

New Modelling and Optimization of Cooling Slope Semi-Solid Process Parameters for Magnesium Alloys Using Full Factorial Design

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ABSTRACT

Cooling-slope (CS) process is a process in preparing the feedstock for the semi-solid process with minimal equipment required. In CS process, optimal selection of CS parameters is important in producing high-quality feedstock. A comprehensive investigation concerning the influence of CS parameters on feedstock quality specifically Tensile strength (TS) and Impact Strength (IS) through an experimental design is conducted. The experiment employs three full factorial designs with added center points for CS parameters, including Pouring temperature (Pt), Pouring distance (Pd), and Slanting angle (Sa). Data from the CS experiment are utilized to develop the mathematical model using regression analysis approach. The models were validated using analysis of variance (ANOVA) and the coefficient of determination (R²). The confirmatory test result shows 3.47% of difference between simulation and experimental. The optimal solution will provide flexibility to the process planner to choose the best parameter settings depending on the application.

Keywords: Cooling Slope Casting Process, Semi-solid process, Optimization, ANOVA.

INTRODUCTION

The Cooling Slope (CS) casting process is one of the sixteen techniques employed in semi-solid metal processing (SSMP). The production of feedstock for SSMP is a straightforward operation that requires only a minimal number of apparatuses [1]. In this process, molten metal heated to an appropriate temperature is poured onto a sloping plate designed to cool the metal, after which the metal solidifies within a mold [2]. Previous studies have shown that the CS process ensures superior performance, including excellent dimensional accuracy, high production rates, superior surface quality, and near-net-shape products—attributes essential for high-quality casting operations [3].

Moreover, the CS process offers several advantages, such as reduced porosity and macro-segregation, as well as improved mechanical properties compared with conventional casting routes [3]. Microstructure and mechanical properties are the key indicators commonly used to assess the quality of feedstock produced via the CS process. Examples of mechanical properties include tensile strength (TS) and impact strength (IS) [4–8].

However, achieving feedstock with the desired mechanical properties through the CS process is challenging due to issues such as oxidation, porosity, and rapid solidification, where molten metal may solidify before completely filling the mold. Several studies have reported that CS processing parameters significantly influence feedstock quality [9–10]. Therefore, to attain high-quality feedstock, these parameters must be

optimized. The major process parameters in CS casting are pouring temperature, pouring distance, and slanting angle, which strongly affect feedstock performance and quality [11–14].

To address this knowledge gap, a mathematical model based on fractional factorial design was developed to systematically evaluate the effects of CS process parameters on tensile strength. This model quantifies the influence of variables such as pouring temperature, pouring distance, and slanting angle, and assists in identifying optimal parameter settings to achieve the desired tensile strength [15]. Furthermore, this study aims to enhance the prediction and optimization of tensile strength in the CS casting process through a regression-based mathematical model.

The Design of Experiments (DOE) approach was employed to establish a structured series of experimental trials. Over the past two decades, full factorial designs have been effectively applied to analyze complex nonlinear input–output relationships in various manufacturing processes. DOE and Response Surface Methodology (RSM) have also been successfully utilized to develop and analyze linear and nonlinear models in cooling slope [16, 17], sand molding [18], and squeeze casting processes [19]. The response model equations derived from these models demonstrated reasonable accuracy in predicting cooling slope process behavior.

In the present work, modeling and optimization of the cooling slope process were carried out, and a regression model for tensile strength was developed using experimental data from the semi-solid CS casting process. These models were used to formulate the optimization problem through the Full Factorial Design approach. Pouring temperature, pouring distance, and slanting angle were considered as the main process parameters. A comparative analysis was then conducted between the experimental results and the Full Factorial approach to evaluate process optimization performance. The results obtained are summarized, presented, and discussed.

METHODOLOGY

The adopted methodology, encompassing modelling, statistical analysis, and optimization of the cooling slope semi-solid casting process, is presented in this section and illustrated in Figure 1.

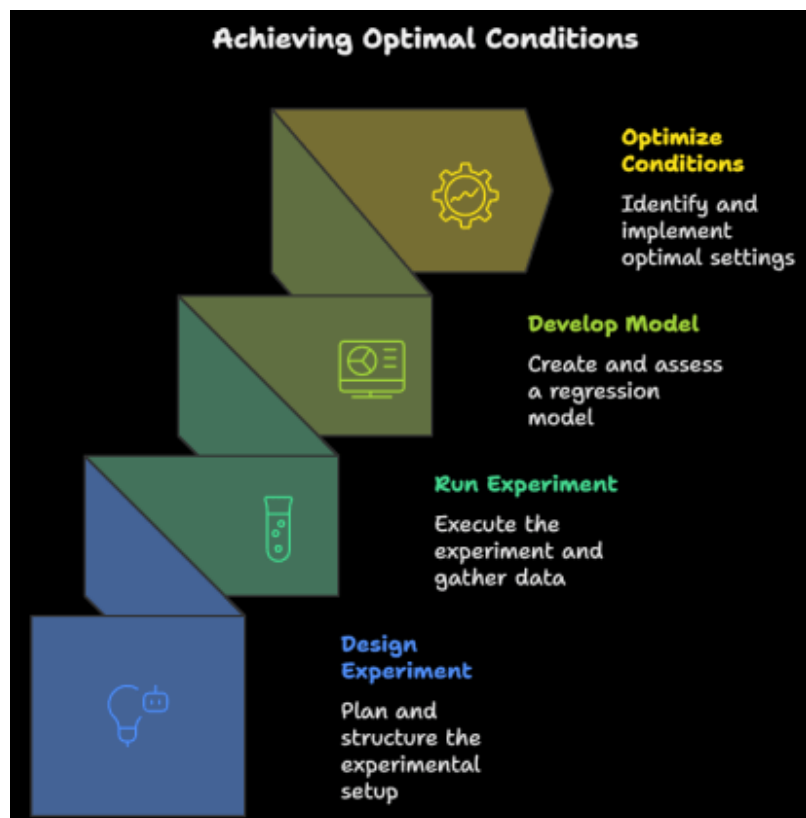


Figure 1: Step in modelling and optimization of cooling slope semi-solid casting process.

Selection of processing parameters

The accuracy of the modelling and optimization of the cooling slope process was influenced by the careful selection of input variables and their respective boundary ranges. The procedure for selecting the input variables, determining their boundary limits, and establishing the operational ranges—following the approach of previous researchers [20-22] is summarized in Table 1. Figure 2 illustrates the input–output model of the cooling slope casting process.

The experimental design for this study was based on a fractional factorial design. Three factors at three levels, with four center points, were established. A total of 27 specimens were produced according to the proposed design. The optimal levels of the process parameters were determined using the fractional factorial optimization technique, and a mathematical model was developed through regression analysis to predict the output within the selected range of process parameters. Confirmation experiments were subsequently conducted to validate the optimal parameter settings.

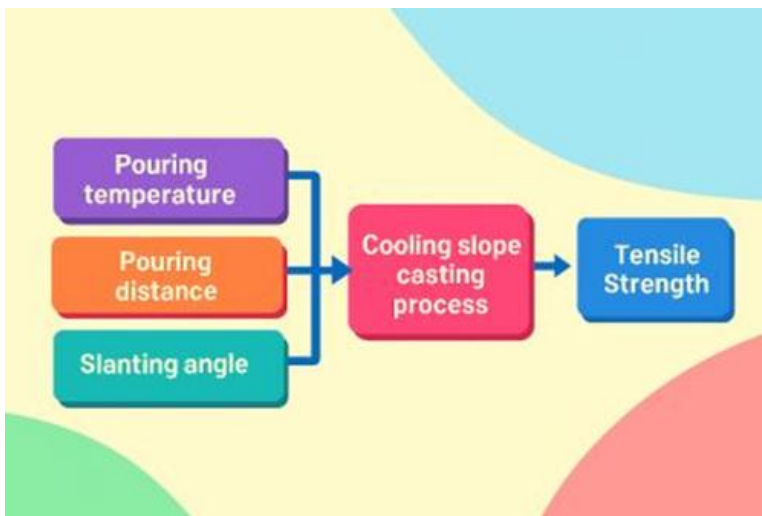


Figure 2: Input-output model for cooling slope casting process

Experimental Setup

Experiments output values are used to find the best combination of optimal parameters. The objective is to maximize the tensile strength of feedstock. Table 1 shows default parameters, factors, levels and four different sets of experimental runs which are completely randomized.

Table 1: Range value of CS parameters

Casting parameters	Unit	Level		
Pouring temperature	°C	680	700	720
Pouring Distance	mm	300	400	500
Slanting angle	°	30	45	60

The experiment was conducted following a three-level factorial design. This design was selected to examine the effect of multiple independent variables on a dependent variable and to identify potential interactions among the independent variables. Experimental setup detail as shown in [24]. A total of 700 g of AZ91D magnesium alloy ingot was placed in a stainless-steel crucible within a heating furnace and melted at temperatures of 680 °C, 700 °C, and 720 °C. Subsequently, the molten metal was poured onto a cooling slope and allowed to flow into a mould according to the specified parameter settings. K-type thermocouples were positioned along the cooling slope to record temperature readings. The cooling slope experiments were performed by varying the pouring temperature, slanting angle, and pouring distance, as summarized in Table 2. Finally, the molten metal that solidified within the mould was designated as the as-cast specimen.

Table 2: Experimental design for the performance of mechanical properties

Standard order	CS parameters		
	Pouring Temperature	Slanting angle	Pouring Distance
1	680	30	300
2	700		
3	720		
4	680	45	
5	700		
6	720		
7	680	60	
8	700		
9	720		
10	680	30	400
11	700		
12	720		
13	680	45	
14	700		
15	720		
16	680	60	
17	700		
18	720		
19	680	30	500
20	700		
21	720		
22	680	45	
23	700		
24	720		
25	680	60	
26	700		
27	720		

Developing the regression model and conducting statistical analysis and testing of models

Mathematical model is developed based on CS experimental data. Regression analysis was performed to establish the functional relationship between CS parameters and feedstock performance. The CS parameters (i.e., slanting angle (S), pouring distance (D), and pouring temperature (T)) served as input variables and feedstock performance (i.e., TS and IS) functioned as output variables. Multiple regression models developed for both responses, which were the degree of sphericity and grain size in the microstructure at 95% confidence level with pouring temperature, slanting angle, and slanting distance as input parameters. Polynomial Regression Model based experiment designs were developed. The models were validated to test the adequacy by using the analysis of variance (ANOVA) and determination coefficients (R²) values, where the values of approaches or close the value one indicates that the models were significant. Then, each model validated by using mean square error (MSE) and root square error (RMSE). A comprehensive comparison also made between the obtained results with results obtained by another researcher [15]. The multiple regression model can be express as in Equation 1:

(1)

RESULTS AND DISCUSSION

Figure 1 consists of two panels. Panel (a) is a photograph of the 3D-printed prototype of the cervical collar, showing its complex, multi-layered structure. A ruler is placed next to it for scale, indicating a length of approximately 200 mm. Panel (b) is a photograph of the 3D-printed prototype of the cervical collar, showing its smooth, cylindrical shape. A technical drawing overlay is present, showing the dimensions of the device. The drawing includes a central section with a diameter of 100 mm and a length of 100 mm, and two side sections with a diameter of 100 mm and a length of 100 mm. The total length of the device is 300 mm.

The models generated for feedstock performances of TS are shown in Equations 2:

(2)

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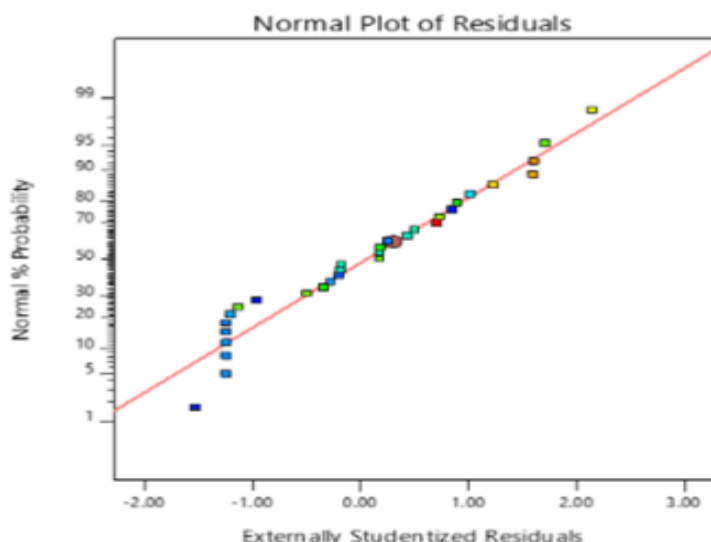


Figure 5: Normal plot of residuals of TS

From Figures 6 shows the residual versus predicted plot for TS in models. The residual versus predicted plots verified the assumption that the residuals were randomly distributed and displayed constant variances for all models. The residual versus predicted plots of all models exhibited no obvious pattern and the results fell within an acceptable range. As the models met the assumptions, the models were indeed adequate and valid to predict.

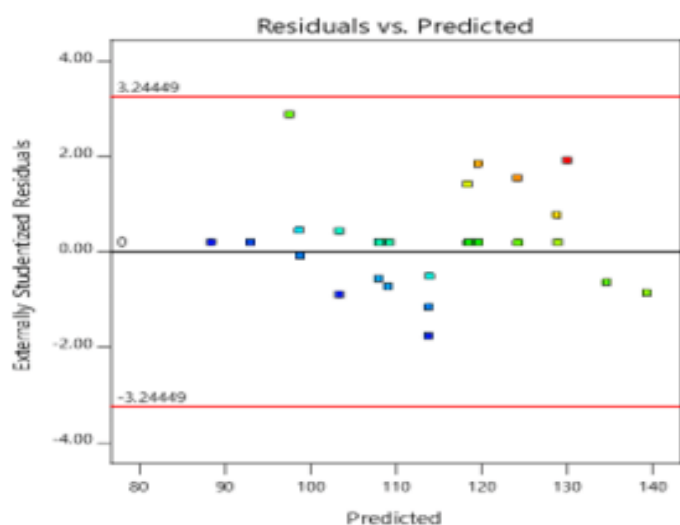


Figure 6: Residuals versus predicted plot of models

Next, ANOVA analysis was used to validate model for TS at the confidence level of 95%. The results were statistically significant as it has a p-value less than 0.05 (< 0.0001). Table 3 shows the simplified ANOVA results for models. The model for TS was statistically significant with a p-value below 0.0001. Hence, the CS process parameters displayed a statistically significant impact on TS.

Table 3: ANOVA for models of TS

Source/ Parameter	Sum of Squares	df	Mean Square	p-value
Model	7275.17		1212.53	< 0.0001
A-Pouring Temperature	89.29	1	89.29	
B-Slanting Angle	748.01	1	748.01	
C-Pouring distance	6418.2	1	6418.2	

AB	1.79	1	1.79
AC	0.4294	1	0.4294
BC	17.45	1	17.45
Residual	1805.29	25	75.22
Total	9080.46	31	

The analysis aimed to assess how well the model fit the data, ensured the goodness-of-fit statistics, and evaluated the predictive capabilities for the CS performances in new observations. The R² values of 80% above indicated strongly positive relationship between independent and dependent variable, indicating model predictability. For TS, the R² for is 0.8012. This implies goodness of fit statistics of 80.12%. Three types of error measurements, MAD, RMSE, and MAPE are used to evaluate the error of TS. The difference between experiment values and predicted values indicates that the prediction model accurately captures the underlying relationship between the input variables and the output variable. This suggests that the model can reliably make predictions for new data points. Table 4 present the error measure of model. It is observed that values of MAD, RMSE, and MAPE for all models are relatively small indicating that the models have a high accuracy for forecasting purpose

Table 4: Model summary error measure of models for TS

Model	MAD	RMSE	MAPE
	2.8930	3.0830	0.0458

Table 5: Percentage error for TS

Model	CS Parameter			Experiment Value	Model value	% error
Model	680	30	300	90.6208	87.2044	3.77
	700	60	300	101.027	99.3396	1.67
	720	45	500	138.033	134.345	2.67
	680	45	400	111.444	110.781	0.59
	700	60	400	121.882	119.459	2.22
	Average percentage difference (%)					2.19

The comparative results (Table 5) of the mathematical model show that the output values obtained in all trials are almost the same since the average percentage difference is small. This ensures that the selected parameters level is closely match with the regression equation. Hence the generated mathematical model can be used to achieve a good quality of the casting. Further, it is used to predict and set the optimal process parameters values in the range of parameters setting.

The confirmatory experiments are conducted in the foundry with the optimal process parametric value, which is validated by the mathematical model. Table 6 shows the simulation results of Tensile strength for confirmatory experiment. In order to validate the results retrieved, the results from the initial experiment and the simulation were compared.

Table 6: Comparison of results from initial experiment and simulation

Algorithm/ Simulation	Pouring temperature(°C)	Slaanting angle	Pouring distance	Tensile strength(MPa)	Percentage Error(Average)
Experiment result (optimal solution)	700	45	400	143.732	3.47%

Simulation results (Average)	700	45	400	148.728	
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The simulation results are tabulated in Table 6, displays the comparative results between the optimal initial experiment and the simulation result. In Figure 7 show the green shade in the simulation for initial experiment that reflects a high TS area. The result of the initial experiment for TS was 143.732 (pouring temperature: 700 oC, slanting angle: 45o, and pouring distance: 400 cm), while the average of simulation results is 148.728 (ranged from 120.3390 MPa to 156.5256 MPa). The percentage error between the initial experiment and simulation was 3.47%. The findings signified the suitability of the software-based computational/simulation technique in this study with an error percentage of less than 20% [24]. Figure 4b show the machined sample of tensile cut from Figure 6a area.

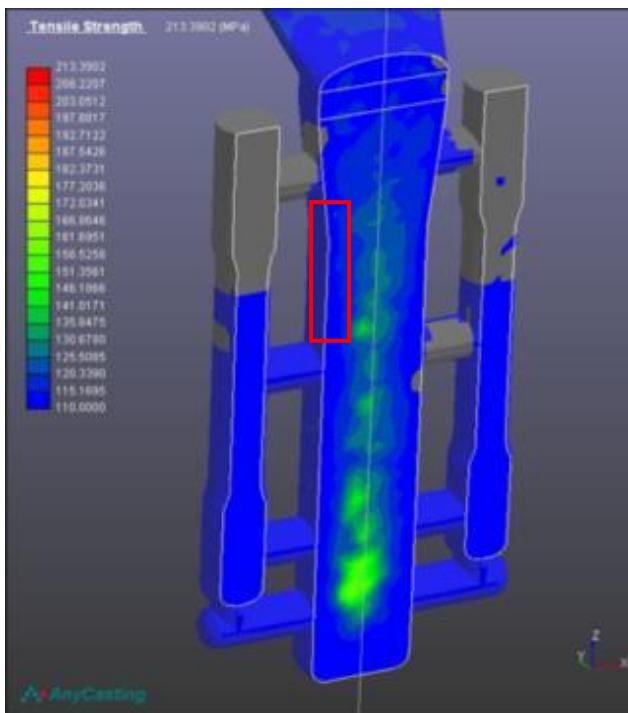


Figure 7: Area simulation results of tensile strength for PRM models

CONCLUSION

In this paper, the mahematical models were used in this study. The significant model and coefficient determination values for model obtained. From the ANOVA analysis, the models were significant since the p-values obtained were less than 0.05. Furthermore, it indicated that all the model explained more than 80 % of the variability in the cooling slope casting process. Next, the accuracies of all the models were validated used MSE and RMSE. The results showed both models are significant since produced small MSE and RMSE values. A comparison of process parameters and objective function values between the model results and confirmation experimental data also carried out, which showed minimal percentage differences for solving the optimization cooling slope process parameter problem. The obtained optimal process parameter values are recommended to the foundry to produce the quality castings feedstock. The optimal solution will provide flexibility to the process planner to choose the best parameter settings depending on the application. Apart from this the defect can further reduced by enhancing the design of gating system with shortest flow path.

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