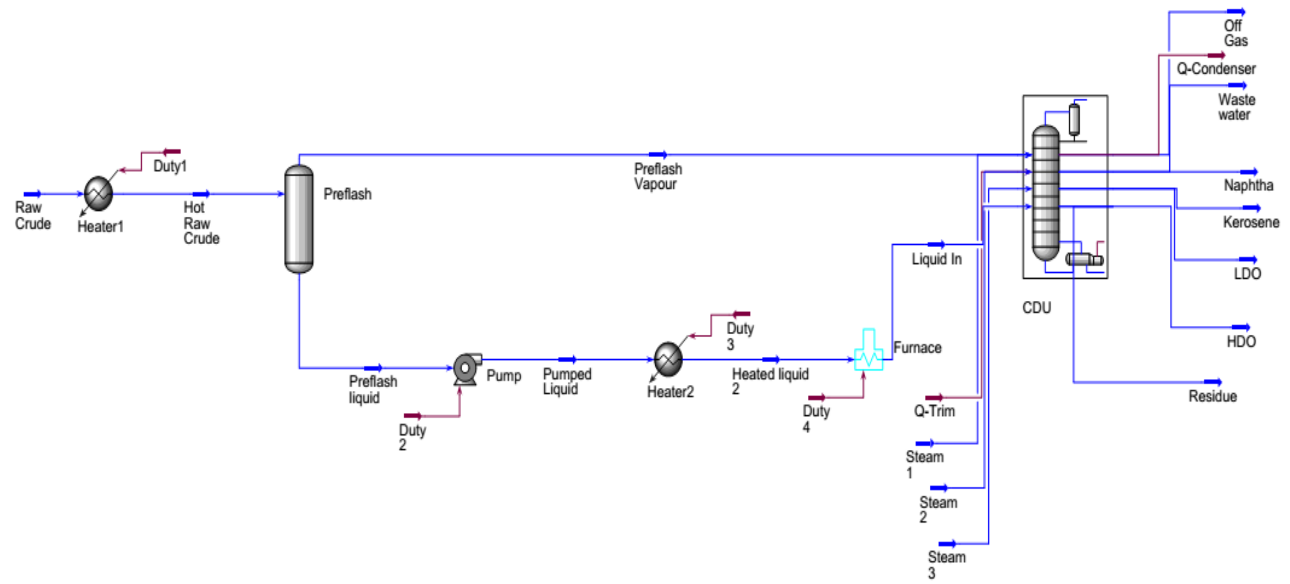
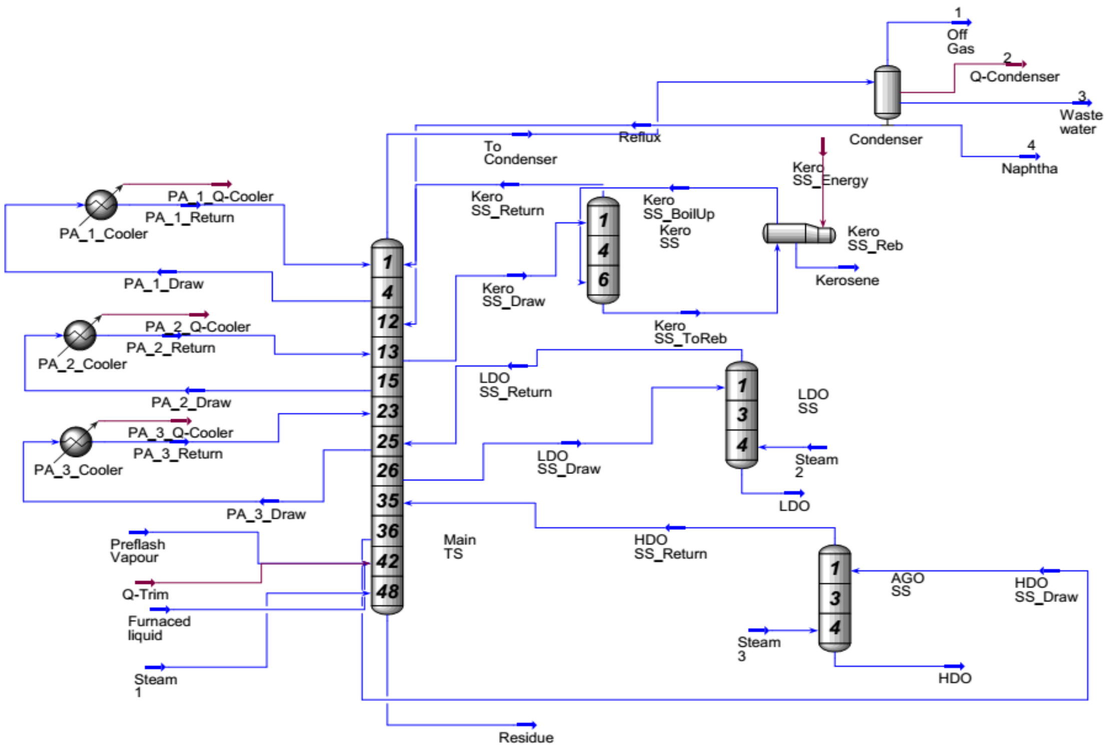


Figure 3: Simulation Diagram of the Atmospheric Distillation Unit



Response Surface Methodology Results

The Box-Behnken design was used to screen the sensitive operating variables in order to optimize the atmospheric distillation unit. The three sensitive operating variables liquid inlet temperature (A), liquid inlet pressure (B and condenser pressure (C) were represented at three levels i.e. low level (-1), medium level (0) and high level (+1). The liquid inlet temperatures at the three levels of low, medium and high are 586.1 K, 646.1 K and 706.1 K respectively. Liquid inlet pressure at the three level of low, medium and high are 345.5 kPa, 470.5 kPa and 595.5 kPa respectively. For the condenser pressure the three levels of low, medium and high are 115kPa, 124kPa and 133kPa respectively.

For all combinations tested, exergy efficiency varied from 35.2% to 69.6% as shown in Table 1. The highest exergy efficiency of 69.6% was calculated from the combination of liquid inlet temperature of 586.1 ^{0}K, liquid inlet pressure of 595.5 kPa and Condenser pressure of 124.0 kPa. The design expert predicted the optimum operating conditions of the ADU when compared with the result of the parametric studies. From the parametric studies, liquid inlet temperature of 586.1 K and liquid inlet pressure of 595.5 kPa gave the best exergy efficiency of 66.6% and 53.7% respectively. Table 2 shows the comparison of the actual simulation value with the predicted model, this shows that the model fits well since the difference is insignificantly low.

Simulation and experimental design result

Based on simulation and experimental design results as shown in Table 3, the regression model was constructed by means of ordinary least square method in order to determine the functional relationship for approximation and prediction of responses. The response variable (Exergy Efficiency) was fitted by a second order polynomial model in other to correlate the response variable to the design variables (A, B, C) as shown in Table 3. The second order RS-models (in terms of coded variables) obtained is as follows:

$$\text{Exergy Efficiency} = 47.54 - 16.13A + 0.82B + 0.26C + 4.13A^2 + 0.07B^2 - 0.12C^2 - 0.84AB - 0.084AC + 3.675E3BC \quad (4)$$

Statistical analysis of RS-models

In Table 4, the computed F-value is 15,672.23 and p-value is <0.0001. This shows that the RS-model for response (Exergy Efficiency) was significant at 95% Confidence Interval. This high F-value and very low P-value indicate the high significance of the model, showing reliability of the response surface quadratic model for predicting the exergy efficiency of the ADU. In this study, A, B, C, A^2, AB are significant model terms as shown in Table 4.

Table 1: The Box–Behnken Design of the Variables with Exergy Efficiency as Response

Run	A (°K)	B (kPa)	C(kPa)	Response (Exergy Efficiency (%))
1	646.10	470.50	124.00	47.54
2	647.10	345.50	133.00	47.03
3	706.10	470.50	133.00	35.59
4	706.10	595.50	124.00	35.74
5	706.10	345.50	124.00	35.54
6	646.10	345.50	115.00	46.55
7	586.10	595.50	124.00	69.62
8	586.10	345.50	124.00	66.08
9	646.10	470.50	124.00	47.54
10	586.10	470.50	115.00	67.36
11	706.10	470.50	115.00	35.22
12	646.10	595.50	133.00	48.46
13	646.10	470.50	124.00	47.57
14	586.10	470.50	133.00	68.06
15	646.10	470.50	124.00	47.54
16	646.10	595.50	115.00	47.95
17	646.10	470.50	124.00	47.54

Table 2: Box-Behnken Design Applied for ADU Process Simulation

	Responses (Exergy Efficiency)	
Standard Order	**Actual Simulation Value**	**Model Prediction**
1	66.08	66.22
2	35.54	35.63
3	69.62	69.62
4	35.74	35.60
5	67.36	67.34
6	35.22	35.26
7	68.06	68.03
8	35.59	35.60
9	46.55	46.42
10	47.95	48.06
11	47.03	46.93
12	48.46	48.58
13	47.54	47.54
14	47.54	47.54
15	47.54	47.54
16	47.54	47.54
17	47.54	47.54

Table 3: Regression Coefficients of Response Surface Quadratic Model

Factor	**Coefficient Estimate**	**Degree of freedom**	**Standard Error**	**95% CI Low**	**95% CI High**
Intercept	47.54	1	0.005	47.41	47.67
A	-16.13	1	0.044	-16.23	-16.03
B	0.82	1	0.044	0.72	0.92
C	0.26	1	0.044	0.15	0.36
A^2	4.13	1	0.060	3.99	4.27
B^2	0.070	1	0.060	-0.073	0.21
C^2	-0.12	1	0.060	-026	0.027
AB	-0.84	1	0.062	-0.98	-0.69
AC	-0.084	1	0.062	-0.23	0.062
BC	3.675E-003	1	0.062	-0.14	0.15

Table 4: Analysis of Variance (ANOVA) for Response (Exergy Efficiency)

Source of variation	SS	DOF	MS	F-value	P-value (prob>F)
Model	2162.01	9	240.22	15672.23	<0.0001
A	2081.04	1	2081.04	1.358E+005	<0.0001
B	5.39	1	5.39	351.52	<0.0001
C	0.53	1	0.53	34.71	0.0006
A^2	71.82	1	71.82	4685.52	<0.0001
B^2	0.020	1	0.020	1.33	0.2862
C^2	0.057	1	0.057	3.70	0.0958
AB	**2.8**	**1**	**2.80**	**182.40**	**<0.0001**
AC	0.028	7	0.028	1.85	0.2155
BC	5.402E-005	3	5.402E-005	3.524E-003	0.9543
Residual	0.11	4	0.015		
Cor Total	2162.11	16			
C.V (%)	0.25				
R^2	1.0000				
R^2_{adj}	0.9999				

Analysis of variance (ANOVA) was used to test statistical significance of the RS-models. Table 4 depicts the statistical results showing the sum of squares (SS), degree of freedom (DOF), mean square (MS), F-value, p-value (Prob>F), and ANOVA coefficients (i.e. coefficients of multiple determination, R^2 and adjusted statistic, R^2_{adj}). Fischer distribution (F-value) and p-value was used to determine the significance of the RS-models. p-value < 0.05 was considered significant. A large F-value and a small p-value (<0.05) implies that the models are significant and are adequate to predict the responses. The goodness-of-fit of the RS-model are evaluated by employing R^2 and R^2_{adj} which indicate the extent of reliability between the observed values (simulation results) and the predicted values. The R^2 value is always between 0 and 1. The closer the R^2 value to 1, the stronger the model is and the better it predicts the response [15]. Employing R^2 and R^2_{adj} which indicate the extent of reliability between the observed values (simulation results) and the predicted values. The R^2 value is always between 0 and 1. The closer the R^2 value to 1, the stronger the model is and the better it predicts the response [15].The values of R^2 and R^2_{adj} are 1.0000 and 0.9999 respectively. These values indicate that the RS-model is statistically significant. Furthermore, Kumari et al, 2008, reported that the closer the R^2 value to 1 the stronger the model is and the better it predicts the response [14]. The value of R^2 (1.0000) indicates that there is a high reliability between the observed values (simulation results) and the predicted values; hence, the fitted model can be used to predict the optimum operating condition of the ADU.

The goodness-of-fit of the quadrate RS-model for the response is illustrated in Figure 4 .This plot shows that there is no much difference between the predicted values and actual values of the variables. The very low coefficient of variation (C.V) of 0.25% as shown in Table 5 reveals a better precision and reliability of the simulation results of the new fitted model.

Optimization of the atmospheric distillation unit

Three Dimensional (3D) response surface plots were generated as shown in Figures 5 and 6. These plots show the predicted effects of process variables (liquid inlet temperature, liquid inlet pressure and condenser pressure) on responses (Exergy efficiency). The 3D plots are the graphical representation of the regression equations in order to determine the optimum value of the variables within the design space [16].

The optimal values of the process variables were found to be combinations of AB and AC. For AB: liquid inlet pressure of 595.5 kPa and liquid inlet temperature of 586.1°K gave the best optimum exergy efficiency of 69.5% as shown Figure 5. For AC: liquid inlet temperature of 586.1 °K and condenser pressure of 133 kPa gave exergy efficiency of 68% as shown Figure 6.

The base case design of the ADU has exergy efficiency of 52.4%. These result shows that the optimal cases from the response surface methodology (RSM) above achieved an increase in exergy efficiency by 32.8% for the AB combination and 30.0% for the AC combination.

Exergoeconomic analysis of the optimized atmospheric distillation unit using RSM

From the predicted value of exergy efficiency of 69.5% following optimization with combination of the three sensitive parameters liquid inlet temperature, liquid inlet pressure and condenser pressure are 586.10 ºK, 595.5 kPa and 124 kPa respectively. The cost in terms of exergy was estimated to be $136.18/s. The exergy cost reduces from $149.77/s which is the base case cost to an estimate of $136.18/s. This showed a reduction of 9.07% in the exergy cost.

Figure 4: Graph of Predicted and Actual Exergy Efficiency [14]

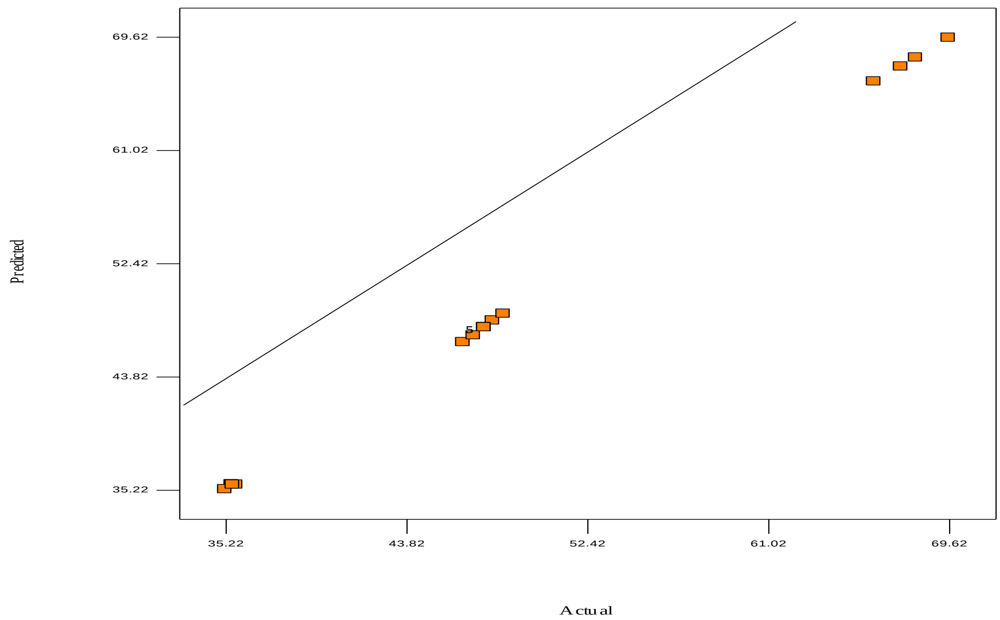


Figure 5: 3-D Response Surface Graph for AB (liquid inlet temperature and liquid inlet pressure) Combination [14]

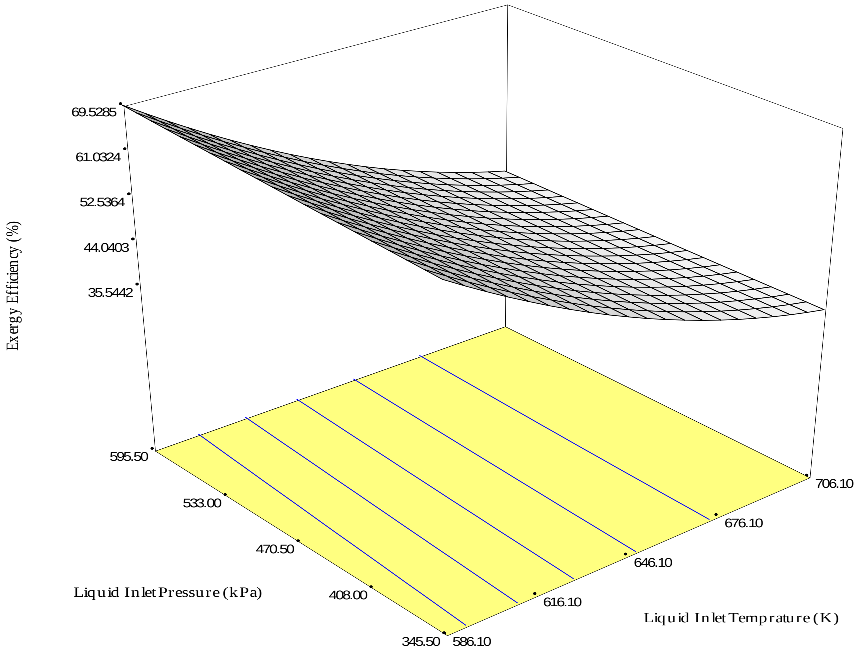
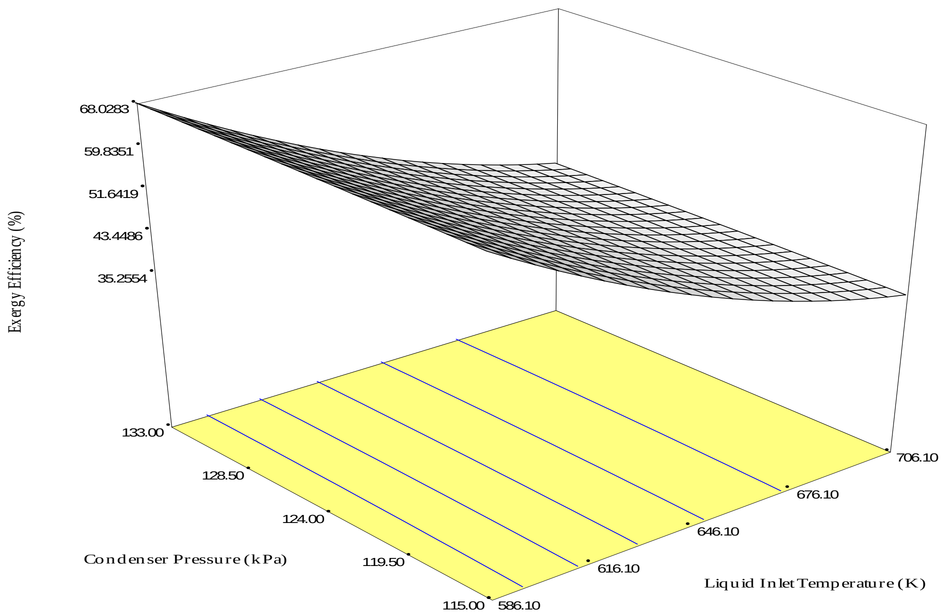


Figure 6: 3-D Response Surface Map for AC (liquid inlet temperature and condenser pressure) Combination [14]



Conclusions

In conclusion, the crude distillation unit of the New Port Harcourt refinery is inefficient and can be improved on in terms of exergy analysis. The knowledge database of the atmospheric distillation unit was well established using statistical model. The model can adequately predict the efficiency of the refinery based on the set of given inputs. It can thus be concluded that this expert systems can provide on-line optimal operating information for operators and process engineers. Also, the optimum operating parameters that will improve the efficiency of the atmospheric distillation unit was critically looked into. The expert system of the atmospheric distillation unit was found to predict the optimal operating conditions of the atmospheric distillation unit for the objective function considered and thus minimizes the energy consumed in the unit.

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