Box-Behnken Design Optimization of Sand Casting Process Parameters

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Abstract- Sand casting is reputed for the manufacture of engine components as a result of its ease of operation. An assemblage of process parameters at optimal conditions leads to enhanced mechanical properties of automobile engine components. The Response Surface Methodology Design of experiment created an experimental layout for the sand casting process parameters and the various levels as applied in the production of engine pistons at the foundry. The Box-Behnken Design provided a matrix of 27 experiments to be conducted. Multiple linear Regression technique was employed to develop a mathematical model for the hardness of the aluminium alloy. The developed model was inputted into the evolutionary Genetic Algorithm tool box as an objective model. The optimal levels determined from the Genetic algorithm were used to carry out actual experiment in the foundry and the result was similar to the predicted hardness value of the developed model. Statistical ANOVA test conducted showed that the mathematical model was adequate with a R^2 value of 81.02% and R^2 (adjusted) value of 60.07%. The developed model has a p-value of 0.016 which indicates that the model was significant. The optimal values obtained for pouring temperature, vibration frequency, vibration time and runner size are 700°C, 31.52Hz, 59.998sec and 469.69mm² respectively.

Keywords: Sand casting, Box-Behnken, Genetic algorithm and Statistical ANOVA

1. Introduction	optimize process parameters and its
In the Design of experiment,	corresponding response variables in an
Response Surface Methodology (RSM)	output-input relationship [2]. These designs
comprises of mainly two nonlinear models	are important for fitting second order
which are Box-Behnken Design (BBD) and	regression polynomial to dimensional
Central Composite Design (CCD) [1]. It is a	response surfaces. The main aim of
technique whose prime objective is to	Response Surface Methodology (RSM) is
	for optimization [3].

This study entails optimization of 4 process parameters (A, B, C, and D) and their response variable.

Box-Behnken Design is an experimental design and a nonlinear model of Response Surface Methodology developed by Box and Behnken in 1960 [4]. Box-Behnken Design creates The an experimental matrix necessary for the combination of the process parameters conditions [5]. The design helps to develop quadratic response surface model which is used for the estimation or prediction of the response values [6].

Optimization technique involves the finding of maximum or minimum value of a function of a set of variables subject to some constraints [7]. In casting, optimization of process parameters are carried out by the following techniques, Finite element, Taguchi design, Response surface Methodology, Genetic algorithm, Artificial Neural network and Particle swarm Algorithm.

In analyzing the effect of mechanical properties on internal combustion engine pistons, an examination of the ultimate yield strength of Al-GHS 1300 was done by [8]. The study showed that the aluminium alloy posses a very high ultimate yield strength of about 1300Mpa when compared to other aluminium alloy and composites.

A study on the hardness of Silumin cast piston alloy was carried out by [9]. It investigated the effect of hardness of the cast engine piston. The study inferred that high hardness of the piston alloy offers great resistance to wear and fatigue of the piston component in an engine.

A mathematical model using a Box Behnken Design made of 3 factors and levels which was used to optimize the process parameters involved in evaluating Pharmaceutical complexes [10]. It was concluded that the resveratrol ratio had

greater influence on the two responses than temperature and time. The checkpoint and R^2 values were very high which shows that the optimization was properly validated. An investigation of the optimization of process parameters of organic ester distillation using Response Surface Methodology was done by [10]. The process parameters employed in the distillation are reboiler duty, reflex and feed ratios. The response variable in this study is the mole fraction of the organic ester. The Minitab software was used to develop Behnken the Box Design experimental matrix needed to display the conditions for the various distillation of 15 process. А total randomized experiments were carried out and the various responses recorded. In analyzing the Box Behnken Design of the Response Surface Methodology a regression model containing main, squared and interaction terms was developed. A confidence level of 95% was employed to determine which of the factors are considered significant. The optimized set of conditions of the process parameters was used for validation of the experiment and the mole fraction of the ester was found to be 0.8435 which showed a great correlation between the theoretical value and the measured organic ester.

Box Behnken Design and Central Composite Design of the Response Surface Methodology were used by [11] to model relationship between responses and the process parameters for squeeze casting. The process parameters of squeeze casting examined in the study are squeeze pressure, pressure duration, die temperature and pouring temperature. A high and low operating level was also assigned to each process parameter. The experiments were conducted to determine 3 selected responses which are Yield strength, ultimate tensile strength and Surface roughness.

The developed models were statistically subjected to model adequacy test. Surface plot showed that parameters like die temperature, squeeze pressure and pouring temperature contributed greatly to the surface roughness model. The study exhibited 15 random test cases that were used to make prediction on the responses by applying the developed model. The response surface roughness had better prediction of test cases for Central Composite Design (CCD) than the Box Behnken Design (BBD) when compared.

Also. а 4-process parameter optimization of EN 19 carried out by [12] used a Box-Behnken Design of Response Surface Methodology to create an experimental matrix in investigating the effect of flow rate of coolant, speed, depth and feed rate of the molten steel on a Material Removal Rate (MRR). A number of 28 experiments of varying conditions were observed. The nonlinear Box-Behnken

Design second order quadratic regression developed. model was The obtained quadratic regression model was used as the objective function for the Genetic Algorithm. It was concluded in the study that the 4 process parameters had great influence on the Materials Removal Rate (MRR).

This study is aimed at optimizing sand casting process parameters using the Box-Behnken Design experimental methodology.

2.0 Materials and Methods

The production of the cast component was carried out by the sand casting process. The mould cavity was prepared to readily accept the molten metal when poured and to help reduce the number of wasteful casting. The mould cavity has the core made of green sand well placed in it to create an internal cavity for the piston. The molten metal was scooped out from the

Crucible on the furnace with the aid of a ladle and introduced into the mould through the pouring basin to the runner before entering the casting cavity. The scrap pistons were heated in the crucible furnace and it attained its molten state for duration of fifty minutes. The pouring temperatures were measured with the aid of digital thermocouple. The molten metal was poured into the already prepared mould cavity on the mould vibrating machine. The poured molten metal was vibrated by the machine during solidification at selected frequency of 10 Hz, 30 Hz and 50 Hz. The Rockwell hardness machine was used to determine the hardness value of the aluminium alloy component. The process parameters used in this experiment are shown in Table 1.

Table 1.0: Process	parameters and their various levels
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Process parameters	LEVELS			
	Level 1	Level 2	Level 3	
Pouring temperature, A (⁰ C)	700	725	750	
Vibration Frequency, B(Hz)	10	30	50	
Vibration time, C (seconds)	30	45	60	
Runner size (mm ²)	180	335	490	

2.1 Box-Behnken Design (BBD)
The Response Surface Methodology
design procedure used in this study as stated
by [13] is as follows

- I. Design of experimental matrix for conducting of the experiment using the conditions ascribed to the process parameters
- II. Developing a column for the response variables after the specified number of runs

- III. Developing a mathematical second order regression response model
- IV. Predicting various response values from each set of process parameters values so as to ascertain the optimal combination
- V. Determining main and interaction effects of experimental parameters through dimensional plots.

The general form of equation for Response Surface Methodology (RSM) is representing a 4-parameter response (Y) in a

$$Y = F(A, B, C, D) \tag{1}$$

 $Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 D + \beta_5 A^2 + \beta_6 B^2 + \beta_7 C^2 + \beta_8 D^2 + \beta_9 A B + \beta_{10} A C + \beta_{11} A D + \beta_{10} A C + \beta_{11} A D + \beta_{10} A C + \beta_{11} A D + \beta_{10} A C + \beta_$

$$+\beta_{12}BC + \beta_{13}BD + \beta_{14}CD + \varepsilon \tag{2}$$

Where A, B, C, and D are the process parameters. While

B₀, β_1 , β_2 , β_3 , β_4 ------ β_{14} are the regression coefficients

The quadratic model developed contains main, squared and interaction terms [14]. The nonlinear model is notable in the Response Surface Methodology (RSM) for addressing experimental design of a minimum of 3 factors and 3 levels [15]. Box-Behnken Design has an advantage of fewer numbers of runs or experiments than Central Composite Design involving 3 or 4 process parameters. In this study, Box-Behnken Design of Response Surface Methodology was employed in carrying out the experiment. Minitab 17 software was used in getting the experimental matrix. The design matrix has a stipulated 27 runs for a

4-process parameter and 3-level experiment. The experimental matrix contains the columns of various factor levels {high (+1), medium (0) and low(-1)}, experimental run orders and the standard orders. The run order was used to conduct the experiments and the standard orders were used for the randomization of experiment and the actual order of the experiment. The randomization ensures independency among the conditions in the various runs. The Box-Behnken experimental design matrix used for obtaining the hardness response values is shown in Table 2.

3. Results and discussion

Hardness Testing Machine is presented in

The results from the hardness Table 2.

experiment conducted using Rockwell

Table 2: Box-Behnken Experimental Values for Hardness

Run	Standard	Pouring	Vibration	Vibration	Runner	Hardness
order	Order	temp,A(°C)	frequency,B(Hz)	time,C(sec)	size,D(mm ²)	Н
1	19	700	30	60	335	67.9
2	15	725	10	60	335	62.7
3	12	750	30	45	490	53.5
4	1	700	10	45	335	55.5
5	6	725	30	60	180	62.6
6	8	725	30	60	490	64.0
7	23	725	10	45	490	57.8
8	5	725	30	30	180	61.0
9	9	700	30	45	180	65.0
10	14	725	50	30	335	63.8
11	13	725	10	30	335	56.6
12	2	750	10	45	335	56.8
13	3	700	50	45	335	60.0
14	16	725	50	60	335	64.6
15	4	750	50	45	335	57.0
16	25	725	30	45	335	69.5
17	10	750	30	45	180	70.0
18	18	750	30	30	335	68.5
19	20	750	30	60	335	59.8
20	26	725	30	45	335	65.5
21	17	700	30	30	335	58.5
22	27	725	30	45	335	68.5
23	11	700	30	45	490	72.1
24	7	725	30	30	490	61.0
25	21	725	10	45	180	57.8
26	22	725	50	45	180	62.0
27	24	725	50	45	490	59.9

In this study a multiple linear regression is needed to establish a relationship between the Hardness as response variable and the various process parameters.

A multiple linear regression model as given response variable Y and predictor variables in equation 3 shows a relationship of A_1, A_2, A_3 and A_4 $Y = \beta_0 + \beta_1 A_1 + \beta_2 A_2 + \beta_3 A_3 + \beta_4 A_4 \dots \dots \dots + \beta_k A_k + \varepsilon$ (3) where β_0 = intercept and $\beta_1, \beta_2, \beta_3, \beta_4$ are are independent variables and ε stands for regression coefficients. Also A_1, A_2, A_3, A_4 the error term

3.1 Box-Behnken Design Analysis for Hardness

The mathematical model for hardness developedregression model of Box-Behnken Design is as givenusing the Response Surface Methodology nonlinearin equation 4

 $H = -2816 + 6.75A + 2.83B + 9.51C + 1.157D - 0.00392A^2 - 0.01550B^2 - 0.00733C^2$ $- 0.000091D^2 - 0.00215AB - 0.01200AC - 0.001523AD - 0.00442BC$

-0.000169BD + 0.000151CD

3.2 Significance Test for the Box-Behnken Design Regression Model for Hardness H

Significance test was carried out for the hardness model obtained from the nonlinear Box-Behnken experimental matrix. The essence of the test is to ascertain the significance of the main, multiple and interaction parameters present in the regression model. The Table 3 depicts the analysis of variance (ANOVA) for the Box-Behnken regression model for hardness.

(4)

Table 5: Analysis of Variance (ANOVA) for Box-Bennken Regression Model for Hardness					
Source	Degree of	Adj SS	Adj MS	F-value	P-value
	Freedom				
Model	14	511.11	36.51	3.61	0.016
Linear	4	69.96	17.49	1.73	0.208
А	1	15.19	15.19	1.50	0.244
В	1	33.67	33.67	3.33	0.093
С	1	12.61	12.61	1.25	0.286
D	1	8.50	8.50	0.84	0.378
Square	4	207.66	51.92	5.13	0.012
A^2	1	32.01	32.01	3.16	0.100
B^2	1	205.01	205.01	20.25	0.001
C^2	1	14.52	14.52	1.43	0.254
D^2	1	25.23	25.23	2.49	0.001
2-way Interaction	6	233.48	38.91	3.84	0.023

Table 3: Analysis of Variance (ANOVA) for Box-Behnken Regression Model for Hardness

INTERNATIONAL JOURNAL of ENGINEERING	TECHNOLOGIES-IJET
Aliemeke and Oladeinde, Vol.6, No.2, 2020	

AB	1	4.62	4.62	0.46	0.512
AC	1	81.00	81.00	8.00	0.015
AD	1	139.24	139.24	13.75	0.003
BD	1	1.10	1.10	0.11	0.747
CD	1	0.49	0.49	0.05	0.830
Error	12	121.502	10.13		
Lack of fit	10	112.84	11.28	2.60	0.309
Pure error	2	8.67	4.33		
Total	26	632.61			

 $R^2 = 81.02\%$ R^2 (Adj) = 60.07%

The Box-Behnken Design (BBD) hardness model showed that two squared effect terms (B^2 and D^2) and two interaction terms (AC and AD) are significant. Also the sharp difference between the R^2 and R^2 (adj) values shows that over fitting occurred in the model. A further test on the model adequacy was carried out by applying the Normal probability and residual plots as shown in Fig. 1



Fig. 1: (a) Normal Probability plot for the Nonlinear Hardness (b) Residual plot for the Hardness Data

The normal probability plot shown in Fig. 1 (a) indicates that the proximity between the residual points and ideal normal distribution diagonal line is very high and this connotes that the data is normally distributed. Also the Fig. 1 (b) showed that the variation of residuals of the treatment levels and the distribution of data satisfy the normality condition.

Also Response surface plot was carried out for the various interaction terms involved in the Box-Behnken Design hardness model. The plot shown in Fig. 2(b) shows that the interaction between pouring temperature and the vibration time is very significant and it also result in high hardness value. The plots on Figs. 2 a, c and d showed interaction of process parameters that have moderate effect on the hardness value.



(C)

(**d**)

Fig. 2: (a-d) Response Surface Plots for Hardness Interaction Terms

3.3 Genetic Algorithm Analysis for the Developed Equation

The regression models obtained through multiple linear regressions were used as the objective function in the MATLAB genetic algorithm tool. The population size used was 50, number of variable used is 4, crossover and mutation probability adopted are 85% and 0.01 respectively. A number of 100 generations and 100 seconds time limit were used for the optimization.

Lower bound of parameters = {700, 10, 30, 180}

Upper bound of parameters = {750, 50, 60, 490}

The Table 4 shows the tested levels used in the hardness model from the genetic and best optimal levels for the parameters algorithm tool.

Factor	Parameter	Level range	Optimal level
А	Pouring temp(0C)	700-750	700.000
В	Vibration frequency(Hz)	10-50	31.523
С	Vibration time(secs)	30-60	59.998
D	Runner size	180-490	469.696

 Table 4: Result of Optimal Levels from Genetic Algorithm on BBD Hardness Model

The fitness value is 70.789

3.4 Validation of Models

In addition to the model validation carried out by ANOVA and R² statistic further model validation was carried out for the developed models by performing experiment using the determined optimal values. The predicted values were determined by inputting the optimal conditions obtained from the optimization model into the developed nonlinear regression models. Also, the conditions were used to carry out actual experiment and the obtained results were compared with the predicted values.

4. Conclusion

The Box-Behnken Design of experiment was used to develop an

experimental layout for the parameters and the various levels applied in this study. It provided an experimental matrix of 27 runs which were conducted and the test results recorded. Multiple linear Regression technique was employed to develop a mathematical model for the response. Statistical ANOVA test conducted showed that the model was adequate with a R^2 (adjusted) value of 60.07%. The developed model has a p-value of 0.016 which indicates that the model was significant. The values obtained for optimal pouring temperature, vibration frequency, vibration time and runner size are 700°C, 31.52Hz, 59.998sec and 469.69mm² respectively. The developed optimal levels were used to carry

Aliemeke and Oladeinde, Vol.6, No.2, 2020

out actual experiment in the foundry and the

result was similar to the predicted hardness

value of the developed model.

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