MODELING AND EXPERIMENTAL INVESTIGATION OF LM26 PRESSURE DIE CAST PROCESS PARAMETERS USING MULTI OBJECTIVE GENETIC ALGORITHM (MOGA)

Received – Prispjelo: 2016-12-10 Accepted – Prihvaćeno: 2017-04-10 Original Scientific Paper – Izvorni znanstveni rad

This present investigation deals with pressure die casting process to produce an automotive valve closer component with better mechanical properties such as micro-hardness(HV), surface roughness (μ m) and porosity (%) on LM26 by varying intensification pressure (α) Kgf/cm², shot velocity (β) m/s and pouring temperature (γ) °C. Using response surface methodology (RSM), the optimal parametric combination is found to be α (186,68) Kgf/cm², β (0,599) m/s and γ (662,93) °C for multi responses (121,18) HV, (0,93) μ m and 0,017 % can be achieved corresponding to highest desirability of 0,73. The optimized results were obtained by the Pareto-optimal solutions using multi objective genetic algorithm (MOGA) provides flexibility to select the best setting depending on suitable applications.

Keywords: aluminium alloy, casting, die, properties, mathematical model

INTRODUCTION

Aluminium alloys are used in aerospace, automobile and train companies because of their attractive characteristics like lighter high strength alloy, stiffness and wear resistance.

[1, 2] suggested that optimization effort has been encourages by the net shape technical characteristics of casting process, in conjunction with its capability to produce complex engineering components. [3, 4] investigated the effect of process parameters such as intensification pressure, shot velocity, phase change over point and holding time on mechanical properties and microstructure exhibited by the castings produced though pressure die casting process. [5] discussed applying external pressure was effective in decreasing the porosity and producing less defective cast components.

[6, 7] studied the effect of casting process parameters on mechanical properties such as hardness, tensile strength and porosity. [8] found that casting temperature had a significant effect on the mechanical properties. [9] analysis of variance tests were conducted to evaluate the statistical suitability of the models and developed an integrated approach to optimize the high pressure die casting. [3] adopted statistically based technique RSM and developed mathematical models using the data collected. [10] genetic algorithm has been proven as one of the most popular multi-objective opti-

EXPERIMENTAL METHODOLOGY

Experimental setup and materials

The experiments have been performed on horizontal pressure die-casting machine (120T technocrat). The standard short sleeve is coupled with maximum shot capacity for aluminium 6,9 kg. A locking force with 400 tonnes capacity inbuilt in the setup and, an electric furnace provided with maximum capacity of melting temperature 2 000 °C with 1 000 litre capacity. After pouring molten metal, intensification pressure with shot velocity were applied at holding time of 15 seconds and retained on the solidifying molten metal for duration of 60 seconds to produce sound casting of automotive valve losing size of 7.5 cm diameter shown in Figure.1 The information on chemical composition of LM26 tested as per ASM are Si 8,5 - 10,5; Fe 1,2 max; Cu 2,0 - 4,0; Mn 0,5 max; Mg 0,5 - 1,5; Ni 1,0 max; Cr 0,1 max; Zn 1,0 max; Pb 0,2 max; Sn 0,1 max; Ti 0,2 max, Al - balance.

Experimental Design

The number of experimental trails increases in full factorial design as the number of parameters and their

mization techniques. Most of the studies attempted on pressure die casting to improve the mechanical properties by using various methods. However, no studies have been reported on the shaping of LM26 alloy on improvement of mechanical properties include of micro-hardness (HV), surface roughness (Ra) and porosity (f) using pressure die casting.

N. Zeelanbasha, V. Senthil, Department of Mechanical Engineering, Coimbatore Institute of Technology, India B. Sharon Sylvester, Department of Mechanical Engineering, Info Institute of Engineering, India, N. Balamurugan, Department of Mechanical Engineering, Kumaraguru College of Technology, India

levels increases. This required a large sum of experimentation cost and extensive time. So, the design matrix selected to perform experiments was a three-factor central composite face centered design (CCD) consisting of 15 sets of actual values and comprising a small fraction, six center points with one replicates of factorial points and one replicates of axial points using Design expert version 10. The casting parameters used in this study were selected are intensification pressure α (180; 200; 220) Kgf/cm², shot velocity β (0,4; 0,5; 0,6) m/s, and pouring temperature γ (640; 670; 700) °C for maximizing micro-hardness (HV), minimizing surface roughness (Ra) and porosity (f). Experimental values with measured responses are presented in Table1

Experimental Procedures

The response variables were selected for this study is micro-hardness, surface roughness and porosity. The samples of casting were machined according to the testing conditions, Vickers micro-hardness tester with 500 g load (HV $_{500}$) was applied for 5 to 10 seconds on the polished surface and micro-hardness values were noted at three different positions in polished specimen surface shown in Figure 2. Further, the density was determined by using conventional Archimedes principle. Calculated porosity = (theoretical density –measured density) / theoretical density * 100 %. Theoretical density of 2,76 g/m³ for LM 26 was chosen as per ASM. Surf tester (Mitutoyo) Sj-201 was used to measure the surface roughness on the cast samples with stylus tip radius 5 μ m and measuring speed 0,5 mm/s.

Table 1 Actual values and responses

α / Kgf /cm²	β / m/s	γ/ °C	HV ₅₀₀	Ra / μm	f / %
200	0,5	640	115	0,7	2,037
180	0,4	640	111	0,41	3,296
220	0,6	640	115	1,25	2,37
200	0,5	670	122	0,53	0,185
200	0,4	670	118	0,82	2,592
220	0,5	670	121	0,97	0,555
200	0,5	670	119	1,1	0,666
200	0,5	670	120	0,89	0,629
180	0,5	670	116	0,78	1,407
200	0,6	670	124	1,2	0,037
200	0,5	670	119	0,69	0,37
200	0,5	670	121	0,89	0,515
200	0,5	700	115	1,2	2,185
220	0,4	700	115	0,94	2,296
180	0,6	700	114	0,89	2,777

Microscopy

Microstructural examinations carried out following standard metallography techniques using metallurgical microscope having 500 X magnifications.



Figure 1 Casted and tested specimens

The specimen samples were grinded using emery papers, further the polished samples were color tint etched with Weck's Reagent. Tested specimens are shown in Figure 1.

RESULTS AND DISCUSSION

Response surface methodology (RSM)

A statistical software Design Expert V.10 was used to calculate the values of these coefficients. ANOVA was performed at 95 % confident level. The developed model F-value for micro-hardness HV (13,99), surface roughness Ra (5,53) and porosity f (22,98) implies that the model is significant. The Lack of Fit F-value of HV (0,03), Ra (0,43) and f (6,02), shows it is not significant relative to the pure error. There is chance that a Lack of Fit F-value HV (87,47 %), Ra (84,75 %), f (7,02 %), occur due to noise. Non-significant lack of fit is good. R² for HV (0,96), Ra (0,60), f (0,97) indicates the closeness of the model representing the process. It is evident from analysis the maximum micro- hardness in range of (115 to 122 HV), minimum surface roughness (0,70 to 0,80 µm) and minimum porosity (0,1 to 0,4 %) can be achieved for casting parameters in between a (210 to 220) Kgf/cm², β (0,55 to 0,60) m/s, γ (650 to 700)°C without influencing of responses each other. It is also noticed that overall optimum solutions from Figure.2,3 maximum Micro- hardness (121,71 HV), minimum surface roughness (0,93µm) and minimum porosity (0.017%) can be achieved for parameters α (186,68) Kgf/cm², β (0,599) m/s, γ (662,93) °C, at desirability of 0,73. The overall desirability functions of the responses shown in bar graph Figure 4. It varies from 0 to 1 depending upon the nearness towards the objective, a value close to one is considered proficient. The micrographs Figure.5 shows that the intensification pressure has significant effect on the microstructure of LM 26 alloy, it is also clear that higher pressure produces smaller and finer α -primary dendrites. The developed mathematical regression models are given below

HV = $-2135,86111 - 0,37647* \alpha - 241,81373* \beta + 6,96781* \gamma - 0,37500* \alpha* \beta + 3,75000E - 003* \alpha* \gamma +$

 $0,41667* \beta * \gamma - 4,55882E - 003* \alpha^2 + 67,64706* \beta^2 - 5,91503E - 003* \gamma^2$ (1)

Ra = $-4,38489 + 9,00000E - 003*\alpha + 1,95000*\beta + 3,72222E - 003*\gamma$ (2)

 $\begin{array}{l} f = +\ 469,99708 + 0,99124 \mbox{*} \ \alpha - 75,18809 \mbox{*} \ \beta - 1,62756 \mbox{*} \\ \gamma + 0,11112 \mbox{*} \ \alpha \mbox{*} \ \beta - 1,94375E - 003 \mbox{*} \ \alpha \mbox{*} \ \gamma - 0,024750 \mbox{*} \\ \text{shot velocity} \mbox{*} \ \gamma + 5,85515E-004 \ \alpha^2 + 56,77059 \mbox{*} \ \beta^2 + 1,51578E - 003 \mbox{*} \ \gamma^2 \end{array} \tag{3}$

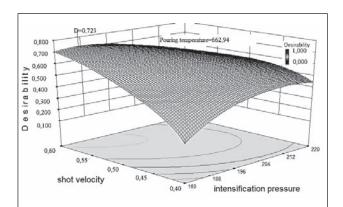


Figure 2 Desirability vs. parameters

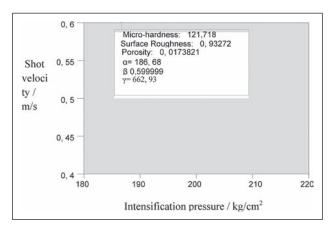


Figure 3 Overlay plot for desirability

Multi objective genetic algorithm

In this investigation, genetic algorithm has been employed for multi objective optimization with constrained

Table 2 Pareto optimal solutions

a / Kgf /cm²	β / m/s	γ/ °C	HV ₅₀₀	Ra / µm	f / %
203,02	0,44	662,00	118,83	0,76	1,61
193,53	0,44	662,09	117,47	0,67	1,84
189,23	0,41	652,15	115,44	0,55	2,52
184,68	0,48	669,81	116,47	0,70	1,43
201,87	0,54	671,17	121,87	0,99	0,12
187,44	0,40	652,23	114,93	0,52	2,81
204,99	0,49	671,47	120,50	0,92	0,62
187,11	0,43	664,27	116,04	0,61	2,11
184,89	0,41	649,81	114,21	0,50	2,66
219,07	0,60	683,31	124,40	1,30	0,32
198,00	0,47	665,08	119,14	0,79	1,05
209,88	0,56	674,65	122,89	1,10	0,09
187,43	0,42	654,26	115,40	0,55	2,40
206,54	0,59	674,69	123,90	1,13	0,16
184,26	0,58	674,23	120,07	0,91	0,46
219,07	0,60	682,19	124,30	1,29	0,32
212,33	0,60	677,23	124,64	1,22	0,25
184,13	0,40	649,18	113,77	0,47	2,97

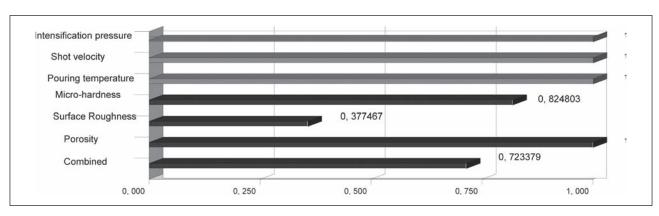


Figure 4 Desirability bar graphs







Figure 5 Optical micrographs 500 X: Intensification pressure 180, 200, and 220 Kgf/cm²

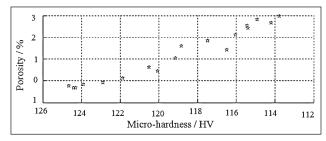


Figure 6 Pareto optimal frontier chart

limits. The developed regression model has been employed in genetic algorithm to predict the optimal relationship between the casting parameters and responses. This function was input to the GA Toolbox of MATLAB 2 010 a as the objective function.

To maximize: HV
To minimize: Ra, f

Within parameter ranges:

$$180 \le \alpha \le 220 \text{ Kgf/cm}^2 \tag{4}$$

$$0.4 \le \beta \le 0.6 \text{ m/s}$$
 (5)

$$640 \le \gamma \le 700 \, ^{\circ}\text{C}$$
 (6)

Figure 6 shows the Pareto optimal frontier distributed points generated from the optimization of responses. The parameter combinations of 18 non-dominated Pareto optimal solutions are presented in Table 2. All the given range of squeeze casting parameters is revealed and no partial hindrance found higher or lower side of the parameters is seen. The critical parameters selected in genetic algorithm are crossover fraction (0,8), population size (100), population fraction (0,35).

CONCLUSION

RSM based MOGA was used to predict the responses by optimizing the casting parameters. From this investigation, the following conclusion has been drawn.

The quadratic and linear regression model developed will provide valuable data that can be predicted from the vast range of experimental database.

Maximum micro- hardness (121,18 HV), minimum surface roughness (0,907 μ m) and minimum porosity (0,03 %) can be achieved for parameters α (184,4) Kgf/cm², β (0,6) m/s, γ (661,47) °C, at desirability of 0,73.

From the statistical analysis, it was found that the intensification pressure was the most significant param-

eter for micro-hardnes, surface roughness and porosity with a contribution percentage of 58,12 %, 48,9 % and 39,39 %.

Non-dominated Pareto optimal solutions obtained are verified and found that all the solutions generated are equally good, error lies in acceptable range between of 0,35 to 0,95 %.

REFERENCES

- [1] G.P. Syrcos, Die casting process optimization using Taguchi methods, journal of materials processing technology 135(2003), 68-74.
- [2] P. Besta, P. WichercThe Optimization of the Production of Sinteras the Feedstock of the Blast Furnace Process, Metabk 56(2017), 131-134.
- [3] Jayant K. Kittur, M. N. Choudhari ,M. B. Parappagoudar, Modeling and multi-response optimization of pressure die casting process using response surface methodology' Int J Adv Manuf Technol 77(2015) ,211–224.
- [4] Ko-Ta Chiang, Nun-Ming Liu, Te-Chang Tsai, Modeling and analysis of the effects of processing parameters on the performance characteristics in the high pressure die casting process of Al–SI alloys, Int J Adv Manuf Technol 41(2009), 1076–1084.
- [5] Bokhyun Kang, Yongsun Kim, Kiyoung Kim, Density and Mechanical Properties of Aluminium Lost Foam Casting by Pressurization during Solidification, J. Mater. Sci. Technol. 23 (2007)6, 110-118.
- [6] Zuqi Hu, Li Wan, Shusen Wu, Han Wu, Microstructure and mechanical properties of high strength die-casting Al–Mg–Si–Mn alloy, Materials and Design 46 (2013), 451–456.
- [7] Anilchandra R. Adamane, Lars Arnberg, Influence Of Injection Parameters On The Porosity And Tensile Properties Of High-Pressure Die Cast Al-Si Alloys, International Journal of Metalcasting 9(2015),43-54.
- [8] L.J. Yang, The effect of solidification time in squeeze casting of aluminium and zinc alloys, Journal of Materials Processing Technology 192-193(2007), 114-120.
- [9] L.X. Kong, F.H. She, W.M. Gao, S. Nahavandi, P.D. Hodgson, Integrated optimization system for high pressure die casting processes, journal of materials processing technology 201(2008), 629–634.
- [10] B. Senthilkumar, T. Kannan, R. Madesh, Optimization of flux-cored arc welding process parameters by using genetic algorithm, Int J Adv Manuf Technol 57 (2015), 187-193.

Note: The responsible translator for English language is Dr. C. Arumugam, Tamilnadu India.