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Parametric Model for Prediction of Mechanical Properties of Motorcycle Brake Levers Produced by Gravity Die Casting

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ABSTRACT: Several attempts have been made in foundry industries to enhance the mechanical properties of cast components. A new study was conducted to develop a parametric model for the mechanical properties of motorcycle brake levers produced through gravity die casting. The experimental work was carried out at the Foundry Workshop, Federal Polytechnic Kaura Namoda, Zamfara, Nigeria, using a permanent metallic mold to measure the mechanical properties of the motorcycle brake levers. This study employed a central composite, rotatable design matrix with four factors (pre-die temperatures, pouring temperatures, solidification time, and filling time) and five levels to optimize the number of experiments. The model's adequacy was tested through analysis of variance (ANOVA), and the results of the experiments agreed with the parametric model, with the maximum error of prediction for compressive strength and hardness being ±3.73% and ±3.80%, respectively. The model suggests that one must consider parameter interactions to predict the compressive strength and hardness of gravity die-casting components accurately. Hence, the optimal combination of testing parameters can be determined and predicted.

Keywords: Parametric, compressive strength, hardness, models, gravity die-casting, aluminium, regression

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INTRODUCTION

Casting defects often occur in casting components due to improper casting parameters and molten metal characteristics. These defects are mainly caused by improper process parameters during mold filling and solidification. Factors such as pouring temperatures of a cast alloy, pre-die temperatures, time of filling a die cavity, and solidification time can affect the quality of gravity die castings. The filling process is where casting defects typically occur, and this can affect the filling ability and, ultimately, the mechanical properties of gravity die casting. The mechanical properties of gravity die castings are mainly dependent on the working variables of the gravity die casting process, casting parameters, thickness of the cast part, type of casting alloy, and molten metal characteristics.

Casting high-quality products is a challenging task due to the complexities involved in knowing the casting parameters and molten metal characteristics during mold filling and solidification. However, the advent of computers, numerical modeling, and simulation technology has made it possible to simulate these processes. By predicting the filling and solidification process during gravity die casting, researchers can effectively optimize the filling state, improve casting technology, and reduce the cost of mold design and production. This parametric modeling and simulation technique help the Casting Engineer to predict potential defects and optimize the gravity die-casting process.

Ozel and Karpat (2005) used regression analysis and neural networks to develop a predictive model for surface roughness in hard turning. The machinability of cold work tool steel AISI D2 was evaluated by Davim and Figueira (2007) during hard turning with ceramic tools. They reported that the feed rate and cutting time influenced the surface roughness. Zheng et al. (2009) developed two modeling techniques, ANOVA and ANN, to predict surface roughness. They considered three input parameters for machining, namely, cutting speed, feed rate, and depth of cut. Mandal et al. (2011) developed an artificial neural network-based surface roughness prediction model to investigate the effects of cutting conditions during the turning of free-machining steel. The author justified the use of ANN as there exist highly non-linear relationships between the output and the cutting conditions. The study by Ozel et al. (2007) involved the development of multiple linear regression models and neural network models to predict surface roughness. They used cutting speed, feed rate, and cutting time as input parameters for experimentation and model development. The study concluded that neural network models were suitable for predicting surface roughness patterns across various cutting conditions. In separate work, Hsu and Anh (2013) developed a multivariable linear model to identify optimal parameters and factors for improving the quality and efficiency of aluminium ADC10 die-casting. While there has been extensive research on optimizing surface roughness models for steel machinability, there is a lack of parametric models for predicting the surface finish of A356 aluminum alloy produced by gravity die-casting.

METHODOLOGY

The gravity die-casting experiment was conducted at the Foundry Workshop, Federal Polytechnic Kaura Namoda, Zamfara, Nigeria using a permanent metallic mold. The experimental investigation involves the use of a permanent metallic mold of motorcycle brake lever, melting of formulated A356 aluminum alloy, pouring of molten metal, and ejection of cast components. The chemical composition (in wt. %) of the A356 alloy used for this study is stated in (Table 1).

The experimental selection was done by design matrix to perform 31 sets of motorcycle brake levers on a four-factor central composite face-centered design using a design experiment with different casting parameters as shown in (Table 2).

The samples were cast by the gravity die-casting process using the different casting parameters and several trial casts were produced by the gravity die-casting process by changing one factor at a time keeping the other three factors at a constant setting. The cast specimens were subjected to hardness and yield strength tests to ascertain the quality of the motorcycle brake lever produced. The second-order equation was fitted by regression to predict the quality of the cast produced. Analysis of Variance (ANOVA) was used to determine the influence of the four (4) input parameters and their interactions.

Flexural strength test

The tensile testing machine used in this research for flexural strength tests was the Testometric Universal Testing Machine located at Material Science, Bayero University Kano, Kano State, with a maximum load capacity of 100KN (10 tonnes) and a test speed of 5.00 mm/min. As defined in ASTM D790, the standard testing procedure was followed by placing the cast component on two supporting pins at a set distance apart. The results for compressive strength of the cast samples for different pouring temperatures, pre-die temperatures, filling time, and solidification time are presented in (Table 3).

Hardness test

The motorcycle brake lever produced was subjected to a hardness test by the ASTM E18 specification for metals on a Welltest Rockwell hardness tester. The test was conducted with a $^{1}/_{16}$ *-inch-diameter (1.588 mm)* steel ball with a minor load of 10N and a major load of 100N on an HRB scale. A similar test procedure was also adopted for all the specimens, and the results are presented in (Table 3).

RESULTS

Results Obtained from Design of Experiment (DOE) and Parametric Model for Prediction of Mechanical Properties of Cast Component Produced

The quality of cast components was evaluated using compressive strength and hardness test.
compressive strength and hardness = f (variable factors)

CS & HRB= f (pouring temperatures, pre-die temperatures, filling time, solidification time)

$$CS \;\&\; HRB = f(X_1, X_2, X_3, X_4).\ Q = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_1X_1^2 + b_2X_2^2 + b_3X_3^2 + b_4X_4^2 + b_{12}X_{12} + b_{13}X_{13} + b_{14}X_{14} + b_{23}X_{23} + b_{24}X_{24} + b_{34}X_{34} \quad (1)$$

Where, Q is the quality responses, X_1 is the un-coded values of pouring temperatures (PT), X_2 is the un-coded values of pre-die temperature (DT), X_3 is the un-coded values of filling time (FT), X_4 is the un-coded values of solidification time (ST). b_0, b_1 etc. are the regression coefficients. The values of the regression coefficients for quality responses were determined using MINITAB-16 Software. The results obtained for regression coefficients, ANOVA and others were stated in (Tables 4a and 4b).

Regression equation for compressive strength

$$CS = 116215 - 158.954\,PT - 563.872\,DT - 29394.1\,FT - 8704.78\,ST + 0.772198\,PT{*}DT + 40.3119\,PT{*}FT + 11.9229\,PT{*}ST + 140.429\,DT{*}FT + 41.7847\,DT{*}ST + 2160.15\,FT{*}ST - 0.192568\,PT{*}FT{*}ST - 0.0572165\,PT{*}DT{*}ST - 2.96203\,PT{*}FT{*}ST - 10.2086\,DT{*}FT{*}ST + 0.0139973\,PT{*}DT{*}FT{*}ST \quad (2)$$

Equation 3.2 shows the regression equation coefficients for compressive strength, which can be used to determine any output response of compressive strength, having known the input parameters. The coefficient of determination (R^2) value for the compressive strength was 0.756, as seen in the model summary below equation 3.2. The results indicate that the developed model for compressive strength is crucial because the summary of the model gives adequate outcomes. The value of adequate precision for CS was 8.60, which indicates an adequate signal. The ANOVA results for compressive strength (CS) are given in (Table 4a).

Table 1: Chemical composition (in wt. %) of the A356 alloy.

Element	Si	Mn	Ti	Fe	Sr	Cu	Ni	Al
% Composition	7.1	0.31	0.23	0.17	0.05	0.01	0.0013	Balance

Table 2: Different casting parameters

Casting Parameters	Un-coded levels				
Pouring temperature (^{0}C)	700	710	720	730	740
Pre-die temperature (^{0}C)	150	175	200	225	250
Filling time (secs)	1	2	3	4	5
Solidification time (secs)	11	12	13	14	15

Table 3: Results of samples along with responses.

Trial No	Input Parameters				Output Parameters	
	X_1 = (PT) (^{0}C)	X_2 = (DT) (^{0}C)	X_3= (FT) (secs)	X_4 = (ST) (sec)	Compressive Strength (MPa)	Mean Hardness No. (HRB)
1	710	175	2	12	177.5	83
2	730	175	2	12	179.4	83
3	710	225	2	12	139.3	70
4	730	225	2	12	177.6	83
5	710	175	2	14	140.9	70
6	730	175	2	14	178.2	83
7	710	225	2	14	164.7	79
8	730	225	4	14	179.7	83
9	710	175	4	12	158.8	77
10	730	175	4	12	179.2	83
11	710	225	4	12	166.6	79
12	730	225	4	12	174.2	82
13	710	175	4	14	161.3	78
14	730	175	4	14	176.1	82
15	710	225	4	14	177.0	83
16	730	225	4	14	178.4	83
17	700	200	3	13	163.9	79
18	740	200	3	13	189.4	86
19	720	150	3	13	174.5	82
20	720	250	3	13	176.8	82
21	720	200	3	11	161.3	79
22	720	200	3	15	179.7	85
23	720	200	1	13	138.1	69
24	720	200	5	13	176.2	82
25	720	200	3	13	177.0	82
26	720	200	3	13	174.5	82
27	720	200	3	13	176.8	82
28	720	200	3	13	174.2	82
29	720	200	3	13	174.5	82
30	720	200	3	13	176.8	82
31	720	200	3	13	174.2	82

The result showed that the model is crucial. Significant model terms are those for which the p-value is less than 0.05. Regarding compressive strength, PT, FT, DT*ST, and PT*DT*ST are significant model terms because their p-values were less than 0.05, as seen in (Tables 4a and b). The coefficient of determination (R^2) is another criterion used to evaluate the adequacy of a model. For an ideal model, the value of R^2 is unity, as stated in Azam et al, (2015). For CS, the value of R^2 is 0.756, as indicated in the summary of the model under equation 3.2. Adequate precision measures the signal-to-noise ratio, and a value of more than 2 is desirable. For CS, the value of adequate precision is 8.60, which indicates an adequate signal.

Regression equation

$$HRB = 43761.3 - 59.9427\,PT - 213.268\,DT - 10820.2\,FT - 3311.68\,ST + 0.292657\,PT{*}DT + 14.8596\,PT{*}FT + 4.545\,PT{*}ST + 51.8403\,DT{*}FT + 16.0097\,DT{*}ST + 807.608\,FT{*}ST - 0.0711975\,PT{*}DT{*}FT - 0.0219714\,PT{*}DT{*}ST - 1.10913\,PT{*}FT{*}ST - 3.83419\,DT{*}FT{*}ST + 0.00526646\,PT{*}DT{*}FT{*}ST \quad (3)$$

Equation 3 shows the coefficients of the regression equation for hardness (HRB), which can be used to determine any output response of hardness having known the input parameters. The coefficient of determination (R^2) value for the hardness was 0.736, as seen in the model summary below in Equation 3.3. The results indicate that the developed model for hardness is

Table 4a: Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	15	3443.78	3443.78	229.586	3.1052	0.017646
PT	1	1467.97	240.90	240.903	3.2583	0.009117
DT	1	4.77	215.97	215.968	2.9211	0.108032
FT	1	529.49	187.32	187.318	2.5336	0.013230
ST	1	40.36	225.34	225.340	3.0478	0.101289
PT*DT	1	28.84	207.61	207.609	2.8080	0.114510
PT*FT	1	133.33	181.52	181.518	2.4551	0.137994
PT*ST	1	0.59	216.85	216.852	2.9330	0.107374
DT*FT	1	91.32	161.87	161.871	2.1894	0.159662
DT*ST	1	336.25	187.97	187.971	2.5424	0.013167
FT*ST	1	20.47	165.31	165.309	2.2359	0.155581
PT*DT*FT	1	147.36	156.59	156.586	2.1179	0.166196
PT*DT*ST	1	240.44	180.47	180.469	2.4409	0.013905
PT*FT*ST	1	36.51	160.00	159.999	2.1641	0.161938
DT*FT*ST	1	232.26	138.51	138.509	1.8734	0.191238
PT*DT*FT*ST	1	133.83	133.83	133.827	1.8101	0.198487
Error	15	1109.03	1109.03	73.935		
Lack-of-Fit	8	1097.21	1097.21	137.151	81.2280	0.000003
Pure Error	7	11.82	11.82	1.688		
Total	30	4552.81				

Table 4b: Fits and diagnostics for unusual observations

Obs	CS	Fit	SE Fit	Residual	St Resid
13	161.3	167.492	8.09748	-6.1923	-2.1409 R
15	177	183.388	8.12569	-6.388	-2.2716 R
23	138.1	161.781	4.77646	-23.681	-3.312 R

R denotes an observation with a large standardized residual.

crucial because the summary of the model gives adequate outcomes. The value of adequate precision for HRB was 2.99, which indicates an adequate signal. The ANOVA results for hardness (HRB) are given in (Table 6). The result showed that the model is crucial. Significant model terms are those for which the p-value is less than 0.05. In the case of HRB, PT, FT, PT*ST, and DT*ST are significant model terms. The coefficient of determination (R^2) is another criterion used to evaluate the adequacy of a model. For an ideal model, the value of R^2 is unity, and the value of R^2 for hardness is 0.736, as indicated in the summary of the model under equation 3. Adequate precision measures the signal-to-noise ratio, and a value of more than 2 is desirable. For HRB, the value of adequate precision is 2.99, which indicates an adequate signal.

Validation of results

Five confirmation tests were carried out to validate the parametric models developed. The values on which the confirmation tests were performed were within the designed space. However, the confirmation tests were performed on values within the central composite design matrix. The experimental and predicted values of the confirmation tests are presented in (Table 6). The error between experimental and predicted values is within the 95% confidence interval, which verifies that the model is adequate and that both the expected and experimental values agree with each other. From (Table 6), the confirmation experiments indicated that the maximum prediction error for compressive strength is $\pm$3.73%, and the hardness is $\pm$3.80%. The result agrees with Bhatt and Parappagoudar (2015). Therefore, it can be concluded that the developed models are applicable to all values within the designed space. Figure 1 shows the variation between experimental and predicted values for compressive strength. The blue line represents experimental values, while the brown represents predicted values. The predicted values are slightly more than the experimental values. There was a broader difference in experimental and predicted values around 720 – 735^{0}C, which showed a prediction error of about $\pm$3.73%. Figure 2 shows the variation between experimental and predicted values for hardness. The blue line represents experimental values, while the brown represents predicted values. The predicted values are slightly more than the experimental values.

Table 5a: Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	15	373.303	373.303	24.8868	2.78476	0.0280
PT	1	135.375	34.259	34.2590	3.83347	0.0491
DT	1	0.375	30.894	30.8943	3.45697	0.0827
FT	1	63.874	25.382	25.3824	2.84021	0.0126
ST	1	3.953	32.615	32.6152	3.64954	0.0754
PT*DT	1	2.448	29.820	29.8199	3.33675	0.0877
PT*FT	1	18.016	24.664	24.6641	2.75984	0.1174
PT*ST	1	0.264	31.511	31.5114	3.52602	0.0489
DT*FT	1	7.928	22.059	22.0591	2.46834	0.1370
DT*ST	1	38.751	27.595	27.5946	3.08775	0.0493
FT*ST	1	2.372	23.106	23.1062	2.58551	0.1287
PT*DT*FT	1	12.962	21.405	21.4050	2.39515	0.1426
PT*DT*ST	1	36.618	26.612	26.6119	2.97778	0.1049
PT*FT*ST	1	4.966	22.434	22.4339	2.51028	0.1340
DT*FT*ST	1	26.457	19.539	19.5386	2.18630	0.1599
PT*DT*FT*ST	1	18.945	18.945	18.9449	2.11988	0.1660
Error	15	134.052	134.052	8.9368		
Lack-of-Fit	8	134.052	134.052	16.7565	*	*
Pure Error	7	0.000	0.000	0.0000		
Total	30	507.355				

Table 5b: Fits and diagnostics for unusual observations

Obs	HRB	Fit	SE Fit	Residual	St Resid
13	78	80.2316	2.81524	-2.23158	-2.21916 R
15	83	85.1769	2.82505	-2.17692	-2.22655 R
23	69	77.3030	1.66063	-8.30296	-3.34018 R

R denotes an observation with a large standardized residual.

Table 6: Comparison of experimental results with predicted results.

S/N	Input Variables				Experimental Value		Predicted Value		% Error of Prediction	
	PT	DT	FT	ST	CS	HRB	CS	HRB	CS	HRB
1	700	150	3	14	140.9	69.0	138.76	66.38	1.52	3.80
2	710	200	3	13	160.7	79.0	162.85	78.47	-1.34	0.67
3	720	200	3	14	170.6	82.5	172.21	81.26	-0.94	1.51
4	730	200	3	14	168.2	81.4	174.48	83.40	-3.73	-2.45
5	740	200	3	14	170.6	83.1	169.01	85.53	0.93	-2.93

There was a broader difference in experimental and predicted values at 700^{0}C and around 730 – 735^{0}C, which showed a prediction error of about $\pm$3.80%.

DISCUSSION

Adequacy measures the fitness of the developed models to predict the output responses. The adequacy of the developed mathematical models was evaluated using Analysis of Variance (ANOVA), coefficient of determination (R^2), and adequate precision. The ANOVA results for compressive strength (CS), and hardness (HRB) were given in (Table 6) respectively. The results showed that all two models are crucial. The above assertion agreed with Zeelanbasha et al, (2017) work. The values of R^2 for CS, and HRB are 0.756, and 0.736 respectively, as indicated in the summary of the model under (Table 6) which showed that the models are ideal as stated in Azam, et al., (2015) work. Adequate precision measures the signal-to-noise ratio, and a value of more than 2 is desirable. For CS and hardness, the values of adequate precision are 8.59 and 2.99 respectively, which indicate an adequate signal. The result agrees with Bhatt and Parappagoudar (2015) work. Therefore, it can be concluded that the developed models are applicable to all values within the designed space.

For all pre-die temperatures, the motorcycle brake levers cast have nearly the same compressive strength range of 160 to 170 MPa and hardness (79 to 83HRB) at pre-die temperatures of 200^{0}C. Compressive strength increases as the temperatures change for the pouring temperatures tested. As seen in this research, which agrees with the

Hasasi, et al, (2019) work, it was found that pouring temperature affected the mechanical properties of the die-cast aluminium alloy. According to Hu et al., (2016) and Grosselle et al., (2009), an increase in the mechanical properties, especially compressive strength and hardness, is observed when the size of silicon (Si) particles is maintained at above 7% because Si particles lead to a low tension field around these particles, which promotes binding mechanism and reduces casting defects, especially porosity (Adamane et al., 2015).

Conclusion

The developed regression model can be used to achieve the desired mechanical properties by combining casting parameters and molten metal characteristics. As a result, regression equations and ANOVA can be useful tools for predicting the mechanical properties of gravity die-cast alloys. The model equation was used to calculate the compressive strength and hardness of an aluminium alloy during gravity die casting. The model results agreed with the experimental measurements. Confirmation trials show a maximum prediction error of ±3.73% for compressive strength and ±3.80% for hardness.

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