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Investigation and Optimization of Production Variables: A Case of Plastic Manufacturing Industry

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The study evaluates and analysis the extrusion plastic production variables in Innoson Plastic Manufacturing Company, Nnewi, Anambra State, Nigeria. The research method adopted is the application of statistical tools and design of expert tools to evaluate and to analyze the influence of the variables. The statistical correlation of the variables is to understand the significant relationship between the variables. The parameters are all significance except time. This show that time is not significant in modeling the system. The use of design expert was applied to evaluate the extrusion plastic production variable to understand what the variables portray and its influence on production. The mixture design method of D-optimal Non-Simplex Screening model was used to optimize the production variables which entails that the best quantity of product that is to produce is 9204.461 units. The results show that the industry should be conscious of highly influence input variable during production.

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1. INTRODUCTION

The production process is about refining a range of inputs into outputs. It deals with two major sets of materials. They are; the transforming materials and the transformed materials. The transforming materials include the buildings, machinery, computers, and people that carry out the transforming processes. The input materials are the raw materials in addition to its components that are transformed into finish products. The production process involves a cycle of materials relation in a production chain. At every stages of production process, some raw materials are added in the track of production. Adding value involves making a product more pleasing to the user. Adding value is not just about manufacturing, but includes the marketing process, advertising, promotion as well as distribution that make the end product more desirable. It is very important for businesses to identify the processes that add value, so that they can enhance these processes to the ongoing benefit of the business. Production is very critical to economic growth, prosperity and a higher standard of living. It is a catalyst for industrial and economic development. It's satisfying economic want of individual, communities and nations by the production of things in workshops by utilizing men, materials, machines, money and methods [1]. Fundamentally, manufacturing can simply be described as value-adding processes by which raw materials of small utility is adding value to its process insufficient material properties and sizes, its finish shapes are rehabilitated into high utility and valued product with definite dimensions and forms [2]. The resources could be people, machines, computers and/or organized integration of one or more of the above mentioned [3]. To achieve higher efficiency, there must be an optimal distribution of these materials to activities of production.

Optimization is simply achieving the highest possible performance under the given constraints, by maximizing desired factors as well as minimizing undesired ones [4]. The researches on related literature were also emphasized to express the empirical related works in the research. Christopher expressed that Manketti oil was used as a feedstock to create the biodiesel that was extracted from manketti nut. An alkali catalyst transesterification process was adopted [5]. A statistical model was developed to show a relationship with the process variables to the yield of fatty acid methyl ester (FAME) using a central composite design (CCD) by a response surface methodology. The process variables were reaction temperature x1, (30°C–65°C), amount of catalyst x2, (0.5–1.5 wt %), amount of methanol in the oil x3, (10–50 wt%) and also the reaction time (30–90 min). The crucial fuel properties such as density, flash point, viscosity, with acid number were measured and compared with other types of biodiesel produced from wild nuts and American Society for Testing and Material (ASTM). From the results, the optimum conditions for the production of FAME obtained were as follows: Reaction temperature 55°C, reaction time 53 min, amount of catalyst 1.02 wt%, and amount of methanol in the oil of 32 wt%. The best possible yield of FAME that can be formed is 98.3%. The result revealed that the significant fuel properties of the biodiesel formed in optimum circumstances met the biodiesel ASTM standard.

Abdullah presents an experimental investigation into the effects of using bio-diesel on diesel engine performance and its emissions [6]. The bio-diesel fuels were produced from vegetable oils using the transesterification process with low molecular weight alcohols and sodium hydroxide then tested on a steady-state engine test rig using a Euro 4 four cylinder Compression Ignition (CI) engine. Production optimization was achieved by changing the variables which included methanol/oil molar ratio, NaOH catalyst concentration, reaction time, reaction temperature, as well as the rate of mixing to maximize bio-diesel yield. The method used was the response surface methodology. In addition, a second-order model was developed to calculate the bio-diesel yield if the production criteria are known. The model was validated using additional experimental testing. Christopher studied biodiesel was produced from waste cooking oil (WCO) using calcium oxide (CaO) as a heterogeneous catalyst [7]. The effect of experimental variables such as temperature, reaction time, methanol to oil ratio, and amount of catalyst was investigated.

In summary, the reviewed literature has shown that the research area under investigation is new and genuine. The researchers however, proceed with the method used for the analysis of this research.

The aim of this research work is to evaluate, analyze and to optimize the production variables of Innoson manufacturing extraction plastic products in Nnewi, Anambra State, Nigeria.

2. MATERIALS AND METHODS

The raw materials used in this research are PVC, stabilizer, calcium, steric acid, Titanium, pigment and its response material is 25 mm extrusion plastic pipes. The raw materials are to be mixed at a particular ratio. When melted and molded, it forms the finished material with 25 mm thickness and 12 feet long.

The research was conducted at Innoson Plastic Manufacturing Company, Nnewi, Anambra State, Nigeria. The research was carried out within the period of 12th November, 2019 to 15th December, 2019.

2.1 Research Method

The research method used for data analysis is the application of some statistical tools in SPSS and Design Expert software to model, evaluate and analysis the production variables under study. Data was analyzed by using Mixture design model to optimize the actual quantity needed to be produced in the plastic under production using the appropriate variables over the month in the manufacturing industry.

2.2 Experimental Design

The design of the experiment is a scientific approach that combines the input parameters optimally to optimize the response of the objective, and this can be achieved through the use of computing devices like design experts. For an adequate polynomial approximation, experimental designs are used to collect the data. There are different types of experimental designs that include mixture design, taguchi design, D-optimal design, factorial design and Latin hypercube designs. The experimental design was developed using the design of expert version 10.0.1.0. However, the design type and study type used is the application of the mixture design method. The tool was used to determine the most appropriate model for the mix experiment and the statistical evaluation of the parameters.

Table 1 shows the production variables experimental runs used for this design.

Table 2 shows a parametric Pearson correlation analysis of the variables. It shows that all the input process parameters are significance to the response parameter.

Table 3 shows a non-parametric Spearman and Kendall's tau_b correlation analyses of the variables. The analyses show that all the input process parameters have high significance to the response parameter.

Table 1. Production variables of the parameters

Std	Run	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Response 1
		A:PVC (kg)	B:Sterbilizer (kg)	C:Calcium (kg)	D:Steric (kg)	E:Titanium (kg)	F:Pigment (kg)	Output
		kg	kg	kg	kg	kg	kg	Units
1	1	17101.8	578	310	5	5	0.2	8060
10	2	17048.8	578	310	58	5	0.2	7600
8	3	17053.4	578	310	58	0.4	0.2	10822
3	4	17352	52	535.6	58	0.4	2	6020
12	5	14414.8	52	3470	58	5	0.2	2340
7	6	13891.6	578	3470	58	0.4	2	6510
5	7	17100	578	310	5	5	2	14310
6	8	17106.4	578	310	5	0.4	0.2	6820
11	9	14472.4	52	3470	5	0.4	0.2	7750
2	10	17352	52	531	58	5	2	4560
4	11	13891.6	578	3470	58	0.4	2	1280
9	12	13940	578	3470	5	5	2	2860

Table 2. Pearson parametric correlations analysis for the variables

		Time	**PVC**	**Stabilizer**	**Calcium**	**Steric**	**Titanium**	**Pigment**	**Output**
Time	Pearson correlation	1	.297	.296	.296	.290	.287	.271	.296
	Sig. (2-tailed)		.349	.350	.350	.360	.366	.394	.350
	N	12	12	12	12	12	12	12	12
PVC	Pearson correlation	.297	1	1.000**	1.000**	1.000**	.960**	.945**	1.000**
	Sig. (2-tailed)	.349		.000	.000	.000	.000	.000	.000
	N	12	12	12	12	12	12	12	12
Stabilizer	Pearson correlation	.296	1.000**	1	1.000**	1.000**	.961**	.944**	1.000**
	Sig. (2-tailed)	.350	.000		.000	.000	.000	.000	.000
	N	12	12	12	12	12	12	12	12
Calcium	Pearson correlation	.296	1.000**	1.000**	1	1.000**	.961**	.944**	1.000**
	Sig. (2-tailed)	.350	.000	.000		.000	.000	.000	.000
	N	12	12	12	12	12	12	12	12
Steric	Pearson correlation	.290	1.000**	1.000**	1.000**	1	.960**	.943**	1.000**
	Sig. (2-tailed)	.360	.000	.000	.000		.000	.000	.000
	N	12	12	12	12	12	12	12	12
Titanium	Pearson correlation	.287	.960**	.961**	.961**	.960**	1	.847**	.961**
	Sig. (2-tailed)	.366	.000	.000	.000	.000		.001	.000
	N	12	12	12	12	12	12	12	12
Pigment	Pearson correlation	.271	.945**	.944**	.944**	.943**	.847**	1	.944**
	Sig. (2-tailed)	.394	.000	.000	.000	.000	.001		.000
	N	12	12	12	12	12	12	12	12
Output	Pearson correlation	.296	1.000**	1.000**	1.000**	1.000**	.961**	.944**	1
	Sig. (2-tailed)	.350	.000	.000	.000	.000	.000	.000	
	N	12	12	12	12	12	12	12	12

Table 3. Nonparametric correlations

Kendall's tau_b	Time	Correlation coefficient	1.000	.182	.182	.182	.168	.201	.260	.182
		Sig. (2-tailed)	.	.411	.411	.411	.450	.392	.279	.411
		N	12	12	12	12	12	12	12	12
	PVC	Correlation coefficient	.182	1.000	1.000**	1.000**	.992**	.905**	.816**	1.000**
		Sig. (2-tailed)	.411	.	.	.	.000	.000	.001	.
		N	12	12	12	12	12	12	12	12
	Stabilizer	Correlation coefficient	.182	1.000**	1.000	1.000**	.992**	.905**	.816**	1.000**
		Sig. (2-tailed)	.411	.	.	.	.000	.000	.001	.
		N	12	12	12	12	12	12	12	12
	Calcium	Correlation coefficient	.182	1.000**	1.000**	1.000	.992**	.905**	.816**	1.000**
		Sig. (2-tailed)	.411	.	.	.	.000	.000	.001	.
		N	12	12	12	12	12	12	12	12
	Steric	Correlation coefficient	.168	.992**	.992**	.992**	1.000	.895**	.823**	.992**
		Sig. (2-tailed)	.450	.000	.000	.000	.	.000	.001	.000
		N	12	12	12	12	12	12	12	12
	Titanium	Correlation coefficient	.201	.905**	.905**	.905**	.895**	1.000	.800**	.905**
		Sig. (2-tailed)	.392	.000	.000	.000	.000	.	.002	.000
		N	12	12	12	12	12	12	12	12
	Pigment	Correlation coefficient	.260	.816**	.816**	.816**	.823**	.800**	1.000	.816**
		Sig. (2-tailed)	.279	.001	.001	.001	.001	.002	.	.001
		N	12	12	12	12	12	12	12	12
	Output	Correlation coefficient	.182	1.000**	1.000**	1.000**	.992**	.905**	.816**	1.000
		Sig. (2-tailed)	.411	.	.	.	.000	.000	.001	.
		N	12	12	12	12	12	12	12	12
Spearman's rho	Time	Correlation coefficient	1.000	.189	.189	.189	.179	.238	.277	.189
		Sig. (2-tailed)	.	.557	.557	.557	.579	.456	.383	.557
		N	12	12	12	12	12	12	12	12
	PVC	Correlation coefficient	.189	1.000	1.000**	1.000**	.998**	.968**	.895**	1.000**
		Sig. (2-tailed)	.557	.	.	.	.000	.000	.000	.
		N	12	12	12	12	12	12	12	12
	Stabilizer	Correlation coefficient	.189	1.000**	1.000	1.000**	.998**	.968**	.895**	1.000**
		Sig. (2-tailed)	.557	.	.	.	.000	.000	.000	.
		N	12	12	12	12	12	12	12	12

Calcium	Correlation coefficient	.189	1.000**	1.000**	1.000	.998**	.968**	.895**	1.000**
	Sig. (2-tailed)	.557	.	.	.	.000	.000	.000	.
	N	12	12	12	12	12	12	12	12
Steric	Correlation coefficient	.179	.998**	.998**	.998**	1.000	.957**	.896**	.998**
	Sig. (2-tailed)	.579	.000	.000	.000	.	.000	.000	.000
	N	12	12	12	12	12	12	12	12
Titanium	Correlation coefficient	.238	.968**	.968**	.968**	.957**	1.000	.848**	.968**
	Sig. (2-tailed)	.456	.000	.000	.000	.000	.	.000	.000
	N	12	12	12	12	12	12	12	12
Pigment	Correlation coefficient	.277	.895**	.895**	.895**	.896**	.848**	1.000	.895**
	Sig. (2-tailed)	.383	.000	.000	.000	.000	.000	.	.000
	N	12	12	12	12	12	12	12	12
Output	Correlation coefficient	.189	1.000**	1.000**	1.000**	.998**	.968**	.895**	1.000
	Sig. (2-tailed)	.557	.	.	.	.000	.000	.000	.
	N	12	12	12	12	12	12	12	12

3. OPTIMIZATION OF THE SOLUTIONS

Table 4 shows that the model F-value of 7.24 implies the model are significant. There is only a 2.27% chance that an F-value this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case, C is a significant model term. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

The "Lack of Fit F-value" of 0.14 implies the Lack of Fit is not significant relative to the pure error. There is a 97.47% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Table 5 shows that the Predicted R-Squared of 0.1248 is not as close to the Adjusted R-Squared of 0.3620 as one might normally expect; i.e. the difference is more than 0.2. This indicates a large block effect or a possible problem with the model and/or data. Things to consider are model reduction, response transformation, outliers. All empirical models should be tested by doing confirmation runs.

Adequate Precision measures the signal to noise ratio. A ratio of 3.93 indicates an inadequate signal.

Fig. 1 shows that calcium is the most important variable among the production variables under study.

The Piepel Plot helps to trace the deviation of the raw material variables from its reference point as shown in Fig. 2.

Table 4. Analysis of variance

Source	Sum of squares	df	Mean square	F value	p-value Prob > F	
Model	2.16	1	2.16	7.24	0.0227	Significant
C-Calcium (kg)	2.16	1	2.16	7.24	0.0227	
Residual	2.98	10	0.30			
Lack of Fit	1.66	9	0.18	0.14	0.9747	Not significant
Pure Error	1.32	1	1.32			
Cor Total	5.14	11				

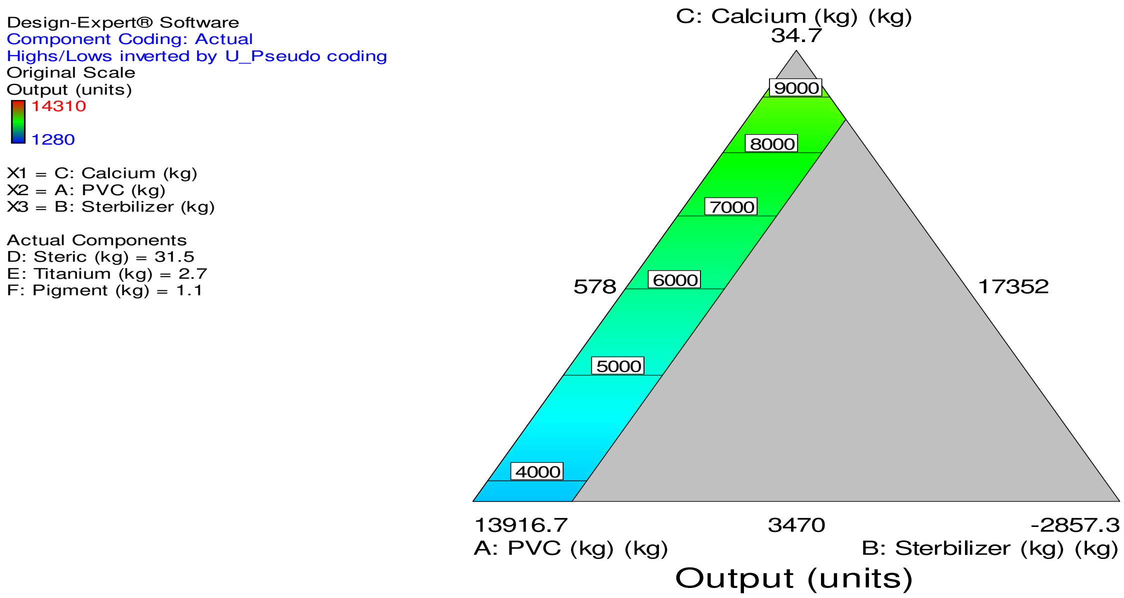

Fig. 1. User define mixture design analysis

Table 5. Model summary analysis

Std. Dev.	0.55	R-Squared	0.4200
Mean	8.61	Adj R-Squared	0.3620
C.V. %	6.34	Pred R-Squared	0.1248
PRESS	4.50	Adeq Precision	3.934
-2 Log Likelihood	17.35	BIC	22.32
		AICc	22.68

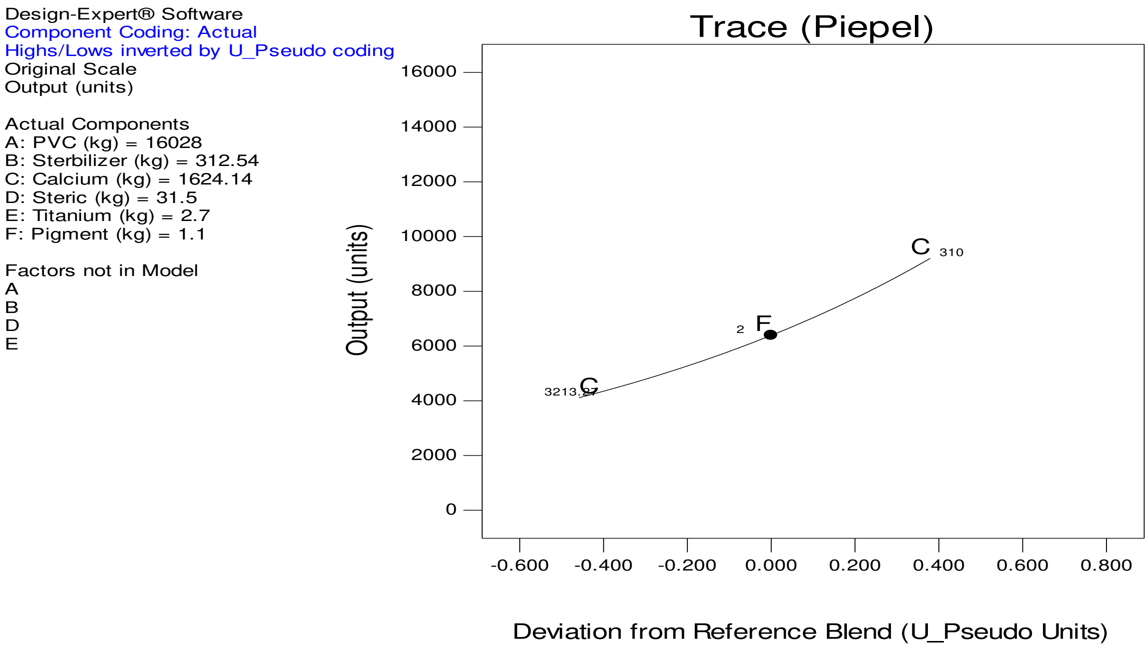

Fig. 2. Trace analysis of the components

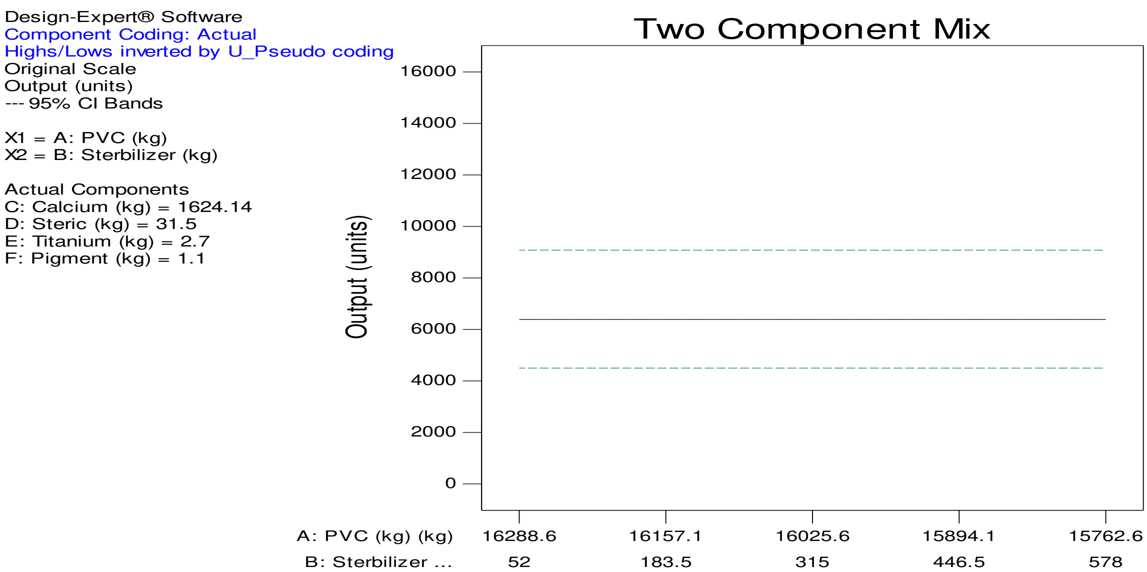

Fig. 3. Two component design analysis

The two components mix analysis helps to show the level of the variables effect to the production output as shown in Fig. 3.

Fig. 4 shows the predicted and the actual plot which reveals their variations from the production output.

In Fig. 5, the normal plot of the residuals shows that the plot is along the mean of the residual, which shows that there were no much errors between the actual data and the predicted variables.

In Fig. 6, cook's distance analysis shows that their plots is between zero and one which shows that all the data used will be able to model the production. If any runs exceed below zero or above one, that means that there is a problem on the data used on that runs.

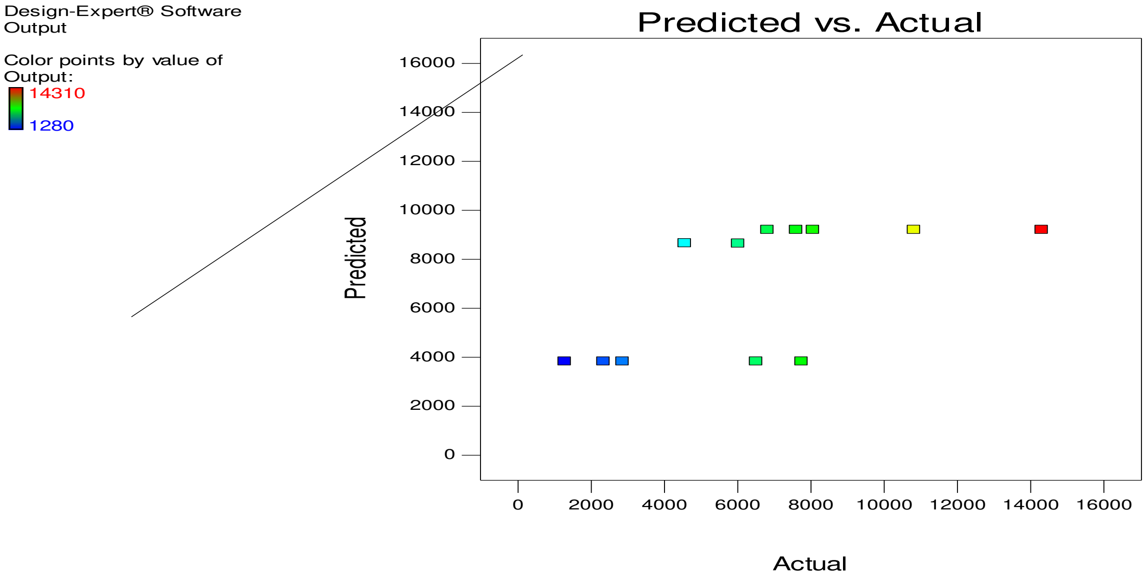

Fig. 4. Predicted and actual analysis of the variables

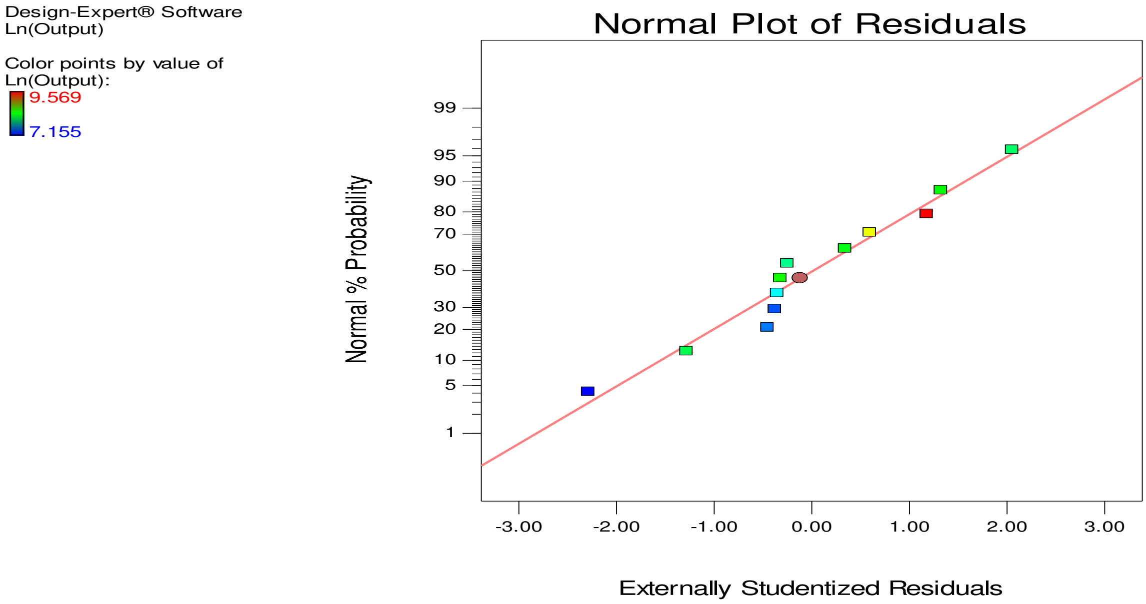

Fig. 5. Normal residual plot analysis

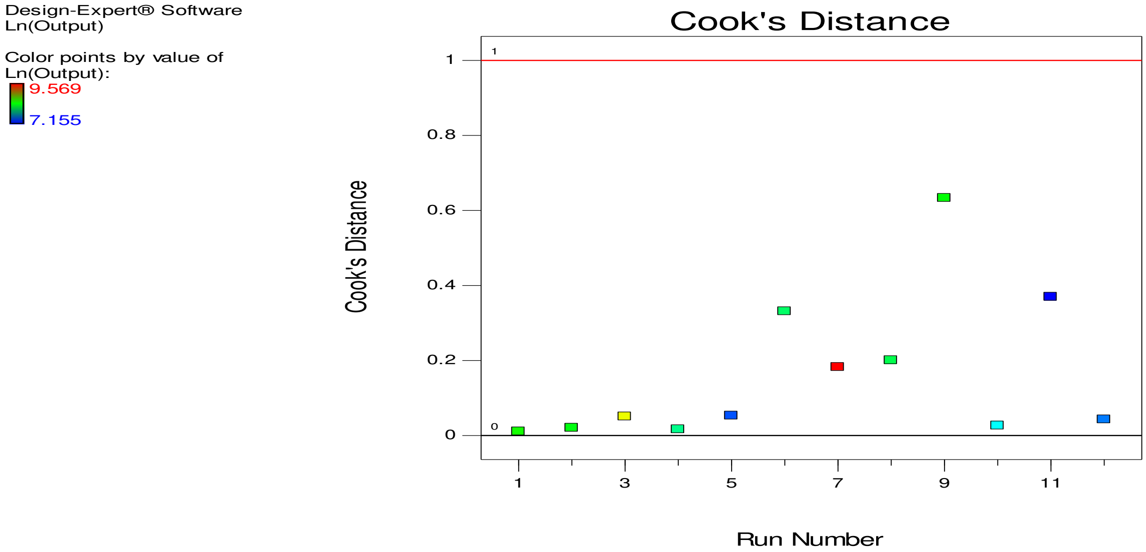

Fig. 6. Cook's distance analysis

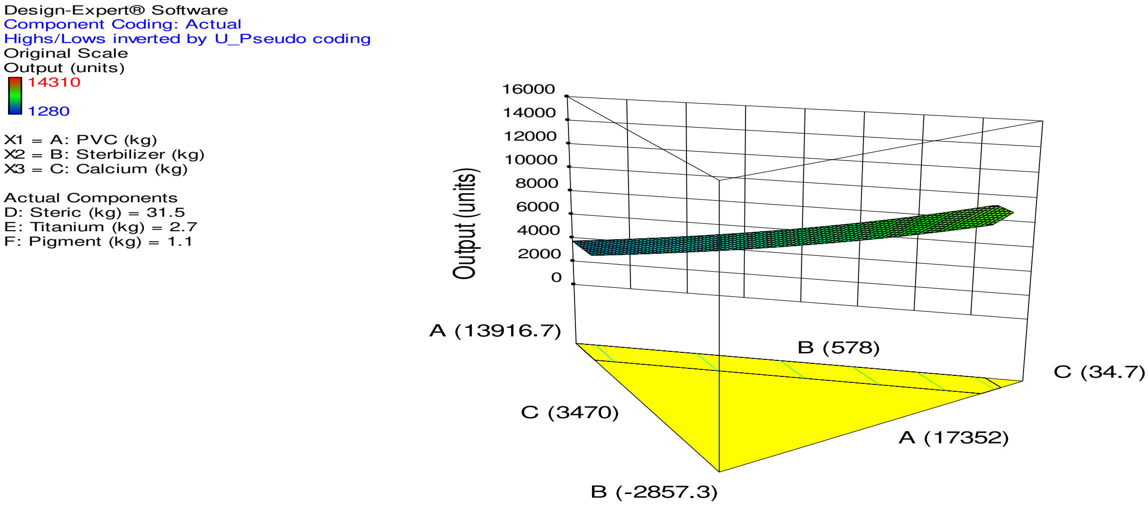

Fig. 7. 3D surface plot analysis of the variables

Fig. 7 showed the 3D surface plot shows the effect of the variables in production system. It describes the variations of the input and output parameters in production of plastic extrusion products.

3.1 Optimization of the Production Variables

Fig. 8 showed the numerical criteria analysis for the optimization of the input and output variables. The degree of importance for these variables will also be signified.

In Table 6, the optimization solution report reveals that the model found eleven (11) Solutions, but the selected desired solution is the first solution with desirability of 95.1% and production output of 9204.461 units of plastic extrusion pipe products. The input parameters with the symbol * has no effect on the optimization results.

Fig. 9 express the graphical results of the optimal solutions selected as it's in Table 6.

Fig. 10 express the rate of desirability of all the variables under investigation. The result shows that calcium is most desired in extrusion plastic pipe production.

Fig. 11 shows the user define mixture design method shows the approximation of the desirability on the optimal solution in the production system.

Fig. 12 showed the user define mixture method shows the approximation of the output on the optimal solution in the production system.

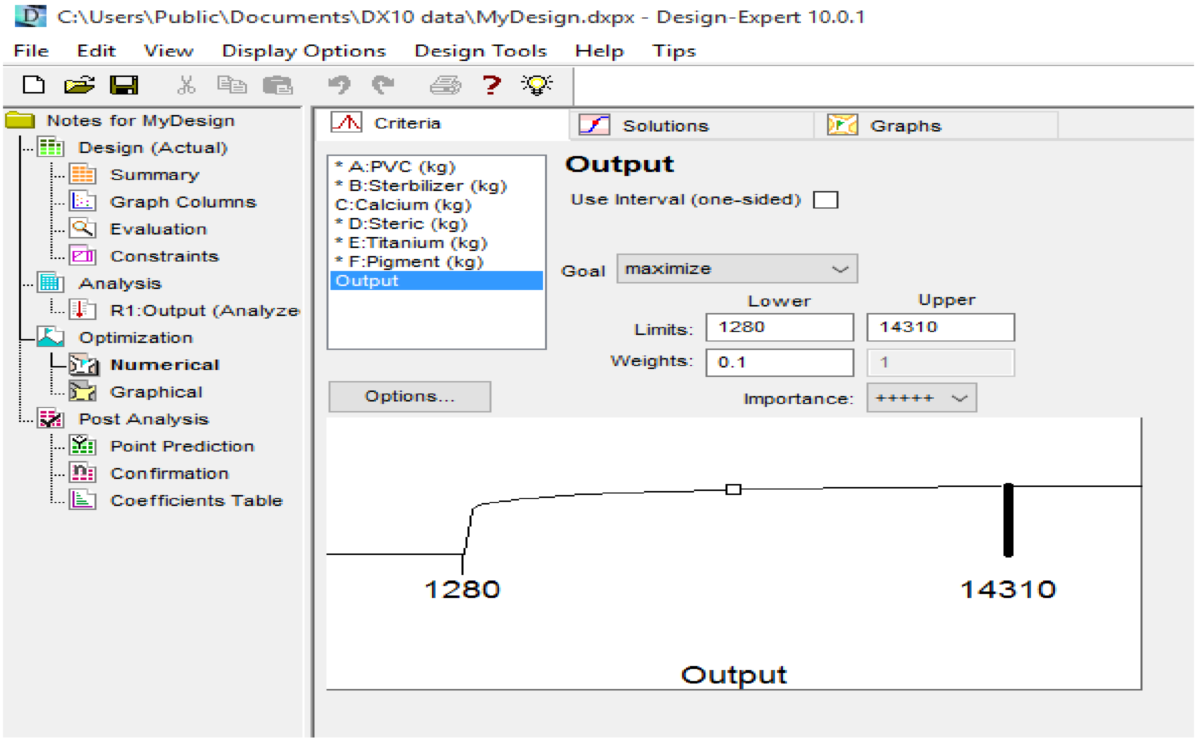

Fig. 8. Numerical criteria analysis of the variables

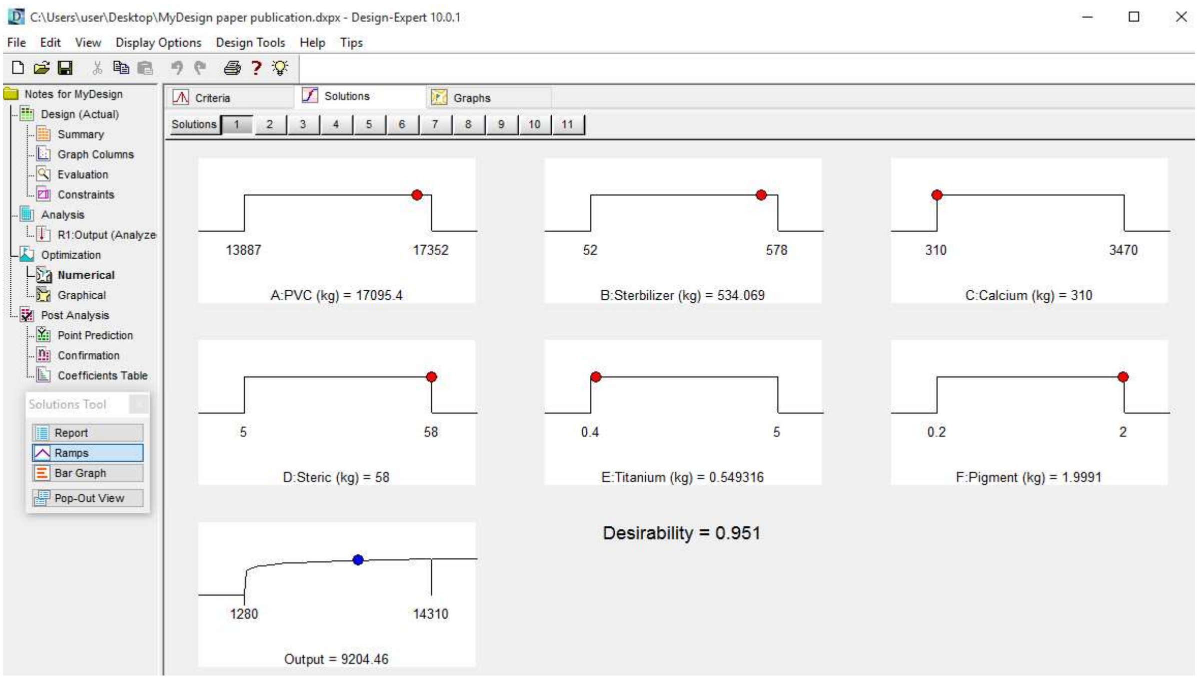

Fig. 9. Optimal numerical solution of the variables

Table 6. Reports on optimization solutions

Number	PVC (kg)	Sterbilizer (kg)	Calcium (kg)	Steric (kg)*	Titanium (kg)*	Pigment (kg)	Output	Desirability	
1	17095.383	534.069	310.000	*58.000*	*0.549*	1.999	9204.461	0.951	Selected
2	17352.000	277.102	310.000	*58.000*	*1.292*	1.606	9204.461	0.951	
3	17159.314	489.967	310.000	*38.758*	*0.400*	1.561	9204.461	0.951	
4	17248.383	424.528	310.000	*15.167*	*0.400*	1.522	9204.461	0.951	
5	17300.893	374.844	310.000	*9.373*	*3.407*	1.483	9204.461	0.951	
6	17352.000	245.103	390.888	*9.491*	*0.518*	2.000	9000.102	0.949	
7	17351.988	218.397	393.858	*28.912*	*4.845*	2.000	8992.686	0.949	
8	17352.000	148.152	456.849	*37.859*	*3.139*	2.000	8836.820	0.947	
9	17352.000	91.145	545.168	*8.944*	*0.742*	2.000	8622.819	0.944	
10	16587.382	278.088	1126.485	*5.646*	*0.400*	2.000	7337.915	0.926	
11	16048.754	309.490	1607.388	*31.474*	*2.693*	0.200	6420.971	0.911	

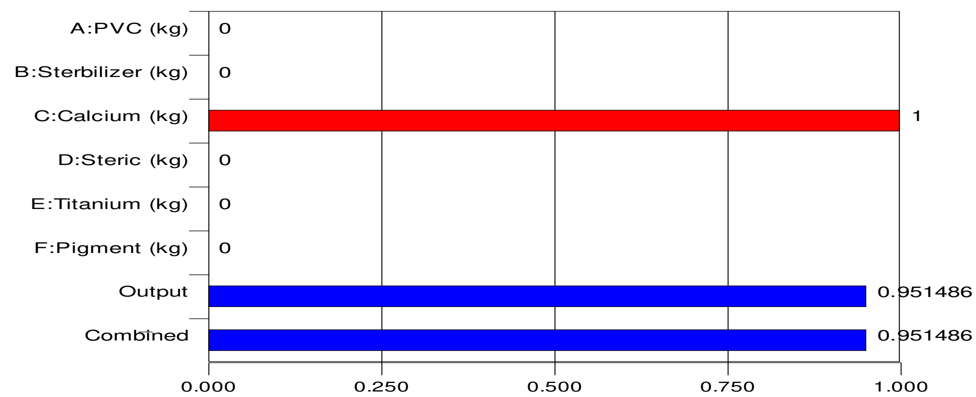

Fig. 10. Desirability solutions

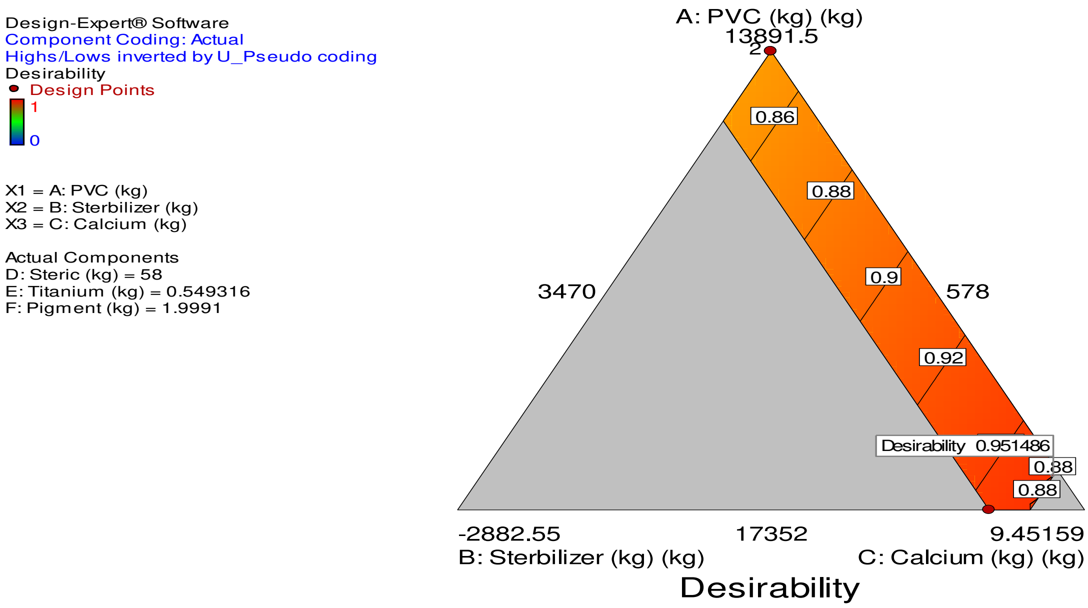

Fig. 11. Desirability user defined solution

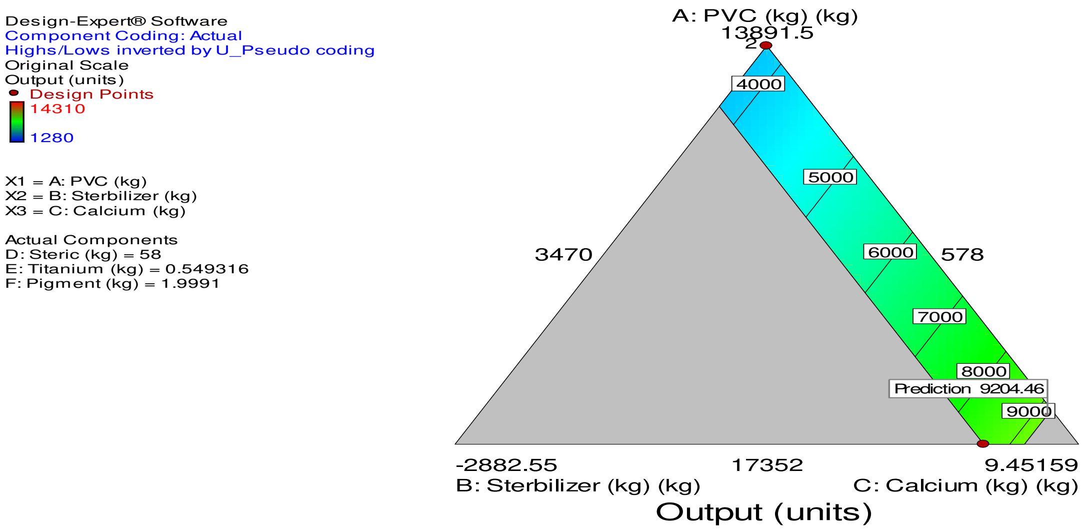

Fig. 12. Predicted optimal solution of the user defined mixture design analysis

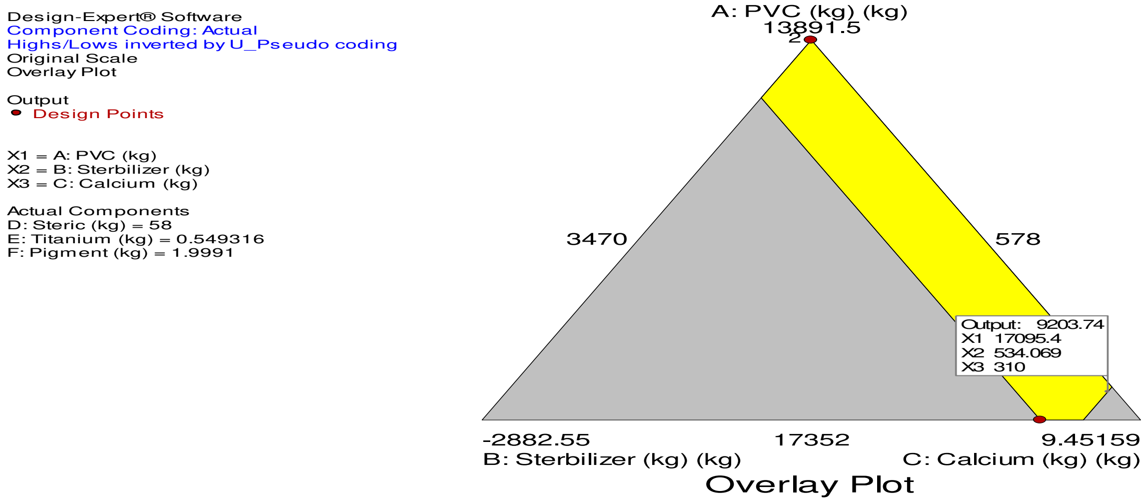

Fig. 13. Overlay plot showing the predicted optimal solutions

The overlay plot in Fig. 13 shows the optimal solutions of both the input and output parameters in the production variables.

4. RESULTS AND DISCUSSION

The results discuss were focused on the evaluation, analysis and optimization of the production variables, the results, tables, figures and charts developed during the analysis of the research. The data is a mixture of the plastic production raw material and the unit quantity of the finished plastic extrusion pipe produced over any given month. The data was evaluated, analyzed and optimized. Pearson correlation was used to express the correlations of the variables. All mixture components are highly correlated with the production quantity except time of mixture. This reveals that time is not a component that influences the production variables and production quantity. This also shows that time are not necessary to be used in modelling the production variables of the plastic extrusion pipe. The used of Kendall' a tau_b and Spearman's rho models were applied to validate the correlations of Pearson model. The application of analysis of variance (ANOVA) reveals that the variables are significance to model the production variables of the system. However, the Predicted R-Squared" of 0.1248 is not as close to the "Adj R-Squared" of 0.3620 as one might normally expect; i.e. the difference is more than 0.2. This may indicate a large block effect or a possible problem with your model and/or data.

The user-defined mixture analysis shows that calcium is of high importance the production when compared with other variables. The Piepel Plot helps to trace the deviation of the raw material variables from its reference point. The two components mix analysis helps to show the level of the effect of the variable to the production output. The predicted and the actual plot reveals their variations from the production output, while the normal plot of the residuals that the plot is along the mean of the residual, which shows that there was not much errors between the actual data and the predicted variables. The cook's distance analysis also shows that their plots is between zero and one which shows that all the data used will be able to model the production. If any runs exceed below zero or above one, that means that there is a problem on the data used on that runs. The 3D surface plot shows the effect of the variables in production system.

Finally, the application of the user-defined mixture design optimization model expresses that the optimal solution quantity that is best to produce every month is 9204.461 units of plastic extrusion pipes. And the best quantity for the PVC, stabilizer, calcium, steric, titanium and pigment raw material variables to be used are 117095.383 kg, 534.069 kg, 310 kg, 58 kg, 0.549 kg and 1.999 kg respectively over the months of production. However, the optimal solutions give desirability of 0.951 or 95.1%.

Furthermore, several researchers have revealed several authors research work in optimization of the products production system. Ezeliora et al. [8] revealed the Niger bar soap mix proportion, to determine the most appropriate raw materials and mix ratio that will yield the most appropriate soap production quality and quantity. Upendra et al. [9] study a mixture experiment of the process variables in which the response is assumed to depend on the relative proportions of the ingredients present in the mixture and not on the total amount of the mixture. Ezeliora and Ejikeme [10] studied the optimal monthly production mixture of the process variables to its response variable for 40 mm diameter of plastic pipe product in Louis Carter manufacturing industry. Okolie et al. [11] improves the productivity of Soap mix using Response Surface to optimize the soap production mix using the previous production data. This related empirical literatures revealed that this research serves a knowledge gap to optimize the production mix of other company's plastic pipe product.

5. CONCLUSION

Having revealed the production variables, it is obvious that the optimization system is the gateway to ensure the best in the production system and in industrialization sectors. The evaluation and analysis of production variables have revealed that the optimal solutions of the system have 95.1 percent desirability. However, the optimal solution for the production output is 9204.461 units of plastic extrusion pipes. Finally, the results were recommended to the case company, to ensure efficient and more preferred production in their industry.

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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