Multi-Objective Optimization of process parameters during solidification of Hypoeutectic Al-Si alloy casting using Genetic Algorithm

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Abstract- The properties of Al-Si alloy are dependent on the grain size and distribution of silicon particles. Grain size and distribution of silicon particles can be affected by grain refinement and modification. Techniques to carry out grain refinement include addition of grain refiners to the melt, subjecting the molten melt to vibration during solidification. In the present work, mold containing the solidifying melt is subjected to mechanical vibration which is considered as one of the process parameters. Other parameters considered were mold material and pouring temperature. Properties evaluated were hardness and wear of the as cast alloy. Factorial design of experiment technique was used to conduct the experiments. The factors were considered at two levels (23factorial design). ANOVA has been conducted to predict the statistical significance of the factors. Genetic algorithm has been used to determine the optimum input parameters and compared with experimental values.

Keywords- Factorial design of experiments, genetic algorithm, mechanical mold vibration.

I. INTRODUCTION

Aluminium-Silicon alloys are one of the most commonly used foundry alloys because they offer many advantages such as good thermal conductivity,excellent cast ability,high strength to weight ratio, wear and corrosion resistance etc. Therefore they are well suited to automotive cylinder heads,engine blocks,aircraft components etc. The mechanical properties of Auminium-Silicon alloys are related to the grain size and shape of silicon.

Imposition of vibration on liquid Al-Si alloy during solidification has shown improvements like grain refinement[1], reduction in shrinkage pipe[2], fragmentation of dendrites and transition of eutectic structures from flakes to fibrous[3], reduction in average size of silicon needle [4], resulting in improved properties.Thus it is clear that subjecting the liquid molten metal to vibration during solidification promotes changes in microstructure and consequently in the properties.

Different methods of inducing vibration into the molten metal like electromagnetic vibration [5],Ultrasonic vibration [6] and mechanical mold vibration [7] have been tried.

In the present work, mechanical mold vibration technique has been used to bring changes in the alloy considered. Also other process parameters likely to affect the solidification process such as mold material [1] and pouring temperature have been considered. The properties under study are Brinell hardness and dry sliding wear of the as cast alloy. Hence the solidification process of the molten alloy can be considered as multi-objective problem in which there exists a close relationship between the properties of the as cast alloy to the various input parameters.

Design of experiments [8] refers to the process of planning the experiment, so that an appropriate set of data can be collected and then analyzed using the regression analysis for drawing inferences on the input- output relationship of a system. Fractional factorial technique has been applied to determine the effect of process parameters in friction welding[9-11], sand molding [12-13], casting defects [14-16], squeeze casting[17]. In this work, full factorial design of experiments with the factors set at their respective two levels (2^3 factorial) has been used to develop linear relationship between the input-output parameters. This analysis provides complete information on the main and interaction effects of the input parameter on the response. This is followed by the conduct of ANOVA for ensuring the statistical significance of the process parameters. Then non-traditional optimization technique namely genetic algorithm (GA) has been used to derive the optimized process parameters of the process. Genetic Algorithm is a computerized search and optimization algorithm based on the mechanics of natural selection and genetics as observed in the biological world. It has been adapted for various applications including design optimization[18] and scheduling[19].

The rest of the paper is organized as follows. Experimental procedures are explained in section II. Experimental results are presented in section III. Concluding remarks are given in section IV.

II.EXPERIMENTAL

A simple mechanical vibrator set up was used to subject the mold to vibration. The set up consists of a power oscillator on which the mold is mounted as shown in Figure 1. The frequency of vibration can be changed in the range of 1Hz - 10 KHz with a maximum displacement of 12mm peak to peak. In the present study frequency and amplitude of vibration was kept constant at 25 Hz and 0.05 mm. Commercial Al-9%Si alloy was melted in a graphite crucible in a 3 phase,12 KW electrical resistance furnace to a temperature of 850°C. After proper degassing with hexachloroethane and removing the slag, the melt was poured into the vibrating mold. Temperature of the charge was measured using chromel-alumel thermocouple just before pouring.The vibration was maintained until the melt was completely solidified. After solidification the castings were removed and specimens were prepared for testing. Molds preheated to 200°C were used to produce the castings. Cylindrical castings of diameter 30 mm x 200mm length were produced.

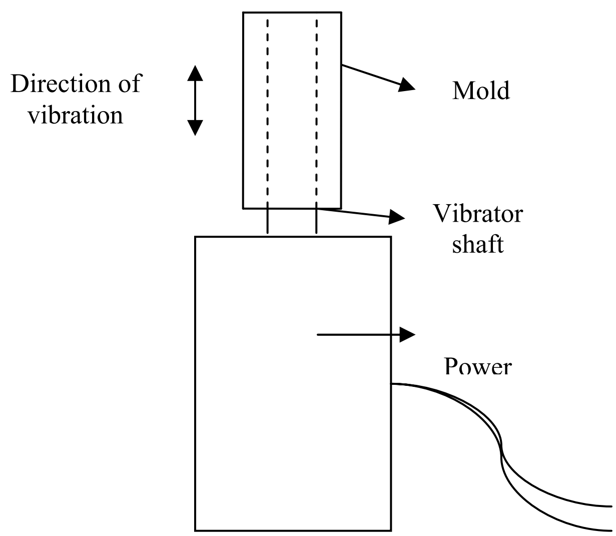


Fig 1. Vibration set up arrangement

The process parameters which may affect the solidification process considered were mold material (A), mechanical mold vibration (B) and pouring temperature(C). The mold materials considered were cast iron and graphite. The effect of vibration was compared to that of without vibration. The molten metal was poured at two temperatures 700 °C and 800°C.

Table 1 shows the factors selected and their levels and experiments were conducted as per the design matrix of full factorial design as shown in Table 2. For each combination of input factors two replicates were considered.

Table 1 Factors and their levels

Notation		Levels	
Factors considered	**Code**	**Low level (-1)**	**High level (+1)**
Mold material	**A**	**Cast Iron**	**Graphite**
Vibration	**B**	**Without vibration**	**With vibration (Frequency 25 Hz Amplitude 0.05mm)**
Pouring temperature	**C**	**700°C**	**800°C**

Table 2 Design Matrix

		Factors		
Experiment Number	**Label**	**A**	**B**	**C**
1	**(1)**	**-1**	**-1**	**-1**
2	**a**	**1**	**-1**	**-1**
3	**b**	**-1**	**1**	**-1**
4	**c**	**-1**	**-1**	**1**
5	**ab**	**1**	**1**	**-1**
6	**bc**	**-1**	**1**	**1**
7	**ac**	**1**	**-1**	**1**
8	**abc**	**1**	**1**	**1**

The outputs measured were Brinell hardness (H) and dry sliding wear (W). The wear test specimen from each casting was prepared with the dimension of diameter 5mm x 20 mm length. Computerized pin on disc wear testing machine having integrated software for data collection was used to conduct the wear test. The test was conducted for duration of 1 hour at speed of 300 rpm under a normal load of 1 kg.The BHN hardness of the specimen was obtained with a 10mm ball indenter and applying 500kg load. Analysis of variance (ANOVA) was conducted for each of the responses to check the adequacy of the models. The detailed analysis of the effects of parameters and their interaction on the responses was also done through the main effect plots. Genetic Algorithm was used to optimise the input process parameters such that the wear was minimised and hardness was maximised. The steps involved are as follows [20]:

Step 1: Choose a coding to represent problem parameters, a selection operator, a crossover operator, and a mutation operator. Choose population size n, crossover probability pc, and mutation probability p_m. Initialize a random population of strings of size l. Choose a maximum allowable generation number t_{max}. Set t = 0.
Step 2: Evaluate each string in the population.
Step 3: If $t > t_{max}$ or other termination criteria is satisfied, Terminate.
Step 4: Perform reproduction on the population.
Step 5: Perform crossover on random pairs of strings.
Step 6: Perform mutation on every string.
Step 7: Evaluate strings in the new population. Set t= t+1 and go to Step 3.

The optimization was carried out using the GA toolbox of Matlab.

III. RESULT AND DISCUSSION

The experimental data collected is shown in Table 3.This data is used to develop linear regression model based on full factorial design using Minitab[21] software.The statistical analysis of the developed model was performed through the ANOVA tests. The input-output relations were studied with the help of main effect and interaction effect plots for the responses, hardness and wear.

Table 3 Experimental data

Trial Number	Input Parameters			Responses			
				Wear (µm)		Hardness BHN	
	A	B	C	Trial 1	Trial 2	Trial 1	Trial 2
1	-1	- 1	-1	895	900	52.93	51.99
2	1	- 1	- 1	875	860	53.93	54.99
3	-1	1	-1	810	796	57.77	56.82
4	-1	- 1	1	910	925	52.05	51.91
5	1	1	- 1	775	760	58.82	57.24
6	-1	1	1	750	775	58.68	57.80
7	1	- 1	1	850	855	54.62	55.01
8	1	1	1	700	710	60.05	59.95

A. Hardness

The linear model based on full factorial design in coded terms is given by the equation:

$$H = 55.91+0.916A+2.4813B+0.3487C- 0.2925AB+0.2325AC +0.38BC+0.0238ABC \quad (1)$$

Significance test was carried out to study the effects, contributions and significance of the input parameters and their interaction terms on the response – hardness. The significance test results are shown in Table 4. The different terms used in Table 4 have been explained as follows: The term 'Coef' indicates the coefficients used in (1) for representing the relationship between the said response and the factors. The term 'SE Coef' represents the standard error for the estimated coefficient, which measures the precision of the estimate.The *T*-values are calculated as the ratio of corresponding value under coefficient and standard error. The *p*- value is the minimum value for the pre-set level of significance, at which the hypothesis of equal means for a given factor can be rejected.

As the *p* values of the terms A, B and BC in Table 4 were found to be less than 0.05, those terms were considered to have significant contributions on the response hardness at 95% confidence level, whereas all other main and interactions terms were found to have no significant contribution.

Table 4 Results of significance test on the model, coefficients, *T*- statistics and *p* values for response – hardness

Term	Effect	Coef	SE Coef	T	P
Constant		55.9100	0.1576	354.65	0.000
A	1.8325	0.9163	0.1576	5.81	0.000
B	4.9625	2.4813	0.1576	15.74	0.000
C	0.6975	0.3487	0.1576	2.21	0.058
AB	-0.5850	-0.2925	0.1576	-1.86	0.101
AC	0.4650	0.2325	0.1576	1.47	0.178
BC	0.7600	0.3800	0.1576	2.41	0.042
ABC	0.0475	0.0238	0.1576	0.15	0.884

Analysis of variance (ANOVA) was performed to test the significance of the factors for the response – hardness. The results of ANOVA are shown in Table 5. The different terms used in this table have been explained as follows: the term 'DF' represents the degree of freedom. The degree of freedom indicates the number of terms that will contribute to the error in prediction. The term 'Seq SS' indicates the sum of squares for each term, which measures the variability in the data contributed by that term.The adjusted sum of errors i.e 'Adj SS' is the sum of squares obtained after removing insignificant terms from the model. The sum of squares is divided by the degrees of freedom to determine the mean square. The adjusted mean square i.e 'Adj MS' is the mean square obtained after removing the insignificant terms from the response equation. The 'F' value for regression is used to test the hypothesis, which is calculated as the ratio of adjusted mean square value to the residual error.

From the table, it is noted that the term A, B, 2- way interaction term BCare found to be significant for this response. The R squared value for this model was found to be equal to 0.9738. The results of ANOVA and the R squared indicate that the developed regression model based on full – factorial design is statistically adequate.

The contributions of the input variables and their interactions are shown in the form of Pareto chart in Figure 2. From the figure it can be seen that vibration contributes significantly to the measured response followed by mold material and finally the interaction of vibration and pouring temperature.The effect of mold material, the interaction effect of mold material with vibration as well as pouring temperature and, the interaction of all three variables is insignificant.

Table 5 Results of ANOVA for the response – hardness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	3	113.884	113.884	37.9613	95.47	0.000
A	1	13.432	13.432	13.4322	33.78	0.000
B	1	98.506	98.506	98.5056	247.73	0.000
C	1	1.946	1.946	1.9460	4.89	0.058
2-way Interactions	3	4.544	4.544	1.5147	3.81	0.058
AB	1	1.369	1.369	1.3689	3.44	0.101
AC	1	0.865	0.865	0.8649	2.18	0.178
BC	1	2.310	2.310	2.3104	5.81	0.042
3-way Interactions	1	0.009	0.009	0.0090	0.02	0.884
ABC	1	0.009	0.009	0.0090	0.02	0.884
Residual Error	8	3.181	3.181	0.3976		
Pure Error	8	3.181	3.181	0.3976		
Total	15	121.618				

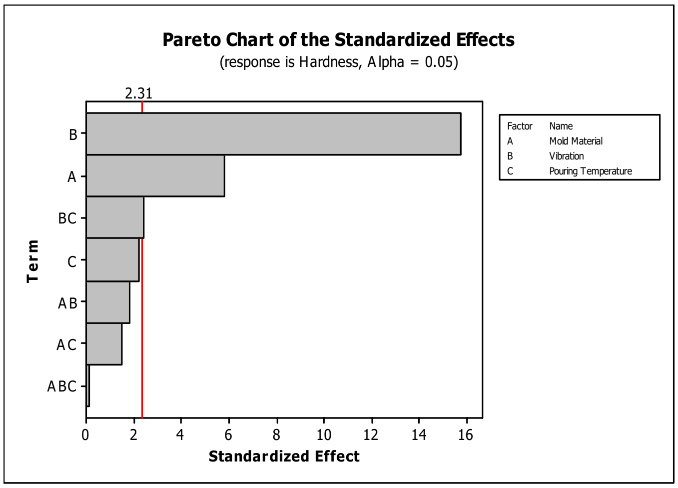
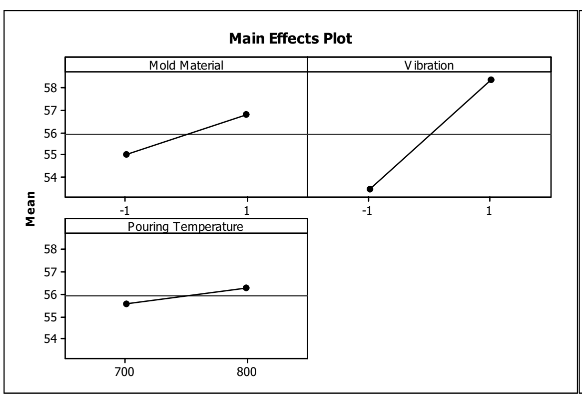


Fig 2 Pareto chart for the response –hardness

The contributions of the input variables and their interactions on the measured response are shown in Figure 3 and Figure 4 respectively.From the main effects plot in Figure 3, it can be seen that graphite as the mold material, with vibration and pouring temperature of 800°C gives higher mean value of hardness. The effect of pouring temperature seems to be negligible.



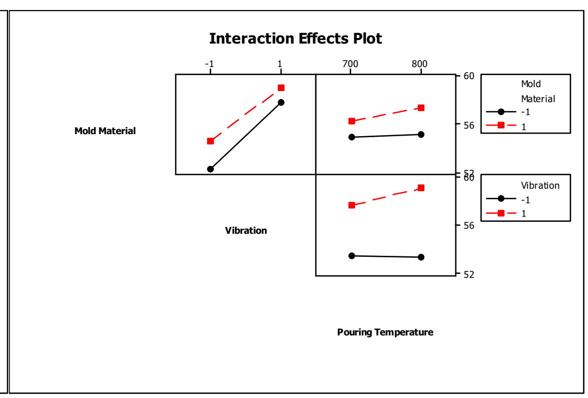


Fig 3 Main effects plot for the response – hardnessFig 4 Interaction Plot for the identified factors, response - hardness

From the interaction plot in Figure 4, it can be seen that the vibrated mold gives higher mean value of hardness as compared to unvibrated mold. Similarly it can be seen that alloy poured at 800°C in graphite mold gives higher

mean value of hardness as compared to alloy poured at 700°C.The effect of pouring temperature on cast iron mold is negligible. Alloy poured at 800°C in a vibrated mold gives better result than an alloy poured in at 700°C. Similiarly it can be seen that the effect of pouring temperature on an unvibrated mold is negligible.
From the normal probability plot for the response hardness in Figure 5, it is found that there is no severe indication of nonnormality, nor is there any evidence pointing to possible outliers.

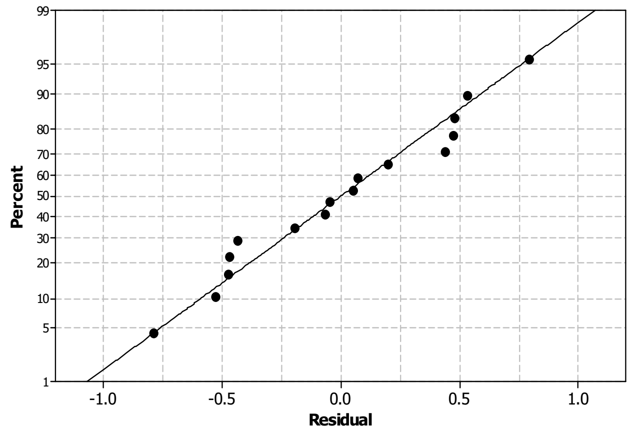


Fig 5 Normal Probability plot of residuals for response – hardness

B. Wear

The linear model based on full factorial design in coded terms is given by the equation:

$$W = 821.63 - 23.50A - 62.13B - 12.25C + 0.25AB - 7.13AC - 13.50BC + 1.63ABC \quad (2)$$

Significance test was carried out to study the effects, contributions and significance of the input parameters and their interaction terms on the response – wear. The significance test results are shown in Table 6 .

As the *p* values of the terms A, B, C, ACand BC in Table 6 were found to be less than 0.05, those terms were considered to have significant contributions on the response wear at 95% confidence level, whereas all other interactions terms were found to have no significant contribution.

Table 6 Results of significance test on the model, coefficients, *T*- statistics and *p* values for response – wear

Term	Effect	Coef	SE Coef	T	P
Constant		**821.63**	**2.536**	**324.03**	**0.000**
A	**-47.00**	**-23.50**	**2.536**	**-9.27**	**0.000**
B	**-124.25**	**-62.13**	**2.536**	**-24.50**	**0.000**
C	**-24.50**	**-12.25**	**2.536**	**-4.83**	**0.001**
AB	**0.50**	**0.25**	**2.536**	**0.10**	**0.924**
AC	**-14.25**	**-7.13**	**2.536**	**-2.81**	**0.023**
BC	**-27.00**	**-13.50**	**2.536**	**-5.32**	**0.001**
ABC	**3.25**	**1.63**	**2.536**	**0.64**	**0.540**

Analysis of variance (ANOVA) was performed to test the significance of the factors for the response – wear. The results of ANOVA are shown in Table 7 . From the table, it is noted that the 2- way interaction term ABand the 3-way interaction term ABC are found to be insignificant for this response. The R squared value for this model was found to be equal to 0.9894. The results of ANOVA and the R squared indicate that the developed regression model based on full – factorial design is statistically adequate.

Table 7 Results of ANOVA for the response – wear

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	**3**	**72989.3**	**72989.3**	**24329.8**	**236.50**	**0.000**
A	**1**	**8836.0**	**8836.0**	**8836.0**	**85.89**	**0.000**
B	**1**	**61752.3**	**61752.3**	**61752.3**	**600.26**	**0.000**
C	**1**	**2401.0**	**2401.0**	**2401.0**	**23.34**	**0.001**
2-way Interactions	**3**	**3729.2**	**3729.2**	**1243.1**	**12.08**	**0.002**
AB	**1**	**1.0**	**1.0**	**1.0**	**0.01**	**0.924**
AC	**1**	**812.3**	**812.3**	**812.3**	**7.90**	**0.023**
BC	**1**	**2916.0**	**2916.0**	**2916.0**	**28.35**	**0.001**
3-way Interactions	**1**	**42.3**	**42.3**	**42.3**	**0.41**	**0.540**
ABC	**1**	**42.3**	**42.3**	**42.3**	**0.41**	**0.540**
Residual Error	**8**	**823.0**	**823.0**	**102.9**		
Pure Error	**8**	**823.0**	**823.0**	**102.9**		
Total	**15**	**77583.8**				

The contributions of the input variables and their interactions are shown in the form of Pareto chart in Figure 6. From the figure it can be seen that vibration contributes significantly to the measured response followed by mold material, interaction of vibration and pouring temperature, pouring temperature and finally the interaction of mold material and pouring temperature.The interaction of all three variables and the interaction effect of mold material with vibration is insignificant.

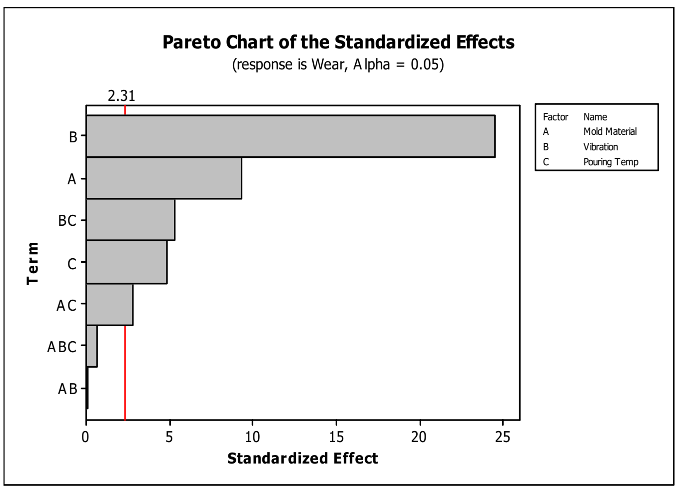


Fig 6 Pareto chart for the response –wear

The contributions of the input variables and their interactions on the measured response are shown in Figure 7 and Figure 8 respectively.From the main effects plot in Figure 7, it can be seen that graphite as the mold material, with vibration and pouring temperature of 800°C gives lower mean value of wear.

From the interaction plot in Figure 8, it can be seen that the vibrated mold gives lower mean value of wear as compared to unvibrated mold. Similiarly it can be seen that alloy poured at 800°C in graphite mold gives lower mean value of wear as compared to alloy poured at 700°C.The effect of pouring temperature in interaction with the cast iron mold on wear is negligible. Alloy poured at 800°C in a vibrated mold gives lower mean value of wear than an alloy poured in at 700°C. Similiarly it can be seen that the effect of pouring temperature in interaction with unvibrated mold is negligible.

From the normal probability plot for the response wear in Figure 9, it is found that there are no severe indication of nonnormality, nor is there any evidence pointing to possible outliers.

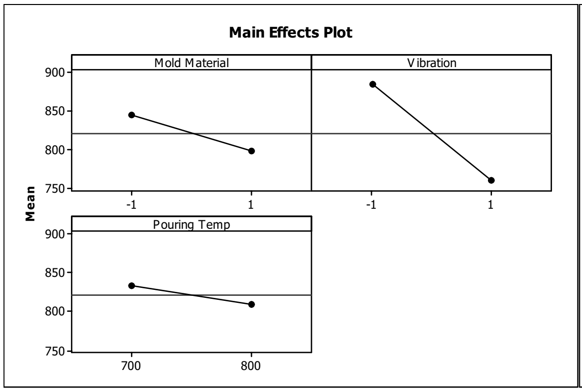


Fig 7 Main effects plot for the response – wear

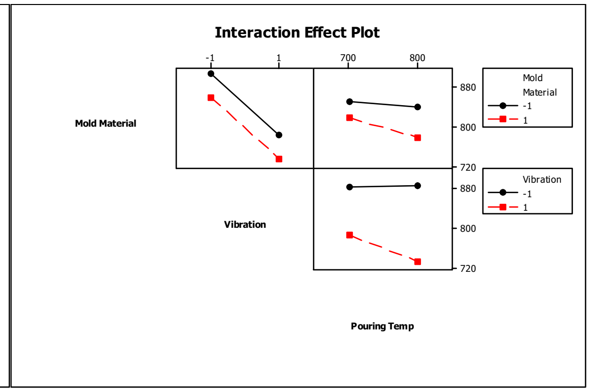


Fig 8 Interaction Plot for the identified factors, response – wear

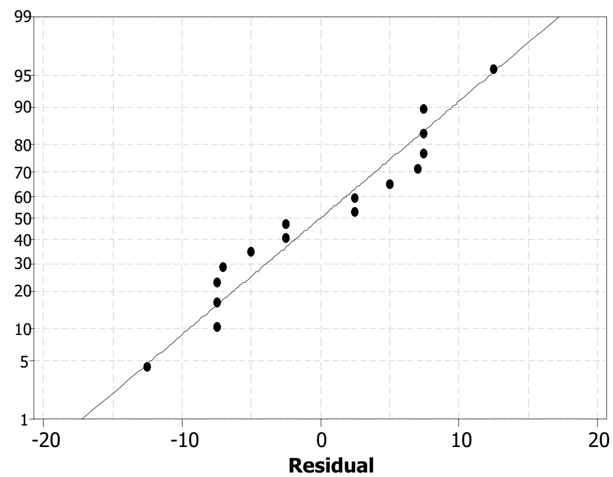


Fig 9 Normal Probability plot of residuals for response – wear

C. Optimization using GA

In the present work, hardness and wear are the two responses which have been measured and the optimum values of process parameters which maximize hardness and minimize wear have to be evaluated. Hence there is a need for a multi-objective optimization method to arrive at the solution. This multi-objective problem is converted to a single objective function after assigning weights to each objective [22]. Hence the objective function can be rewritten as

$$\text{Maximize } Z = w_1 \times f_1 + w_2 \times f_2 \qquad (3)$$

where f_1 is the objective function for hardness, f_2 is the objective function for wear, w_1 and w_2 are the weights assigned to each objective functions. The weights are selected such that their sum is equal to one. Here equal weights have been assigned to both hardness and wear. Hence $w_1=w_2=0.5$.The constraints imposed here are the mold material, vibration and pouring temperature. The values of all the constraints in coded terms vary between -1 and 1. The parameters used in GA are population size = 50, selection operator = stochastic uniform, probability of crossover =0.8, probability of mutation = 0.2. Fig 10 depicts the converged results obtained in GA. The convergence occurred at 52nd iteration. The optimum value of the combined objective function as given by equation 3 is

322.5019. Table 8 compares the optimized values of parameter for obtaining the maximum hardness and minimum wear with the experimental values. The optimum parameters are graphite as mold material subjected to vibration with the pouring temperature of the alloy being 800° C.

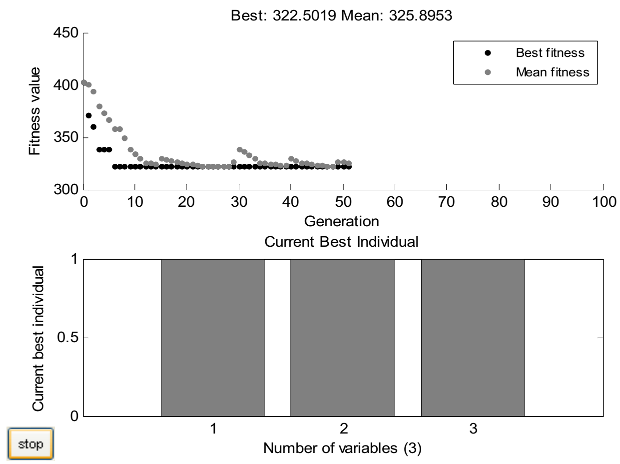


Fig 10 Screenshot depicting the convergence result obtained using GA

Table 8 Comparison of results obtained by GA with experimental

	Mold Material	Vibration	Pouring Temperature	Hardness (BHN)	Wear (µm)
GA	**1**	**1**	**0.99988**	**59.999**	**705**
Experimental	**1**	**1**	**1**	**60.05**	**700**

IV.CONCLUSION

In this study, mechanical mold vibration during solidification of Al-9% Si alloy has been applied successfully to improve the hardness and dry sliding wear properties. Other parameters studied were mold material and pouring temperature. Design of experiments technique has been used in this study and the statistical significance of the process has been determined using ANOVA. Mold vibration has contributed significantly in enhancing the properties whereas the effect of pouring temperature is least. The optimization of process parameters has been carried using GA and there is narrow deviation between the predicted value and experimental value.

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