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Modeling and Prediction of the Mechanical Properties of Feedstock by Cooling-Slope Casting Process using MOJaya Algorithm

Rahaini Mohd Said[1,*], Mohamad Ridzuan Mohamad Kamal[2], Nor Hafizah Hussin[1], Sinarwati Mohamad Suhaili[3], Siti Haryanti Hairol Anuar[1], Adam Samsuddin[4], Nurul Hajar Mohd Yussoff[2], Eko Arip Winanto[5]

[1] Fakulti Teknologi dan Kejuruteraan Elektronik & Komputer, Universiti Teknikal Malaysia Melaka, 76100 Durian Tuggal,Melaka, Malaysia
[2] Fakulti Teknologi dan Kejuruteraan Industri dan Pembuatan , Universiti Teknikal Malaysia Melaka, 76100, Durian Tunggal, Melaka, Malaysia
[3] Centre of Pre-University, University Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia
[4] Fakulti Teknologi dan Kejuruteraan Elektrik, Universiti Teknikal Malaysia Melaka, 76100, Durian Tunggal, Melaka, Malaysia
[5] Deparment of Computer Engineering, Universitas Dinamika Bangsa, Jambi 36134 Indonesia

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ABSTRACT

Cooling-slope (CS) casting parameters optimization is very challenging due to the uncertainties of parameter values that are influenced by many factors. Therefore, a combination of estimation and optimization models that can solve multi-objective problems using limited data is proposed to reduce the real casting operational cost and time. In casting optimization, modeling and optimization of CS parameters have been considered to identify optimal CS parameters that would lead to better feedstock performance. Computational techniques have been suggested by previous researchers to solve the optimization in the manufacturing process. The study assessed the CS process to determine the feedstock's quality by evaluating its mechanical qualities, namely Tensile strength and Impact strength. Hence, computational methods namely the MOJaya algorithm are utilized to model and optimize the parameters of CS to address the CS problem and forecast the performance of the feedstock. This work conducted a thorough analysis of the impact of CS process parameters on the tensile strength and impact strength using an experimental design. The experiment was conducted using a three-level full factorial design (FFD) of the experiment (DOE), for the parameters of pouring temperature, slanting angle, and pouring distance. The modeling technique involved the development of multiple polynomial regression (MPR) as an objective function in the MOJaya Algorithm. The outcome of the optimization procedure revealed that the optimal solutions obtained from MOJaya were projected to surpass both the initial experimental data and the MOJaya algorithm in terms of the highest values of tensile strength and impact strength. The difference between the two sets of values is 10.92% and 15.76%, respectively. Subsequently, this technique may be employed by a caster to forecast the performance of the feedstock without using repeated experiments that are costly and time-consuming.

* *Corresponding author.*
E-mail address: rahaini@utem.edu.my

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1. Introduction

Semi-solid metal processing (SSMP) is a metal processing technology that harnesses the benefits of both liquid metal casting and solid metal forging. The SSMP technique has been utilized to produce near-net-shape goods, often referred to as feedstock, with microstructures that are globular and free from dendrites. The feedstock, billet, bloom, slab, and ingot are raw materials produced by the continuous casting process, forming various forms (such as round, square, and rectangular) according on their purpose [1]. A widely used technique in SSMP is known as cooling-slope (CS) casting. This method guarantees a seamless casting procedure by subjecting the metal to a consistently low level of overheating, maintaining a constant temperature that is either close to or slightly over the point at which it becomes fully liquid. The flow of molten metal can be achieved by pouring it into a cool slope where it collects in a mold, or it can be employed directly in conjunction with a shaping process like rolling [2].

The primary objective in today's manufacturing industry is to enhance product productivity by achieving optimal quality while minimizing costs and time. The quality assessment of feedstock generated by the CS process commonly relies on the evaluation of its microstructure and mechanical properties [3]. Tensile strength (TS) and impact strength (IS) are examples of mechanical qualities. Producing feedstock with the intended mechanical qualities using the CS casting process is difficult due to common issues such as oxidation, porosity, and fast solidification (where the molten metal solidifies before fully filling the mold). Multiple research has revealed that the processing parameters of CS have a noteworthy influence on the quality of the feedstock [4,5].To get superior feedstock, the process parameters must align with their optimal values. The CS casting process typically takes into account many key factors, including pouring temperature, pouring distance, and slanting tilt.

The choice of CS casting process parameters is commonly determined by experience, iterative experimentation, a well-established processing plant guide, trial and error, or a manufacturing handbook [6]. Choosing CS casting parameters to achieve optimal feedstock performance is a complex and expensive task, since the ideal combination of parameters does not necessarily ensure the best performance in the CS process. Altawabeyeh *et al.,* [7] elucidated that the absence of a well-defined theoretical framework typically leads to the adoption of a trial-and-error approach in the parameter selection phase of the design process.

Due to the laborious nature of manually selecting parameters, researchers have employed several computer methods to determine the most appropriate values for process parameters [8]. During the early stage of the computational method, the relationship between the selection of parameter values and the performance of the output is analyzed by mathematical modeling. A correlation study or mathematical model is developed in accordance with the experimental work. Subsequently, the suggested mathematical model was used in conjunction with the chosen optimization procedure to acquire the ideal value parameters [9]. Prior investigations included several mathematical modeling approaches, including the regression model [10], response surface methodology (RSM) [11], and numerical simulation [12]. The regression model, whether it is single or multiple regression, has been extensively utilized to evaluate the linear or non-linear relationship between one independent variable and multiple independent variables [13,14].

For instance, in this study, linear regression was used to create a model for CS parameters such as pouring temperature, pouring distance, and slanting slope angle [15]. In another study, a polynomial regression model was used to describe the relationship between casting performance and casting process parameters [16]. Manjunath *et al.,* [19] employed a non-linear regression model to establish a correlation between squeeze cast process parameters and squeeze cast performance. They further enhanced the model's performance by utilizing genetic algorithm optimization [17].

Regression analysis was employed in an experimental investigation to construct a mathematical model that accurately depicts the considerable correlation between process parameters and output responses.

Once the suitable mathematical model is constructed, it is subsequently employed as the objective function in the chosen optimization procedure. The complexities of casting production become increasingly apparent when the number of variables involved rises and there is a restricted timeframe for finding a solution. Therefore, we are actively seeking a feasible approach to address the issues. In this context, it is necessary to employ adaptable optimization methods to aid the decision-maker in choosing the most favorable parameters that will result in the best possible outcome. Due to the presence of several mechanical property parameters and other parameters with changing values, the multi-objective optimization (MOO) technique produces more favorable outcomes compared to a single optimization method. This study examined how various process parameters (such as pouring temperature, slanting angle, and pouring distance) affect the performance of multiple feedstocks (TS and IS) using experimental design. The study found that the multi-objective optimization (MOO) approach was more appropriate than the single objective optimization approach.

Prior research has demonstrated the application of optimization algorithms, specifically metaheuristic algorithms (MAs), in a variety of fields. These include the utilization of the multi-objective genetic algorithm (MOGA) [18], multi-objective particle swarm optimization (MOPSO) [19], multi-objective whale optimization algorithm (MOWOA) [20], multi-objective artificial bee colony (MOABC) [21], Cubature Kalman Optimizer [22], Firefly algorithm [23], Ant Colony algorithm [24], and others. The majority of MOO techniques have algorithm-specific parameters that serve distinct tasks inside the algorithm, which might impact the efficiency performance of the algorithm. Improper adjustment of algorithm-specific parameters can have a negative impact on the algorithm's performance, including its convergence rate, diversity, efficiency, scalability, and capacity to explore and exploit the solution space [25].

Roa *et al.,* [26] proposed a novel approach called multi-objective Jaya (MOJaya) that incorporates particular parameters. MOJaya is an extension of the Jaya algorithm, which is a parameter-free algorithm. The unique parameters in MOJaya include the population size and the maximum number of iterations. The Jaya technique was originally developed to address both limited and unconstrained optimization problems. The MOJaya algorithm employs a search strategy that aims to approach optimal solutions by seeking the global best solutions. Additionally, it endeavors to avoid suboptimal answers by utilizing the MOJaya equation [26].

The MOJaya algorithm has been extensively applied in several domains to solve manufacturing problems, including plate-fin heat exchangers, knapsack problems, and optimum power flow [27]. Researchers have suggested other MOO ways to address the challenges encountered in the casting process. However, the majority of these approaches are derived from the use of different metals in other casting processes. Furthermore, there have been few studies that have taken into account the use of MOO to enhance industrial processes especially optimization of CS parameter process using a computational approach which has not yet been done by any researcher. The current work created a mathematical regression model and applied the MOJaya algorithm to estimate optimized CS casting process parameters. This was done to forecast the mechanical characteristics of two feedstocks: tensile strength and impact strength.

2. Methodology

The present study focused on the analysis of the materials employed, the process of modeling and optimizing, and the prediction of feedstock performances. The objective was to evaluate the most favourable machining conditions in CS casting. In summary, this study consisted of three main stages, which are outlined below. The flow of the investigation is illustrated in Figure 1.

i. Experimental and casting data collection: During this phase, data on the performance of the feedstock, as well as the parameters and limits, were gathered through experimentation. The mechanical parameters of tensile strength and impact strength were evaluated as indicators of feedstock performance. The variables considered were Pouring temperature (Pt), Pouring distance (Pd), and Slanting angle (Sa).
ii. Modelling: In the second phase of this investigation, polynomial regression models were created and used to measure the performance of the feedstock. These models were then employed as an objective function for optimization. Before optimization, statistical studies were conducted to assess the validity of the models.
iii. Optimization and Prediction: The last stage involves optimizing the CS parameters and forecasting the feedstock performance using the MOJaya algorithm. The obtained findings were compared to the experimental results, which were regarded as standards.

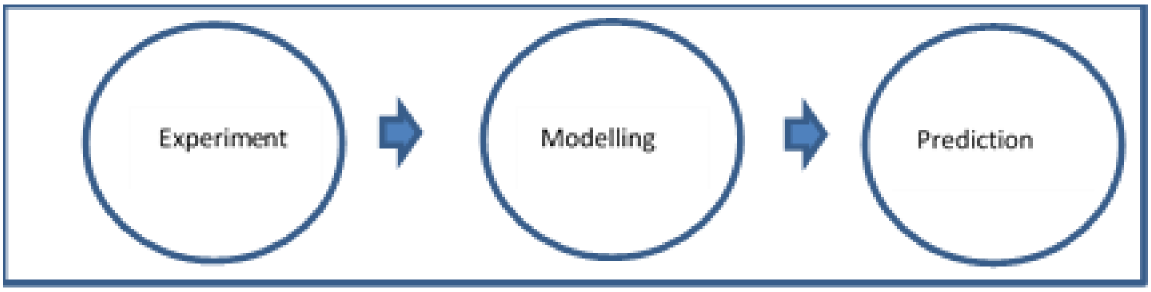


Fig. 1. The flow of the study

2.1 The CS Casting Process

The experiment pertained to the CS casting process. The experiment was conducted following a three-level factorial design. Figure 2 depicts the schematic representation of cooling-slope casting, while Figure 3 showcases the construction of an instrument used for cooling-slope casting. 800 grams of AZ91D magnesium ingot were introduced into a stainless-steel melting crucible within a heating furnace and subsequently liquefied at temperatures of 680 °C, 700 °C, and 720 °C. Subsequently, the liquefied metal was discharged onto a chilled surface and subsequently directed into a metallic cavity according to the established parameters. Multiple K-type Thermocouples were positioned on the CS to gauge the temperature. The experimental method in the field of computer science was conducted by systematically altering the values of pouring temperature, slanting angle, and pouring distance by referring to previous researchers, as indicated in Table 1. Ultimately, the liquid metal that completely occupied the mold was designated as "as-cast”.

Table 1
The range CS parameter values

Casting parameters	Unit	Level		
Pouring temperature	Degree Celsius	680	700	720
Pouring Distance	Mm	300	400	500
Slanting angle	Degree	30	45	60

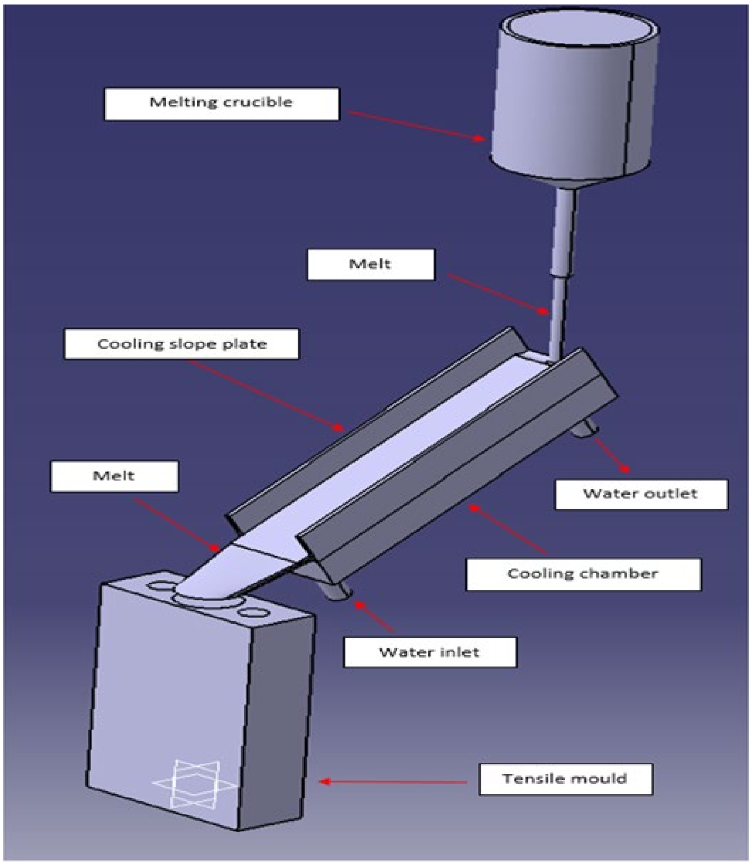


Fig. 2. A schematic illustration of cooling-slope casting

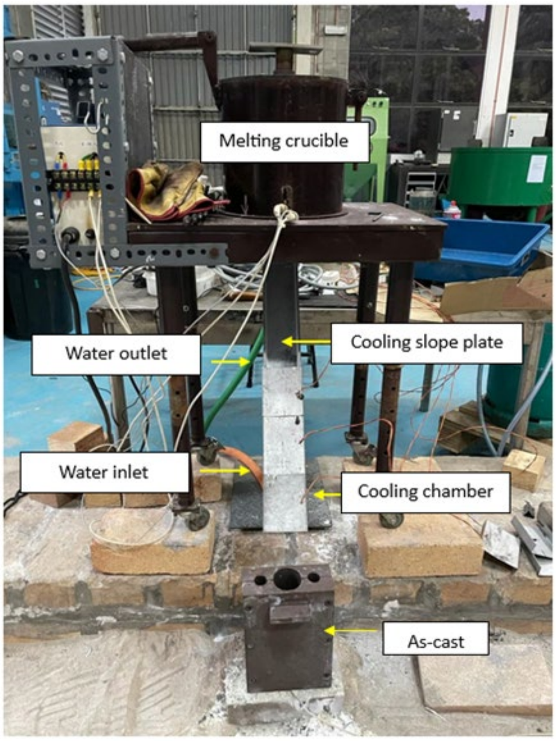


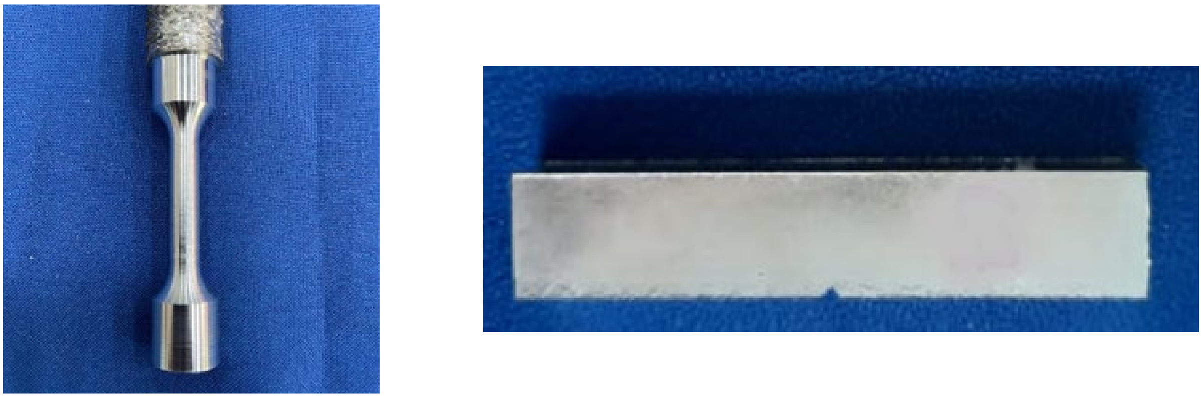
Fig. 3. A cooling-slope casting apparatus setup

A total of 27 experiment runs were done, following a three-level factorial design, which was mirrored in the experimental arrangement as Table 2. The architecture was configured to accommodate all potential input factors at every level. Figure 4 display the appearance of the material after the CS procedure experiment namely as-cast, that obtained from the cooling-slope experiment. Subsequently, the as-cast material underwent machining using a designated machine to achieve a specified form for conducting TS (tensile strength) and IS (impact strength) tests. The as-cast was machined by adhering to the standard (ASTM – B557M – 10). The TS for as-cast was measured by using the Universal Tensile Machine Instron 5982 , whereas the impact strength (IS) test performed using Ceast 9050 Test Machine was deployed to evaluate the absorption energy of the as-cast. Figure 5 (a) and (b) depict the form of the TS specimen and the form of the IS specimen.

Table 2
Experimental results for Tensile strength

Order	CS parameters			Response	
	Pouring temperature	Slanting angle	Pouring distance	Tensile strength	Impact Strength
1	680	30	300	90.6208	4.013
2	680	45	300	104.06	3.276
3	680	60	300	100.527	4.521
.	.	.	.	…	…
.	.	.	.	…	…
.	.	.	.	…	…
25	720	30	500	126.499	4.112
26	720	45	500	131.116	4.581
27	720	60	500	129.1	4.578

Fig. 4. As-cast after Cooling-slope experiment



(a) (b)

Fig. 5. Specimen shape for (a) Tensile strength test (b) Impact strength test

2.2 Developing the Regression Model and Conducting Statistical Analysis

Regression modeling has been developed to evaluate the correlation between input factors, such as pouring temperature, slanting angle, and pouring distance, and output variables, namely TS and IS.This project involved the development of multi polynomial regression models. The model's fitness and appropriateness were assessed by the use of ANOVA and p-value. The normal plot residual was utilized to determine the distribution of the data. Subsequently, the precision of the regression model was evaluated using statistical error metrics, namely Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). To assess the relevance of the model, many statistical measures were utilized, including R-square (R2), adjusted R-square (Adj-R2), predicted R-square (Pred-R2), normal probability plot, and residual and predicted plots. Figure 6 illustrates the procedural steps involved in the modeling of the CS casting process.

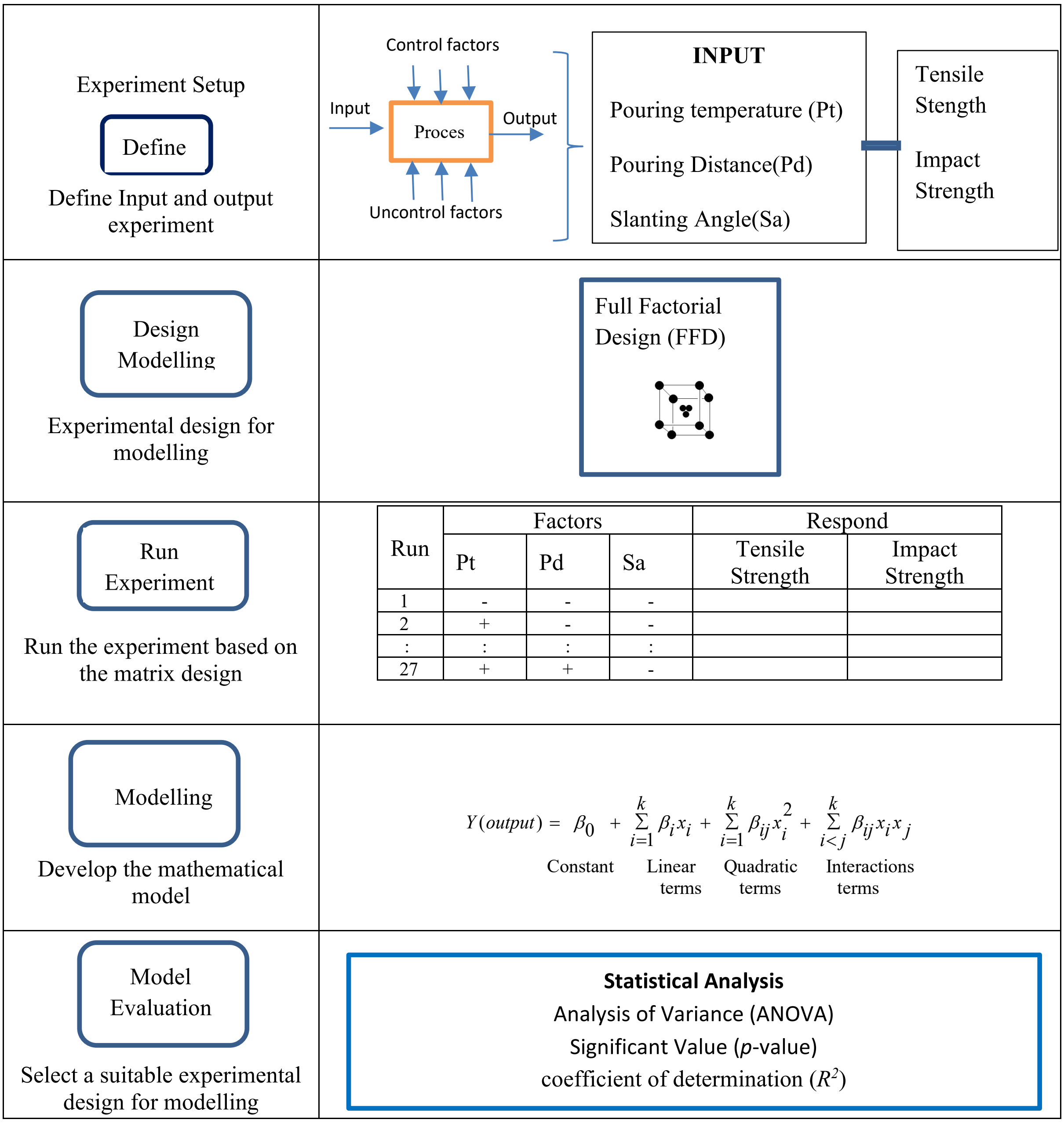


Fig. 6. The step for modelling of CS casting process

2.3 Optimization of CS Process using MOJaya Algorithm

The MOJaya algorithm developed in this study was employed to optimise the CS parameters for predicting optimal feedstock performance in terms of mechanical properties (tensile and impact strengths) via the MOO approach.

The following steps describe the MOJaya algorithm to solve the multi-objective optimization in CS process:

Step 1 Define the input process parameters (Pt, Pd, and Sa) and objective functions (tensile and impact strengths).
Step 2 Identify the population size, number of variables, and stopping criteria.
Step 3 Generate Initial population size (P) randomly.

Step 4 Evaluate objective function which is the the mathematical models for Tensile strength and Impact strength expressed as Eq. (1) and (2), respectively as a function for MOJaya algorithm. The process parameters bounds are expresses by Eq. (3).

Maximize:

$$\begin{aligned} TS_{PRM} &= 6845.35299 + 19.1798 * Pt - 2.85782 * Sa - 0.253892 * Pd \\ &+ 0.001288 * Pt * Sa + 0.000804 * Sa * Pd + 0.013738 * Pt * Pt \\ &+ 0.022938 * Sa * Sa + 0.000508 * Sd * Sd \end{aligned} \tag{1}$$

Maximize

$$\begin{aligned} IS_{PRM} &= 141.50016 + 0.404600 * Pt + 0.018684 * Sa + 0.008372 * Pd \\ &- 0.000031 * Pt * Sa - 0.000017 * Pt * Pd - 0.000050 * Sa * Pd + \\ &0.000297 * Pt * Pt + 0.000372 * Sa * Sa + 0.000012 * Sd * Sd \end{aligned} \tag{2}$$

Parameter

$$\begin{aligned} 680 \le A \le 720 \\ 300 \le B \le 500 \\ 30 \le C \le 60 \end{aligned} \tag{3}$$

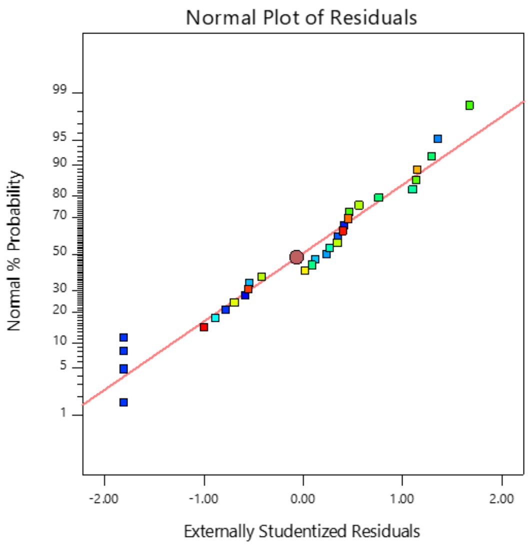
Step 5 Identify the best and worst candidates among the population in terms of identified objective functions generated from Eq. (1) and Eq. (2). The parameter boundaries from Eq. (3)
Step 6 Based on the best and worst solutions from step 5 , substitute the value to modify all Candidate solutions using expressed as Eq. (4):

$$x_{(i+1,j,k)} = x_{(i,j,k)} + r_1 * \left[x_{(i,j,b)} - \left| x_{(i,j,k)} \right| \right] - r_2 * \left[x_{(i,j,w)} - \left| x_{(i,j,k)} \right| \right] \tag{4}$$

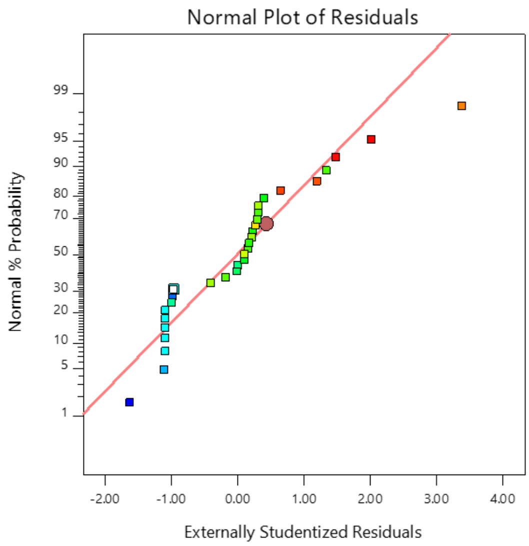
Step 7 Combine modified solution with initial solutions. Calculate the Crowding distance and ranking using non-dominated sorting considering both functions.
Step 8 If the termination criterion satisfied then exit proceed step 11, if not Go back to step 5;
Step 9 The stopping criteria is applied in the algorithm; if the solutions satisfy the condition, the algorithm will stop, and otherwise, return to Step 4.

3. Results and Discussion

The present study utilized a mathematical regression model to evaluate the Tensile strength in Eq. (1) and impact strength in Eq. (2) (feedstock performance) as objective functions in the MOJaya algorithms. Prior to utilizing the models in the optimization process, it is necessary to confirm the importance of these models. Firstly, the normal plots of residuals for TS and IS in the PRM model are portrayed in Figures 7 (a) and (b) accordingly The normal probability plots of the PRM models for TS and IS showed all points forming a straight line. When all the points are normally distributed, it means that the errors cumulated are small during performing the experiments. Overall, it can be summarized that the developed for both models tensile strength and impact strength was signified the adequacy and validity. Next, the ANOVA table for the models is presented in Tables 3 and 4, respectively. The models were subsequently employed to optimize the CS process parameters.



(a)



(b)

Fig. 7. Normal plot of residuals for tensile strength and impact strength

Table 3
ANOVA of Tensile strength

Source	Sum of Squares	df	Mean Square	p-value
Model	8154.20		1019.28	< 0.0001
A-Pouring Temperature	89.29	1	89.29	0.010594
B-Slanting Angle	748.01	1	748.01	0.0004
C-Pouring distance	6418.20	1	6418.20	< 0.0001
AB	1.79	1	1.79	0.008385
BC	17.45	1	17.45	0.005264
A^2	212.02	1	212.02	0.0352
B^2	187.02	1	187.02	0.0467
C^2	181.33	1	181.33	0.0499
Residual	926.26	22	42.10	
Total	9080.46	30		

The ANOVA table for tensile strength indicates that the factors “Pouring Temperature”, “Slanting Angle”, and “Pouring Distance”, along with their interactions “AB”, “BC”, and all the squared term “A^2 ,B^2 , and C^2”, significantly influence the model, as evidenced by their p-values being less than 0.05. This suggests that changes in these factors will have a statistically significant impact on tensile strength. However, the high residual sum of squares suggests that there is still a substantial amount of variation in tensile strength that the model does not account for. This could be due to measurement errors, other unconsidered factors, or inherent randomness in the data. Therefore, while the model provides valuable insights, there may be a need for further refinement or additional research.

Table 4
ANOVA of Impact strength

Source	Sum of Squares	df	Mean Square	*p* -value
Model	3.22		0.3582	< 0.0001
A-Pouring Temperature	0.0578	1	0.0578	0.02117
B-Slanting Angle	0.4128	1	0.4128	0.0024
C-Pouring distance	2.29	1	2.29	< 0.0001
AC	0.0144	1	0.0144	0.05269
BC	0.0684	1	0.0684	0.01757
A^2	0.0991	1	0.0991	0.01064
C^2	0.1010	1	0.1010	0.01033
Residual	0.7313	21	0.0348	
Total	3.95	30		

Referring to Table 3 and 4, the outcomes retrieved from ANOVA revealed that the impact strength model for 95% confidence interval was statistically significant with a p-value less than 0.0001. All the parameters emerged as significant to the model with a p-value less than 0.05.

Table 5
Summary of Correlation Analysis

Model	R^2	Adj-R^2	Pred-R^2
Tensile Strength	0.8959	0.8698	0.8849
Impact strength	0.8112	0.7537	0.6315

In Table 5, the MPR model summary of correlation analysis for TS and IS is shown. These statistics are derived from the values of R2, Adj-R2, and Pred-R2. TS and IS both had R2 values of 89.80% and 81.12%, respectively, in their respective scores. The value of the Adj-R2 for a model shows whether or not the interaction variables ought to be included in order to improve the model's fit characteristics. Taking into consideration the data shown in Table 5, the TS and IS in the MPR model received adjusted R2 values of 86.80% and 74.58%, respectively. On the basis of Pred-R2, the subsequent phase involved determining the degree to which the model accurately projected feedstock performances for fresh data. It was clear from the Pred-R2 values of both TS and IS that the model was able to provide better predictions. For prediction, the models were deemed acceptable and significant because the difference between Adj-R2 and Pred-R2 was less than 0.2 for each of the models.

In the following Table 6, the optimal values for the CS parameters that were produced by MOJaya algorithms are as follows: Pouring Temperature = 700.23 degrees Celsius, Slanting angle = 45.02 degrees, and Pouring distance = 399.95 centimetres. After that, the MOJaya algorithm was used to provide the prediction of feedstock performance, which was then tabulated in Table 4. The tensile strength was calculated to be 145.08, and the impact strength was calculated to be 4.70. The following step is to determine by contrasting the result that was optimum by MOJaya with the first experiment. The findings indicated that the discrepancy between the results of the experiment and the results obtained by MOJaya algorithm is 10.92% for tensile strength and 15.76% for impact strength. the findings are presented in Table 7, which illustrates the findings. Since there is a minor percentage improvement, the findings of MOJaya are regarded to be acceptable. Because of this, MOJaya may be utilized to assist casters in resolving actual issues that arise throughout the CS casting process in order to achieve the desired level of feedstock performance without the need for repeated experiments that are both expensive and time-consuming.

Table 6
Optimal value for CS parameters

Model	Method	Pouring Temperature (Pt)	Slanting angle (Sa)	Pouring Distance (Pd)
MPR	MOJAYA	700.2302	45.0184	399.9518
	Experiment	700	45	400

Table 7
Comparison of the Prediction value and initial experiment for Feedstock performance

Feedstock Performance	Method	Value	Percentage difference(%)
Tensile strength	MOJaya	145.08	10.92%
	Experiment	130.72	
Impact strength	MOJaya	4.70	15.76%
	Experiment	4.06	

4. Conclusions

In light of the results of the CS casting optimization with MOJaya algorithm that was carried out in the present investigation, the following findings were ascertained:

i. A prediction model for feedstock performance (tensile and impact strengths) was effectively constructed through the use of regression analysis. In addition, the projected values were in good agreement with the measured output responses, and the R2 adjusted values were high (more than 80 percent), which indicates that the models had a superior capacity to forecast.
ii. The optimal parameters for CS casting were the pouring temperature of 700.23 ^{o}C, the slanting angle of 45.02 ^{o}, and the pouring distance of 399.95mm .
iii. When compared to the initial experimental data, the values prediction for tensile and impact strengths from MOJaya are superior to the values obtained from the first experiment. The difference between the two sets of values is 10.92% and 15.76%, respectively. Through the utilization of this technique, feedstock performance was achieved without the need for repeated experiments, which are both expensive and time-consuming.

The limitation of casting optimization with the MOJaya algorithm may be its sensitivity to the choice of parameters. The performance of the algorithm could heavily depend on the specific settings chosen for factors such as population size, mutation rate, and convergence criteria. Inaccurate parameter tuning may lead to suboptimal results or hinder the convergence of the algorithm. This limitation could affect the robustness and general applicability of MOJaya for different casting scenarios. Additionally, a potential avenue for future research in casting optimization is integration of MOJaya with other optimization algorithms or techniques to create hybrid approaches. Combining the strengths of MOJaya with complementary optimization methods could result in more powerful and versatile optimization tools for casting processes. Hybrid approaches might provide better convergence, improved exploitation of the search space, and increased efficiency in finding optimal casting solutions.

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