American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-5, Issue-8, pp-98-104
www.ajer.org
Research Paper Open Access

Improvement of Waste Plastic Plant for Crude Oil Recovery

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***ABSTRACT**: The Optimal performance and operational parameters of a waste plastic plant for crude oil recovery was determined using Response surface method. The operational parameters of the machine investigated include temperature of the reactor, waste plastics in the reactor chamber, catalyst and water flow rate. While volume of recovered crude oil, time required for proper melting and vaporising the waste plastics and time required to properly condense the vapourised crude oil constitutes the performance parameters. The interactions of these factors (operational parameters) and responses (performance parameters) were evaluated and estimated using full factorial design while desirability function approach was the optimization technique applied. The study revealed the reactor temperature (T), quantity of waste plastics (M_p), quantity of catalyst (C) and water flow rate (Q) of 370^{o}C, 5kg, 2.5kg and 4lit/min respectively as the optimal operational parameters of the waste plastic plant for crude oil recovery. While the performance analysis showed that the waste plastic plant with the quantity of recovered crude oil (V_c), time required to completely vaporize the plastics (t_r) and total time required to condense the vaporised oil (t_c) of the plant were 4.29liters, 41.94mins and 16mins respectively at the optimal factor setting.*

***Keywords**: Crude oil, response surface, optimal performance, factorial design and plastics.*

I. INTRODUCTION

Plastics play a significant role in the environmental, societal and economical dimensions of sustainable development [1]. Plastics are light, durable, clean and versatile and therefore have been increasingly used to make packaging, automotive, building, electronic and electrical products. If we use other materials to replace plastics, the cost and environmental impacts will more likely to increase. For example, Americans use 100 billion plastics bags a year, made from about 12 million barrels of oil; instead, the use of 10 billion paper bags each year means cutting down 14 million trees [2]. The use of crude oil for producing plastics consumes a scarce resource (energy) but the use of paper means the reduction of the capability of the planet earth to absorb CO2.

Plastics have become an indispensable part in today's world. Due to their light weight, durability, energy efficiency coupled with fast rate of production and design flexibility, thus plastics are employed in entire industrial and domestic areas.

Plastics are composed primarily of hydrocarbons but also contain additives such as antioxidant, colorants, and other stabilizers. Disposal of the waste plastic, poses a great hazard to the environment and effective method has not yet been implemented. Plastics are slowly biodegradable polymers mostly containing carbon-hydrogen, and a few other elements like nitrogen. Due to its non-biodegradable nature the waste plastic contributes significantly to the problem of waste management. Today about 129million tonnes of waste plastic are produced annually all over the world at which 77million tones are produced due to economic growth, and consumption change and also the pattern in which things are being produced has resulted into rapid increase in the production of waste plastics in the world.

Due to the incremental of generation of waste, plastic are becoming a major stream in solid waste. After food waste and paper waste, plastic waste is the major constituent of municipal and industrial waste in the cities. By converting plastic waste to fuel, we solve two issues, one of the large plastic seas and the other of the fuel shortage. This benefit though would exist only as long as the waste plastic lasts, but will surely provider a strong platform for us to build on a sustainable, clean, and green future. The conversion of waste plastic into fuel depends on the type of plastics to be targeted and properties of other waste that might be used in the process.

Recognizing the importance of plastics and the fact that plastics are made of scarce resources, there have been a lot of efforts in research and development to make plastics reusable and recyclable. According

[3], the UK government has set out to achieve 45% recycling target by 2015. In 2008-09, 27.3 million tonnes of municipal waste was collected by UK local authorities but 50.3% was sent to landfill, 36.9% was recycled or composted, 12.2% was incinerated for energy recovery [4]. Despite knowing that plastics are difficult to be degraded naturally, UK is throwing away four plastic bottles out of every five [7]. There appears to be a lack of emphasis and research on the management of the end-of-life (EOL) of products made of plastics and other scarce resources. There are a lot of research efforts in many different disciplines attempting to find technologies and ways to make a cleaner and sustainable world. From a simple question such as the use plastic or paper bags for shopping in the supermarkets to the more complex questions about the most sustainable approaches to design, manufacture, distribute, and recycle a product, more research is required to help logistics and supply chain managers to make informed decisions. The trouble is that most of the research efforts are carried out in isolation without a “cradle-to-grave” or life-cycle approach. Even though recycling is believed to conserve materials and reduce greenhouse gas (GHG) emission, recycling activities involve transportation and production activities which consume energy and natural resources and simultaneously produce emissions/pollutions. Without understanding of the environmental impacts of recycling logistics systems, managers will not be able to make better decisions on product design, production, distribution, choice of materials, and the design of recycling logistics systems. Understanding of the environmental impact of various logistics solutions for managing product life cycle including product end-of-life (EOL) is a crucial step towards a cleaner and sustainable world.

Plastic have woven their way into our daily lives and pose a tremendous threats to the environment, over a 100million tones of plastic are produced annually worldwide, and the use products have become a common feature at over flowing bins and landfills though work has been done to make futuristic biodegradable plastics, there have not been many conclusive step towards cleaning up the existing problems. Here the process of converting waste plastic into value added fuels is explained as a viable solution for recycling of plastic. Thus two problems such as problem of waste plastic and problem of fuel shortage are being tackled simultaneously. The waste plastics are subjected to deploy merisation, pyrolysis, catalytic cracking and fractional distillation to obtain different value added fuels such as petrol, kerosene, and diesel, lube oil, furnace oil fraction and coke.

The main purpose of this project is to improve the performance of the existing crude oil recovery plant from waste plastics using Response surface method to minimize total reaction time and maximize crude oil recovery.

II. MATERIALS AND METHODS

2.1 Research Materials

The materials used in the test include: waste plastic to crude oil converter, waste plastics, catalyst, thermometer, and bucket filled with distilled water with a control valve, hose, and a beaker.

The plastic waste converter consists of two distinct units; the cooking pot/reactor and the condenser unit. The cooking pot has a feed gate which is the inlet in which the waste plastic is feed into the machine, and also an outlet to discharge off the residue.

The cooking pot also comprises of a heater which heats up the plastic inside the pot. The cooking pot is been connected to a condenser via the steam tube where the vapour is been condensed into liquid.

2.2 Data Analysis Procedure

The choice of the type of experimental design was based on the number of variables available (i.e. number of independent and dependent variables), availability of resources, source of data collected, available time and cost implication. The effects of four operational parameters – on three performance indicators – were studied. The independent variables were coded using the transformation equation given in equation 1 according to [5].

$$Xi = \frac{x - \frac{xhigh + xlow}{2}}{\left(\frac{xhigh + xlow}{2}\right) - xlow} \qquad (1)$$

Where is the independent variable in natural factor, is the independent variable in coded factor, X_{low} and X_{high} are respectively the minimum and maximum values of the independent variables and. Two-level full-Factorial design is used in this study basically for its economic viability as it permits the analysis of a marginally small number experimental runs from a high factorial point.

The factorial design was generated using MINITAB to first of all, develop a first order model for the factors under study. This shows that the responses are individually functions of the factors as follows;

$$Ym = X_1, X_2, \ldots X_i + \varepsilon \qquad (2)$$

Where, Y represents the responses in actual (natural) form, m is the number of responses in the design, X represent factors in coded forms and *i* is the number of factors in the design and ε is the error in the design. Since four factors were considered in this study, the number of experimental run is given by;

$n = 2^k$ (3)

For a two-level factorial design with a single replicate and no center point, k is the number of factors, the number of experimental runs therefore is. The two-level first order factorial design was analyzed with the aid of MINITAB. This design is completely randomized, with both single replicate and block. The analysis gave rise to a first order regression model of the form;

$y = \beta oi + \beta 1i\ X1i + \beta 2iX2i + \ldots. \beta kiXki + \varepsilon i$ (4)

Where I = 1,2,3,…n

Using MINITAB software, the analysis of variance (ANOVA) of the design was conducted to check the model adequacy to fit the measured data. If the calculated value of *exceeds the tabulated value, that is,* the fitted models are said to be adequate approximations of the data. The coefficient of determination (R^2) and adjusted coefficient of determination (adj-R^2) for each response models were determined using MINITAB, to show how well the estimated models fit the measured data. The values of R^2 lies between zero & one (i.e.*)* and as the value of R^2 approaches one (1), the estimated model fits the data better. R^2 which is measured in percentage (%), thus, shows the percentage (%) variation of the estimated data*)* from the measure data *(*The standard error of regression (S) and sum of square of error (SS_E) also indicate how closely the estimated response approximates the measured response. The smaller the value of the standard error and the sum of square of error, the model, approximates the data better [8].

Normal probability plots of residuals, histogram plots, residual versus fit, residual versus observational order generated using MINITAB in a four-in-one format are diagnostic plots employed in the model adequacy analysis of the predicted models. The diagnostic plots which show the distribution of the residuals in each plot graphically shows the adequacy of the predicted model to fit the measured data well. When and p-value < 0.05, the corresponding factor is said to be statistically significant for *a* two-tailed test, hence α = 0.05. The significance of individual factors was also investigated using the main effect plots generated using MINITAB.

Factor interactions and quadratic effects were further created after the critical evaluation of the first order models to augment the lapses associated with the first order model. Thus, a second order model of the form in equation 3.4 and an improved first order models with interactions of the form in equation 3.5 were obtained for the responses.

$Y = \beta o + \beta iXi + \beta jXj + \beta iiXi^2 \ldots + \beta ijXiXj$ (5)

After developing, analysing and validating the improved first order models with interactions for the response function, 3-D surface plots and contour plots for each of the responses against any pair of factors, were generated using MINITAB software. The optimal settings of each response and the pair of factors were visualized on the plots. This method is most suitable when there are only two factors in the design. When the model comprises of more than two factors, it's difficult to estimate exactly the optimal settings of the factors for a given response. This is because of the prevalence of more than one surface or contour plots with varying topographies for a given response.

In the bid to obtain a simultaneous solution of the predicted response models, desirability function approach was adopted. This was achieved using the response optimizer tool embedded in MINITAB. It's an iterative method which can be used to maximize, minimize, or hit target of the responses. This optimization was based on the "target is best" kind [9].

III. RESULTS AND DISCUSSION

3.1 Results

Table 1: Limits of the operational parameters of the machine

s/n	Factor Description	Factor symbols		Factor Values	
		Coded	Actual	High (+1)	Low (-1)
1.	Temperature of the reactor (°C)	X_1	T	370	120
2.	Quantity of Plastics (kg)	X_2	M_p	5	1.5
3.	Quantity of Catalyst (kg)	X_3	C	2.5	0.25
4.	Water flow rate (l/s)	X_4	Q	4	1

Table 2: Response Optimization

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
tc	Minimum	15.0	35	1	1	
tr	Minimum	40.0	192	1	1	
Vc	Maximum	0.9	4.3	1	1	

Solution

Solution	x1	x2	x3	x4	tc Fit	tr Fit	Vc Fit	Composite Desirability
1	1	1	1	1	16.5625	41.9375	4.28687	0.967848

Table 3: Model confirmatory Test for response optimization

Run Order	Coded values of factors				Actual Responses			Predicted Responses		
	x1	x2	x3	x4	Vc	Tr	Tc	Vc	Tr	Tc
1	1	1	-1	1	3.9	68	25	4.05	68.63	22.13
2	1	-1	1	1	1.35	40	15	1.45	41	15.88
3	-1	-1	-1	1	0.9	170	18	1.02	172.13	18.5
4	1	-1	-1	1	1.31	53	15	1.24	51.88	14.13
5	-1	1	1	-1	4.02	150	25	4.02	150.5	25.38

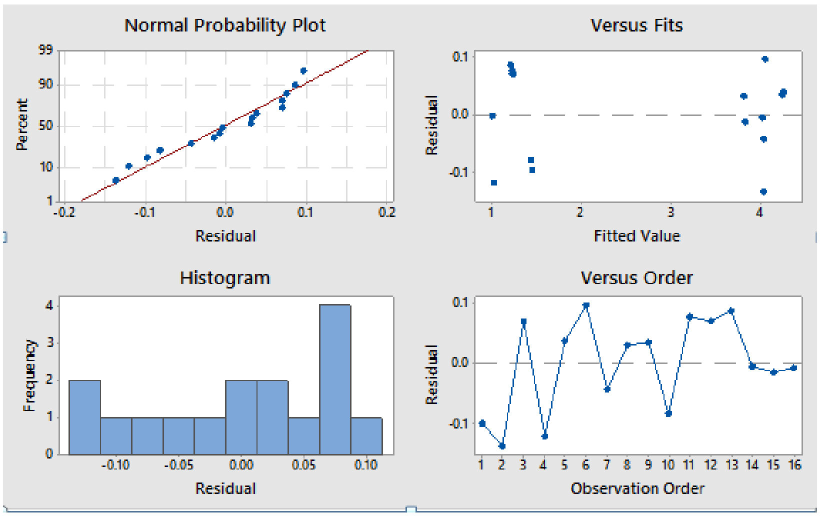

Figure 1: Residual plot for Quantity of recovered crude oil

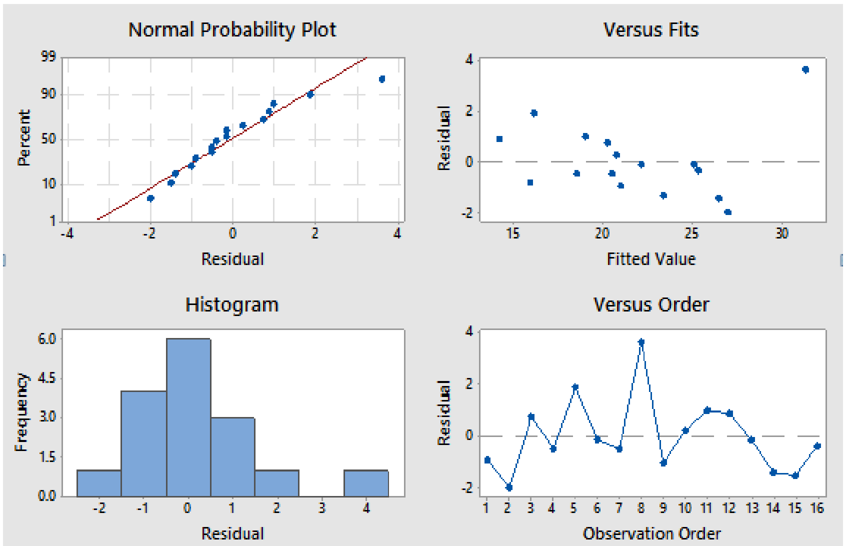

Figure 2: Residual plot for Time of Liquefaction of vapourised crude oil

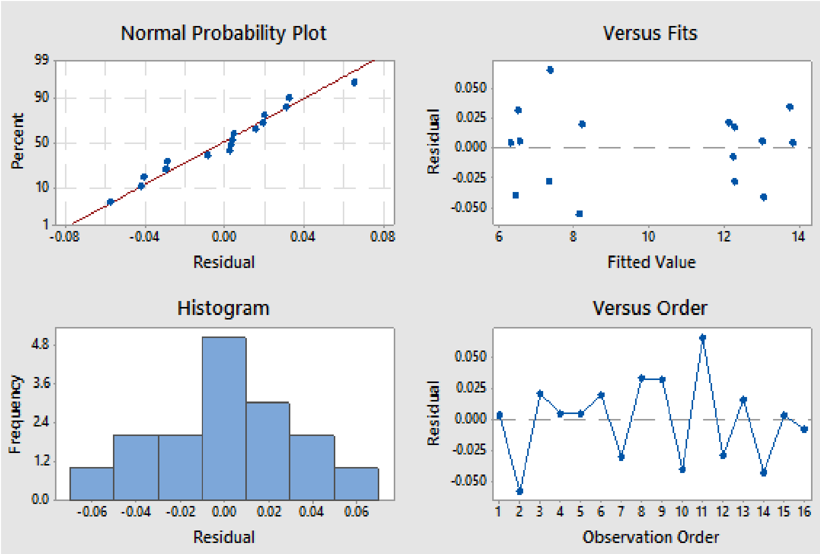

Figure 3: Residual plot for Time of vapourising waste plastics

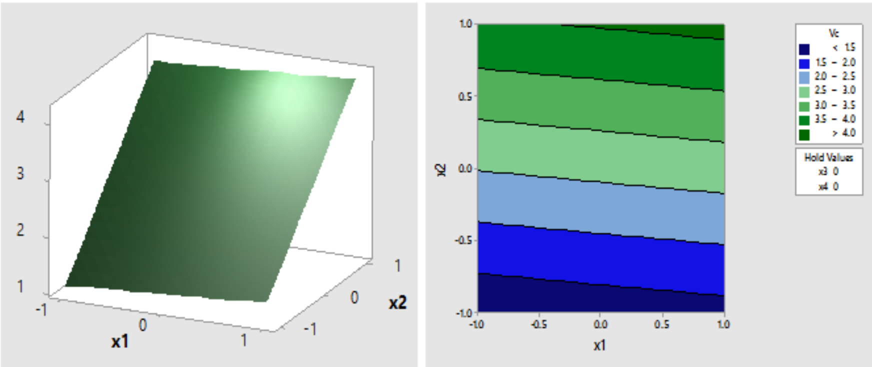

Figure 4: contour and surface plot of V_c

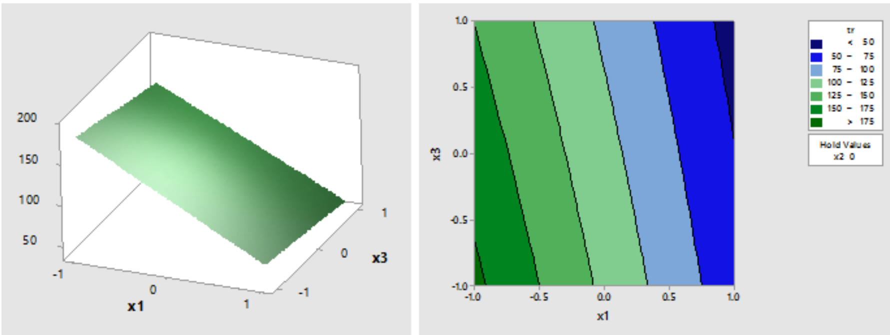

Figure 5: contour and surface plot of t_r

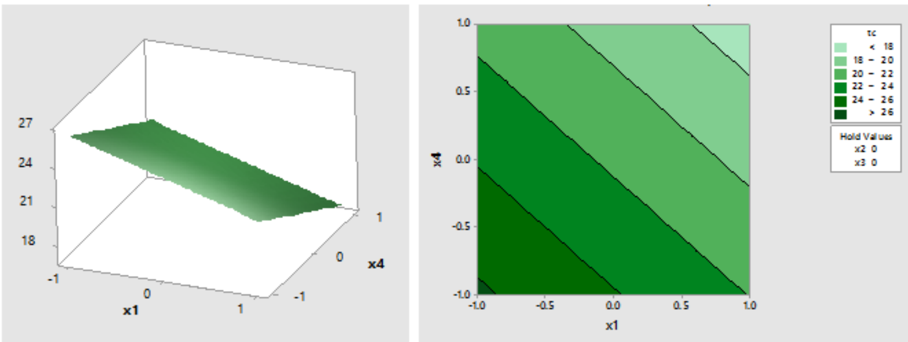

Figure 6: contour and surface plot of t_c

3.2 Discussion

The application of response surface analysis in describing the relationship between the performance indicators (responses) of the crude oil recovery plant, its operational parameters (factors) and the determination of the optimal settings of the parameters involves; Development of appropriate RSM experimental plan, fitting, selection, optimization of the best response surface function for the response. The performance indicators of the crude oil recovery plant that were evaluated in this investigation are the quantity of recovered crude oil (V_c), time required to completely vaporize the plastics (t_r) and total time required to condense the vaporized oil (t_c).

The independent factors –operational parameters- of the machine under study are the reactor temperature (T), quantity of waste plastics (M_p), quantity of catalyst (C) and water flow rate (Q) and with X_1, X_2, X_3, X_4 as their respective coded symbols are the operational parameters. The limits of the operational parameters which influence the performance of the machine as determined experimentally are shown in table 1.

The adequacy of the estimated models was tested using MINITAB 17 and the standardized residual plots which includes, normal probability plot, histogram of residuals, residual versus fits and residual versus observation order as shown in figure 1 to 6 for the quantity of recovered crude oil, total time taken for vapourization of the plastics, time taken for condensation/liquefaction of the vapourised crude oil. The plots show that the normal curve approximates along the straight line with little deviations, no or little outliers, reduced or no skewness, good distribution of residuals and cluster around the mean (zero) line as shown in the normal probability plot, histogram of residuals, residual versus fits and residual versus observation order of standardized residual which implies that the models fit the data adequately.

3.2.1 Performance Optimization of the Modified Crude Oil Recovery Plant

The relationship between each of the responses and combination of any two (or pair) of the factors was represented in the response surface and contour plots generated using MINITAB 17 as shown in the figures below. Only statistically significant predictors were considered in these plots. The topography of each of the plots indicates the effect of each pair of factors on each of the responses keeping all others constant. The contour curves (fig.4-6) were used to visualize the direction of the optimal settings for the predicted models, deeper colouration indicates region of maximum response and light colouration indicates region of minimum response with respect to the factors at a time. However, this approach is technically unreliable when there are more than one intermediate response and more than two factors. So the response surface and contour plot can lead to unnecessary multiplicity of optimal settings.

A closer look at the shape of the graph (fig. 6) would reveal that some of them for a particular response indicate maximum optimal region, others show minimum optimal regions while some are intermediate (i.e. showing saddle points). Therefore, there is need to adopt a method that can define the optimal settings for all the responses with respect to all the factors simultaneously. The multi-response multi-factor optimization of the response models was performed using MINITAB 17 response optimizer capability, based on principle of Derringer modified Harrington's desirability function approach which provides a combination of the factor settings that simultaneously optimize a set of responses and defines the best settings for the solution of set of multivariate objective functions.

The optimization result in Table 2 indicates that optimal setting of the quantity of crude oil, time required to vaporise the plastics and time required to condense or liquefy the vapourised crude are respectively 4.49liters, 41.94mins and 16mins respectively. While the approximate optimal values of the reactor temperature, quantity of waste plastics, quantity of catalyst and water flow rate are respectively 370^{o}C, 5kg, 2.5kg and 4lit/s. The optimization results have been tested to establish the adequacy of the predicted models as shown in the Table 3.

Using the point prediction capability of the MINTAB software, the quantity of crude obtained, time required to melt the plastics and the time required to properly liquefy the vapourised crude oil of these experiments were predicted based on the selected models as shown in table 2. Thereafter, predicted values were compared with the actual experimental results by computing the residuals and their percentage errors as shown in Table 3. This table shows that the percentage error range between the actual and predicted value for Vc, Tr and Tc are as follows; 5.34 to -13%, 2 to -2.5% and 11 to -5.87% respectively. Therefore, the empirical models developed are reasonably accurate since the results of the confirmation runs (actual values of the responses) are within 95% prediction interval. The 95% prediction interval is the range in which any individual value (predicted) is statistically expected to fall into. Thus, the models developed were used to determine the optimal setting of the plastic waste to crude oil machine's performance parameters.

IV. CONCLUSION

This study revealed the reactor temperature (T), quantity of waste plastics (M_p), quantity of catalyst (C) and water flow rate (Q) of 370^{o}C, 5kg, 2.5kg and 4lit/s respectively as the optimal operational parameters of the waste plastic plant used for crude oil recovery. While the performance analysis showed that the waste plastic plant with the quantity of recovered crude oil (V_c), time required to completely vaporize the plastics (t_r) and total time required to condense the vaporised oil (t_c) of the plant as 4.49liters, 41.94mins and 16mins respectively with these optimal factor setting. Conclusively it can be showed that for maximum recovery of crude oil from waste plastic, the machine should be operated at maximum reactor temperature, maximum quantity of catalyst and a corresponding water flow rate. Furthermore, this analysis showed that all the factors investigated influenced the performance indicators of the waste plastic plant for crude oil recovery significantly.

V. RECOMMENDATIONS

Based on the findings from this study, it is therefore recommended that;

1. With the optimal factors setting known, manufacturers are encouraged to adopt them when transforming waste plastics into crude oil.
2. This machine should be adopted and commercialized in order to alleviate the dependence on fossils fuels.
3. The Federal Government should look into waste plastic to crude oil recovery and erect massive industries for the processes as an alternative means to fossil fuels.

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