Parameter Optimization of Sandcasting of Silumin (Aa6061) Using Genetic Algorithm

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Abstract
Automobile and engine components are often sand cast during manufacture because of its simplicity in operation. Manufacturing processes and conditions were appropriately carried out by developing a Design of Experiment platform to effect a fair randomization of the various experimental runs. Taguchi Orthogonal array was used to develop a layout for the sand casting experiment. Multiple linear Regression technique was used to develop mathematical models for the 3 responses-fatigue strength, wear rate and hardness. The Weighted Average method was applied in ascribing criteria weights. The single composite objective function generated was inputted into the Genetic algorithm tool box which yielded optimal levels for the four cases adopted. Case 4 which is the maximum importance for fatigue strength had its optimal conditions to be 749.99°C, 49.999Hz, 30.01seconds and 265.35mm^2 for pouring temperature, vibration frequency, vibration time and runner size respectively. Validation test conducted showed that the values obtained from the actual experiment were similar to that yielded by the predictive models.
Keywords: Sand casting , Optimization, Genetic algorithm and Taguchi design
DOI: 10.7176/IEL/13-1-06
Publication date: April 28th 2023

1. Introduction

Sand casting is the most widely used metal casting process in manufacturing [1]. It involves the pouring of molten metal into the sand mould, the solidification of the casting within the mould, and the removal of the casting Almost all metallic engine components can be sand cast. Sand castings range in size from very small to extremely large. Examples of components manufactured by sand casting process in modern industry are valves, pistons, cylinder heads, machine tool bases, pump bases and engine blocks [2].

An advantage of sand manufacturing applications is that sand is not expensive. Another vital advantage of sand in the manufacture of products in metal casting industry is that it offers resistance to elevated temperatures . Most sand casting operations uses silica sand [3].

A proper examination of the importance of sand casting on aluminium alloys yielded a robust comparison between single aluminium blank sand casting and double aluminium blank sand casting by [4]. The study showed that single aluminium blank sand casting process thrived better than the double aluminium blank sand casting process. The experimental result confirmed the effects of applying sand casting process parameters in the aluminium blank casting process. The process parameters investigated were sand grain size, , sprue size, clay content, riser size and moisture content

The need to optimize process parameters involved in sand casting is paramount in achieving efficient cast products. Optimization technique is a mathematical method of finding a maximum or minimum value of a function of a set of variables subject to some constraints [5]. In casting, optimization of process parameters are carried out by technique like Taguchi design, Response Surface Methodology, Genetic algorithm, Artificial Neural network and Particle swarm Algorithm[6].

It appears sometimes in an attempt to optimize process parameters conflicting objectives may erupt in the process which makes it important for multi-objective optimization to be conducted so as to arrive at optimal level of the process parameters irrespective of the conflicting responses [7]. In addressing the challenge posed by the conflicting objectives, an optimization evolutionary algorithm tool known as Genetic Algorithm which uses the tendency of natural selection and genetics was applied. The Genetic algorithm works with mechanics of copying and swapping binary strings. The algorithm involves genetic processes like reproduction, selection, crossover and mutation [8]. This above processes were applied to the developed models to generate optimal levels for the process parameters and fitness values for the response variables.

The Genetic algorithm was used by [9] to study the multi-objective optimization of Silumin. The study showed that the optimal values of process parameters involved in the casting of the aluminium alloy are 700^{o}C for pouring temperature and 10Hz for vibration frequency. The optimized process parameters yielded maximum hardness and minimum wear on the cast hypoeutectic Al-Si alloy.

Similarly, genetic algorithm was widely used in multi-objective optimization for proffering optimal solutions for conflicting objectives as applied in [10]. In the study, genetic algorithm was used to optimize squeeze cast process parameters inherent in a Response Surface methodology developed non linear model. The study showed that the results generated by genetic algorithm are similar to that generated by the particle swarm optimization algorithm.

Multi-objective optimization became so imperative in the study because of the conflicting nature of the responses [11]. The hardness and the fatigue strength were responses for maximization while the wear rate was a response targeted for minimization.
This study is aimed at optimizing the sand casting process parameters of multiple responses using genetic algorithm and Taguchi design.

2. Material and methods

In considering research and publication ethics for every step of this study experiments were conducted using the parametric conditions in the Taguchi Orthogonal array. The process parameters and the levels shown in Table 1 were arrived at after careful study of related literature. Sand casting was used to produce ingots which were machined to specimen used for fatigue strength, hardness and wear rate tests. Three different replicates were observed and the results recorded as shown in Tables 1 and 2.The hardness experiment was carried out using Rockwell hardness testing machine while the wear and fatigue tests were conducted with the Pin-on-disc and fatigue testing machines respectively.

Table 1. Process parameters and their various levels

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,D (mm^{2})	180	335	490

Table 2. Standard L9 orthogonal array

Experiment No.	Pouring temp, A(^{0}C)	Vibration Frequency,B(Hz)	Vibration time ,C(seconds)	Runner size, D (mm^{2})
1	700	10	30	180
2	700	30	45	335
3	700	50	60	490
4	725	10	45	490
5	725	30	60	180
6	725	50	30	335
7	750	10	60	335
8	750	30	30	490
9	750	50	45	180

In order to carry out successful multi-objective optimization the wear rate model was modified for maximization by taking its inverse in consonance with research and publication ethics. The best form of multi–objective optimization is achieved when the various response models are attached criteria weights. The sum of intended criteria weights is equal to one [12]. The multi-objective optimization is meant for optimizing multiple responses [13]. Also, weights can be apportioned to the response models by the Weighted Average method which entails attaching weights of equal and maximum importance to the response. In performing the multi-objective optimization in this study the 3 response functions were converted to form a single composite objective function. The single composite objective equation obtained from the linear model was introduced as objective function in the Genetic algorithm for the multi-objective optimization[14]. The mathematical models were developed by the application of Multiple linear regression technique [15].

3. Results and discussion

The engine piston components produced from the sand casting experiment using the Taguchi Design is shown in Figure 1.

Figure 1. Sand cast Aluminium alloy pistons

The experimental results observed from the 3 replicates are used to generate Table 3.

Table 3. Experimental values for the 3 responses

Experiment No.	Random order of experiment	Pouring temperature, A(^{0}C)	Vibration frequency, B(Hz)	Vibration time, C(secs)	Runner size, D(mm^2)	Fatigue stress, F(kpa)	Wear rate W_R(mg/m)	Hardness, H
1	2	700	10	30	180	123000	0.136	50.50
2	5	700	30	45	335	132000	0.120	52.00
3	7	700	50	60	490	141000	0.097	54.80
4	8	725	10	45	490	159000	0.087	53.20
5	3	725	30	60	180	171000	0.075	56.60
6	1	725	50	30	335	194000	0.064	57.10
7	6	750	10	60	335	201000	0.046	58.50
8	9	750	30	30	490	220000	0.037	56.60
9	4	750	50	45	180	231000	0.026	59.50

In applying the multiple linear regression technique to the data in Table 2 three relationships (one each for a response) between the responses and the various process parameters were developed. The minitab 17 software was employed to develop the mathematical models. The developed hardness model is given as

$$Hardness\ H = -32.60 + 0.1153A + 0.0767B + 0.0633C - 0.00215D \quad (1)$$

The mathematical model for the wear rate, W_R is given as

$$WR = 57.29 - 0.07213A - 0.03083B - 0.00922C - 0.000742D \quad (2)$$

While the mathematical model for the fatigue strength is given as

$$Fatigue\ strength\ = -1069616 + 1706.7A + 691.7B - 266.7C - 5.38D \quad (3)$$

A multi-objective optimization involves assigning criteria weight to the response parameters and converting the various response models into a single objective function.

In this study the response parameters are hardness H, wear rate W and fatigue strength F. The single composite objective equation used as objective function in the multi-objective genetic algorithm was formed by modifying the wear rate objective function into maximization form by taking it's reciprocal or inverse. The modified wear rate function was added to the hardness and fatigue strength functions with the various criteria weights attached and the final single composite equation maximized. The weighted single objective equation developed for maximization is given in Equation (4).

$$MaxZ_1 = W_1H + W_2/W_R + W_3F \tag{4}$$

Where W_1, W_2 and W_3 are criteria weights assigned to hardness, wear rate and fatigue strength functions respectively.

The total sum of the chosen criteria weights is equal to one. In this study different criteria weights were assigned to the different response parameters as described in the Weighted Average method. The equal criteria weight importance, maximum criteria weight importance for hardness, maximum criteria weight importance for wear and maximum criteria weight importance for fatigue strength were taken to be cases 1, 2, 3, and 4 respectively.

In carrying out the multi-objective optimization using Genetic Algorithm a number of 4 variables and their levels were used, a population size of 50, a crossover probability of 0.85 and mutation probability of 0.01 was employed. The combined multi-objective function Z was inputted as objective function in the Genetic algorithm toolbox

3.1 Multi-objective optimization of the Taguchi model using equal criteria weight importance (Case 1)

In applying equal importance to the Taguchi model the criteria weights are W_1=W_2=W_3=0.333. The equation to be maximized is given as Equation (5)

$$MaxZ_2 = (-345.34 + 0.6064A + 0.2552B - 0.0676C - 0.00267D) + {}^{0.333}\Big/\left(\begin{matrix}1.291 - 0.00163A - 0.000683B - \\ 0.000211 - 0.000017D\end{matrix}\right) \tag{5}$$

Where Z_2=Fitness function value for equal importance The genetic algorithm optimal values for the equal importance maximization model is shown in Table 4.

Table 4. Genetic algorithm result for equal weight importance

Parameter	Optimal values
Pouring temperature, A(^{0}C)	**749.99**
Vibration frequency, B (Hz)	**49.99**
Vibration time, C (secs)	**30.02**
Runner size, D (mm^2)	**421.35**
Fitness value	**122.74**

3.2 Maximum criteria weight importance for Hardness (Case 2) in linear model

In applying maximum weight importance for hardness, the weight attached to the hardness is W_1=0.8 and that of wear rate (W_2) and fatigue strength (W_3) are 0.1.

The equation to be maximized is

$$MaxZ_3 = (-133.04 + 0.2627A + 0.1306B + 0.02393C - 0.0023D) + 0.1/\left(\begin{matrix}1.2914 - 0.00163A - 0.000683B - \\ 0.000211C - 0.000017D\end{matrix}\right) \tag{6}$$

Where Z_3=fitness value for maximum weight importance for hardness
The Genetic algorithm optimal values for the maximum weight importance for hardness is shown in Table 5

Table 5. Genetic algorithm result for maximum weight importance for hardness

Parameter	Optimal values
Pouring temperature, A(^{0}C)	749.99
Vibration frequency, B(Hz)	49.99
Vibration time, C(secs)	59.98
Runner size, D(mm^2)	273.50
Fitness value	77.14

3.3 Maximum weight importance for Wearrate in the Taguchi Design (Case 3)

The wear rate model was ascribed a criteria weight, W_2 of 0.8. The fatigue strength and hardness attached weights are 0.1 each (i.e W_1=W_3=0.1).
The equation to be maximized is

$$MaxZ_4 = (-110.22 + 0.1835A + 0.0768B - 0.02034C - 0.0008D) + 0.8/\begin{pmatrix}1.2914 - 0.00163A - 0.000683B - 0.000211C \\ -0.000017D\end{pmatrix} \quad (7)$$

Where Z_4=fitness function value for maximum weight importance for wear rate
The Genetic Algorithm optimal values for the maximum weight importance for wear rate is shown in Table 6.

Table 6. Genetic algorithm for maximum weight importance for wear rate

Parameter	Optimal value
Pouring temperature, A(^{0}C)	749.99
Vibration frequency, B(Hz)	49.99
Vibration time, C(secs)	59.99
Runner size, D(mm^2)	435.69
Fitness value	84.15

3.4 Maximum weight importance for fatigue strength (Case 4) in linear model

The fatigue strength model was attached maximum weight of 0.8 i.e W_3=0.8 while the hardness and wear rate weight are 0.1 each (W_1=W_2=0.1). The equation to be maximized is

$$\mathrm{Max}Z_5 = (-858.96 + 1.3767A + 0.5611B - 0.207C - 0.0049D) + 0.1/(1.2914 - 0.00163A - 0.000683B - 0.000211C - 0.00017D) \quad (8)$$

Where Z_5=Fitness function value for maximum weight importance for fatigue strength.
The Genetic algorithm optimal values for the maximum weight importance for the fatigue strength are shown in Table 7.

Table 7. Genetic algorithm result for maximum weight importance for fatigue strength

Parameter	Optimal value
Pouring temperature, A(^{0}C)	749.998
Vibration frequency, B(Hz)	49.999
Vibration time, C(secs)	30.001
Runner size, D(mm^2)	265.573
Fitness value	198.287

3.5 Multi-objective optimization result analysis

The multi-objective optimization result obtained examined 4 cases of criteria weight importance. The tabular summary of multi-objective optimization of linear model is shown in Table 8.

Table 8. Genetic Algorithm result for Multi-objective optimization of linear models

Parameters	Case 1 $W_1 = 0.333$ $W_2 = 0.333$ $W_3 = 0.333$	Case 2 $W_1 = 0.8$ $W_2 = 0.1$ $W_3 = 0.1$	Case 3 $W_1 = 0.1$ $W_2 = 0.8$ $W_3 = 0.1$	Case 4 $W_1 = 0.1$ $W_2 = 0.1$ $W_3 = 0.8$
Pouring Temperature {A}	749.99	749.99	749.99	749.998
Vibrating Frequency {B}	49.99	49.99	49.99	49.999
Vibration Time {C}	30.02	59.98	59.99	30.001
Runner Size {D} (mm^2)	421.35	273.50	435.69	265.573
Fitness Value {Z}	122.74	77.14	84.15	198.287

Table 8 shows that optimization result of the composite response equations obtained from the linear Taguchi design has the maximum fitness values for equal weight importance, maximum weight importance for hardness, maximum weight importance for fatigue strength and maximum weight importance of wear rate as 122.741, 77.140, 84.151 and 198.287 respectively. The maximum fitness value of the criteria weight importance of fatigue strength is considered optimal for the developed linear models.

3.6 Confirmatory Test

The case 4 conditions which are the optimal levels of the process parameters obtained from the Genetic algorithm were used to carry out actual experiment in the foundry workshop of Auchi Polytechnic, Nigeria. The responses obtained from the experiment were similar to the predicted values from the developed model. Appropriate ASTM codes were used to measure fatigue strength, wear rate and hardness values during the experiment. High fatigue strength and hardness, with low wear rate values as suggested by the maximum importance for fatigue strength (case 4) were obtained to be the optimal conditions for the casting. The comparisons between predicted and experimented values are shown in Table 9.

Table 9. Comparison of Predicted and Experimental Values of the Linear Models

	Pouring temp.(^{0}C)	Vibration frequency,Hz	Vibration time, (sec)	Runner size (mm^2)	Hardness(HRC)	Wear rate (µg/m)	Fatigue strength (Mpa)
Predicted value	749.98	49.998	30.002	285.305	60.92	2.588	227.478
Experimental value	749.98	49.998	30.002	285.305	61.50	2.620	232.450
Prediction error (%)					0.943	1.201	2.139

4. Conclusion

Design of Experiment Taguchi Orthogonal array was used to create a platform for the sand casting experiment. Multiple linear Regression technique was used to develop mathematical models for the 3 responses. Weighted Average method was used to ascribe criteria weight to the conflicting objectives. A single composite objective function formed was inputted into the Genetic algorithm tool box which yielded optimal levels for the 4 cases adopted. Case 4 which is the maximum importance for fatigue strength was considered optimal with the highest fitness value of 198. The optimal conditions from case 4 were used to carry out actual experiment. The optimal values obtained from the Multiobjective optimization of the linear models were inputted into the developed models of hardness, fatigue strength and wear rate to arrive at predicted values utilized for the validation process. The result of comparison between the predicted and experimental values is shown in Table 9. The prediction percentage error result shows slight difference exists between the predicted and experimental values. The values obtained from the actual experiment were similar to that yielded by the predictive models.

Conflict of Interest

There is no conflict of interest declared by the authors.

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