International Journal of Engineering and Mathematical Intelligence
Volume 6, Number 1, April 2019
ISSN: 2276-8815
Published By
International Centre for Integrated Development Research, Ikot Ekpene, Nigeria
In collaboration with
Copperstone University, Luanshya, Zambia.

Modeling and Optimization of Sand Casting Process

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ABSTRACT

The manufacture of quality engine components has always been a major focus in the technological world. One of the easiest and affordable means of realizing high quality automobile components and casting integrity is sandcasting. In order to produce quality casting it will be important to carry out the experiment in a developed layout using Design of Experiment technique. A nonlinear mathematical model used for the prediction of hardness was developed by the Response Surface Methodology. ANOVA result showed that the developed model is adequate with R^2 (adjusted) of 50.05% and R^2 of 71.09%. The difference in the coefficient of determination values indicate that there exist over fitting in the developed model. The developed model was used as objective function in the evolutionary Genetic algorithm tool box to determine the optimal level of the process parameters. The optimal parametric setting for sand casting as investigated by the study is 680^0C, 31.524Hz, 59.998 seconds and $309.696mm^2$ for pouring temperature, vibration frequency, vibration time and runner size respectively. A confirmatory test carried out showed that the actual experimented values are similar to the predicted values.

Keywords: *Response Surface Methodology, Genetic Algorithm, Sand casting and Nonlinear model*

INTRODUCTION

The technological world is awash with various manufacturing processes in the production of engine components. Sandcasting has so many advantages in the world of manufacturing components (Mohiuddin, Krishnaiah and Hussainy, 2015). It has an advantage of making use of relative cheap materials like silica sand, green sand clay and water (Upadhye and Keswani, 2012). Automobile engine components like cylinder head and pistons are known to be produced through sandcasting (Ozioko, 2011). Entrepreneurs target high quality

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manufactured products at the same time minimizing production cost. That is why it is important to have well planned layout occasioned by Design of Experiment (Montgomery and Runger, 2003). A robust designed formulation by Design of Experiment will ensure that the parametric conditions employed in a production system are optimally set (Kumar and Grewal, 2013). The important Design of Experiment used are Taguchi orthogonal design, full factorial design and Response Surface Methodology (Patel, Krishna and Parappagouder, 2015). The Taguchi Design is a technique reputed for a fewer number of experimental runs while targeting high quality product at a very low cost of production (Oji, Sunday and Adetunji, 2013). The Full Factorial technique is applied when all the necessary combinations of factor levels in an experimental trial are to be observed (Mudakappanavar and Nanjundaswamy, 2013). The total experiment to be conducted can be estimated by expressing the level of the parameter, n to the index power of the number of process parameters, p (i.e n^p) (Mohiuddin, Krishnaiah and Hussainy, 2015).

The Response Surface Methodology is a nonlinear model used for estimating main, multiple and interaction terms (Manohar, Joseph, Selvaraj and Sivakumar, 2013). It also show the local shape brought about by the interaction effects (Patel, Krishna, Vundavilli and Parappagouder 2016). The Response Surface Methodology comprises mostly of two nonlinear models which are Central Composite Design (CCD) and Box-Behnken Design (BBD) (Anuar, Adnan, Saat, Aziz and Taha, 2013).

In this study the Box-Behnken Design was adopted for its fewer number of runs and dexterity for handling a 4 parameter and 3 level design. The Box-Behnken Design experimental matrix provided a layout for 27 randomized runs for the parametric conditions (Manohar, Joseph, Selvaraj and Sivakumar, 2013). A number of related literature has shown that the Box-Behnken Design is efficient and dependable (Patel et al, 2016). Agarwal, Kharb and Saharan (2014) developed 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. The 3 process parameters considered in the study are temperature, time and resvaratrol ratio. The experiment was carried out in 3 levels each for the process parameters. The models developed were used to predict the responses for the 15-run test and to determine the optimal set of process parameters. 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

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In a related development, Patel, Krishna and Parappagouder (2015) modeled relationship between responses and the process parameters for squeeze casting by using the Response Surface Methodology nonlinear models. Box Behnken Design and Central Composite Design are the Response Surface Methodology nonlinear models (Praveen and Arun, 2015) employed in this study. The process parameters of squeeze casting examined in the study are squeeze pressure, pressure duration, die temperature and pouring temperature. In a similar development, a 4-process parameter optimization of EN 19 carried out by Praveen and Arun (2015) 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 technological world makes great use of sand casting in the manufacture of engine components (Patel, 2014). Very few researchers on sand casting had embarked on determining optimal levels of input parameters necessary for the manufacture of automobile components. Also, there exist huge challenge in modeling and analyzing engineering and manufacturing processes for optimal application for mankind. This study aims at developing suitable mathematical model that can predict hardness of a sandcast aluminum silicon alloy component. The specific objectives are as follows:

i. To determine of chemical composition of aluminium alloy scraps,
ii. To develop of Box-Behnken Design for the conduction of experiments
iii. To development of sandcast aluminium silicon alloy
iv. To determine of hardness of the various casting
v. To develop of an empirical mathematical model that can predict hardness.
vi. To determine of the optimal levels of the sandcast process parameters using Genetic algorithm.

MATERIALS AND METHOD

The materials used in this study are graphite crucible furnace, digital thermocouple, aluminium alloy scraps, mechanical mould vibrating machine, frequency meter, stop watch and Rockwell hardness testing machine. The experimental research entails carrying out sandcasting operation using some process parameters. In the Design of experiment, Response Surface Methodology (RSM) which comprises of mainly two nonlinear models - Box-

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Behnken Design (BBD) and Central Composite Design (CCB) was employed in this study. Box-Behnken Design was adopted in this study for its advantage of fewer numbers of runs or experiments than Central Composite Design involving 3 or 4 process parameters (Patel *et al*, 2016). 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 (Patel, 2014). 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 3

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

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 D + \beta_5 A^2 + \beta_6 B^2 + \beta_7 C^2 + \beta_8 D^2 + \beta_9 AB + \beta_{10} AC + \beta_{11} AD + \beta_{12} BC + \beta_{13} BD + \beta_{14} CD \qquad \text{...............................1}$$

Where A, B, C, and D are the process parameters, while $\hat{A}_0$, $\hat{a}_1, \hat{a}_2, \hat{a}_3, \hat{a}_4 \ldots \hat{a}_{14}$ are the regression coefficients.

The process parameters and levels used in this study resulted from deep review of related literature of Patel (2014) and Oji, Sunday and Adetunji (2013). The process parameters and their levels are shown in table 1.

Table 1: Process parameters and their various levels

Process parameters	**LEVELS**		
	L_1	**L_2**	**L_3**
Pouring temperature,A (^{0}C)	680	710	740
Vibration Frequency,B(Hz)	20	35	50
Vibration time,C (seconds)	20	40	60
Runner size,D (mm^2)	180	245	310

Source: Researcher

Aluminium-Silicon alloys scraps were collected from various metal scavenging points and recycled through melting process. Sand casting process was adopted in this study. The experiment was carried out in accordance with the parametric conditions prescribed by the Box-Behnken Design experimental matrix for 4 process parameters with 3 levels each. The Al-Si alloy scraps was charged into a crucible furnace and heated to a temperature of 750^{0}C as indicated by a digital thermocouple. The sand casting was done on a mechanical

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mould vibrating machine with an attached variable frequency machine for effective grain refinement. The molten metal was poured into silica sand mould made with various sizes of runners. The resultant casting was made into specimen of diameter 10mm and length 16mm. Rockwell Hardness testing machine (Oji, Sunday and Adetunji, 2013) was used to measure the hardness of the Al-Si alloy. Also, the spectrographic test result shown in table 2 was carried out to determine the chemical composition of the aluminium alloy

RESULTS AND DISCUSSION

The spectrographic test was conducted to determine the chemical composition of the aluminium alloy. The test result is shown in table 2.

Table 2: Chemical composition of Al-Si alloys

Element	**Si**	**Mg**	**Al**	**Ti**	**Cr**	**Mn**	**Fe**	**Ni**	**Cu**	**Zn**	**Pb**	**Sb**
Composition	**12.04**	**0.02**	**77.78**	**0.01**	**0.02**	**0.87**	**1.44**	**0.20**	**3.04**	**4.38**	**0.17**	**0.02**

Source: Researcher

Table 3: Box-Behnken experimental values for hardness

Run order	Standard Order	Pouring temp, A (^{0}C)	Vibration frequency, B (Hz)	Vibration time, C (sec)	Runner size, D (mm^2)	Hardness H
1	19	680	35	60	245	62.8
2	15	710	20	60	245	53.6
3	12	740	35	40	310	67.8
4	1	680	20	40	245	55.6
5	6	710	35	60	180	62.6
6	8	710	35	60	310	64.0
7	23	710	20	40	310	56.8
8	5	710	35	20	180	60.0
9	9	680	35	40	180	63.0
10	14	710	50	20	245	65.8
11	13	710	20	20	245	54.6
12	2	740	20	40	245	60.8
13	3	680	50	40	245	58.0
14	16	710	50	60	245	68.6
15	4	740	50	40	245	56.0
16	25	710	35	40	245	68.5
17	10	740	35	40	180	59.0
18	18	740	35	20	245	63.5
19	20	740	35	60	245	57.8
20	26	710	35	40	245	70.5
21	17	680	35	20	245	56.5
22	27	710	35	40	245	62.5
23	11	680	35	40	310	58.1
24	7	710	35	20	310	57.6
25	21	710	20	40	180	60.8
26	22	710	50	40	180	60.0
27	24	710	50	40	310	58.9

Source: Researcher

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Box-Behnken Design Analysis for hardness

The mathematical model for hardness developed using the Response Surface Methodology nonlinear regression model of Box-Behnken Design is given as:

....3

Significance test for the Box-Behnken Design regression model for hardness H

Significance test was carried out for the hardness model obtained from the non linear 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 4 depicts the analysis of variance (ANOVA) for the Box-Behnken regression model for hardness.

Table 4: Analysis of Variance (ANOVA) for Box-Behnken regression model for hardness

Source	DF	Adj SS	Adj MS	F-value	P-value
Model	14	341.911	24.951	1.57	0.000
Linear	4	69.96	17.49	1.73	0.284
A	1	15.19	15.19	1.50	0.341
B	1	33.67	33.67	3.33	0.053
C	1	12.61	12.61	1.25	0.331
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	0.799
D^2	1	25.23	25.23	2.49	0.016
2-way Interaction	6	233.48	38.91	3.84	0.020
AB	1	4.62	4.62	0.46	0.050
AC	1	81.00	81.00	8.00	0.474
AD	1	139.24	139.24	13.75	0.171
BD	1	1.10	1.10	0.11	0.044
CD	1	0.49	0.49	0.05	0.642
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			

$R^2 = 71.02\%$ $R^2(Adj) = 50.07\%$

Source: Researcher

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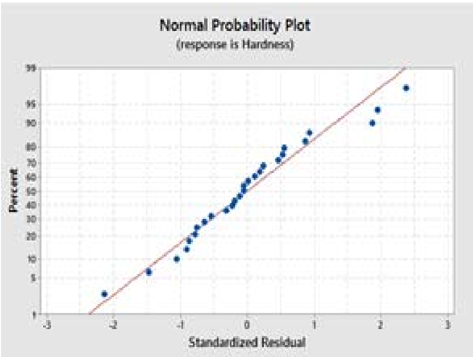
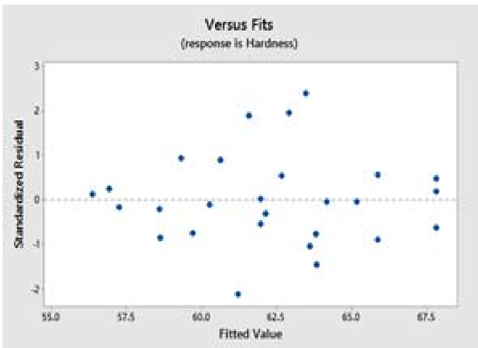
The Box-Behnken Design (BBD) hardness model showed that two squared effect terms (B_2 and D_2) and two interaction terms (AC and AD) are significant. Also the sharp difference between the R^2 and R^2(adj) values shows that over fitting occurred in the model.

A further test on the model adequacy was carried out by applying the Normal probability and residual plots as shown in figure 1. The normal probability plot shown in figure 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 figure 1 (b) shows that the variation of residuals of the treatment levels and the distribution of data satisfy the normality condition.





(a) (b)

Figure 1: (a) Normal probability plot for the nonlinear hardness (b) Residual plot for the hardness data

Genetic Algorithm application

The regression model obtained through multiple linear regression technique was 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 (Azhagan et al, 2014).

Lower bound of parameters = {680, 20, 20, 180}

Upper bound of parameters = {740, 50, 60, 310}

The table 5 shows the tested levels and best optimal levels for the parameters used in the wear rate model from the genetic algorithm tool.

Table 5: Result of optimal levels from genetic algorithm on BBD hardness model

Factor	Parameter	Level range	Optimal level
A	Pouring temp(^{o}C)	680-740	680.000
B	Vibration frequency(Hz)	20-50	31.523
C	Vibration time(secs)	20-60	59.998
D	Runner size	180-310	309.696

The fitness value is 70.789

Source: Researcher

Confirmation test

Experiment was conducted in the foundry with the optimal levels obtained from the evolutionary algorithm. A runner size of about 310mm^2 was used to prepare a sand mould that accommodated the molten metal of 680^{0}C at a vibrated frequency of 31.52Hz on approximately 60 seconds duration. The casting was measured for hardness using the Rockwell hardness testing machine. The value of hardness from the actual experiment (70.58) was noticed to be similar to that predicted by the developed nonlinear model (70.78).

The spectrographic test carried out on the aluminium alloy scraps showed that the alloy had 12.04% silicon content which infers that the alloy is eutectic. The developed mathematical model showed that 50.7% of the variation in hardness response is explained by the predictor variables. This connotes that the developed regression model is adequate. Also, the difference between the R^2 and adjusted R^2 values indicates that over fitting exist in the developed model. In addition, the probability plot shown in figure 1 reveals that normality conditions were satisfied. The results of optimization from the Genetic algorithm showed that the pouring temperature, vibration frequency, vibration time and runner size which are 680^{o}C, 31.52Hz, 59.99s and 309.70 respectively yielded hardness fitness value of 70.78 which was very close to the confirmatory test value obtained for hardness.

CONCLUSION

A Response Surface Methodology nonlinear Box-Behnken Design was used to create an experimental layout for the conditions employed in the study. Experiments were conducted and the test result was used to develop a model for the response hardness. ANOVA test conducted shows that the developed model is adequate and significant. Also, the difference between the R^2 (71.02%)

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and adjusted R^2 (50.09%) reveals that there exist sign of over fitting in the model. Optimal levels of the process parameters were determined and used to carry out confirmatory test whose actual experimental values align with predicted values of the model

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