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OPTIMIZATION OF CASTING PROCESS BASED ON BOX BEHNKEN DESIGN AND RESPONSE SURFACE METHODOLOGY

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Abstract: *Sound and accurate castings reveal the quality of a foundry unit. In this case study, an attempt has been made to optimize the production of grey cast pump adapter castings using Box - Behnken design of experiments (DOE) approach in a foundry producing grey cast iron components. Process parameters like Clay percentage, Moisture percentage and Mold hardness were found to be dominant factors to control during the production process. Three different levels of each factor were considered for experimentation using BBD. Experimental trials were conducted using the design matrix and response in each experiment was measured and the results were tabulated. Design Expert software was used to analyse and optimize process parameters for confirmatory experiments. Analysis of Variance (ANOVA) test was conducted to identify significant parameters. The parametrical settings of the confirmatory experiments produced defect free pump adapter castings. The effects of variation of the process parameters and their influence on the quality of the castings were discussed. The research concluded that careful adjustment of process parameters is necessary since bonding strength is directly related to these parameters; in turn have an effect on the quality of castings produced.*

Keywords: *Design of Experiments, Box-Behnken Design, Response surface methodology, Analysis of Variance (ANOVA), Optimization*

1. Introduction

Most of the automotive and allied components in today’s world are produced by metal casting. Sand casting is the oldest method of producing castings in which a molten metal is poured into the mold cavity made of sand. The essential components of sand casting process are sand (Silica, SiO_2), clay such as Bentonite, and water. The silica sand is bonded with clay and water to mold the sand. The silica sand can be used for number of times but each and every time, it is required to add clay and water in a sufficient amount to aid bonding strength. Variation in bonding strength of sand would produce defects in castings. Optimal settings can be defined as the best level of process parameters that would produce the desired response. Optimal settings can be obtained with the parameters like green strength, moisture content, permeability and mold

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hardness using Taguchi and Artificial Neural Network (Lakshmanan, 210). Taguchi method can be used to determine the best parametrical settings for the green sand casting process (Guharaja *et al.*, 2006). Taguchi technique can be successfully used to produce appreciable effect over the produced casting to give the highest value of tensile strength in the ferrous material (Kumar and Singh, 2011). Computer simulation technique can be performed to develop a mathematical model (Makino *et al.*, 2003). Casting defects can be analyzed using design of experiments and computer assisted casting simulation techniques to reduce shrinkage porosity and improve yield (Dabade and Bhedasgaonkar, 2013). Artificial neural networks and genetic algorithms can used to determine best parametrical settings (Karunakar and Datta, 2003; Karunakar and Datta, 2007). Central composite design of experiments can be performed to investigate on parameters like Bentonite, Water and curing time and stated that the sand mixture is a dominant factor that affects the properties of the sand mold (Kundu and Lahiri, 2008). Mixture experimental design and response surface methodology can be used to optimize the composition of the molding sand mixture for reducing the number of casting defects (Saikaew and Wiengwiset, 2012). A strategy to find optimum process factors in casting process and a considerable improvement in the reduction of casting defects to 37.6% was achieved (Upadhye, 2012). In Taguchi methodology, the design desired is finalized by selecting the best performance under conditions that produce a consistent performance. The Taguchi approach provides systematic, simple and efficient methodology for the optimization of near optimum design parameters with only a few well defined experimental sets and determines the main factors affecting the process (Nekere and Singh, 2012). Many research works have been done based on Taguchi's orthogonal array and various other DOE methods. However, the present study provides an insight on use of Box Behnken design of experiments, response surface methodology (RSM) in the iron casting sand mold process for eliminating the defects and improves the quality of castings.

2. Material and methods

A Pareto chart is used to highlight the most frequently occurring defects, the most common causes of defects or the most frequent causes of customer complaints (Awaj *et al.*, 2013). A Pareto analysis was constructed with six months production data of the pump adapter castings. The Pareto chart revealed that blow-hole defect is the key defect that recur and account for the loss in quality of the castings produced as shown in figure 1. The quality of present experiment was analyzed by using Ishikawa diagram. The fishbone diagram (also called Ishikawa diagram) is a tool for identifying the root causes of quality problems (Tegegne and Sing, 2013). Ishikawa diagram helps to identify the key parameters affecting the quality of castings during production. Key parameters namely Clay Content, Moisture content and Mold hardness that were controlling the quality of castings were identified from the fishbone diagram as shown in figure 2.

For carrying out the experiments, following steps were adopted for each setting for the preparation of molds for pump adapter casting. A mass of 200 kg of fresh dry molding sand was taken in the Muller for each experimental setting. Quantities of clay say 4 kg, 6 kg and 8 kg were added along 6 liters, 8 liters and 10 liters of water to molding sand as per requirement. The mold hardness is kept in the range between 70 and 90 psi (5 to 6 kg/cm^2) so that permeability can be maintained within acceptable limits. Mold hardness was tested by means of a portable mold hardness tester which has a steel ball indentation that ranges from 0 to 100 psi (lb/in^2).

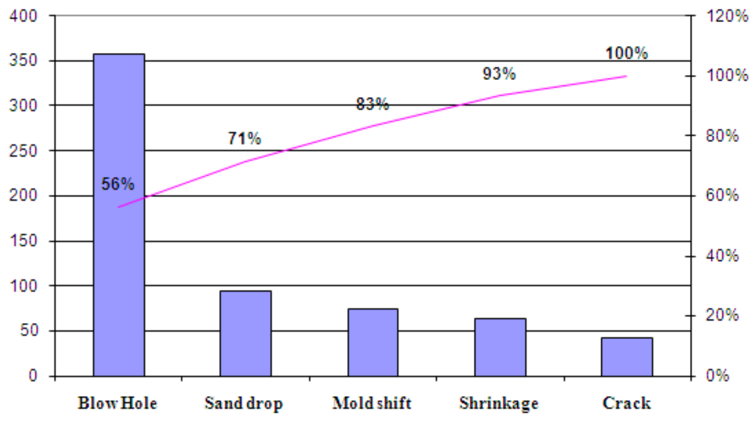

Figure 1. Pareto analysis of defects in castings

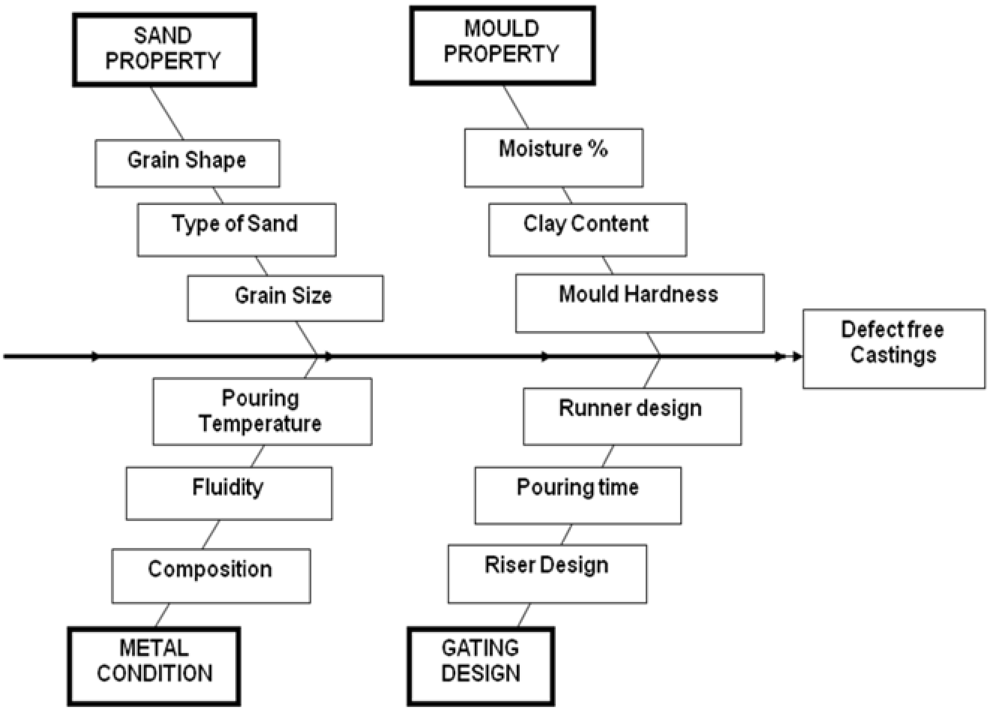

Figure 2. Ishikawa Diagram for Casting defect analysis

The molten metal is poured into molds as per the Box- Behnken design matrix and then allowed to cool and solidify to form castings. With each parametrical setting ten cast adapters were produced. The castings were removed from the mold and were designated as per order of experiment. It was then followed by fettling and shot blasting process. Visual inspection was carried out for defect identification in the cast components. The defective components were separated from the good ones.

3. Theory of experimental design

3.1 Box Behnken experimental design

The main objective of experimental design is studying the relations between the response as a dependent variable and the various parameter levels. It provides an opportunity to study not only the individual effects of each factor but also their interactions. Design of experiments is a method used for minimizing the number of experiments to achieve the optimum conditions (Kwak, 2005). Design of Experiments (DOE) is an effective tool for maximizing the amount of information gained from a study while minimizing the amount of data collected (Kwak, 2005).

Box-Behnken design is an efficient design for fitting second order polynomials to response surfaces. With fewer points and less expensive than central composite designs with the same number of factors, the design ensures that all the process parameters operate in a safe operating level. Box–Behnken design (Telford, 2007; Box and Benhken, 1960; Box *et al.*, 1978) is rotatable second-order designs based on three-level incomplete factorial designs. The special arrangement of the Box–Behnken design levels allows the number of design points to increase at the same rate as the number of polynomial coefficients. For three factors, for example, the design can be constructed as three blocks of four experiments consisting of a full two-factor factorial design with the level of the third factor set at zero (Anderson and dos Santos Walter, 2005). A response surface method, Box-Behnken design, was utilized to carry out the optimal design of the EWMA parameters, λ and L, while the robustness of the control chart was still maintained when there was no shift in the process (Kandananond, 2013).

Setting the objective:

The main objective was to optimize the compositions of new Molding sand, Bentonite (Clay) and water.

Fixing the upper and lower limits of the composition:

The mixing ranges of the new molding sand, bentonite, and water were 90–99.9%, 4 - 6%, and 6 – 10 %, respectively. These ranges were selected from literature and foundry experience as per IS 1987 – 1974 standard. The properties of a product depend on the proportion of the components rather than the quantity of them (Scheffé, 1958). This means that the response is a function of proportion, not of quantity (Anderson and Whitcomb, 2005).

Development of design matrix based on Box Behnken DOE:

The experiments consisted of 15-run Box Behnken design points generated with the aid of Design-Expert® V7 software package (Montgomery, 2001).

Conducting the experiments in design matrix and experimental data:

Mold hardness test was conducted according to the design matrix. There were ten samples produced for each run and the experiments were run in random order to avoid a statistical error in the analyses.

Optimizing the composition for quality improvement of iron castings:

The objective of this study was to optimize response variable of the sand mold (i.e., quality) Implementation of the desirability function and optimization were conducted using the Design-Expert® V7 software package. Design Expert provided a three-dimensional plot of the response surface and a two-dimensional plot of the contour for the response variable and overall desirability of the composition. Design-Expert® is used an optimization method developed by StatEase Inc., (StatEase, 2005) which is described by Myers and Montgomery (Mayrs and Montgomery, 2002; Montgomery, 2001).

Comparing surface and mechanical properties of the iron castings:

The surfaces of the iron castings were analyzed qualitatively from the quality expert of the company and the hardness test was conducted using a Rockwell hardness testing machine in the laboratory.

In this study, the goal is to optimize the response variable y (defect free components). It is assumed that the independent variables like clay percentage, moisture percentage and mold hardness are continuous and controllable by experiments with negligible errors. It is required to find a suitable approximation for the true functional relationship between independent variables and the response surface. Usually a second-order model is utilized in response surface methodology. The objective of this study is to minimize the defects in the cast components that will reduce rejects. Present study emphasizes on the development of an empirical relationship for correlating the parameters like clay percentage, moisture percentage and mold hardness which are predominant in predicting the quality of the castings. The parameters have been optimized using the response surface methodology utilizing the experimental data obtained from experiments. The adequacy of the model was also tested by means of Analysis of Variance (ANOVA). Numerical optimization of the process parameters was achieved for the control of quality in the castings. In the investigation of experiments, the effects of conditions of process parameters like clay percentage, moisture percentage and mold hardness on the quality of castings were studied. This involves a total of 15 experiments as per Box-Behnken design matrix and the coded level of each parameter is shown in Table 1.

Table 1. Coding level of process parameters

Process Parameters	**Designation**	**Range**	**Factor Levels**		
			Level 1	**Level 2**	**Level 3**
Clay (%)	A	2 to 4	2	3	4
Moisture (%)	B	3 to 5	3	4	5
Mold hardness (kg/cm^2)	C	5 to 6	5	5.5	6

4. Response surface modeling

Response surface methodology is a collection of statistical and mathematical methods that are useful for the modeling and analyzing engineering problems. In this technique, the main objective is to optimize the response surface that is influenced by various process parameters. RSM is a collection of mathematical and statistical techniques that are useful for modelling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response(s). Response surface methodology also quantifies the relationship between the controllable input parameters and the obtained response surfaces (Kwak, 2005). The design procedure of response surface methodology is as follows (Gonaraj, and Murugan, 1999):

I. Designing of a series of experiments for adequate and reliable measurement of the response of interest.
II. Developing a mathematical model of the second order response surface with the best fittings.
III. Finding the optimal set of experimental parameters that

produce a maximum or minimum value of response.

IV. Representing the direct and interactive effects of process parameters through two and three dimensional plots.

In order to study the effects of the casting parameters on the above criteria, second order polynomial response surface mathematical model can be developed. RSM designs helps in quantifying the relationship between measured response(s) and the vital input factors. Regression analysis was performed in order to describe the data collected and an empirical variable (response) was approximated based on a functional relationship between the estimated variable (y) and the input variables.

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_1 x_2 + b_5x_1 x_3 + b_6x_2 x_3 + b_7x_1^2 + b_8x_2^2 + b_9x_3^2 + \text{Error} \quad \ldots\ldots\ldots\ldots \quad (1)$$

Response surface methodology helps to understand, evaluate the effects of parameters and their interactions with each other in bringing out the response. All the parameters like clay percentage, moisture percentage and mold hardness can be measured. Hence the response surface can be expressed in terms of all the parameters.

5. Results and discussions

The results obtained by conducting the experiments as per Box-Behnken DOE is presented in the Table 2

Table 2. Box-Behnken Design matrix

Run Order	Clay %	Moisture %	Mold Hardness (kg/cm2)	Defective components in Percentage
1	3	5	6	50
2	2	5	5.5	10
3	3	3	5	30
4	3	4	5.5	20
5	3	5	5	30
6	2	4	6	20
7	2	4	5	0
8	3	4	5.5	20
9	4	4	6	30
10	3	4	5.5	20
11	4	5	5.5	20
12	2	3	5.5	10
13	4	3	5.5	20
14	3	3	6	30
15	4	4	5	20

The results are given as input to the Design Expert Software for further analysis. On examining the fit summary, it was understood that the quadratic model is statistically significant for the response.

5.1 ANOVA analysis

Analysis of Variance (ANOVA) is a proficient statistical decision making tool that is used to test the satisfactoriness of a model for the response in experiments. Table 3 summarizes the analysis of variance (ANOVA) for response surface quadratic model. It is noted that the models of Clay percentage and Mold hardness which have less than 0.05 P-value are statistically significant at 95% confidence level, when the P-values of regression models are considered. Hence it can be understood that Clay percentage and Mold hardness are major contributing factors in controlling defects in castings than moisture percentage.

Table 3. ANOVA analysis (Partial Sum of Squares) for response surface quadratic modelling (Response: Defective %)

Source	**Sum of Squares**	**DOF**	**Mean Square**	**F-Value**	**p-value**	
Model	1765	9	196.11	13.07	0.0056	Significant
A-Clay	312.5	1	312.50	20.83	0.0060	Significant
B-Moisture	50	1	50.00	3.33	0.1275	
C-Mold Hardness	312.5	1	312.50	20.83	0.0060	Significant
AB	0	1	0.00	0.00	1.0000	
AC	25	1	25.00	1.67	0.2532	
BC	100	1	100.00	6.67	0.0493	
A^2	467.31	1	467.31	31.15	0.0025	
B^2	144.23	1	144.23	9.62	0.0268	
C^2	282.69	1	282.69	18.85	0.0074	
Residual	75	5	15			
Lack of Fit	75	3	25			
Pure Error	0	2	0			
Cor Total	1840	14				

The Model F-value of 13.07 implies the model is statistically significant. P-value less than 0.0500 indicate model terms that are significant. In the experiment, A, C, BC, A^2, C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant.

$$Y\ (\text{Defect }\%) = f\ (A, B, C) \quad (2)$$

Where:
A = Clay percentage
B = Moisture percentage
C = Mold hardness

A second order polynomial model equation can be used to find a suitable approximation for the functional relationship between the process parameters and the response surface.

The regression equation reveals the relationship between each of the parameters i.e., clay percentage, moisture percentage and mold hardness using the experimental data. This equation in turn can be used to estimate the expected values of the response.

The predicted response (Defect %) obtained is as follows:

$$Y=1117.5+101.25*A-102.5*B-397.5*C-5*AC+10*BC-11.25*A^2+6.25*B^2+35*C^2 \quad (3)$$

The value of R^2 (0.9592) close to 1, indicate good relation between the experimental and predicted values of the response. The value of adjusted R2 (0.8859) suggests that the total variation of 88.6% for defect is attributed to the independent parameters. The closeness between R2 and adjusted R2 reveals goodness of the model. "Adeq Precision" measures the signal to noise ratio. The obtained ratio of 14.626 can be noted as an adequate signal which is greater than 4 as shown in Table 4.

Table 4. Different statistical values from ANOVA analysis

R-Squared	Adj R-Squared	Pred R-Squared	Adeq. Precision
0.9592	0.8859	0.3478	14.626

Hence, this model can be used to navigate the design space. Taguchi methods can be used to efficiently optimize any manufacturing process by means of orthogonal arrays. However, Response Surface Methodology can be applied specifically where several input parameters greatly influence a performance measure or quality characteristic in a process. ANOVA is useful to segregate the significant parameters in experiments and to estimate the proper level of each important parameter in order to yield optimum end results.

5.1 Model validation

The main purpose of this step is to predict and verify the response using the optimum values of the process parameters involved in the experiments. Normal probability plot of the residuals and the plots of the residuals versus predicted responses for defective % are shown in the figure 3 and figure 4. Figure 3 revealed that the residuals almost fall in a straight line meaning that the errors are distributed normally. Figure 4 revealed that there is no unusual pattern or structure.

Figure 5 shows the perturbation plot exhibiting the effect of process parameters on the quality of castings. It is useful to compare the effect of all factors at a particular point in a design. The response can be plotted by changing one factor over its entire range while keeping the other factors as constant. Parameter A has larger deviation than B and C from the reference point. B and C have little deviations comparatively.

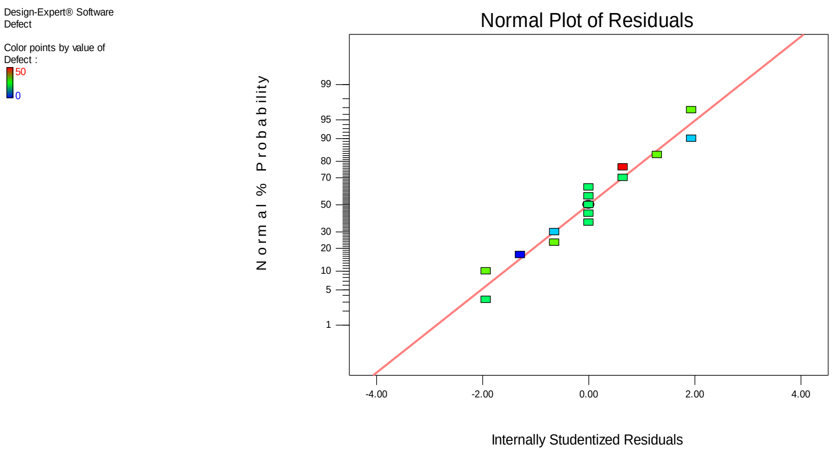

Figure 3. Normal probability plot of residuals for Defective percentage

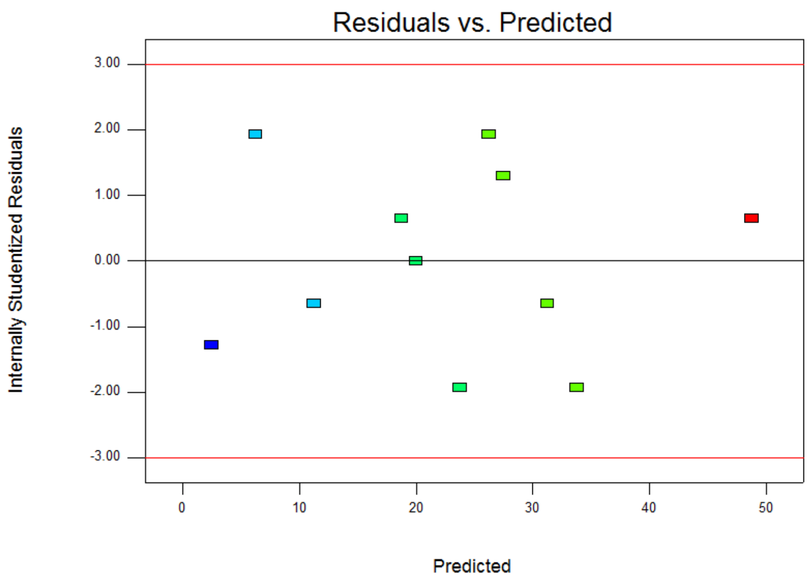

Figure 4. Residuals versus Predicted for Defective percentage

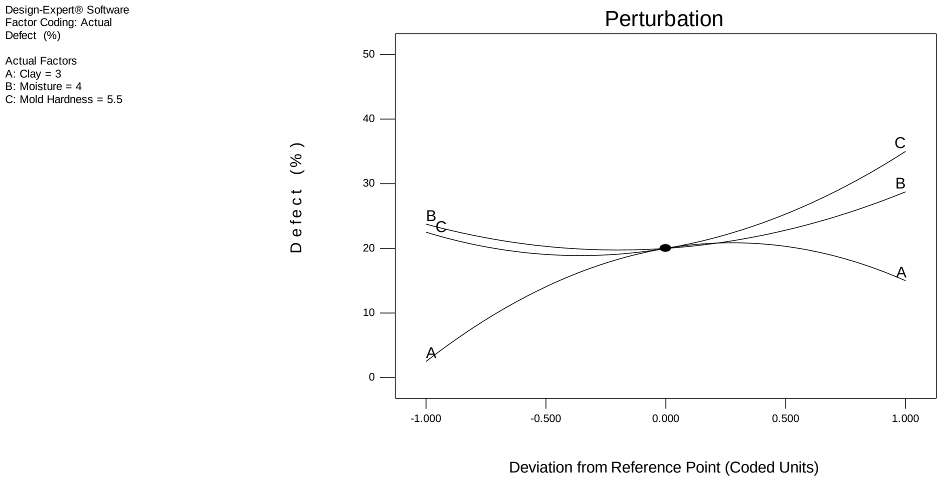

Figure 5. Perturbation plot of defective percentage data

Figure 6 shows the actual versus predicted values of responses while conducting the experiments. It shows that the models are adequate because the residuals in prediction of each response are negligible, since the residuals are close to the diagonal line. The mathematical model including interactions between the parameters indicates that there are strong relations between the considered casting parameters on their effects on the response.

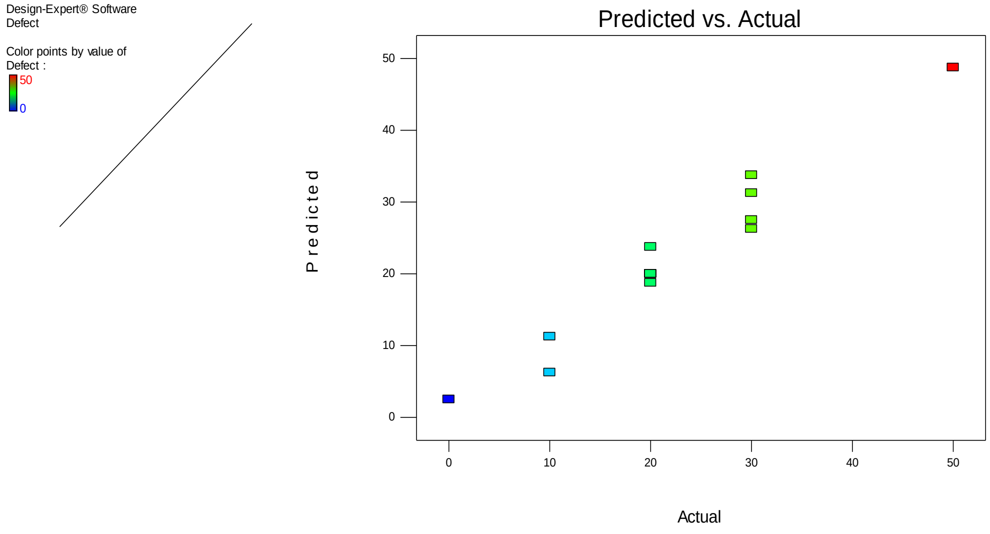

Figure 6. Predicted versus Actual responses

Figure 7 shows a 3D graph plot of clay versus Mold hardness.

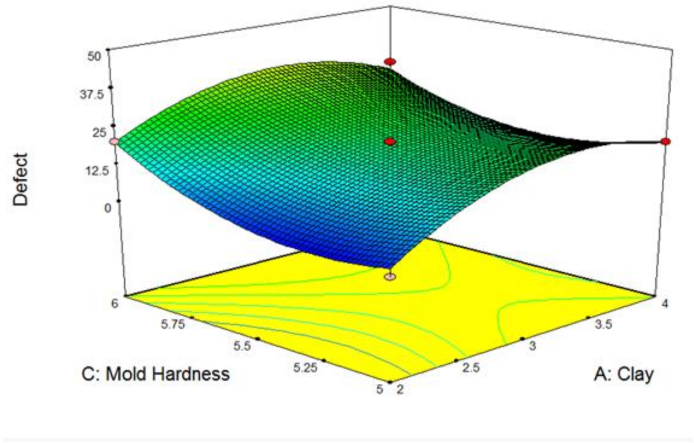

Figure 7. 3D surface graph of Clay versus Mold Hardness

These parameters were found to be significant from the ANOVA analysis. The plot provides a curvilinear profile in relation with the model fitted. The contour plot of the defect percentage with respect to clay and mold hardness is shown in figure 8.

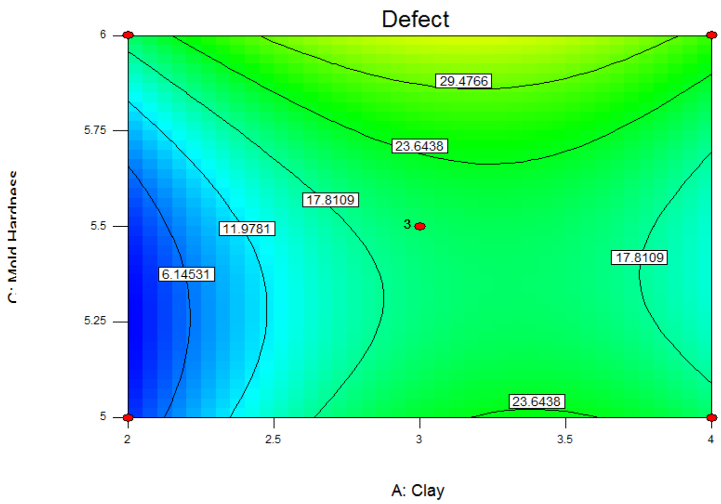

Figure 8. Contour plot of Clay versus Mold hardness

It is clear from the figure that medium clay percentage and mold hardness provided a better quality of castings. With increase in clay percentage, the defects are also noted to be increasing.

6. Optimization

6.1 Numerical optimization

By numerical optimization, the target or the goal of the experiment can be set. Here the aim is to minimize the defective components in pump adapter castings. From Table 5, it was noted that there were 5 possible solutions for minimizing the defect percentage close to zero.

Table 5 Optimal conditions obtained by numerical optimization

Solutions	Clay %	Moisture %	Mold Hardness (Kg/cm2)	Defect %	Desirability
1	2	4.00	5.25	0.31	0.937
2	2	3.96	5.26	0.32	0.936
3	2	4.00	5.21	0.36	0.928
4	2	3.92	5.35	0.61	0.879
5	2	3.87	5.45	1.58	0.684

Confirmation experiments were conducted in the optimal limit settings.

6.2 Confirmation experiments

Before moving to the manufacturing with the optimized setting, it is necessary to perform confirmation experiments to validate the parametric settings. The main purpose of these confirmation experiments is to validate the setting obtained from Design expert software which is likely to achieve the defect free castings. A set of 10 confirmation experiments were conducted three times with the optimal settings producing 30 samples of pump adapter castings. On inspecting the samples for defects, all the 30 castings were found to be defect free.

Table 6. Comparison of existing and experimented settings

S.No	Factors	Existing Range	Experimental Range
1	Clay Percentage	1 %	2%
2	Moisture Percentage	4 %	3.87 - 4%
3	Mold Hardness	No measure	5.21 - 5.45 kg/cm^2
% Approved castings		58.7 %	100 %

Hence, the parametric settings may be taken as optimal for producing large quantities of Pump adapter castings with minimal or no defects. In general, the use of higher clay content and mold hardness with moderate moisture percentage led to better castings as shown in Table 6.

7. Conclusions

In this work, parametric optimization for controlling casting defects in FG 200 Pump adapter was attempted by Box-Behnken design of experiments (DOE). Relevant experiments were conducted in a foundry producing pump components. The major parameters that were responsible for producing casting defects in pump components were identified as proportions of clay, moisture and Mold hardness respectively. Each parameter was analyzed with three different levels. Further the contribution of the parameters was analyzed using ANOVA technique to find their effects. Interaction effects between the factors were also studied.

F-Test of the ANOVA revealed that the parameters of proportion of clay and Mold hardness were equally significant in the casting process. These parameters were noted to be more critical in producing quality cast components.

The optimized parametric setting was determined by Design expert software:

Clay – 2%

Moisture – 3.87 to 4 %

Mold Hardness – 5.21 to 5.45 kg/cm^2 as a range of values for the input conditions that can be easily practiced by workmen in industries.

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References:

Anderson S.S., dos Santos Walter N.L. (2005). Ferreira Se´rgio LC. Application of Box–Behnken design in the optimization of an on-line pre-concentration system using knotted reactor for cadmium determination by flame atomic absorption spectrometry. *Spectrochimica Acta* Part B *609*, 737–42.

Anderson, M.J., Whitcomb, P.J. (2005). *RSM Simplified: Optimizing Process Using Response Surface Methods for Design of Experiments*. Productivity Press, New York.

Awaj, Y.M., Singh, A.P., & Amedie, W.Y. (2013). Quality improvement using statistical process control tools in glass bottles manufacturing company, *International Journal for Quality research, 7*(4)*, 107- 126.*

Box, G.E.P., & Benhken, D.W. (1960). *Technometrics*, 2, 195.

Box, G.E.P., Hunter, W.G., & Hunter, J.S. (1978). *Statistics for experimenters*. New York: Wiley.

Dabade U.A., & Bhedasgaonkar, R.C. (2013). Casting Defect Analysis using Design of Experiments (DoE) and Computer Aided Casting Simulation Technique, *Forty Sixth CIRP Conference on Manufacturing Systems*, Procedia CIRP 00 (2013) 000–000.

Guharaja, S., Noorul, H.A., & Karuppannan, K.M. (2006). Optimization of green sand casting process parameters by using Taguchi's method. *International Journal of Advanced Manufacturing Technology, 30,* 1040–1048.

Gunaraj, V., & Murugan, N. (1999). Application of response surface methodologies for predicting weld base quality in submerged arc welding of pipes. *Journal of Material Processing Technology*, *88*, 266–75.

Kandananond, K. (2013). The application of Box-behnken method to optimize the design of EWMA chart for autocorrelated processes, *International Journal for Quality research 7*(2), 175-186.

Karunakar, D.B., & Datta, G.L. (2003). Modelling of green sand mold parameters using artificial neural networks, *Indian Foundry Journal*, *49*(12), 27–36.

Karunakar, D.B., & Datta, G.L. (2007). Controlling green sand mold properties using artificial neural networks and genetic algorithms-a comparison. *Applied Clay Science 37* (1–2), 58–66.

Kumar, A., & Singh, J. (2011). Optimization of Sand Casting Process Parameters for Ferrous Material by using Design of Experiments, *International Journal of Emerging Technologies 2*(2), ISSN: 0975- 8364, 122-127.

Kundu, R.R., & Lahiri, B.N. (2008). Study and statistical modelling of green sand mold properties using RSM, *International Journal of Materials and Product Technology,* 31 (2/3/4), 143–158.

Kwak, J.S. (2005). Application of Taguchi and response surface methodologies for geometric error in surface grinding process. *International Journal of Machine Tools Manufacturing*, *45*, 327–34.

Lakshmanan, S. (2010). Improving Quality of Sand Casting using Taguchi Method and ANN analysis, *International Journal on Design and Manufacturing Technologies*, 4(1).

Makino, H., Hirata, M., & Hadano, Y. (2003). Computer simulation and optimization of sand filling using the distinct element method. *WFO Technical Forum*.

Montgomery, C.D. (2001). *Design and analysis of experiments*. Singapore: John Wiley and Sons, Pte. Ltd.

Myers, R.H., & Montgomery, D.C. (2002). *Response Surface Methodology Process and Product Optimization Using Designed Experiments, 2nd ed*, Wiley Interscience, New York.

Nekere, M.L., & Singh, A.P. (2012). Optimization of Aluminium blank sand casting process by using Taguchi's Robust design method, *International Journal for Quality research*, *6*(1).

Saikaew, C., & Wiengwiset, S. (2012). Optimization of molding sand composition for quality improvement of iron castings, *Applied Clay Science*, *67-68*, 26-31

Scheffé, H. (1958). Experiments with mixtures. *Journal of Royal Statistical Society Series B*(20), 344–366.

StatEase, (2005). *Inc., Design Expert 7 User's Guide*, Minneapolis.

Tegegne, A., & Singh, A.P. (2013). Experimental Analysis and Ishikawa diagram for Burn on Effect on Manganese silicon alloy medium carbon steel shaft, *International Journal for Quality research*, *7*(4), 545-558.

Telford, J.K. (2007). A Brief introduction to Design of Experiments, *Johns Hopkins APL Technical Digest*, 27(3).

Upadhye, R.A. (2012). Optimization of Sand Casting Process parameter using Taguchi Method in Foundry, *International Journal of Engineering Research & Technology*, *1*(7), ISSN: 2278-0181.

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