The Effect of Sand casting Process Parameters on the Fatigue Strength of Aluminium Silicon alloy using Taguchi Design and Genetic Algorithm

B. N. G. Aliemeke
O. G. Ehibor
V. E. Aideloje

ABSTRACT

Automobile parts are important in any technological sector. Aluminum alloys reputed for lightness in weight and good conductivity are mostly used in the production of pistons. The Design of Experiment employed in the sand casting process is the Taguchi Orthogonal array method. It provided a platform on which the various experimental conditions were observed. Mathematical model was developed using Multiple Linear Regression technique and ANOVA test was carried out to ascertain the developed model adequacy. The model was adjudged adequate with an adjusted R^2 of 99.85%. Signal-to-noise ratio technique was used to determine the optimal level of the sand casting process parameters which are 750^0C, 5cm^2/s and 180mm^2 for pouring temperature, pouring rate and runner size respectively. Furthermore, the developed model was used as objective function in the Genetic algorithm tool box and the result obtained was in consonance with that obtained in Signal-to-noise ratio technique. In confirmation of test carried out it was noticed that the actual experimental values were similar to that predicted by the model.

Keywords: *Genetic Algorithm, Signal-to-noise ratio, and Taguchi Orthogonal array*

INTRODUCTION

Aluminium silicon alloys are reputed for some distinguishing advantages that stand them out amongst metallic material used for the production of engine components (Eklund, 1991). The alloys are known to be relative light in weight which gives an edge while it used in aviation industry (Bergsma, Kassner, Li and Wall, 1998). Al-Si alloys are used in automobiles because of their excellent ability to resist corrosion in the presence of water and moist air (Feng, Yi, Xianglong and Jingcheng, 2011). Also aluminium alloys offers an important property of high thermal conductivity this makes

***B. N. G. Aliemeke, O. G. Ehibor** and **V. E. Aideloje** are Lecturers in the Department of Mechanical Engineering Technology, Auchi Polytechnic, Auchi, Edo State, Nigeria. E-mail: aliemeka@yahoo.com, vickycoker2014@gmail.com.*

ISSN: 2141-6745

it possible for it to be highly sort after in the electrical industry (Atzori, Meneghetti and Ricotta, 2010). Aluminium alloys which may turned scraps after some years of usage are easily recycled with less energy to form various components while efficiency is still been maintained (Al-Mosawi, Rijab, Abdulsada and Ajmi, 2015).

Casting is a vital process in the manufacturing of engine components (Ozioko, 2011). To effectively produce metallic parts various casting process parameters are needed in varying quantity and proportion (Oji et al, 2013). In squeeze casting, process parameters like squeeze pressure, die temperature, pressure duration and squeeze time are highly important while in sand casting process parameters like pouring temperature, pouring time, pouring rate, green sand strength, mould temperature, runner size, riser size and solidification time portray high level of importance (Mohiuddin, Krishnaiah and Hussainy, 2015). This study will examine the effect of pouring temperature, pouring rate and runner size on the fatigue strength of Al-Si alloys.

Taguchi method is an important tool used for optimization in engineering and other fields of production (Nekere and Singh, 2012). It was first used by a Japanese scientist, Gienechi Taguchi in the early 1950s (Upadhye and Keswani, 2012). The optimization technique is a Design of Experiment reputed for fewer number of experimental runs (Mohiuddin, Krishnaiah and Hussainy, 2015).The method targets high quality and low cost of production. In this study the experimental design is done by selecting 3 process parameters (pouring temperature, pouring rate and runner size) at 3 levels each. The Taguchi parametric design provides 9 experimental runs as against 27 runs which have been provided for a Full Factorial method (Mohiuddin, Krishnaiah and Hussainy, 2015). The 9 experiments were conducted for different conditions to achieve fatigue strength response. Signal-to-noise ratio was computed for the nine experiments to ascertain the optimal level of the process parameters. The Taguchi method entails 3 quality characteristics which are larger-the-better, Norminal-the-best and Lower-the-better (Oji et al, 2013). This study is focused on developing maximum fatigue strength for Al-Si alloy components hence the larger-the-better quality characteristics for fatigue strength was employed.

The manufacturing world is faced with the huge challenge of controlling sand casting input process parameters in order to achieve high yield of cast products of desired quality (Mohiuddin, Krishnaiah and Hussainy, 2015). There is great need to investigate mechanical properties of aluminium silicon alloy so as to ascertain their strength in the production

ISSN: 2141-6745

of engine components. Also, the limited number of mathematical models to predict mechanical properties of aluminium alloys components has been a recurrent challenge in the development of engine components. This study will develop mathematical model that can predict fatigue strength and also optimize the sand casting process parameters.

In order to investigate the effect of sand casting process parameters on the fatigue strength of aluminium alloy the following objectives were pursued

i. To develop an L_9 Taguchi orthogonal array for the experiment
ii. sand cast component from aluminum scraps using the Taguchi experimental design
iii. determine the fatigue strength of the developed component
iv. develop mathematical model for the prediction of fatigue strength
v. determine the optimal levels of the process parameters using signal to noise ratio and genetic algorithm

MATERIALS AND METHOD

The materials employed for this study are graphite crucible furnace, aluminium alloy scraps, digital thermocouple, stopwatch, CNC lathe machine and fatigue strength testing machine. Sand mould was prepared using silica sand as the foundational material, bentonite as the binder and water. Aluminium silicon scraps were collected and melted in the crucible furnace fitted with digitalized thermocouple which recorded the temperature of the melt. Nine different moulds are prepared with varying runner sizes in the foundry. All the nine moulds received the molten metal to produce castings at various conditions specified by the Taguchi orthogonal array. The molten metal was scooped from the crucible with the aid of a ladle and introduced into prepared sand mould via the pouring basin before getting into the runner prepared in various sizes. Upon solidification the casting is allowed to cool for ten minutes before being detached from the mould. The process parameters applied in this study are pouring temperature, pouring rate and runner size. They were considered after profound review of related literature of Oji *et al* (2013) and past workshop experience. The pouring temperature was poured at 700^0C, 725^0C and 750^0C. The pouring rate ran at 2.5cm/s, 4.0cm/s and 5.0cm/s while the runner sizes had $180mm^2$, $200mm^2$ and $285mm^2$. Table 1 shows the process parameters and their experimental levels while table 2 shows the L_9 Taguchi orthogonal array used for this study.

ISSN: 2141-6745

Table 1: Process parameters and their levels

Process parameters	Levels		
	L_1	L_2	L_3
Pouring temperature (A) ^0C	700	725	750
Pouring rate (B) cm/s	2.5	4.0	5.0
Runner size mm^2	180	200	285

Source: Experimentation, 2018

Table 2.0 L_9 Taguchi orthogonal experimental design

Experiment No.	Pouring temperature (A) ^0C	Pouring rate (B) cm/s	Runner size (C) mm^2
1	700	2.5	180
2	700	4.0	200
3	700	5.0	285
4	725	2.5	200
5	725	4.0	285
6	725	5.0	180
7	750	2.5	285
8	750	4.0	180
9	750	5.0	200

Source: Experimentation, 2018

Finally, ingots from the sandcasting were prepared into fatigue strength standard specimen using the ASTM-E466-82 standard, 42mm length and 7mm neck diameter. The machine consists of a shaft, digital counter, a flat metal base and bearing housing (Avalle, Belingardi and Cavatorta, 2011). The installed counter on the machine recorded the number of cycles at which the specimen failed. Variable loads (weights) were used for the experiment. The applied stress, ó was calculated by using load P(N) in the equation 1.0

$$\sigma = \frac{125.7P \times 32}{\pi \times D^3} \qquad .... 1$$

Where P = load in Newton

D=diameter of specimen in millimeters. In this study 5.5mm was used.

Fatigue strength machine at ObafemiAwolowo University, Ile-Ife was used for the test. The isometric drawing of the test specimen is shown in Figure 1.

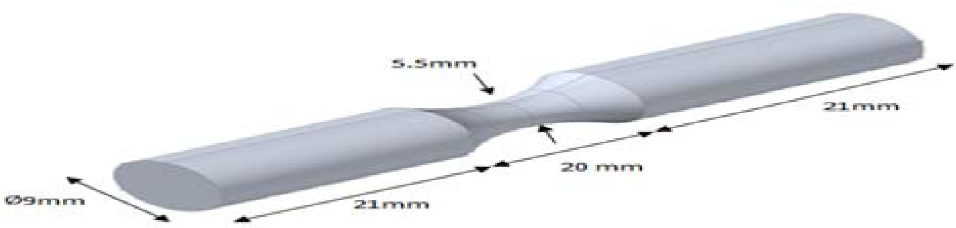

Figure 1: Fatigue test specimen

ISSN: 2141-6745

The Taguchi design data was used to develop mathematical model for the fatigue strength response using multiple linear regression technique. The mathematical model was developed with the aid of Minitab 17 software. The developed model was subjected to Analysis of Variance (ANOVA) test of significance to ascertain the model adequacy. The developed model was used as objective function for the Genetic algorithm which was used to optimize the process parameters such that fatigue strength was maximized (Jayaram, 2015). The Genetic algorithm applied steps are as follows (Mudakappanavar and Nanjundaswamy, 2013):

I. Encoding and Initialization of the chromosomes in the population
II. Evaluation of the chromosomes in the population by the fitness function
III. Selection of fitted chromosomes in accordance to fitness values
IV. Performance of crossover among selected strings
V. Performance of mutation on the chromosomes
VI. Evaluate the chromosomes in the new population and repeat the above steps until there is a convergence of the result

RESULTS AND DISCUSSION

Table 3: Experimental Data

Experiment	Pouring temperature (A) ^{0}C	Pouring rate (B) cm/s	Runner size (C) mm^3	Fatigue strength (Mpa)	No. of cycles X 10^3	
1	700	2.5	180	121	20.7	21.0
2	700	4.0	200	131	14.7	15.6
3	700	5.0	285	142	13.1	13.0
4	725	2.5	200	148	8.4	7.8
5	725	4.0	285	155	5.0	4.8
6	725	5.0	180	174	3.0	2.6
7	750	2.5	285	186	1.6	1.5
8	750	4.0	180	199	0.53	0.58
9	750	5.0	200	213	0.14	0.16

Source: Experimentation, 2018

The mathematical linear model developed for the fatigue strength based on the Taguchi design data is given in equation 2.0

$$Fatigue\ strength = -851.9 + 1.360A + 9.61B - 0.035C \qquad .... 2$$

The measured fatigue strength values and their corresponding signal to noise ratio values are shown in table 4.

ISSN: 2141-6745

Table 4: Fatigue strength and signal to noise ratio values

Experiment	Fatigue strength (Mpa)	Signal to noise ratio (db)
1	121	41.66
2	131	42.34
3	142	43.05
4	148	43.41
5	155	43.81
6	174	44.81
7	186	45.39
8	199	45.97
9	213	46.57

Source: Experimentation, 2018

The signal to noise ratio response with respect to the factor levels is shown in table in 5.0.The average signal to noise ratio values for the factor levels displayed in table 5.0 explains the optimal levels of the process parameters. Pouring temperature which is the most influential has an optimal level of 750^0C while pouring rate been the second influential has an optimal level of 5.0cm/s. The optimal level of the runner size is 180 mm^2.

Table 5: Average Signal to noise ratio values for the factor levels

Level	**Pouring temp. (A)**	**Pouring rate (B)**	**Runner size (C)**
1	42.35	43.48	44.15
2	44.01	44.04	44.11
3	45.98	44.81	44.08
Delta	3.63	1.32	0.07
Rank	1	2	3

Source: Experimentation, 2018

The pictorial display of the various levels is represented by the Main effect plot for signal to noise ratios in Figure 2.The main effect plots for the Signal to noise ratio show the various levels of the process parameters with the uppermost level been regarded as the optimal level. The uppermost level of pouring temperature, pouring rate and runner size is 750^0C, 5.0 cm/s and 180mm^2 respectively.

The significance test was carried out to determine the level of significance of each process parameter present in the model. The test result in table 6 shows a column for the coefficients of the model and the standard error of the estimated coefficient. Using significance level of 0.05, the p-values for the pouring temperature and the pouring rate are inferred to be significant since they are known to be less than 0.05.The runner size is insignificant having a p-value of 0.385 which is far more than 0.05.

ISSN: 2141-6745

Figure 2: Main effect plot for Signal to noise ratio

Table 6: Significant test result for the model

Term	Coefficient	SE coefficient	T-value	P-value
Constant	-851.900	60.500	-14.090	0.000
A	1.360	0.082	16.550	0.000
B	9.610	1.630	5.890	0.002
C	-0.035	0.037	-0.950	0.385

Source: Experimentation, 2018

The Analysis of Variance (ANOVA) test was carried out to determine the adequacy of the regression model. The test result shows that the adjusted coefficient of determination (R^2adj) and R^2 are 97.46% and 98.41% respectively. The coefficient of multiple determination values show that the developed model is adequate.

Table 7: Analysis of variance (ANOVA) test for the response-Fatigue strength

Source	DF	Adj SS	Adj MS	F-value	P-value
Regression	3	7836.97	2612.22	103.14	0.000
A	1	6936.00	6936.00	273.96	0.000
B	1	878.08	878.08	34.68	0.002
C	1	22.89	22.89	0.90	0.385
Error	5	126.59	25.32		

The R^2 (Adj)=97.46% and R^2 =98.41%

Source: Experimentation, 2018

The probability plot of the fatigue strength shown in Figure 3 was conducted for further model adequacy. The plot shows that the residuals lie close to the ideal normal distribution. Also, the p- values which is 0.838 portrays that there is not enough evidence to show that there is any deviation so it can be said that normality conditions are observed.

ISSN: 2141-6745

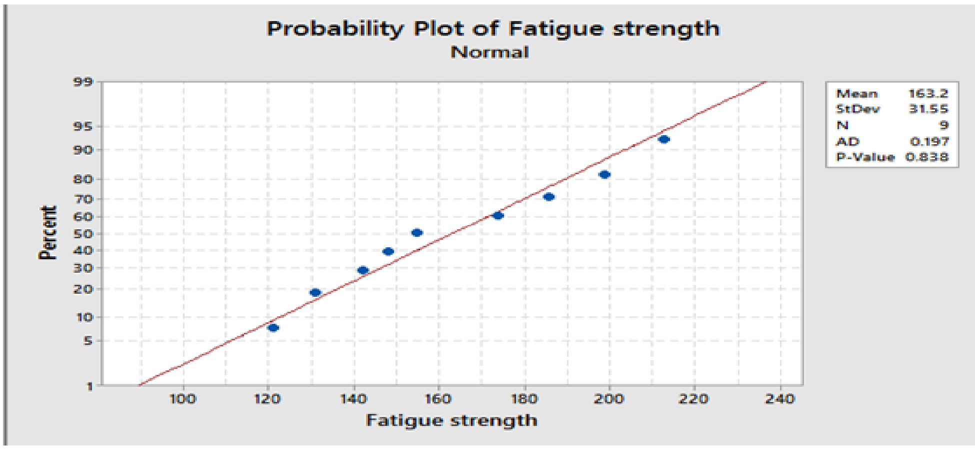

Figure 3: Probability plot for fatigue strength

Genetic Algorithm Result

The evolutionary Genetic algorithm was applied in this study to search for the optimal conditions of the process parameters. A crossover probability rate of 0.85 and mutation rate of 0.1 were applied in the search of optimal levels of process parameters. Also a population size of 50 and 100 generations were employed in this study (Azhagan et al, 2014). The Genetic algorithm operation was carried out by inputting the developed mathematical model into the MATLAB Genetic algorithm box as objective function. The result obtained after running a 100 generations is shown in table 8. The optimal fitness value for the fatigue strength is 209.847Mpa.

Table 8: Genetic algorithm result on fatigue strength

Factor	Parameter	Level range	Optimal level
A	Pouring temp(^{0}C)	700-750	749.998
B	Pouring rate (cm/s)	2.5-5.0	4.998
C	Runner size(mm^2)	180-285	180.013

Source: Experimentation, 2018

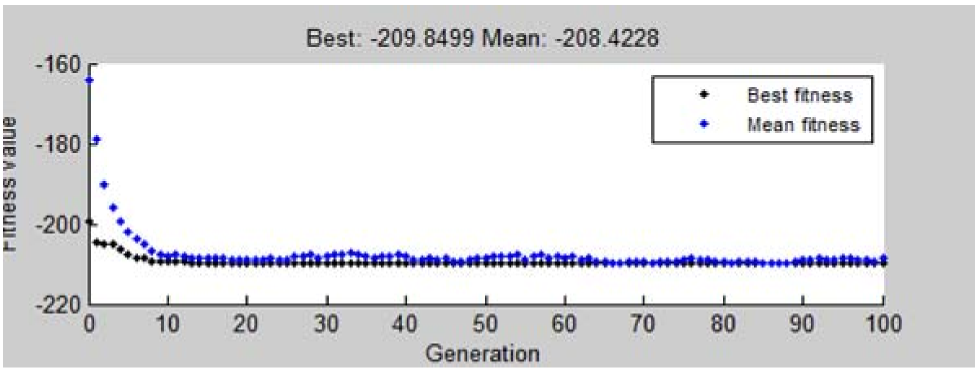

Figure 4: Genetic algorithm plot

ISSN: 2141-6745

Comparison between Taguchi method and Genetic algorithm results

The comparison between Taguchi method and Genetic algorithm results shows that the obtained values of the process parameters and fatigue strength are approximately the same. The compared result is depicted in tables 9 and 10.

Table 9: Comparison of Genetic algorithm and Taguchi method results

Serial number	Process parameters	Taguchi method	Genetic Algorithm method
1	Pouring temp.(A) ^{0}C	750.000	749.998
2	Pouring rate (B) cm/s	5.000	4.998
3	Runner size(C) mm^2	180.000	180.013

Source: Experimentation, 2018

Table 10: Comparison of Fatigue strength results

Response parameters	Taguchi method	Genetic Algorithm method
Fatigue strength (Mpa)	209.850	209.847

Source: Experimentation, 2018

The experimental table 3 shows that the higher the fatigue strength values of the aluminium alloy the lower the number of cycles to failure. This study shows that the developed mathematical model is adequate with an adjusted coefficient of determination (R^2 adj) value of 97.46%. In addition, the p-value of the regression model is 0.000 as contained in the ANOVA table 7. This connotes a highly significant developed model. The model adequacy is further buttressed by the use of probability plot shown in figure 3 which indicates that there is no possible outliers in the distribution and the residuals lie very close to the ideal diagonal distribution line. The Signal to noise ratio result shown in table 5 indicates that the pouring temperature is the most influential process parameter in the developed mathematical model. Also, pouring temperature is noticed to be statistically significant with a p-value of 0.001 as shown in table 7. The optimization result indicates that pouring temperature is 749.9^{o}C, pouring rate is 4.999cm/s and runner size is 180.031mm^2. The results of comparison shown in table 9 reveal that the optimal values obtained from the Taguchi and Genetic algorithm approaches are similar.

ISSN: 2141-6745

CONCLUSION

The effect of Sandcasting process parameters on the fatigue strength of aluminium silicon alloy were investigated using Taguchi method as the Design of Experiment in developing a template for the parametric conditions for the study. Optimal process parameters were successfully determined by applying Taguchi method and Genetic algorithm approach. The results from both approaches are approximately similar. In addition the signal to noise ratio reveals that pouring temperature is the most influential parameter followed by pouring rate.

REFERENCES

Al-Mosawi A. I., Rijab M., Abdulsada S. A. and **Ajmi R. K.** (2015). Recycling of Aluminium Castings. *Ecronicon Chemistry Journal,* 2 (1), 48-55

Atzori B., Meneghetti G. and **Ricotta M.** (2010). Analysis of the Fatigue Strength under two Load Levels of a Stainless Steel Based on Energy Dissipation. EDP Sciences No. 6. Pp. 1-8.

Avalle M., Belingardi G. and **Cavatorta M.** (2011). Static and fatigue Strength of a Die Cast Aluminium Alloy Under Different Feeding Conditions. *Journal for Metallurgical Science and Technology,* 2 (2), 9-13

Azhagan M. T., Mohan B. and **Rajadurai A.** (2014). Optimization of Process Parameters to Enhance the Hardness on Squeeze Cast Aluminium Alloy AA6061. *International Journal of Engineering and Technology,* 6 (1), 183-190.

Bergsma S. C., Kassner M. E., Li X. and **Wall M. A.** (1998). Strengthening in the New Aluminum Alloy AA 6069. *Journal Materials Science and Engineering,* 2, 112–118,

Eklund, J. E. (1991). On the effect of impurities on the solidification and mechanical behaviour of Primary and secondary commercial purity aluminium and aluminium alloys. Doctoral thesis, HelsinkiUniversity of technology, Espoo, Finland.

Feng L., Yi Y., Xianglong L. and **Jingcheng S.** (2011). Optimization of Casting Process Based on the Theory of Inventive Problem Solving. *Journal of China Foundry,* 8 (2), 182-187.

Jayaram, M. (2015).Parameter Optimization of WEDM for AA6061 Using Genetic Algorithm. *International Research Journal of Latest Trends in Engineering and Technology,* 2 (3), 96-104.

ISSN: 2141-6745

Mohiuddin V., Krishnaiah A. and **Hussainy F.** (2015). Influence of Sand Moulding Process Parameter on Product Quality of Al-Si Alloy casting – An ANOVA Approach, *International Journal of Advanced Research in Science and Engineering,* 4(1), 1751-1760.

Mudakappanavar, V. S. and **Nanjundaswamy, H. M.** (2013). Multi-objective Optimization of Process Parameters During Solidification of Hypoeutectic Al-Si Alloy Casting Using Genetic Algorithm. *International Journal of Latest Trends in Engineering and Technology,* 2 (4), 424-434

Nekere, M. N. and **Singh, A. P.** (2012). Casting process by using Taguchis Robust Design Method. *International Journal for Quality Research,* 6

Oji J. O., Datau S. G., Akinluwade K. J., Taiwo A. T., Isadare D. A., Pamtoks S. H. and **Adetunji A. R.** (2013). Numerical Optimization of Sand Casting Parameters Using the Dantzigs Simplex Method. *Journals for Minerals and Material Characterization and Engineering,* 1, 250-256.

Ozioko, F. U. (2011). Development and Testing of a Permanent Mould for Casting AX 100Motorcycle Engine Piston, M.Eng. Thesis, Federal University of Technology Minna, Niger State, Nigeria.

Upadhye, R. A. and **Keswani I. P.** (2012). Reduction in Casting Defects in a Foundry Using Taguchi Techniques. National Conference on Improving Productivity and Quality of Manufacturing System, Nagur, 12, 201-209.

ISSN: 2141-6745