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Adoption of Pareto Charts in the Analysis of Input Variables Interaction and Selection of Input-Output Pairings in a Refinery Fluid Catalytic Cracking Unit

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Abstract

This paper presents a study of the effects of input variables (main factors) and their couplings on key process variables(responses) in a refinery fluid catalytic cracking (FCC)unit using pareto analysis. Five responses namely, Riser temperature(T_{rx}),Regenerator temperature(T_{rg}) ,flue gas oxygen concentration, (O_d),Gasoline yield(y_2), Light gases yield(y_3)) and four main factors, namely gasoil feed rate(F_{gr}), regenerated catalyst flow rate(F_{rc}),combustion air flow rate(F_a), combustion air temperature(T_a)and were studied in a regular two-layer experimental design that generated 32 numerical experiments. A combination of Design Expert software and an in-mouse FCC unit simulator was used to conduct the numerical experiments from which pareto plots were generated as a tool for response-factor analysis. Results from this study show that F_{rc} and F_{gr} are the only significant main factors with respect to riser temperature response. While the significance is of the order Frc> Fgr, Frc produced negative effect while Fgr produced positive effect on riser temperature while the interaction factor (F_{gr}+F_{rc}) is the only cross-coupling .Cross -coupling of variables is more significant in the regenerator as two interaction factors (F_{gr}+F_{rc}) and (F_{rc}+F_a) featured prominently and produced significant effects on regenerator temperature and flue gas oxygen concentration, respectively. The ranking of the effects on regenerator temperature is F_{rc}>F_a> F_{gr} while that on flue gas oxygen concentration is F_{rc}>F_{gr}>F_a. Results further show that while Frc, Fgr and Fa produced positive effects on regenerator temperature, only Fa produced negative effects in flue gas oxygen concentration. Moreover, the four main factors in this study and their couplings did not dhow direct effects on gasoline yield and light gases yield respectively. The results are in tandem with FCC unit behaviour and thus assert the merit in the adopted tool.

Keywords: Pareto, Couplings, Numerical Experiment, Fluid Catalytic Cracking, Main Factor.

I. Introduction

Variables interaction refers to the cross couplings that may exist between input variables (factors) such that the effect on a response(output variable) is due to the combined influence of more than one factor .A good knowledge of interaction is a precursor to control structure selection which is the proper pairing of output and input variables in multiloop control systems. Interaction makes the task of multiloop process control formidable, resulting in a poorly controlled processes with consequences such as run- away temperature, equipment malfunction, loss of manhours, production cuts and safety risks to operators. Interaction analysis is important to the extent that it gives insight to the factors and the degree to which they affect responses and shape control structure selection. In particular, in the light of its role as a major contributor to the gasoline pool in a refinery, interaction analysis of fluid catalytic cracking (FCC)unit is attractive. The FCC unit converts low value, high molecular weight feeds such as vacuum gas oil and certain atmospheric residues to high value, low molecular weight products such as gasoline and liquified petroleum gas (LPG).Although there is paucity of information in the literature on its application in the field of process systems and control, pareto analysis and the variants have been successfully applied in other disciplines.However, there is a plethora of interaction measures in the open literature and focus has been on relative gain array, Hankel norm and their variants while not much is known of the experimental design and pareto analysis approach to interaction analysis as a tool for examining couplings and consequent control structure selection [1-10].

Luan et al (2017) extended the Relative normalized gain array (RNGA) loop pairing criterion to accommodate complex multivariable models under step, ramp and other general types of set-point changes and presented a loop pairing technique around the new frame work. Apart from the significant improvements offered by the method, the authors concluded that the method is independent of input signals [11]. Nevertheless, challenges associated with matrices such as skewness and diagonal dominance were not addressed to improve the merits of the method.

In Arrafiz and Birk (2017) it was shown that Gaussian noise excitation of acquired process data is a suitable route to interaction analysis. In addition, participation computation was combined with uncertainty bounds principle to arrive at automatic and robust control structure selection decision. However, since the data that was used is secondary, the accuracy of the outcomes depend largely on the fidelity of the data and its acquisition process [12].

However, Hofmann et al (2019) studied variables interaction in a biomass pyrolysis process based on relative gain array (RGA), singular value analysis (SVA)and dynamic relative gain array (DRGA) and gave useful insight to the importance of loops decoupling in control systems. Although the study hinges on established methodology, the authors demonstrated the benefits from DRGA and established the place of their concept in the mitigation of challenges such as time delays and non-measurable disturbances. However, unlike Josiah et al (2019) and elsewhere that focus was on simulation, Hofmann et al (2019) navigated in the stormy waters of matrix intricacies of their procedure and did not suggest schemes for circumventing matrix manipulations [13,14].

Elsewhere, a method that guarantees individual control loop design that is based on the parametisation of RGA entries was reported in Shahmansoorian (2019). As presented, the method is local to transfer functions with four input and four output that have identical RGA entries. It is shown that four input-four output transfer functions with identical RGA entries in zero frequency exist and such transfer functions can be parameterized. Four input-four output transfer function entries are parameterized with respect to entries of RGA. The extension of the method to a general square transfer function is trivial and the matrix bias of the method is in tandem with Arrafiz and Birk (2017), Luan et al (2017) and Hofmann et al (2019) but at variance with Josiah et al (2019) [11-16].

A study of four different methods for interaction quantification applied to MIMO converters was presented in Upadhyyaya and Veerachary (2021). H 2 -norm based interaction participation matrix (PM) method, relative gain array (RGA) method and Hankel interaction index array (HIIA) method were implemented in MatLab. The study gave insights to the performance rankings of the methods and provides ready clues to guide researcher's choice of methods. However, the narrative on heavy reliance on matrix remained unaltered. Bengtsson and Wik (2021) demonstrated that their modified method which entails the scaling of Gramians and extended to sparse matrix control structures, results in considerable improvement over the classical Gramian based interaction measures. They showed that what yields the best result is when two different scaling methods are combined in which one is used to find feedforward connections while the other is used to design a decentralized controller. However, the framework is basically in the class of previous others whose contributions heavily relied on matrix-oriented methods.

Considerably away from relative gain array (RGA) and its variants that have been made popular, a new data- based scheme was presented in Vlaswinkel et al (2021) [17]. In the two-step method, input-output scaling was based on the Sinkhorn-Knopp algorithm, while input-output pairing was determined using a Gramian-based interaction measure .A simulated combustion engine example was given in the paper, to demonstrate the applicability of the method.

A dynamic input-output model of a falling film evaporator that accounted for dominant time delays was developed in Hofmann et al (2021) to solve the problem of interaction. The paper solves the control loop pairing problem of the falling evaporator process. Like similar others studies, participation matrix and Hankel interaction index array were employed in the study. It could be inferred from Hofmann et al (2021) that when a selected control structure is incumbered by large time delays, a triangular structure should be selected to mitigate interaction of variables in control loops [18].

According to Sujatha et al (2022), all the complex non-square chemical processes may have several measurement and control loops and these loops should be paired properly. In this regard, they proposed a method for control configuration selection for non-square Multi Input Multi Output (MIMO) systems that is an extension of that for square MIMO systems. been addressed in this paper. The proposed method of dynamic loop interactions is based on the computation and comparison of areas under responses for all possible combinations of manipulated and controlled variables. Although there is merit in extending the square system method to accommodate non-square systems, the exhaustive enumeration of the pairing of input-output variables can be quite frustrating and cumbersome, especially for systems with high dimensions [19].

Bengtsson et al. (2022) argued that although variable scaling in Hankel-based methods ensures equal ranges in output and input variable suffice, it could lead to incorrect pairings of variables. In this regard, an alternative method for scaling the Gramian-based measures, using either row or column sums or by utilising the Sinkhorn-Knopp algorithm was proposed and demonstrated. Based on application of the proposed method to a large number of systems, the new method with the option of Sinkhorn-Knopp algorithm showed good promise of improvement. The position of Bengtsson et al (2022) regarding the implications of scaling the classical Gramians was not alluded to in the work of Arrafiz and Birk (2017), Luan et al (2017) and Hofmann et al (2019), Shahmansoorian (2019) [11-13,15,20] .

Chukanov (2022) modelled the structure of complex systems based on the well-advanced relative gain array (RGA), dynamic relative gain array (DRGA), participation matrix (PM) and the Hankel interaction index array (HIIA). In addition, the construction of a weighted graph for visualizing the interaction of the subsystems of a complex system was introduced in the study. Moreover, other propositions such as a method for realizing controllability Gramian on the vector of output signals that is state vector transformations invariant and pre-group of the components of the input and output signals vectors , are positive departures from other matrix-oriented propositions that appeared elsewhere in the literature [21].

However, Thota et al (2023) attempted to solve the problem of interaction in a digital converter using gain-based interaction measures [9]. Their simulation-oriented approach consists of studying the effects of design parameters, changes in the values of design parameters and changes in operating conditions on selected response variables from which input-output variables pairings were successfully inferred. The approach which is uncommon and offers good promise of fidelity, is similar to that in Josiah et al (2019) [14]. This paper presents a novel procedure for identifying and ranking variable interaction and the application of the outcomes to the control structure selection applied to fluid catalytic cracking. The main contributions are that data for process behaviour was obtained through simulation following a well-designed numerical experiment. Apart from boosting data integrity and the fidelity of the procedure in the light of the outcomes, incumbrances associated with matrix manipulations are circumvented. Moreover, the task of quantification or ranking interaction in multivariable systems has been reduced to that of mere reading of bar charts in the light of the novel procedure that this paper presents.

2. Research Method

2.1. Algorithm

(i): Launch design expert and set up a design matrix using two levels of each of the manipulated variables

(ii): For each set of manipulated variables (factors) as obtained from the design matrix as input, run simulation in MatLab to obtain the outputs (responses)

(iii): Complete the responses columns in the design matrix in (i) above and complete the design of experiment.

(iv): Run the designed numerical experiment in Design Expert and obtain correlations between factors and responses.

(v): Interpret Pareto plots

2.2. Experimental Design Matrix

Four factors (process variables) namely regenerated catalyst flow rate (F_{rc},) ,Gasoil feed rate (F_{gr}), Air flow rate into the regenerator (F_a), Regenerator air temperature (T_a) and five responses(input variables) namely riser exit temperature (T_{rx}), regenerator temperature(T_{rg}), flue concentration in regenerator flue gas (O_d), gasoline yield (y_2) and light gases yield (y_3) were studied . A regular two-level factorial design was employed in this paper using the data shown in Table 1 as input in Design Expert software where coded values (-1 and 1) which represent the lower and upper limits for each of the four factors were used to generate thirty-two numerical experiments. An instance of a regular two levels factorial design window is as shown in figure 1 while figure 2 shows the design matrix that was generated as the outcome of step 1 in the algorithm.

Thirty-two runs of numerical experiments, as indicated in the 25 factorial design were conducted to obtain the responses, using an FCCU simulator that was developed in a previous study.

Symbol	Manipulated Variables	Actual levels at coded factor levels	
		-1	1
F_{rc}	Flow rate of regenerated catalyst	238	476
F_{rg}	Gas oil feed rate	33.9	67.8
F_a	Flow rate of regenerator air	27.705	55.41
T_a	Temperature of air entering regenerator	298	497

Table 1: Actual Values of Coded Inputs Levels used in the RTL Factorial Design

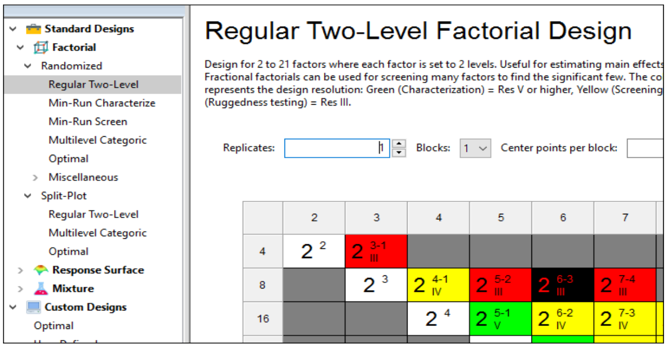

Figure 1: Regular Two-Level (RTL) Factorial Design Window

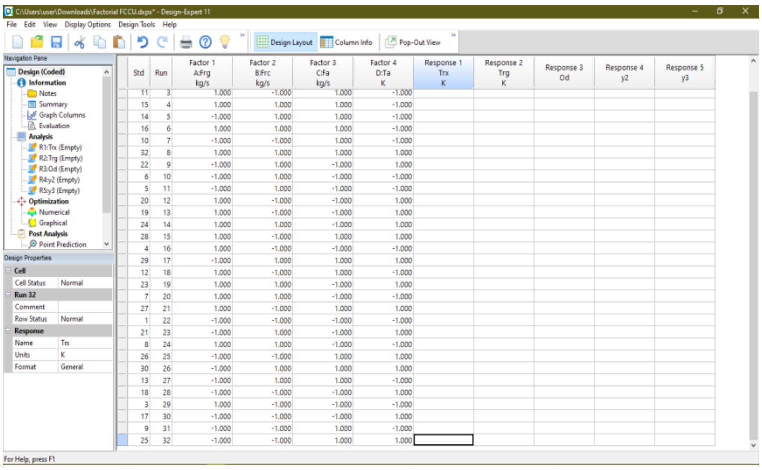

Figure 2: Regular Two-Level (RTL) Factorial Experimental Design Screenshot

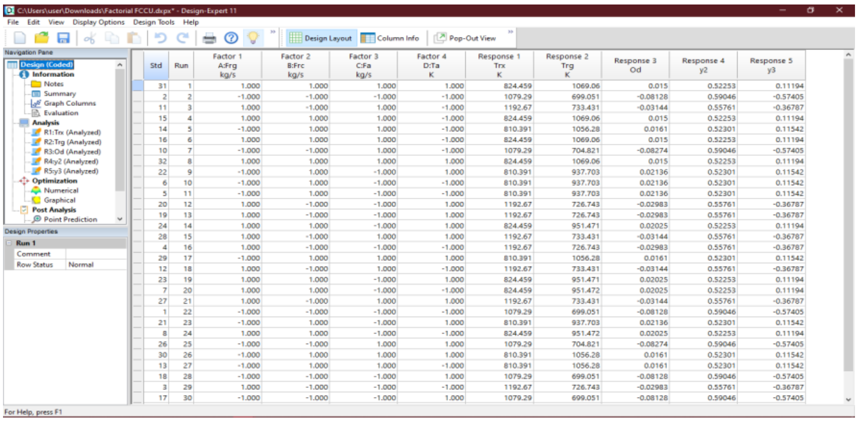

Figure 3: Screen shot of complete factorial experimental design

2.3 Development of Interaction analysis Measures

The developed experimental design was then used to generate Pareto plots that serve as interaction analysis tools. Pareto plot is a two-dimensional diagram with slim bars that project either above or below a reference horizontal line. The magnitude of the effect of a factor is depicted by the height of a bar while the impact (positive or negative) is deduced from the colour of a bar.

3. Results and Discussion

3.1. Riser Temperature Response to Factors

Figure 4, 5,6,7 and Figure 8 show Pareto plots relating the five responses to the four factors. As shown in figure 4, out of the factors that were studied, those that affect riser temperature are the regenerated catalyst flow rate, (F_{rc}), gas oil flow rate (F_{gr}), and the interaction between the two single factors (F_{rc} + F_{gr}). The magnitude of the effects is in the order $F_{rc} > F_{gr} > F_{rc} + F_{gr}$. The flow rate of regenerated catalyst, Frc gave a t-value of 901 on the parateto chart, producing the highest bar. All things being equal, this factor is the most important one to riser temperature response. The colour coding on the pareto chart indicates that F_{rc} effects negatively impact on riser temperature. This means that increasing the value of regenerated catalyst flow rate from low to high would change the value of riser temperature from high to low. However, gas oil flow rate positively affects riser temperature and shares a directly proportional relationship with riser temperature. Concerning factors interaction and its impact on riser temperature, feed flow rate and regenerated catalyst flow rate (F_{rg} + F_{gr}) present concerns, with a t-value of above 10, as shown in figure 4. Considering that regenerated catalyst flow rate, Frc produced highest effects on riser temperature, it is a good candidate for its regulatory control. However, in the light of the negative effects produced from the interaction between the two factors, riser temperature is susceptible to inverse response behaviour. The meaning, importance and relevance of the observed trends can be addressed within the framework of depletion of regenerator bed loading, forced cooling in the regenerator, availability of coke, coke combustion in the regenerator, poor feed vapourization and diminishing heat of reaction in the riser. Increasing the flow rate of regenerated catalyst leaving the regenerator and entering the riser lowering catalyst loading in the regenerator. The implication is that as more and more catalyst exit from the regenerator, less of coke- bearing catalyst becomes available to provide the exothermic heat of combustion, thus causing forced cooling the regenerator and increasingly lower regenerated catalyst temperature. We recall from theory that the regenerated catalyst provides the heat required to raise the temperature of gas oil feed from its inlet to reaction temperature, vapourize the feed and provide the heat required to sustain the endothermic riser reactions. However, increasing the inflow of a low temperature regenerated catalyst increases the catalyst to oil ratio that results in dilution in the riser. The implication is the attendant poor feed vapourization whose deleterious effect is a complex three phase hydrodynamics in the riser, and temperature drop in the riser. The aspects of the results which include process operation, control and process safety are all important to the refiner. In particular

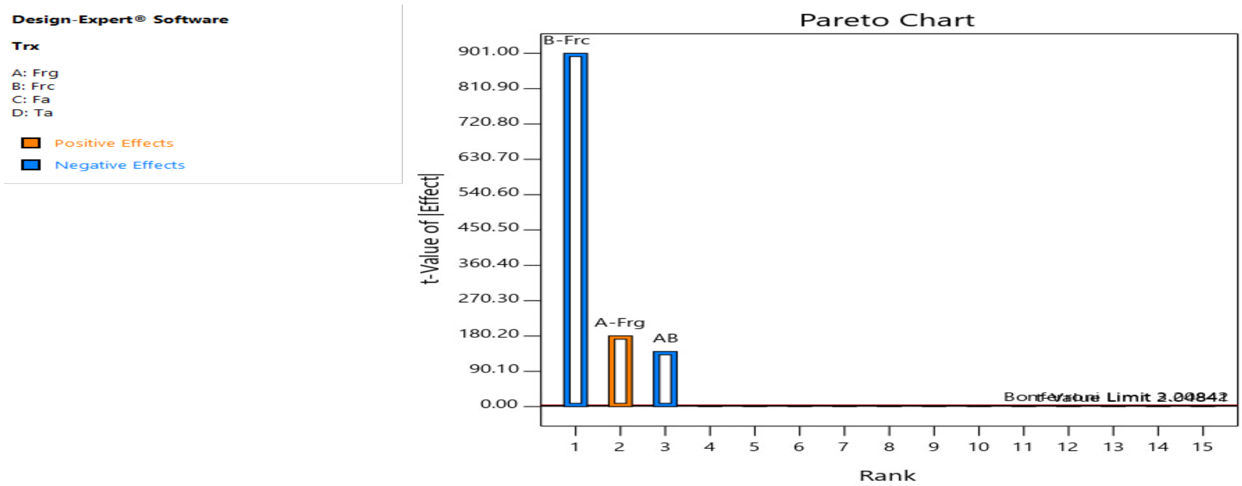

Figure 4: Pareto Chart for Riser Temperature (T_{rx})

3.2. Light Gases and Gasoline

The factor bars in figure 5 show that only three factors, A, B and A+B can be associated with gasoline yield while and figure 6 suggests the same factors as well. However, the bars are all below the bond-value, indicating that the responses which the factors light gases (y3) and gasoline yields (y2) are meant to address are insignificant in the scheme of interaction analysis. The implication is that the effects of the factors on responses on y2 and y3 cannot be measured directly, hence y2 and y3 are secondary responses and must be treated as such.

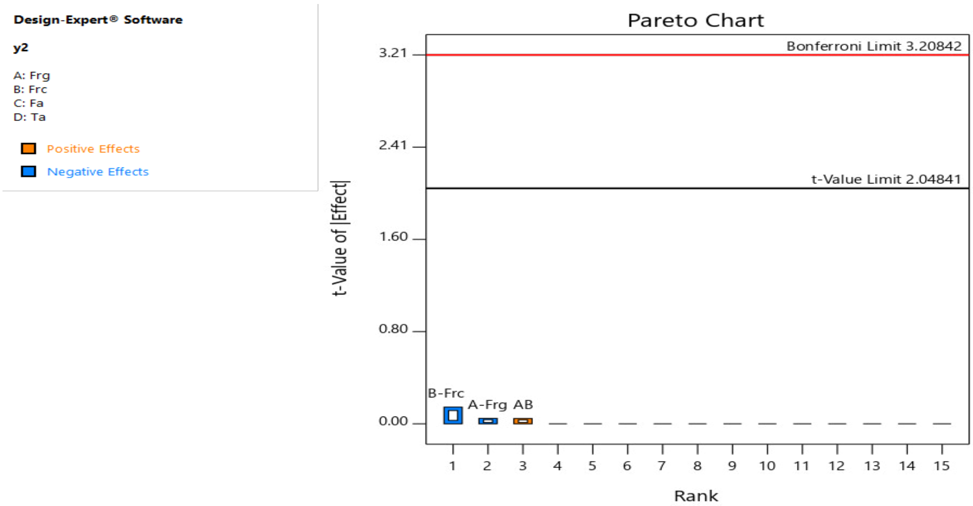

Figure 5: Pareto Chart for gasoline yield (y2)

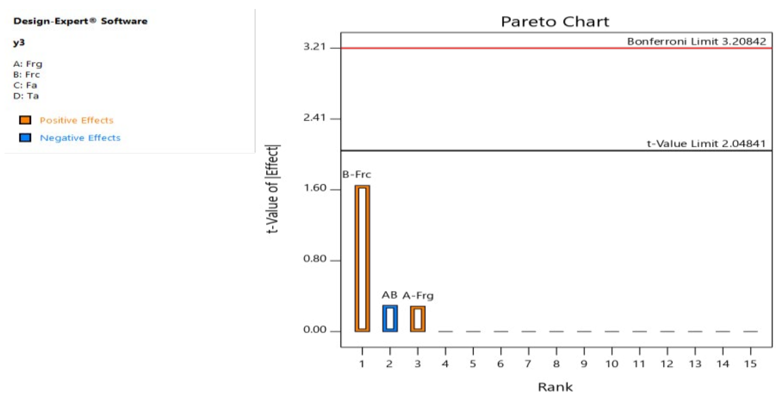

Figure 6: Pareto Chart of LPG yield(y3)

3.3. Regenerator Temperature

Figure 7 shows the relationship between regenerator temperature, the main factors (A, B, C, D) and interaction factors (AB, AC, AD, BC, BD, CD, ABC, ABD, BCD, ABCD). According to the figure, Temperature in the regenerator is affected by three single factors namely the regenerated catalyst flow rate (F_{rc}), combustion air flow rate (F_a), Gasoil flow rate (Fgr)and two interaction factors ($F_{rc} + F_{gr}$) and ($F_{rc} + F_a$). While the interaction factor (Frc + Fgr) is significant but small relative to others, (Frc + Fa) is observed to have a strong positive interaction on the temperature in the regenerator and FCC operations. The implications of the observed responses are that in considering a choice of manipulated variable in multiloop control structure selection, regenerated catalyst flow rate (factor B), combustion air flow rate (factor C) and gasoil flow rate (factor C) are possible candidates that would produce positive effects on regenerator temperature. However, while attention should be given to the interaction between factor B and factor C, factor B, being the most significant should be accorded the position of manipulated variable for regenerator temperature regulation, except it is has been taken in another loop and no longer available for pairing.

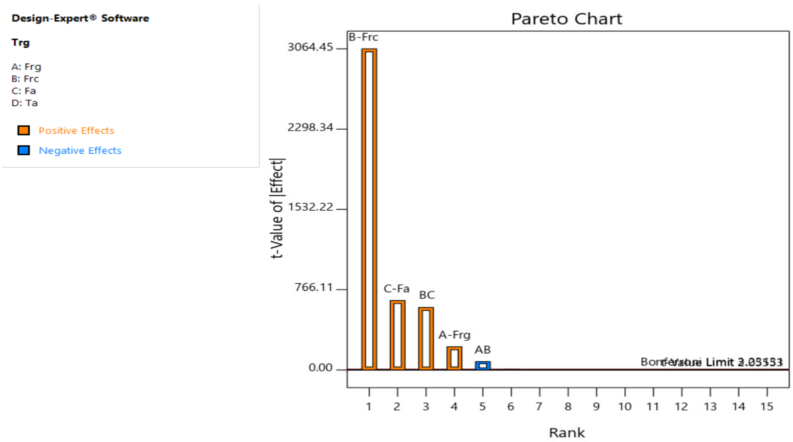

Figure 7: Pareto Chart for Regenerator temperature (Trg)

3.4. Flue gas Oxygen concentration

Figure 8 shows that in driving flue gas oxygen concentration, six factors produced significant effects out of four main factors(A,B,C,D), six second- order factors(AB, AC, AD, BC, BD,CD),three third- order factors(ABC, ABD,BCD)and one fourth-order factor(ABCD. The factors, in decreasing order of their effects are (B) which is the regenerated catalyst flow rate (F_{rc}),interaction (F_{rg}+F_{rc})between factor A, which the flow rate of gasoil(F_{rg}) and F_{rc}, factor A, factor C, being combustion air flow rate(F_a)and the interaction factors ($F_{rc} + F_a$) between factor A and factor B. Although factor B produced positive effect on the concentration of oxygen, factor C produced negative effect while the combined effect of the two (interaction) produced negative effect on the response variable. The implications of these results are that in a control loop where factor B is paired with the response factor for regulation, increasing B from low to high would cause the response variable to increase from low to high. Should factor C be paired with the response factor. However, changing the value of factor C from low to high would cause the response variable to go from high to low. The choice of a negative effect factor as a manipulated variable is very unpopular and can be very misleading from control point of view. Moreover, from significant effects point of view, regenerated catalyst flow rate is the best variable for regulating flue gas oxygen concentration, followed by gas oil flow rate. However, to circumvent inverse response behaviour in the light of the negative-effect interaction between factor A and factor C, controller design needs to provide for either static or dynamic decoupling or resort to the use of effective transfer functions, to say the least.

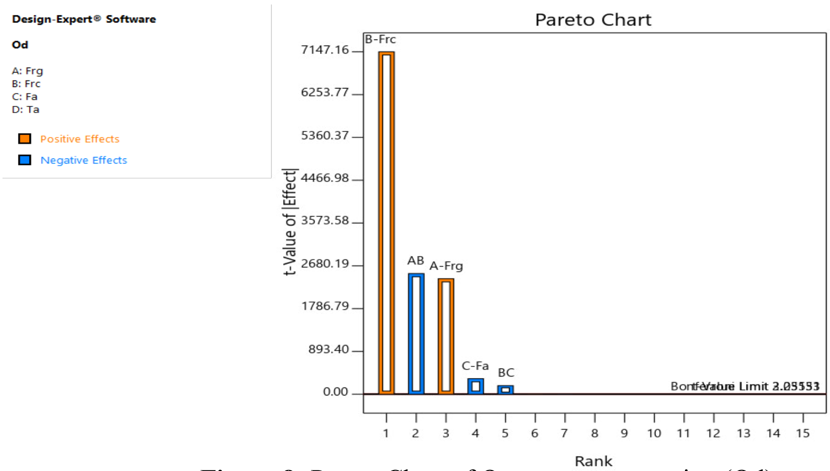

Figure 8: Pareto Chart of Oxygen concentration (Od)

4. Conclusion

This paper addressed the problem of main factors, interaction between factors, the responses they produce and the significance of the insights from factor-response analysis to a fluid catalytic cracking unit. Pareto analysis was applied to the response- factor data that were generated following numerical experiments that were conducted using Design Expert and MatLab. In the light of the observed trends, this study concludes as follows

(i) Regenerated catalyst flow rate is the most significant main factor among

(ii) The fluid catalytic cracker exhibits second-order interaction between factors as its highest level of input variables coupling.

(iii) The only coupling of variables that is of significance to riser temperature is the negative effect interaction between gasoil flow rate and regenerated catalyst flow rate (F_{gr}+F_{rc})

(iv) Inlet air temperature is not a significant factor to any of the responses studied

(v) Pareto analysis is a suitable tool for factor-response study of the FCC unit and offers merit for application in other process systems.

Author Contributions

P. N. Josiah: Conceptualization, Methodology, Software implementation, Writing of original draft.

I. J. Otaraku: Conceptualization, Supervision, review and editing.

B.O. Evbuomwan: Conceptualization, proofreading and editing.

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