Optimal Productivity And Design Of Production Quantity Of A Manufacturing Industry

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Abstract: The ever-increasing demand on engineers to lower production costs to withstand global competition has prompted engineers to look for rigorous methods of decision making such as optimization methods, to design and produce products and systems both economically and efficiently. This paper improved the batch production per month of Glass production, a case study of Beta Glass limited. Their production data was optimized using Response surface modeling tool to obtain the optimum production process of the raw materials. Response surface regression analysis was used to estimate the coefficient of the dependent variables using the production raw data with the coefficient of determination (R-sq.) being 100%, this shows the relationships of the variables.From the analysis, their production yield increased from 4,280 batches of bottles per month, to an optimal value of 5,340 batches of bottles per month.

Index Terms: Optimization, Prediction, Batch, Model, Raw Material, Surface Response Plot, Residual Plot.

1 INTRODUCTION

Over the decades, the world has witnessed population increase. This caused increase in demand for average cost of living, which results in increased consumption of bottle-packed items [1]. The growth of manufacturing industries and firms put pressure on the management involved. These led to the adoption of theories and models applicable in analyzing practical problems and also solving the practical business problems in the industry. Theoretical and quantitative techniques are adopted to model and analyze the various decision problems. Optimizationis the selection of a best element (with regard to some criteria) from some set of available alternatives.In the simplest case, an optimization problem consists of maximizing or minimizing a real function by systematically choosing input values from within an allowed set and computing the value of the function. The generalization of optimization theory and techniques to other formulations comprises a large area of applied mathematics. More generally, optimization includes finding "best available" values of some objective function given a defined domain (or a set of constraints), including a variety of different types of objective functions and different types of domain.

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The model to be used is the Least Square/Regression model since it will use mathematical method in providing acute knowledge of the right trend to follow in order to attain an optimized production processes resulting to improved production output and profit over a period of time [2]. This research work is aimed at optimizing the production mix of the products. However, The Objectives of the study are; collecting the raw materials and production processes data from Beta Glass PLC, analysing the data using square/regression method and its optimization tool, applying Response Surface Design optimization tool to validate the optimal production process and comparing the result of the analysis with the practical achievement made by the company over the given period analysed.

2 RESEARCH METHODOLOGY

2.1 Response Surface Methodology

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response. Originally, RSM was developed to model experimental responses, and then migrated into the modeling of numerical experiments. The difference is in the type of error generated by the response. In physical experiments, inaccuracy can be due, for example, to measurement errors while, in computer experiments, numerical noise is a result of incomplete convergence of iterative processes, round-off errors or the discrete representation of continuous physical phenomena [1, 2, 3]. In RSM, the errors are assumed to be random [4]. The application of RSM to design optimization is aimed at reducing the cost of expensive analysis methods (e.g. finite element method or CFD analysis) and their associated numerical noise [5]. Assume that y denotes the response and x_g denotes the variables, $g = 1,\ldots,N$. When a linear function of variables can effectively model a response, then the response surface is a first-order model, as follows

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_N x_N \tag{1}$$

Where *g* is the regression coefficients, *g* = 1, …,*N*.
When specifying curvature of a response surface, a polynomial of a high order is appropriate for the response surface [6] For instance, a second-order model of the response surface is

$$\hat{y} = \beta_0 + \sum_{g=1}^{N} \beta_0 x_g + \sum_{g=1}^{N} \beta_{gg} x_g^2 + \sum_{g<f}\sum \beta_{gf} x_g x_f \qquad (2)$$

The fitted response surface is an adequate approximation of the true response function when an appropriate model is selected. Furthermore, model parameters are estimated effectively when proper experimental designs are used to obtain experimental data [7].

2.2 Data Collection

The data covering the seven raw materials used in the production of bottles over a period of three years were collected from the case study company.

3 RESULTS AND ANALYSIS

3.1 Response Surface Regression: Batches per month versus sand, soda ash, limestone, etc.

Surface response experimental design method is the method used to design, analyze and to optimize the production mix quantity of the glass production output. Production data and its mixture quantity were used to analyze the work.

Table 1. Estimated Regression Coefficients for Batches per month

Term	Coef	SE Coef	T	P	Term	Coef	SE Coef	T	P
Constant	4117.5	0.000000	*	*	sand*sand	-20971.3	0.000000	*	*
sand	2385.7	0.000000	*	*	soda ash*soda ash	307.0	0.000000	*	*
soda ash	-1289.9	0.000000	*	*	limestone*limestone	-504.2	0.000000	*	*
limestone	-898.6	0.000000	*	*	feldspar*feldspar	-24.0	0.000000	*	*
feldspar	33.4	0.000000	*	*	sodium sulphate*sodium sulphate	-21187.5	0.000000	*	*
sodium sulphate	22.3	0.000000	*	*	selenium*selenium	27.9	0.000000	*	*
selenium	0.8	0.000000	*	*	charcoal cobalt*charcoal cobalt	-0.0	0.000000	*	*
charcoal cobalt	-0.2	0.000000	*	*	sand*sodium sulphate	42406.1	0.000000	*	*
sand*selenium	-54.9	0.000000	*	*					
R-Sq = 100.00% R-Sq(pred) = *% R-Sq(adj) = 100.00%									

Table 1 shows estimated regression coefficients for batches per month. Since the regression model is a combination of both linear and non-linear variables, the table helped in analyzing the coefficients for both the linear variables (i.e. sand, soda ash, limestone, feldspar, charcoal cobalt, selenium and sodium sulphate respectively) and the coefficients for non-linear variables (I.e. sand*sand, soda ash*soda ash, limestone*limestone, feldspar*feldspar, sodium sulphate*sodium sulphate, charcoal cobalt*charcoal cobalt and selenium*selenium respectively).
The mathematical summary of the model is given below as;
Batches per Month $(\gamma) = \beta_0 + \sum_n^{i=1} \beta_i X_i + \sum_n^{j=1} \beta_i \beta_j X_i$(3)
Where Sand =β_1, soda ash=β_2, limestone = β_3, feldspar = β_4, sodium sulphate = β_5, selenium = β_6 and charcoal cobalt =$\beta_{7,}$i=1 to7 and j=1 to 7.

Table 2: Analysis of Variance for Batches per month

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	16	626413	626413	39150.8	*	*	limestone*limestone	1	0	0	0.0	*	*
Linear	7	626413	140044	20006.3	*	*	feldspar*feldspar	1	0	0	0.0	*	*
sand	1	626413	0	0.0	*	*	sodium sulphate*sodium sulphate	1	0	0	0.0	*	*
limestone	1	0	0	0.0	*	*	selenium*selenium	1	0	0	0.0	*	*
feldspar	1	0	0	0.0	*	*	charcoal cobalt*charcoal cobalt	1	0	0	0.0	*	*
sodium sulphate	1	0	0				Interaction	2	0	0			

0.0 * *	0.0 * *
selenium 1 0 0 0.0 *	sand*sodium sulphate 1 0 0 0.0 * *
charcoal cobalt 1 0 0 0.0 * *	sand*selenium 1 0 0 0.0 * *
Square 7 0 0 0.0 * *	Residual Error 19 0 0 0
sand*sand 1 0 0 0.0 * *	Pure Error 19 0 0 0.0
soda ash*soda ash 1 0 0 0.0 * *	Total 35 626413

Table 2,analyses the variance for batches per month for linear variables (i.e. sand, soda ash, limestone, feldspar, sodium sulphate, charcoal cobalt and selenium), the square variables (i.e. sand*sand, soda ash*soda ash, limestone*limestone, feldspar*feldspar, sodium sulphate*sodium sulphate, charcoal cobalt*charcoal cobalt and selenium*selenium respectively) and the interaction which is sand*sodium sulphate and sand*selenium.

Table 3: Estimated Regression Coefficients for Batches per month using data

Term	Coef	Term	Coef
Constant	3.42088	sand*sand	-0.864476
sand	-27.6759	soda ash*soda ash	0.144501
soda ash	-244.340	limestone*limestone	-0.254120
limestone	347.168	feldspar*feldspar	- 0.724167
feldspar	141.325	sodium sulphate*sodium sulphate	- 10958.2
sodium sulphate	-300.722	selenium*selenium	2483431
selenium	-6183.83	charcoal cobalt*charcoal cobalt	- 57502.2
charcoal cobalt	1200.92	sand*sodium sulphate	195.804
sand*selenium	-105.152		

Table 4: Predicted Response for New Design Points Using Model for Batches per month

Point	Fit	SE Fit	95% CI	95% PI		Point	Fit	SE Fit	95% CI	95% PI	
1	4278	0	(4278, 4278)	(4278, 4278)		19	4216	0	(4216, 4216)	(4216, 4216)	
2	3944	0	(3944, 3944)	(3944, 3944)	X	20	4216	0	(4216, 4216)	(4216, 4216)	
3	4216	0	(4216, 4216)	(4216, 4216)		21	4216	0	(4216, 4216)	(4216, 4216)	
4	4020	0	(4020, 4020)	(4020, 4020)	X	22	4278	0	(4278, 4278)	(4278, 4278)	
5	4154	0	(4154, 4154)	(4154, 4154)	X	23	4260	0	(4260, 4260)	(4260, 4260)	X
6	4170	0	(4170, 4170)	(4170, 4170)		24	4340	0	(4340, 4340)	(4340, 4340)	
7	4340	0	(4340, 4340)	(4340, 4340)		25	4371	0	(4371, 4371)	(4371, 4371)	X
8	4309	0	(4309, 4309)	(4309, 4309)	X	26	3864	0	(3864, 3864)	(3864, 3864)	X
9	4170	0	(4170, 4170)	(4170, 4170)		27	4278	0	(4278, 4278)	(4278, 4278)	
10	4247	0	(4247, 4247)	(4247, 4247)		28	4200	0	(4200, 4200)	(4200, 4200)	

11 4140 0 (4140, 4140) (4140, 4140)	29 4340 0 (4340, 4340) (4340, 4340)
12 4278 0 (4278, 4278) (4278, 4278)	30 4140 0 (4140, 4140) (4140, 4140)
13 4278 0 (4278, 4278) (4278, 4278)	31 4247 0 (4247, 4247) (4247, 4247)
14 3948 0 (3948, 3948) (3948, 3948) X	32 4278 0 (4278, 4278) (4278, 4278)
15 3999 0 (3999, 3999) (3999, 3999)	33 4140 0 (4140, 4140) (4140, 4140)
16 4140 0 (4140, 4140) (4140, 4140)	34 3999 0 (3999, 3999) (3999, 3999)
17 4278 0 (4278, 4278) (4278, 4278)	35 3870 0 (3870, 3870) (3870, 3870) X
18 4200 0 (4200, 4200) (4200, 4200)	36 4247 0 (4247, 4247) (4247, 4247)

Table 4, shows the Predicted Response for New Design Points Using Model for Batches per month, it can be seen that it shows 95% CI (Confidence intervals) and 95% PI (Prediction intervals). It means that we are 95% confident that the confidence intervals contain the mean numbers for the specified values of the variables in the model. The confidence interval helps to access the practical significance of the result.With 95% prediction interval we are 95% confident that the new observations will fall within interval of the best fit.

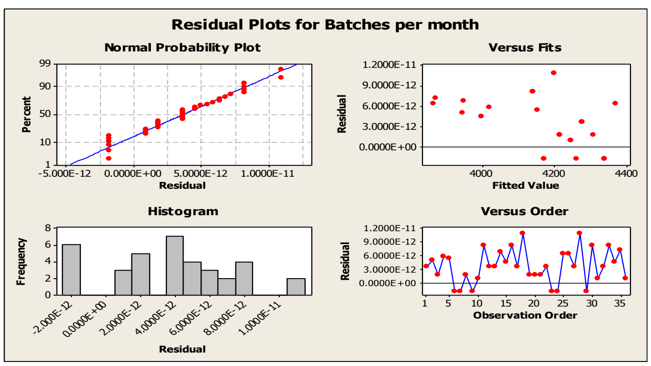

Figure 1: Residual Plots for Batches per month

Figure 1a, illustrates the Normal probability plot, at which the percentage (1-99) is plotted against Residual with range from (-5.000E-12 – 1.0000E-11). As we can see, much of the variables reflected almost along the normality line, the implication is that the method (Response Surface Method) selected is highly valid. In Figure 1b, the residuals is plotted against the fitted values, it can be seen that more of the valuables reflected above the line on the positive side which also shows the validity of the choice of method used which is the Response Surface Method. Figure 1c shows the histogram of the residuals as occurred in the chart. It points out the occurrence of the variables in the residual range. Figure 1d shows the plot of Residual against Observation Order. It can be seen that it is almost the same with the fig. 1b just that the fig. 1d is a multiple of fig. 1b, which means six variables out of the thirty six variables represents the monthly batches for the three years.

3.3 Surface Plot

Surface plot is a 3D surface and 3D wireframe plots with graphs that can be used to explore the potential relationship between variables. The predictor variables are displayed on x- and y- scales, and the response (z) variable is represented by smooth surface (3D surface plot) or grid (3D wireframe plot).

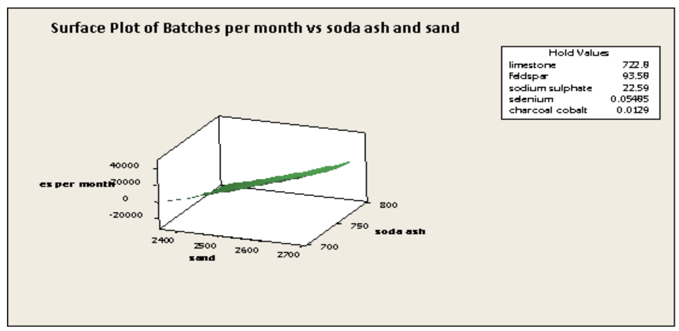

Figure 2: Surface Plot of Batches per month vs. soda ash and sand

In figure 2**,** it observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. soda ash and sand). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in sand from 2400 to 2700 batches decreases soda ash from 800 to 700 batches per month but increases the monthly production in the plotted chart.

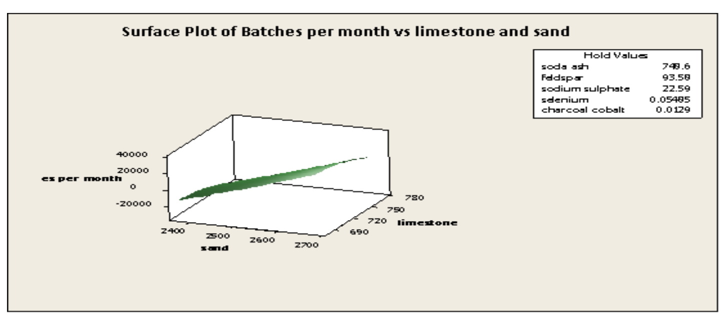

Figure 3: Surface Plot of Batches per month vs. limestone and sand

Figure 3, observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. limestone and sand). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in sand decreases limestone from 790 to 690 batches but increases the monthly production in the plotted chart.

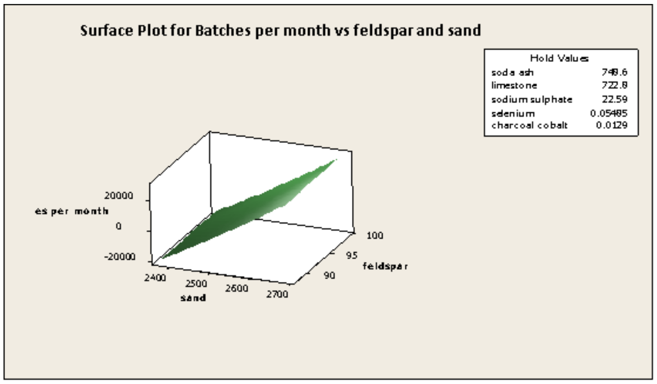

Figure 4: Surface Plot of Batches per month vs. feldspar and sand

Figure 4**,** it observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. feldspar and sand). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in sand from 2400 to 2700 batches slightly increases feldspar from 0 to 90 batches but increases the monthly production in the plotted chart.

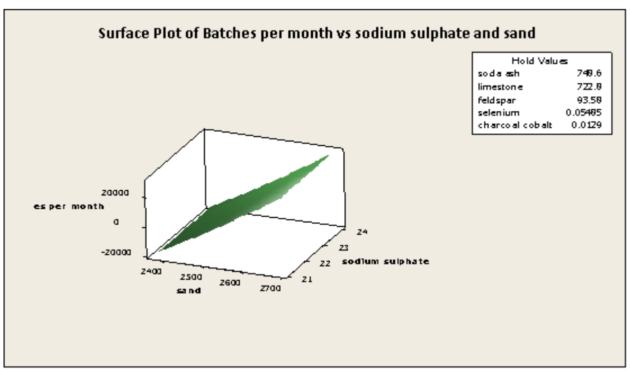

Figure 5: Surface Plot of Batches per month vs. sodium sulphate and sand

Figure 5,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. sodium sulphate and sand). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in sand from 2400 to 2700 batches but slightly increases sodium sulphate from 21 to 24 batches but increases the monthly production in the plotted chart.

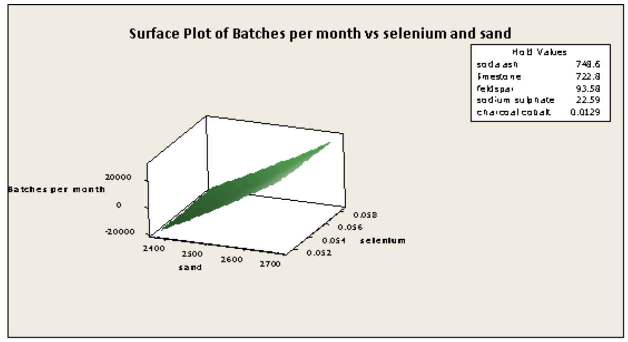

Figure 6: Surface Plot of Batches per month vs. selenium and sand

Figure 6,observes the surface plot of the dependent and the independent variables. The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in sand from 2400 to 2700 batches increases selenium from 0.012 to 0.018 batches but increases the monthly production in the plotted chart.

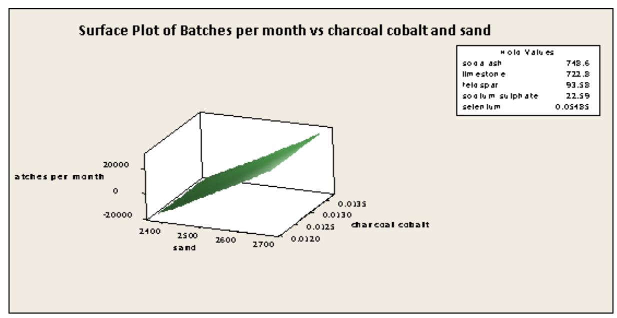

Figure 7: Surface Plot of Batches per month vs. charcoal cobalt and sand

Figure 7, observes the surface plot of the dependent and the independent variables. The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in sand from 2400 to 2700 batches increases charcoal cobalt from 0.0120 to 0.0135 but increases the monthly production in the plotted chart.

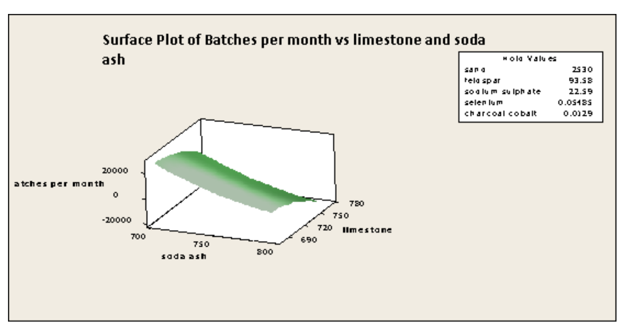

Figure 8: Surface Plot of Batches per month vs. limestone and soda ash

Figure 8, observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. limestone and soda ash). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increases in the monthly production decreases soda ash from 1300 to 200 batches but increase limestone 690 to 750 in the plotted chart.

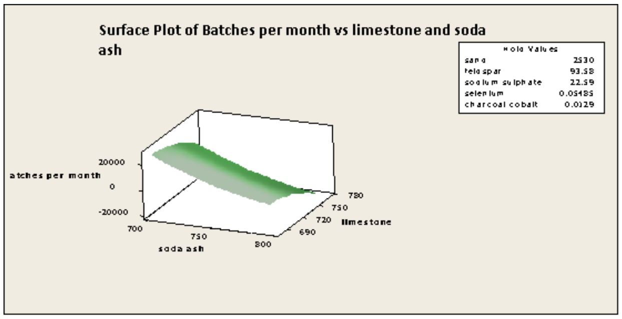

Figure 9: Surface Plot of Batches per month vs. feldspar, soda ash

Figure 9, observes the surface plot of the dependent and the independent variables. The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production decreases soda ash from 1300 to 200 batches but slightly increase limestone from 690 to 750 batches in the plotted chart.

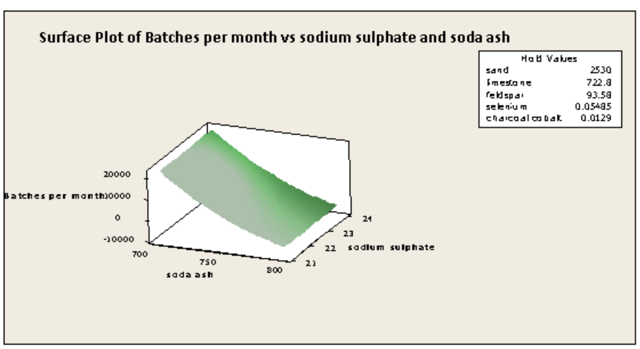

Figure 10: Surface Plot of Batches per month vs. sodium sulphate and soda ash

Figure 10,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. sodium sulphate and soda ash). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production decreases soda ash from 1300 to 200 batches but slightly increase sodium sulphate from 21 to 23 batches in the plotted chart.

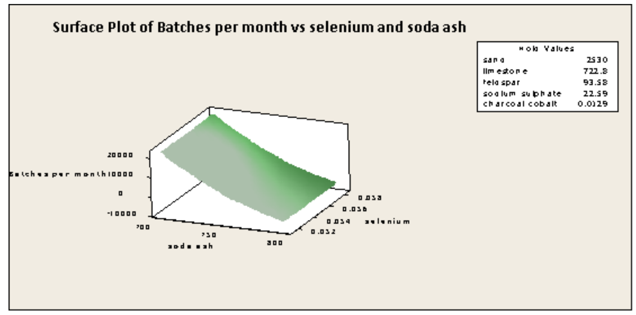

Figure 11: Surface Plot of Batches per month vs. selenium and soda ash

Figure 11**,** it observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. selenium and soda ash). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production decreases soda ash from 1300 to 200 but slightly increase selenium from 0 to 0.056 in the plotted chart.

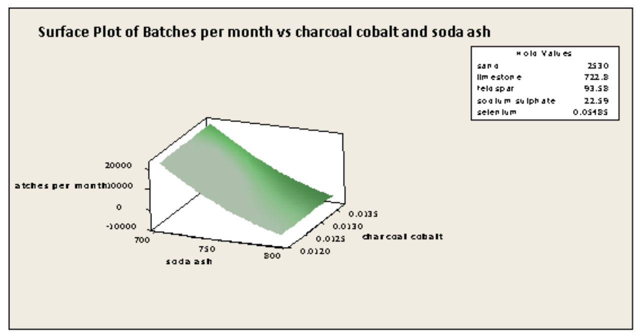

Figure 12: Surface Plot of Batches per month vs. charcoal cobalt and soda ash

Figure 12,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. charcoal cobalt and soda ash). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production decreases soda ash from 1300 to 200 but slightly increase Charcoal cobalt from 0.0120 to 0.0135 in the plotted chart.

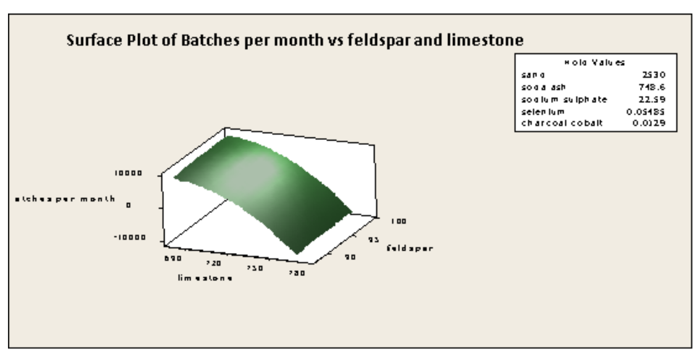

Figure 13: Surface Plot of Batches per month vs. feldspar and limestone

Figure 13,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. feldspar and limestone). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production decreases limestone from 720 to 690 batches but slightly increase feldspar from 0 to 95 batches in the plotted chart.

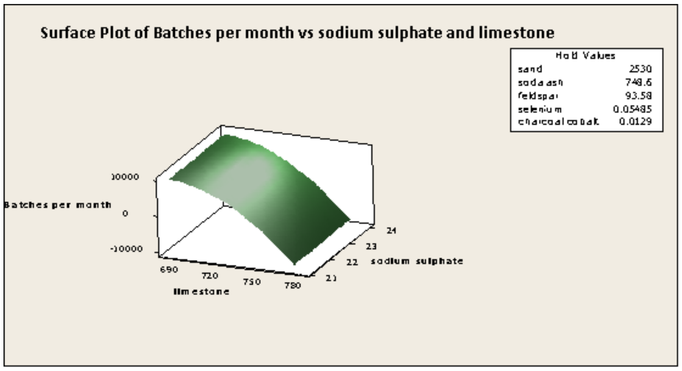

Figure 14: Surface Plot of Batches per month vs. sodium sulphate and limestone

Figure 14,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. sodium sulphate and limestone). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views (i.e. 3D). The surface plot shows that increase in the monthly production decreases limestone from 720 to 690 batches but slightly increase sodium sulphate from 21 to 24 in the plotted chart.

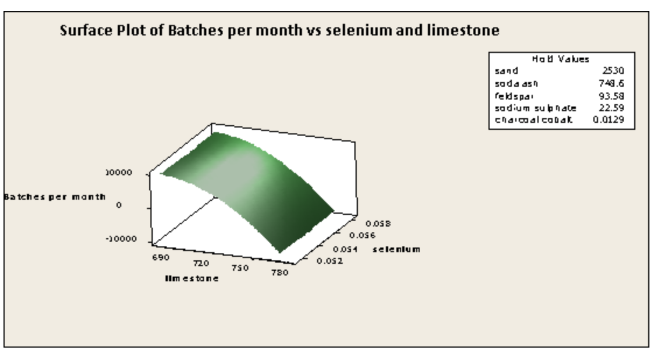

Figure 15: Surface Plot of Batches per month vs. selenium and limestone

Figure 15,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. selenium and limestone). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production decreases limestone from 720 to 690 batches but slightly increase selenium from 0 to 0.016 in the plotted chart.

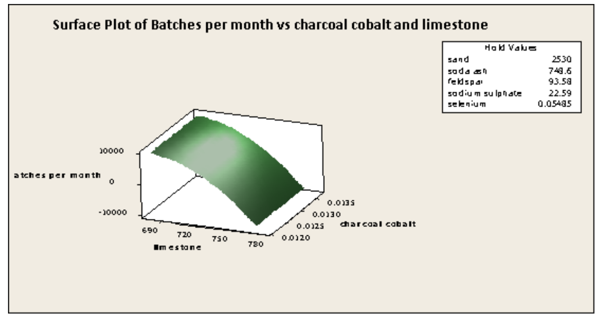

Figure 16: Surface Plot of Batches per month vs. charcoal cobalt and limestone

Figure 16,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. charcoal cobalt and limestone). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production decreases limestone from 720 to 690 batches but slightly increase charcoal cobalt from 0 to 0.0130 in the plotted chart.

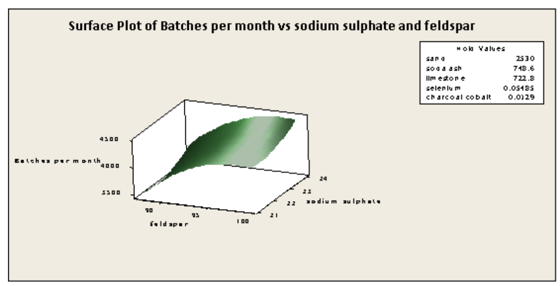

Figure 17: Surface Plot of Batches per month vs. sodium sulphate and feldspar

Figure 17, observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. sodium sulphate and feldspar). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production increases from 90 to 100 batches feldspar but increase sodium sulphate from 0 to 21 to 24 batches in the plotted chart.

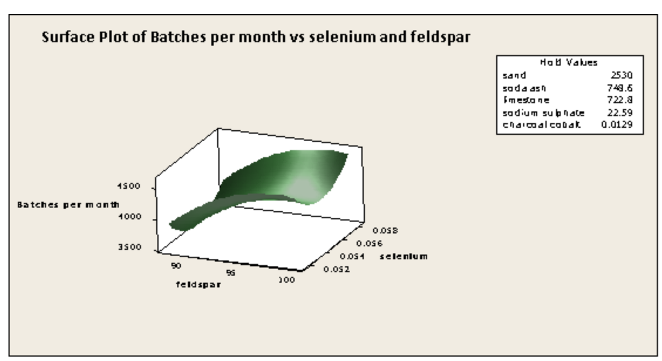

Figure 18: Surface Plot of Batches per month vs. selenium and feldspar

Figure 18,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. selenium and feldspar). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production increases feldspar from 90 to 100 batches and increase selenium from 0.012 to 0.018 in the plotted chart.

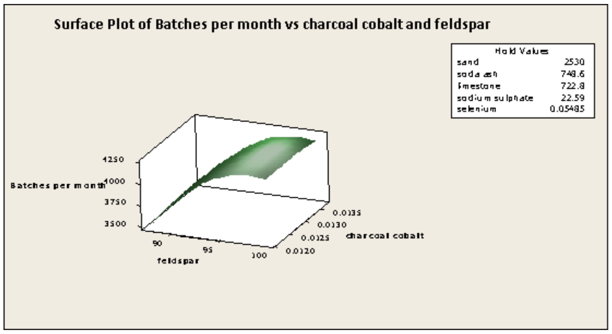

Figure 19: Surface Plot of Batches per month vs. charcoal cobalt and feldspar

Figure 19, observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. charcoal cobalt and feldspar). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production increases feldspar from 90 to 100 batches but slightly increase charcoal cobalt from to 0.0135 in the plotted chart.

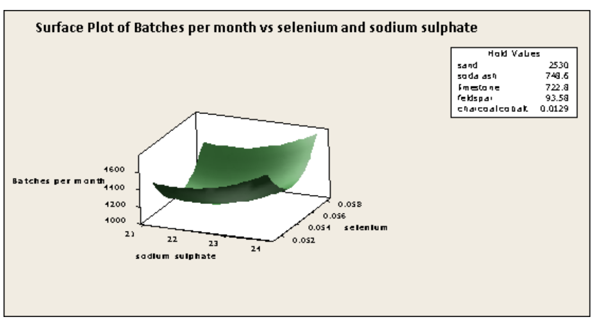

Figure 20: Surface Plot of Batches per month vs. selenium and sodium sulphate

Figure 20,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. selenium and sodium sulphate). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production increases sodium sulphate from 23 to 24 batches but decreases at initial point from 23 to 21 and also increases feldspar towards the optimal of monthly batch production from 0.014 to 0.018 in the plotted chart.

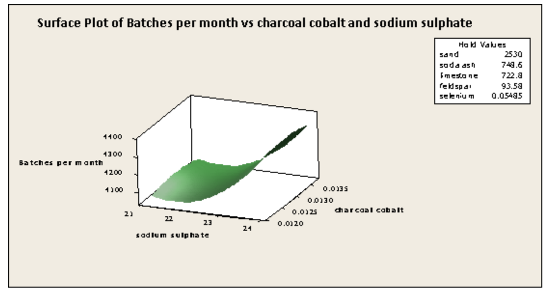

Figure 21: Surface Plot of Batches per month vs. charcoal cobalt and sodium sulphate

Figure 21,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. charcoal cobalt and sodium sulphate). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. The surface plot shows that increase in the monthly production increases sodium sulphate from 22 to 24 batches but slightly increase charcoal cobalt from 0.0120 to 0.0135 in the plotted chart.

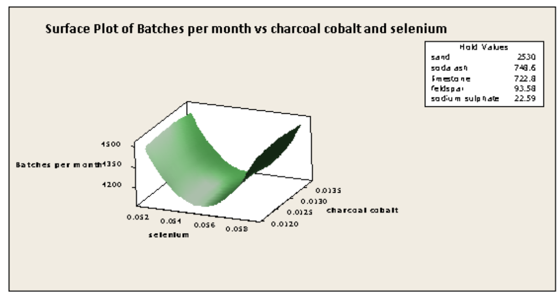

Figure 22: Surface Plot of Batches per month vs charcoal cobalt and selenium

Figure 22,observes the surface plot of the dependent (i.e. hold values) and the independent variables (i.e. charcoal cobalt and selenium). The figure shows the impact of the independent variables of their raw material mixture to the dependent variables on their monthly production batches in three dimensional views. It reveals whether the increase of the dependent variables increases or decreases the independent variables over a given period of the production. The surface plot shows that increase in the monthly production increases selenium from 0.016 to 0.018 but decreases at initial point from 0.016 to 0.012 and also increases charcoal cobalt towards from 0.0120 to 0.0135 the optimal of monthly batch production in the plotted chart.

3.4 Response Optimization

Figure 23, illustrates Response Surface Optimization plot of monthly production batches of the seven variables. D represents desirability. Since the desirability is 1.000, it shows a hundred percent desirability which signifies a successful optimization. From the equation (y =5.340E+03), y is the yield or batches per month (i.e. 5.340 exponential 03), which yields 5340 batches per month as the yield after optimization. The red values indicate current values, while the upper and values in their respective rows shows values for high and low variables. The deflections shows decrease or increase of the variables in the raw material mix.

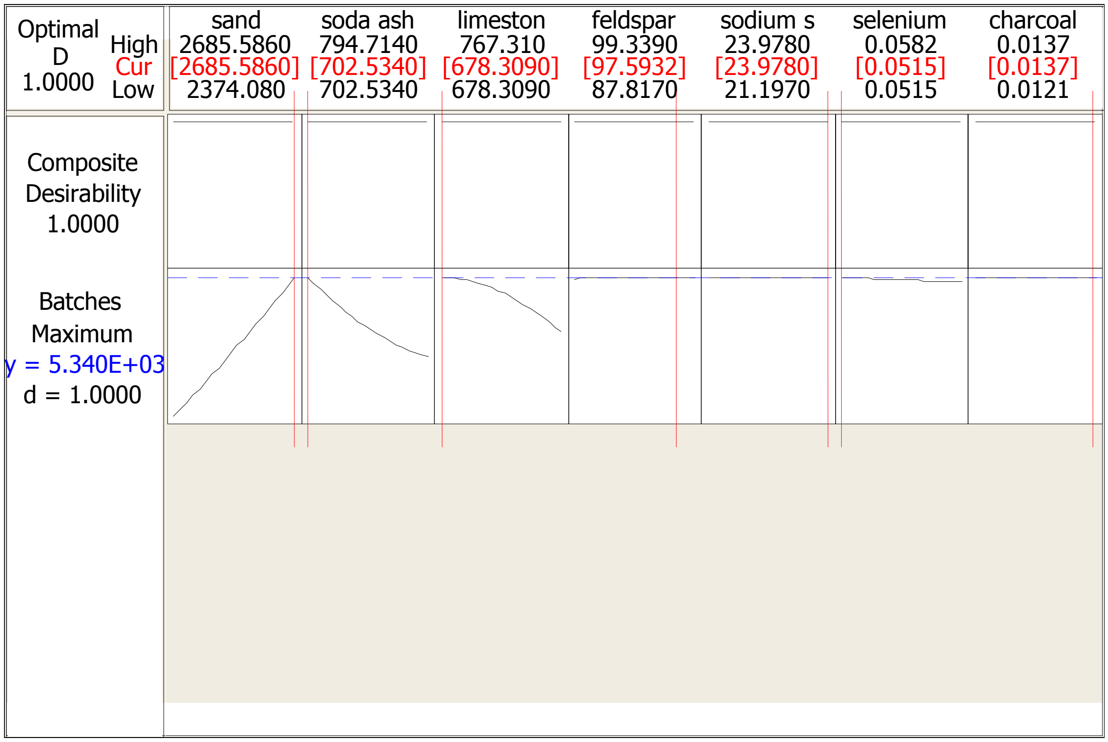

Figure 23: Optimization Plot using Response Surface Methodology

4. CONCLUSION

After the successful analysis of the production process of Beta Glass Company Limited, the results show the optimized yield with Surface response. The end of the analysis showed an increase in production quantity, from an average value of 4,280 batches of bottles per month, to an optimal value of 5,340 batches per month, showing that the case study company was not utilizing their production process for the normal yield.

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