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Modelling and Optimisation of Cooling-Slope Parameters of Magnesium AZ91D using Improvement Multi-Objective Jaya Approach for Predicted Feedstock Performance

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ABSTRACT

The cooling-slope (CS) casting technique is one of the simple semi-solid processing (SSP) processes a foundryman uses to produce the feedstock. This study attempts to develop mathematical regression models and optimise the CS parameters process for predicting optimal feedstock performance, which utilises tensile strength and impact strength to reduce the number of experimental runs and material wastage. This study considers several parameters, including pouring temperature, pouring distance, and slanting angles for producing quality feedstock. Hence, multi-objective optimisation (MOO) techniques using computational approaches utilised alongside the caster while deciding to design are applied to help produce faster and more accurate output. The experiment was performed based on the full factorial design (FFD). Then, mathematical regression models were developed from the data obtained and implemented as an objective function equation in the MOO optimisation process. In this study, MOO named multi-objective Jaya (MOJaya) was improved in terms of hybrid MOJaya and inertia weight with archive K-Nearest Neighbor (MOiJaya-aKNN) algorithm. The proposed algorithm

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was improved in terms of the search process and archive selection to achieve a better feedstock performance through the CS. The study's findings showed that the values of tensile and impact strengths from MOiJaya_aKNN are close to the experiment values. The results show that the hybrid MOJaya has improved the prediction of feedstock using optimal CS parameters.

Keywords: Chaotic inertia weight, cooling-slope casting process, feedstock, impact strength, k-nearest neighbour, MOJaya, tensile strength

INTRODUCTION

The cooling-slope (CS) casting technique is a simple semi-solid processing (SSP) method utilised by foundrymen or casters to procure feedstock. The SSP is a near-net-shaped approach for processing metal and alloys in a semi-solid state and has been employed extensively in manufacturing processes (Nafisi & Ghomashchi, 2019). Among the advantages of SSP-fabricated components processed conventionally are reduced porosity, macro-segregation, and better mechanical properties (Son et al., 2021). Consequently, SSP has been commercially applied for producing feedstock in several approaches, such as cooling-slope casting (CSC), continuous casting with magneto-hydrodynamic (MHD), and semi-solid and gas-induced semi-solid rheocasting (GISS).

This study uses magnesium (Mg) AZ91D as a metal in producing feedstock using the CS process. AZ91D is one of the earliest and lightest metal steels with potential applications across various industries, including electronics, aerospace, and automotive (Annamalai et al., 2019). The metal has also gained attention among researchers, thus resulting in several investigations on magnesium and its alloys, including alloy design and optimisation, microstructure characterisation and observation, and functional materials (Wu et al., 2021). Furthermore, the metal is considered the best green material in the 21st century due to its excellent physical and chemical properties, including low density, high specific strength and stiffness and good damping performance biocompatibility (Guo et al., 2018). Consequently, the advantages of AZ91D necessitate evaluations to produce feedstock via the CS casting approach.

The CS is one of the methods employed by industries to produce feedstock. The technique is one of the steps applied at the precursor level to ensure the quality of the processed feedstock. These feedstocks, known as treatment feedstock, are utilised as raw materials in manufacturing to produce quality products. Accordingly, the primary challenge of procuring excellent feedstock is providing high-quality precursor resources, especially controlling process parameters during casting (Balachandran, 2018).

Grain refinement strengthening is the primary issue casters encounter during designing and producing quality feedstock, which, alongside numerous other parameters, would affect the feedstock performance (tensile and impact strengths) obtained. Commonly, experts select CS casting process parameters based on experience, established processing plant guide, or casting handbook (Kumar et al., 2014). Nevertheless, determining the optimum multi-parameters for producing feedstock with excellent performance is complicated and costly because the best parameter combination has arguable results, as the results do not guarantee the CS process's optimal performance.

The primary objective of the designing stage is to produce high-quality feedstock and products at optimal conditions. Consequently, choosing ideal process parameters is crucial (Rao, 2011). Nonetheless, the selection process is currently conducted on a trial-and-error basis due to a lack of fixed theoretical procedures (Kor et al., 2011). The present study proposed utilising computational techniques to acquire the optimal conditions during the decision-making step. The application of the approach during design process selection could aid in faster and more accurate output procurement.

Rao (2018) highlighted the modelling and optimisation stages to obtain ideal parameters. The report also specified that representing the manufacturing process as a model for optimisation is necessary. Accordingly, developing the mathematical model is the first step of process parameter enhancement. The process is critical as the model is developed as an objective function for optimisation.

Researchers considered several approaches to model a casting process, such as regression (Brezocnik & Župerl, 2021), response surface methodology (RSM) (Patel et al., 2015), numerical simulation (Zheng et al., 2020), and artificial neural network (ANN) (Zhou et al., 2022). The regression model is one of the most practical and well-known modelling techniques applicable to soft computing (Esonye et al., 2021; Fadaee et al., 2022; Onifade et al., 2022; Singh et al., 2021). For example, Khosravi et al. (2014) adopted the regression approach to model the CS parameters: the pouring temperature (Pt), pouring distance (Pd), and slanting slope angle (Sa).

Most studies on casting optimisation that applied the multi-objective approach employed regression as a modelling technique. Binesh and Aghaie-Khafri (2017) generated a polynomial regression model to represent the relationship between casting performance and the process parameters. In another report, the non-linear regression model was utilised to procure the model denoting the relationship between the squeeze cast process parameters and its performance before optimising it via a genetic algorithm (Patel et al., 2015). Moreover, multiple regression is a flexible method to examine the relationship between a variable and multiple outcome variables. This model was used as the objective function in the optimisation process.

In optimisation, algorithms are designed and developed to solve the problems using computers. It can be classified into two categories: deterministic and stochastic. The deterministic approach finds the same solution in each run but becomes trapped in locally optimal solutions due to local optimisation. However, stochastic approaches find different solutions in each run due to stochastic mechanisms. It assists them in avoiding sub-optimal solutions better. Most stochastic approaches are applied in most heuristic and metaheuristic approaches that can be classified into single and multi-objective optimisation (Premkumar et al., 2021).

Optimisation could be classified into single- and multi-objective (MOO) optimisations. Nevertheless, the single-objective approach provides insufficient information for casters to analyse decisions holistically. Consequently, MOO provides a practical technique for selecting ideal casting process conditions (Rao, 2018). The MOO approach is employed in casting optimisation to solve design issues, including multiple design variables, conflicting objectives, and numerous constraints. Furthermore, MOO computing methods are easy to implement and require lower energy, time, and cost than the trial-and-error practice.

Recently, the metaheuristic algorithm (MA), which is more flexible and convenient, has been widely utilised to procure near-optimum solutions in manufacturing processes (Li et al., 2020; Mishra & Sahu, 2018; Agarwal et al., 2018; Mohd Said et al., 2021; Tavakolpour-Saleh, 2017). A variety of MA has been investigated for application in manufacturing processes, such as multi-objective genetic algorithm (MOGA) (Feng & Zhou, 2019), non-dominate sorting genetic algorithm II (NSGA II) (Asadollahi-Yazdi et al., 2018), multi-objective partial swarm optimisation (MOPSO) (Patel et al., 2016; Wu et al., 2021) multi-objective whale optimisation algorithm (MOWOA) (Tanvir et al., 2020), and multi-objective artificial bee colony (MOABC) (Feng et al., 2018; García-Alcaraz & Pérez-Domínguez, 2014), multi-objective ant colony optimisation (MOOACO) (Ji & Xie, 2008), and multi-objective Jaya (MOJaya) (Rao et al., 2016).

The MOJaya technique that Rao introduced has been successfully applied in several real-world settings (Raed et al., 2020). The method is a simple, flexible, and efficient population-based search algorithm to solve constrained and unconstrained optimisation issues. The MOJaya algorithm is a parameters-less approach that iterates towards the best solution search space. Furthermore, the MOJaya algorithm has the advantage of avoiding the difficulty of adjusting parameters as well as reducing the amount of time required for optimisation. Recently, the Jaya or MOJaya technique gained attention due to the simplicity of its framework and the fact that it only requires a single operator. The approach has also reportedly solved optimisation issues in various fields (El-Ashmawi et al., 2020; Jian & Weng, 2020; Rao et al., 2019; Vinh & Nguyen, 2020; Zamli et al., 2018). However, as a metaheuristic algorithm, MOJaya suffers from a few limitations and inescapable drawbacks during the search process. The search process in MOJaya focuses more on exploitation than exploration. It causes the solution to be easily trapped in local minima and get less diversified solutions.

Several improvements in the exploitation abilities of the search process in MOJaya were proposed to ensure the optimal solution is not easily trapped in local minimal. Wu and He (2020) combined the basic Jaya algorithm with the mutation and crossover operator to enhance the diversity of the population and exploration ability. The results showed that both improvement algorithms from their studies obtained superior results in terms of solution quality, such as diversity and convergence. Goudos et al. (2019) proposed hybrid Jaya algorithms and self-adaptive differential evolution algorithms. The simulation results showed the efficiency of the purpose algorithms, such as the Jaya-JDE algorithm, by achieving good trade-off solutions.

Zhenghao et al. (2020) enhanced the Jaya algorithm using a combination of the Tree Seeds algorithm and K-means clustering, namely C-Jaya-TSA. The clustering strategy is used to replace solutions with low-quality objective values. The results show the effectiveness of the C-Jaya-TSA algorithm to enhance the exploitation ability. Premkumar et al. (2021) enhanced the Jaya algorithm with a chaotic mechanism to classify the parameters of various photovoltaic models, including single-diode and double-diode models. Adaptive weight chaos is added to the proposed algorithm to regulate the trend and avoid the worst solution. The proposed technique utilises self-adaptive weights to reach the best solution during the first phase, followed by a second phase that includes a local search, which increases exploration capacity. Based on comprehensive analysis and experimental results, the suggested algorithm is highly competitive in accuracy and reliability compared to other algorithms in the literature.

Based on Narayanan et al. (2023), early MOO algorithms evaluated two solutions simultaneously based on Pareto dominance throughout the iterative process to find the optimal solution to achieve ultimate outcomes. An effective approach for multi-objective optimisation problems is the Pareto optimal front method, which can elicit sets of optimum solutions widely known as Pareto-optimal front solutions (Zitzler et al., 1999). Recently, many researchers used Pareto optimal front approach to solve MOO problems such as Multi-objective Moth Flame Optimization (MaOMFO), Decomposition-based multi-objective symbiotic organism search (MOSOS/D), Multi-Objective Marine-Predator Algorithm (MOMPA), Multi-Objective Generalized Normal Distribution Optimization (MOGNDO), and Multi-Objective Plasma Generation Optimization (MOPGO) (Abdin et al., 2022; Ganesh et al., 2023; Jangir et al., 2023; Kumar et al., 2021; Pandya et al., 2022). However, another limitation reported in the literature is the selection criteria of solutions for solving MOJaya problems using the Pareto approach. Warid et al. (2018) proposed fuzzy decision-making and incorporated it into the Jaya algorithm as selection criteria for best and worst solutions using the Pareto approach.

Moreover, some recent work used an archive mechanism of non-dominated solutions to approximately the Pareto front to solve MOO problems. Britto et al. (2012) explored several archiving methods from the literature used by MOPSO to store the selected leaders into MOO problems. The main goal was to observe how each method influences the MOPSO algorithm in terms of convergence and diversity over the Pareto front. This method guided the MOPSO search to a region near the knee of the Pareto front.

Li et al. (2019) proposed two archives evolutionary algorithms for constrained to solve MOO problems. The author highlighted an important issue in MOO: balancing convergence, diversity, and feasibility. This paper proposes a parameter-free constraint handling technique, a two-archive evolutionary algorithm, for constrained multi-objective optimisation to address this issue. The first archive, denoted as the convergence archive, is the driving force that pushes the population toward the Pareto front. The second archive, denoted as the diversity archive, mainly tends to maintain population diversity.

Premkumar et al. (2022) have developed a bio-inspired multi-objective grey wolf optimisation algorithm (MOGWO) that includes Pareto optimality, dominance, and external archiving. Archives are storage units that store or retrieve the non-dominated Pareto optimal solution. Archives are managed by archive controllers when solutions enter the archive, or the archive is completely occupied. According to the performance comparison of the MOGWO algorithm with other algorithms selected, the MOGWO algorithm provides the best solution. Thus, it is motivated to propose MOiJaya_aKNN to enhance MOJaya performance and get the optimal CS casting parameters to produce optimal feedstock performances.

Although researchers have proposed various MOO approaches to solving the issues involved during the casting process, most are based on different metals employed in other casting processes. Moreover, limited studies have considered MOO to improve manufacturing processes. Accordingly, the present study developed a mathematical regression model and enhanced the MOJaya algorithm for estimating optimised CS casting process parameters to predict two feedstock performance mechanical properties: tensile and impact strength.

MATERIALS AND METHODS

The current study focused on the material used, modelling and optimising feedstock performances to assess the optimal machining conditions in CS casting. Overall, this study comprised three major stages as follows (Figure 1):

1. Experiment and casting data: Experimental data of feedstock performances, parameters, and boundaries were collected. Two mechanical properties, tensile and impact strengths, were considered feedstock performance. The parameters involved were Pt, Pd, and Sa.
2. Modelling: Polynomial regression models for

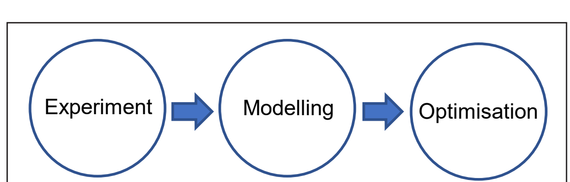


Figure 1. The basic flow of the study

feedstock performance were developed and utilised as an objective function for optimisation. Statistical analyses were performed to evaluate the validity of the models before conducting optimisation.

3. Optimisation: The final step comprised CS-produced feedstock performance optimisation with the improved MOJaya. The results were compared with actual experiment results, which were considered benchmarks.

Material

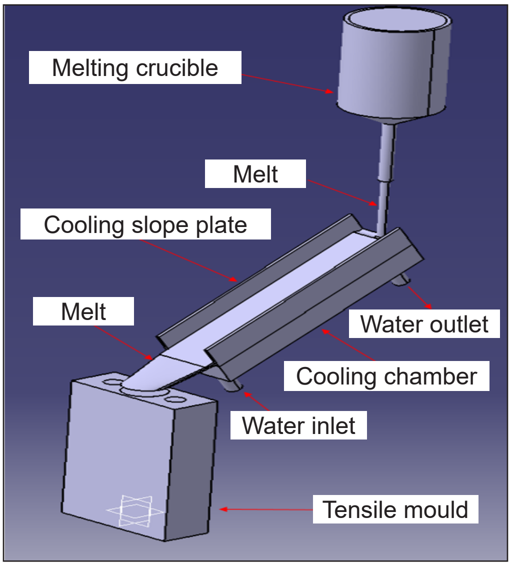
A commercially available Mg AZ91D composite was employed in the present study. The detailed chemical composition and mechanical properties of the metal are listed in Table 1.

The CS Casting Process

The present study utilises the CS casting process, a gravity-based casting technique. 800g of AZ91D magnesium ingot was fed inside the stainless-steel melting crucible in the heating furnace and melted at 680°C, 700°C and 720°C. Then, the melt was poured onto the cooling plate and flowed into a metal mould according to the parameter's setup. K-type thermocouples were placed

Table 1
The chemical composition of AZ91D

Element	**Mass (%)**
Aluminium (Al)	8.50
Manganese (Mn)	0.20
Zinc (Zn)	0.55
Silicon (Si)	0.10
Copper (Cu)	0.03
Nickel (Ni)	0.002
Iron (Fe)	0.005
Mg	Balance



(a)

(b)

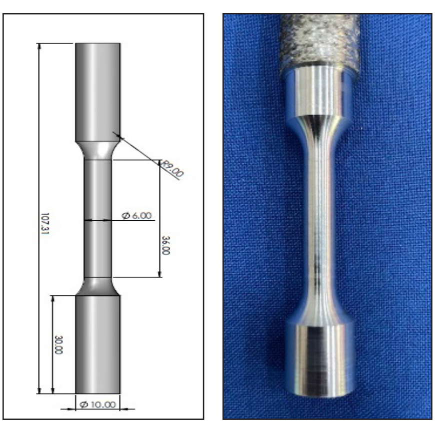
Figure 2. (a) Computer Aided Diagram (CAD) diagram of C and (b) CS experiment setup

on the cooling slope to measure the temperature. The cooling slope experimental process was performed by varying the pouring temperature, slanting angle, and pouring distance (Table 2). Finally, the molten metal flow was full of the mould and defined as as-cast. Figure 2(a) shows the Computer Aided Diagram (CAD) diagram of CS, while Figure 2(b) details the CS experiment setup.

Figure 3 demonstrates an as-cast specimen post the CS procedure. After machining them into specific shapes, the specimens obtained were subjected to tensile and impact strength evaluations. Figures 4(a) and (b) and Figures 5(a) and (b) display the respective measurements and shapes of the as-cast samples for the tensile and impact strength evaluations. The as-cast subjected to impact strength assessment was prismatic bar-shaped, while the sample evaluated for its tensile strength had a transverse notch cut in the middle of a side.

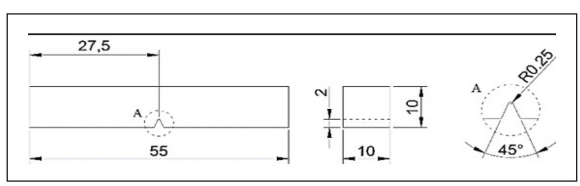
Tensile strength assesses the ability of a metal to resist breaking or pulling apart into two pieces. On the other hand, the value of impact energy absorbed by a material during fracturing under impact denotes the strength of the material. The tensile strengths of the specimens in this study were evaluated with a Universal Tensile Machine, Instron 5982, while an Instron Ceast 9050 Test Machine was utilised to determine their impact strengths. The estimation models in the present study were then developed with a design of experimental (DOE) software by employing the CS casting process parameters data.

Figure 3. An as-cast specimen

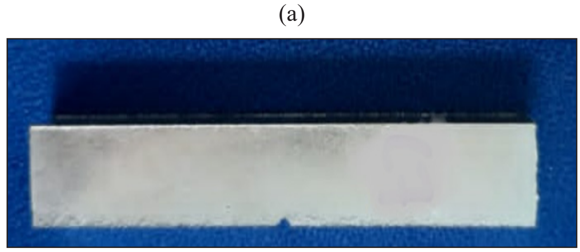


(a) (b)

Figure 4. The (a) measurement and (b) shape of the tensile strength test specimen (unit dimension = mm)



(a)



(b)

Figure 5. The (a) measurement and (b) shape of the impact strength test specimen (unit dimension = mm)

Design of Experimental (DOE)

The DOE is a systematic and efficient method of examining the relationship between multiple input (factors) and key output (responses) variables. This study performed experiments based on a full factorial design (FFD) that involved three levels and three parameters as input variables. The three selected CS parameters, namely the Pd, Pt, and Sa, were considered the most significant factors affecting the related response based on previous reports. The selection of the range for CS parameters is based on the type of metal used, which is AZ91D magnesium that has a characteristic and chemical composition that needs to be considered and also based on previous researcher recommendations (Abdelgneia et al., 2019; Khosravi et al., 2014; Kumar et al., 2014; Kumar et al., 2013; Tugiman et al., 2019). The fractional combinations of the conditions were obtained by employing the Design Expert 11.0 software. Table 2 summarises the range values of the parameters.

Table 2
The range value of CS parameters

Casting parameters	Unit	Level		
		1	2	3
Pouring temperature	Celsius	680	700	720
Pouring Distance	mm	300	400	500
Slanting angle	Degree	30	45	60

In this study, the Pt employed ranged between 680–720°C, Pd was from 300 to 500 cm, and Sa was between 30–60°. Based on the values, 27 runs with four centre points resulted in a 3^3 FFD. A full factorial denotes a design setting that includes all possible input parameters. Table 3 shows the full factorial design experimental layout of the CS.

The regression estimation models in the current study were developed from the CS casting parameters with the Design expert software. The adequacy and significance of the models, indicated by coefficient (R^2) values, were determined with variance analysis (ANOVA). Each model was validated with mean square error (MSE) and root means square error (RMSE). Equation 1 expresses the Stepwise regression model of the CS process, and the modelling process flow of the CS casting is illustrated in Figure 6.

$$y = b_0 + b_1(Pt) + b_2(Pd) + b_3(Sa) + +b_4(Pt)(Pd) + b_5(Pt)(Sa) + b_6(Pd)(Sa) + b_7(Pt)^2 + b_8(Pd)^2 + b_9(Sa)^2 + x\varepsilon \quad [1]$$

Where is b_0 constant, b is the coefficient of regression mode. The input process parameters are slanting angle (Sa), pouring distance (Pd) and pouring temperature (Pt). The flow process of modelling for the CS casting process is illustrated in Figure 6. The tensile and impact strength equations were expressed as Equations 2 and 3.

Table 3
The full factorial design experimental layout of the CS

Standard order	CS parameters			Feedstock performance	
	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
4	680	30	400	97.6055	4.225
5	680	45	400	111.444	3.644
24	720	60	400	138.033	4.334
25	720	30	500	126.499	4.112
26	720	45	500	131.116	4.581
27	720	60	500	129.1	4.578

Figure 6. The process of modelling for the CS casting process

$$\text{Maximize tensile strength} = a + \text{slanting angle} + \text{Pouring temperature} + \text{Travelling distance} + \text{slanting angle}^{2} + \text{Pouring temperatue}^{2} + \ldots + e \quad [2]$$

$$\text{Maximize impact strength} = a + \text{slanting angle} + \text{Pouring temperature} + \text{Travelling distance} + \text{slanting angle}^{2} + \text{Pouring temperatue}^{2} + \ldots + e \quad [3]$$

Multi-Objective Optimisation (MOO) Problems

Optimisation problems are among the most common problems in engineering practical and scientific research. The MOO problem is an area of multiple criteria decision-making that concerns mathematical optimisation problems involving more than one objective function being optimised simultaneously. The primary study objective for conducting MOO optimisation and using the Pareto front approach to solve MOO optimisation problems is to find the optimal solution. The standard equation for the MOO optimisation process is given in Equations 4 to 6.

Therefore, the MOO will take the following mathematical formulation:
Maximise or minimise:

$$F(x,u) = [f_1(x,u), f_2(x,u)]^T, \ldots, f_k(x,u)]^T \qquad [4]$$

Subject to:

$$g(x,u) = 0 \qquad [5]$$

and

$$h(x,u) \leq 0 \qquad [6]$$

where $F(x,u)$ and k represents the vector and a total number of objective functions, $g(x,u)$ is a set of equality constraints, $h(x,u)$ is the set of inequality constraints, x is the vector of dependent variables or state variables, and u is the vector of independent or control variables.

Hybrid Chaotic Inertia and Archive K Nearest Neighbour in MOJaya

There is a two-phase improvement for MOJaya in this study. The first phase, the movement update equation operator, is improved by adding a chaotic random inertia weight called MOiJaya.

In the first phase of improvement, adding the chaotic inertia weight in the MOJaya solation update equation possesses specific attributes, including ergodicity and randomicity, which enabled the algorithm to overcome the optimal local solution. During the early iteration of the algorithm, the current study selected the best and random solution to explore more search space processes. The optimal solution was chosen to guide the population to a better region, while the random solution was selected to expand the search space. Nevertheless, the best solution at each generation might be trapped in local minima when solving conflicting objectives, affecting the succeeding solution update equation. Hence, the modified solution update equation in the present study was conducted according to the following steps:

Step 1: Select a random number, Z, in the interval of [0,1] then, select a random number, $rand()$, in the interval [0,1].

Step 2: Produce logistic mapping: $z = 4 \times z \times (1 - z)$;

Step 3: $\varpi = 0.5 \times rand(\ ) + 0.5z$

Step 4: Modify the solution update Equation 7 by incorporating the chaotic inertia weight mechanism.

$$x_{(i+1,j,k)} = x_{(i,j,k)} + \varpi * r_{(i,j,1)} \left[x_{(i,j,)} - \left| x_{(i,j,k)} \right| \right] - \varpi * r_{(i,j,2)} \left[x_{(i,j,w)} - \left| x_{(i,j,k)} \right| \right] [7]$$

Where $X'_{i,j,k}$ denotes the modified value of the *i*-th design variable, the second term represents the approach of the modified solution to proceed nearer to the optimum solution, and the third expression is attributed to the proclivity of the solution to avoid the worst solution.

The next improvement is made in the selection criteria process where archive K-nearest neighbour (aKNN) is employed and known as MOiJaya_aKNN. In this phase, improvements are made to the selection criteria, which are the best and worst solutions. The selection of the first P is based on the non-dominated ranking and crowding distance. The selection is important during the selection process because this solution is a guide and search towards the Pareto-optimal set. Potential solutions might be rejected and not selected due to the crowded region during the selection search space. Consequently, the process is crucial to choose a set of solutions that could lead to convergence toward true Pareto-optimal. Furthermore, the step is essential to avoid Pareto breakouts when it is stuck in local optima, which would occur. An improper selection might also delay the convergence as it is required to break the local optima. Hence, the rejected or not selected solutions in the crowded region were considered for the next iteration during the step and applied to the archive KNN.

This study employed an external archive mechanism as a repository to store potential solutions among the rejected and not selected solutions. Consequently, the archive could potentially possess solutions closer to the Pareto front as it possesses higher chances of comprising the best potential solution. The KNN was employed to obtain the possible solution close to the Pareto front. The method is a simple classification algorithm that utilises the Euclidean metric as the distance metric, where the K parameter controls the classification. The KNN was also employed to reduce the archive size by manipulating the K values and selecting archive members close to the most optimum solution in the Pareto front.

The second strategy adopted in the present study was improving the selection process to reduce the complexity of multi-objective problems based on Pareto dominance. Figure 7 demonstrates the improvements implemented on the hybrid MOJaya. The hybrid MOJaya with chaotic inertia weight and archive KNN (MOiJaya_aKNN) was then utilised to optimise the CS casting parameters process to predict optimal feedstock performance.

Algorithm Performance

These proposed improvement algorithms were evaluated using ZDT bio-objective test problems. These test problems are chosen because ZDT is a set of test problems that focuses on multi-objective optimisation and consists of two objective functions (Table 4). These

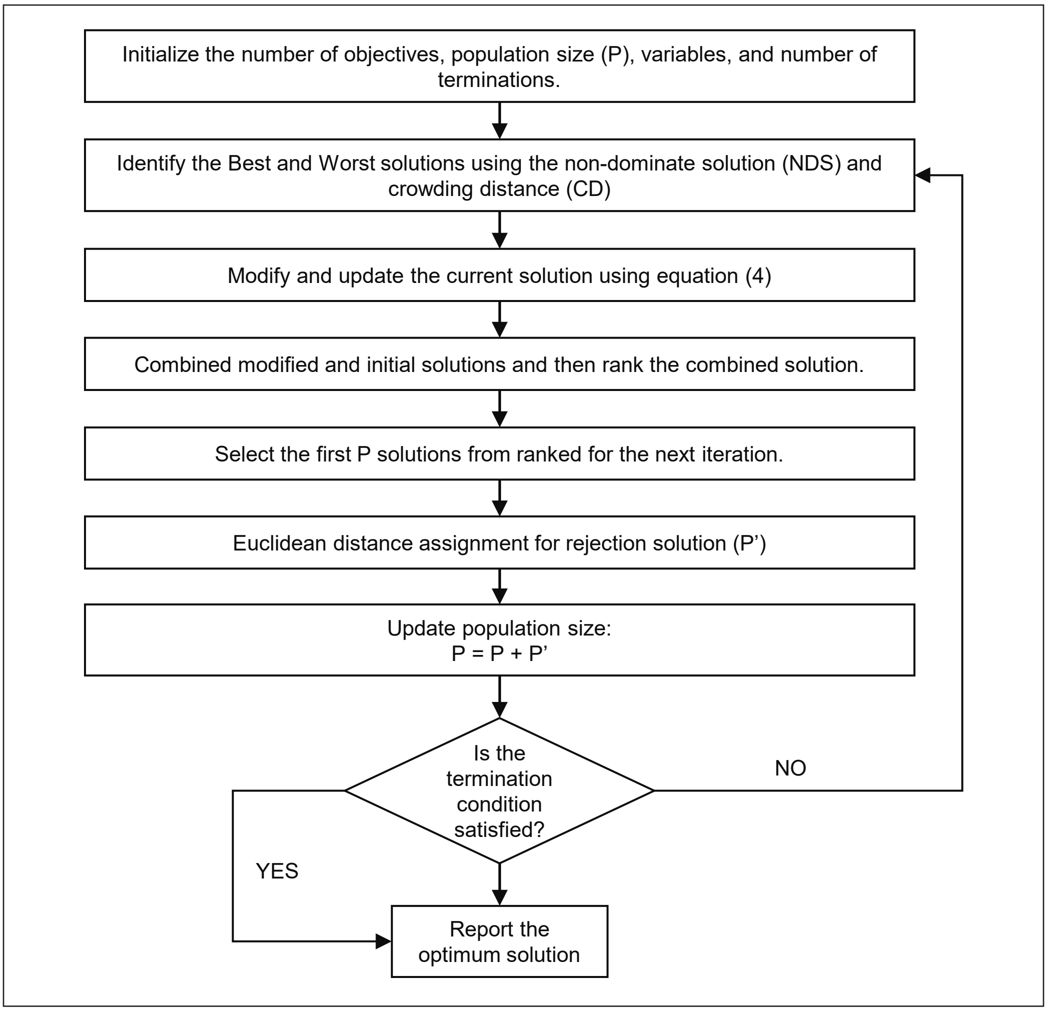


Figure 7. Flowchart of MOiJaya_aKNN algorithm

types of problems are suitable for CS casting process optimisation, which consists of two objective functions: tensile strength and impact strength. Then, the proposed algorithm performance using the ZDT test problem was evaluated using the convergence metric (Generational distance) and diversity metric (spread). ZDT is also easy to implement and has several test cases with different difficulties. For each ZDT test problem, 30 times experiments were conducted. Then, the results of MOiJaya and MOiJaya_aKNN algorithms were compared with previously published results. All analyses regarding the algorithm's performance are discussed.

The main evaluation of algorithm performance used in this study is convergence and diversity metrics. Convergence metrics were developed and introduced by Deb et al. (2002). These metrics measure the distance between the reference set and the obtained Pareto front.

Table 4
ZDT bio-objective test problems (Deb et al., 2002)

Problem	N	Variable bounds	Objective Functions	Optimal Solutions	Comments
ZDT 1	30	[0,1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{x_1 / g(x)}\right]$ $h(f_1) = 1 + 9\left(\sum_{i=2}^{n} x_i\right)(n-1)$	$x_1 \in [0,1]$ $x_1 = 0$ $i = 2, \ldots, n$	Convex
ZDT 2	30	[0,1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - (x_1/g(x))^2\right]$ $h(f_1) = 1 + 9\left(\sum_{i=2}^{n} x_i\right)(n-1)$	$x_1 \in [0,1]$ $x_1 = 0$ $i = 2, \ldots, n$	Nonconvex
ZDT 3	30	[0,1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{x_1 / g(x)} - \frac{x_1}{g(x)} \sin(10\pi x_1)\right]$ $h(f_1) = 1 + 9\left(\sum_{i=2}^{n} x_i\right)(n-1)$	$x_1 \in [0,1]$ $x_1 = 0$ $i = 2, \ldots, n$	Convex Disconnected
ZDT 4	30	[0,1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1 - \sqrt{x_1 / g(x)}\right]$ $h(f_1) = 1 + 10(n-1) + \sum_{i=2}^{n} x_i^2 - 10\cos(4\pi x_i)$	$x_1 \in [0,1]$ $x_1 = 0$ $i = 2, \ldots, n$	Convex
ZDT 6	30	[0,1]	$f_1(x) = 1 - \exp(-4x_1)\sin^6(6\pi x_1)$ $f_2(x) = g(x)\left[1 - (x_1/g(x))^2\right]$ $h(f_1) = 1 + 9\left[\left(\sum_{i=2}^{n} x_i\right)(n-1)\right]^{0.25}$	$x_1 \in [0,1]$ $x_1 = 0$ $i = 2, \ldots, n$	Nonconvex Nonuniformly spaced

A reference set (Pareto-optimal front) can be defined as a set of optimal true Pareto Front solutions or a non-dominated set of solutions. The convergence measurement produces a better algorithm when the solution obtained is closer to the reference point. Then, a lower convergence metric value can produce a better MOO algorithm.

Convergence Metric

The following steps can compute the convergence metric:

Step 1: Find the non-dominated $F(t)$ population set.

Step 2: For each solution, i in $F(t)$, calculate the smallest normalised Euclidian Distance, d_i to the reference set as Equation 8:

$$d_i = \min_{j=1} N \sqrt{\sum_{K=1}^{M} \left(\frac{f_k(i) - f_k(j)}{f_k \max - f_k \min} \right)^2} \quad [8]$$

Here, M is the number objective, f_k max and f_k min are the maximum and minimum function values of the k[th] objective function in the reference set, respectively, and N is the size of the reference set.

Step 3: Find the convergence metric value $C(P(t))$ by finding the normalised distance average for all points in $F(t)$ as Equation 9.

$$C(P(t)) = \frac{\sum_{i=1}^{|F(t)|} d_i}{|F(t)|} \quad [9]$$

Diversity metric can be calculated using Equation 10:

$$DIV = \frac{d_f + d_l + \sum_{i=1}^{N-1} \left| d_i - \overline{d} \right|}{d_f + d_l + (N-1)\overline{d}} \quad [10]$$

Here $\overline{d}$ is the average of all distances $d_i \left(i = 1, ..., N\right)$, assuming N solutions are in the obtained non-dominated set. d_i is the Euclidean distance between the consecutive solutions in the obtained non-dominated set of solutions. $\left(N-1\right)$ is total d_i produced. d_f and d_l represent the Euclidean Distance between the boundary solutions and extreme value.

Comparison Results with Benchmark MOO Algorithm

The results were compared with three well-known multi-objective algorithms (MOEA/D, PESA-II and MOALO) to investigate the efficiency of the proposed MOiJaya_aKNN. The parameter settings were adopted for all the algorithms: population size P = 100 and Number of iterations =500. Table 5 shows the performance metric's comparison of MOEA/D, PESA-II, MOALO, MOMSA, MOJaya, MOiJaya, and the MOiJaya_aKNN. As

Table 5
Performance metric comparison for convergence and diversity metric evaluation metrics on ZDT bi-objective between MOiJaya_aKNN and other algorithms

Case	Algorithm	Convergence (mean±sd)	Diversity (mean±sd)
ZDT1	MOMSA	0.028±0.014	0.581±0.696
	MOEA	0.159±0.102	1.044±0.133
	MOALA	0.044±0.026	1.345±0.081
	PESA-II	0.079±0.026	0.763±0.052
	MOJAYA	0.233±0.055	0.020±0.042
	MOiJAYA_aKNN	**0.009±0.001**	**0.015±0.00065**
ZDT2	MOMSA	0.029±0.024	1.011±0.153
	MOEA	**0.033±0.043**	1.045±0.048
	MOALA	**0.033±0.015**	1.126±0.091
	PESA-II	0.095±0.015	0.721±0.065
	MOJAYA	0.265±0.225	0.044±0.027
	MOiJAYA_aKNN	**0.033±0.055**	**0.023±0.015**
ZDT3	MOMSA	0.017±0.005	0.910±0.033
	MOEA	0.220±0.150	1.330±0.044
	MOALA	0.028±0.022	1.552±0.082
	PESA-II	0.0875±0.056	0.958±0.082
	MOJAYA	0.046±0.005	0.066±0.122
	MOiJAYA_aKNN	**0.0071±0.007**	**0.026±0.004**
ZDT4	MOMSA	0.391±0.294	1.102±0.160
	MOEA	7.901±1.504	1.161±0.031
	MOALA	21.070±16.94	1.008±0.008
	PESA-II	17.466±10.931	0.973±0.029
	MOJAYA	**0.217±0.0516**	0.255±0.0644
	MOiJAYA_aKNN	0.29512±0.03720	**0.01017±0.00180**
ZDT6	MOMSA	0.063±0.024	1.476±0.195
	MOEA	0.1311±0.207	1.137±0.052
	MOALA	0.325±0.198	1.425±0.053
	PESA-II	0.325±0.464`	1.211±0.190
	MOJAYA	0.560±0.470	0.076±0.084
	MOiJAYA_aKNN	**0.022±0.010**	**0.01329±0.00197**

can be seen, the developed MOiJaya algorithm was superior in most standard bi-objectives compared to others.

Regarding the convergence metric, while MOiJaya_aKNN with the lowest mean convergence metric outperformed other algorithms in optimising were 0.009 for ZDT 1, 0.0071 for ZDT3, and 0.022 for ZDT6 benchmark functions, the MOEA and MOALA algorithms demonstrate same results of 0.0033 for ZDT2. Moreover, MOJaya algorithms obtained better results were 0.217 for ZDT4. Therefore, it can be said that the MOiJaya_aKNN could find the non-dominant solutions with minimum distance from the Pareto front and had a better distribution than the five other algorithms.

In terms of the diversity metric, the MOiJaya_aKNN with the lowest diversity metric outperformed all the ZDT bi-objective benchmark functions. For example, the average value of the diversity metric for the ZDT1 benchmark function obtained by the MOiJaya_aKNN algorithm was 0.015, while the corresponding values for MOMSA, MOEA/D, MOALA, PESA-II, MOJaya and MOiJaya algorithms were 0.581, 1.044, 1.345,0.763, 0.020 and 0.016, respectively, indicating the higher performance of the MOiJaya_aKNN compared to the other algorithms. The results for other diversity metrics (dm) demonstrated that the MOiJaya was 0.02354 for ZDT2, 0.02687 for ZDT3, 0.01017 for ZDT4, and 0.01329 for ZDT6. As seen in Table 6, the proposed MOiJaya_aKNN was the only model with impressive diversity results. It could produce a better distribution and spread for the non-dominated solutions on the Pareto front compared to the original MOJaya. Meanwhile, integration with aKNN provides a possible solution for obtaining the best solution value for optimisation.

These results indicate that the probability of premature convergence and the unbalancing of exploration and exploitation of MOJaya has been improved by introducing chaotic random inertia weight and archiving K-nearest neighbour, which improves both convergence and diversity.

Optimisation of Cooling Slope Casting Process using Hybrid MOJaya

The proposed MOiJaya_aKNN hybrid algorithm developed in this study was utilised to improve the basic MOJaya algorithm. Subsequently, the enhanced algorithm 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 first step in developing the MOiJaya_aKNN algorithm was parameter initialisation, which was required before optimisation. During the initialisation step, a population-sized solution space was generated randomly between the high and low values of the variables (Pt, Sa, and Pd) range limits. Table 6 lists the details of the parameters executed in MATLAB software employed in this study. Steps 1–11 describe the MOiJaya_aKNN algorithm development.

The following steps describe the MOiJaya_aKNN algorithm to solve the multi-objective optimisation in the CS process:

Table 6
MOiJaya_aKNN initialisation

Parameters	Command
Population size	100
Maximum iteration (MI)	500
Number of variables (NVAR)	3
Lower Boundary (LB)	[680, 30, 300]
Upper Boundary (UB)	[720, 60, 500]

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 the Initial population size (P) randomly.

Step 4: Evaluate the objective function, which is the mathematical model for Tensile strength and Impact strength expressed in Equations 5 and 6, respectively, as a function for the MOJaya algorithm. The process parameters bounds are expressed by Equations 11 to 15. Maximise:

$$\begin{aligned} \textit{Tensile Strength} = {} & 6790.30937 - 19.12184 * Pt - 1.63463 * Sa \\ & - 0.21772 * Pd + 0.013738 * Pt * Pt \\ & + 0.022938 * Sa * Sa + 0.000508 * Pd * Pd \end{aligned} \tag{11}$$

Maximise

$$\begin{aligned} \textit{Impact strength th} = {} & 147.34224 - 0.412945 * Pt - 0.003288 * Sa - 0.003761 * Pd \\ & - 0.00050 * Sa * Pd + 0.000297 * Pt * Pt \\ & + 0.000372 * Sa * Sa + 0.00012 * Pd * Pd \end{aligned} \tag{12}$$

Parameter

$$680 \leq A \leq 720 \tag{13}$$

$$300 \leq B \leq 500 \tag{14}$$

$$30 \leq C \leq 60 \tag{15}$$

Step 5: Identify the best and worst candidates among the population in terms of identified objective functions generated from the equation and parameter boundaries from Equations 5 to 9.

Step 6: Based on the best and worst solutions from Step 5, substitute the value to modify all candidate solutions using expressed as Equation 4.

Step 7: Combine the modified solution with the initial solutions. Calculate the crowding distance and ranking using non-dominated sorting, considering both functions. Then, select the first P for the next iteration.

Step 8: Sort P' (rejection solution) by ascending ranking and descending crowding distance. Trim P' into its original size of P

Step 9: Update using KNN, P=P' + K size archive

Step 10: If the termination criterion is satisfied, exit and proceed with Step 11; if not, go back to Step 5.

Step 11: The stopping criteria are applied in the algorithm; if the solutions satisfy the condition, the algorithm will stop and, otherwise, return to Step 4.

RESULTS AND DISCUSSION

The current study employed a mathematical regression model to validate the impact strength in Equation 11 and tensile strength in Equation 12 (feedstock performance) as objective functions in MOJaya algorithms. Their significance needs to be validated before the models are used in the optimisation process. The significance and coefficient determination values for the models are summarised in Tables 7 and 8. The models were then utilised to optimise the CS process parameters.

Tables 7 and 8 indicate that the SR model for tensile strength and impact strength with a 95% confidence interval is statistically significant with a *p*-value less than 0.0001. A *p*-value equal to or less than 0.5 is considered significant, while a *p*-value higher than 0.5 is considered insignificant. The result of each CS casting process parameter for both SR models shows that all parameters are significant to the model with *p* a p-value less than 0.05.

Both models proposed in the present study were significant since their p-values were under 0.05. The models also recorded R^2 values over 80%, as tabulated in Table 9, indicating

Table 7
ANOVA of tensile strength

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	6281.41		1046.90	10.00	< 0.0001
A-Pouring Temperature	384.20	1	384.20	3.67	0.00673
B-Slanting Angle	1941.01	1	1941.01	18.55	0.0002
C-Pouring distance	1961.32	1	1961.32	18.74	0.0002
AC	415.53	1	415.53	3.97	0.0578
A^2	808.82	1	808.82	7.73	0.0104
B^2	455.15	1	455.15	4.35	0.0478
Residual	2511.31	24	104.64		
Total	8792.72	30			

Table 8
ANOVA of impact strength

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	3.21		0.4583	14.11	< 0.0001
A-Pouring Temperature	0.0578	1	0.0578	1.78	0.01952
B-Slanting Angle	0.4128	1	0.4128	12.71	0.0016
C-Pouring distance	2.29	1	2.29	70.68	< 0.0001
BC	0.0684	1	0.0684	2.11	0.01602
A^2	0.0991	1	0.0991	3.05	0.00940
B^2	0.0493	1	0.0493	1.52	0.02303
C^2	0.1010	1	0.1010	3.11	0.0910
Residual	0.7468	23	0.0325		
Total	3.95	30			

Table 9
Model summary statistics for tensile strength and impact strength

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

a perfect fit and the models explained over 80% of the performance feedstock variance, which arose from the CS process parameters. Furthermore, the accuracy of both models was validated with actual data and mathematical models.

The pred-R^2 value in the current study defines the ability of a model to predict feedstock performance for new observations, where a higher value indicates a significant prediction ability. Both models obtained in this study were documented under a 0.2 difference between the adj-R^2 and pred-R^2 values. Then, the models were acceptable. The results demonstrated that the regression model equations for mechanical properties (tensile and impact strengths could be utilised to predict feedstock performance effectively.

Next, the optimal CS parameters values generated from MOiJaya_aKNN; Pouring Temperature= 701.5456°C, Slanting angle =44.0902° and Pouring distance = 411.82938cm. Next, the algorithm performances were determined by comparing the generated output from MOiJaya_aKNN and the initial experiment. Table 10 shows that the difference between experiment results and MOiJaya_aKNN results is only 2.17% per cent different for Tensile strength, and Impact strength is 5.52% per cent different. MOiJAya_aKNN results are considered accepted since there is a slight percentage improvement. Hence, MOiJaya_aKNN can help the caster solve real problems in the CS casting process for predicted optimum feedstock performance without using repeated experiments that are costly and time-consuming.

Table 10
Optimisation result of the CS casting process

Feedstock Performance	Method	Value	Percentage improvement (%)
Tensile strength	MOiJAYA_aKNN	146.8586	2.17%
	Initial Experiment	143.732	
Impact strength	MOiJAYA_aKNN	4.8751	5.52%
	Initial Experiment	4.606	

CONCLUSION

Based on the AZ91D magnesium alloy CS casting optimisation with MOiJaya_aKNN algorithm performed in the current study, the following conclusions were derived:

1. The results indicate that the probability of premature convergence occurring and the unbalance of exploration and exploitation have been improved by introducing

chaotic, random inertia weight and archiving K-nearest neighbour while improving both convergence and diversity of the original MOJaya algorithm.

2. The regression analysis successfully developed a prediction model for feedstock performance (tensile and impact strengths). Furthermore, the predicted values were in good agreement with measured output responses, where the R^2 adjusted values were high (> 70%), indicating the models' superior ability to predict.
3. The optimum CS casting parameters were 701.5456^{o}C of Pt, 44.0902^o of Sa, and 411.82938cm of Pd.
4. Compared to initial experimental data, the values tensile and impact strengths from MOiJaya_aKNN are close to the initial experiment values as the difference is 2.17% and 5.52%, respectively.

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REFERENCES

Abdelgneia, M. A. H., Omar, M. Z., Ghazalib, M. J., Gebrilb, M. A., & Mohammed, M. N. (2019). The effect of the rheocast process on the microstructure and mechanical properties of Al-5.7Si-2Cu-0.3Mg alloy. *Jurnal Kejuruteraan, 31*(2), 317-326. https://doi.org/10.17576/jkukm-2019-31(2)-17

Abdin, Z., Prabantariksob, R. M., Fahmy, E., & Farhan, A. (2022). Analysis of the efficiency of insurance companies in Indonesia. *Decision Science Letters, 11*(2022), 105-112. https://doi.org/10.5267/j.dsl.2022.1.002

Agarwal, N., Pradhan, M. K., & Shrivastava, N. (2018). A new respond Jaya algorithm for optimization of EDM process parameters. *Materials Todays Proceedings, 5*(11, Part 3), 23759-23768. https://doi.org/10.1016/j.matpr.2018.10.167

Annamalai, S., Periyakgoundar, S., & Gunasekaran, S. (2019). Magnesium alloys: A review of applications. *Materials and Technology, 53*(6), 881-890. https://doi.org/10.17222/mit.2019.065

Asadollahi-Yazdi, E., Gardan, J., & Lafon, P. (2018). Multi-objective optimization of additive manufacturing process. *IFAC-PapersOnLine*, *51*(11), 152-157. https://doi.org/10.1016/j.ifacol.2018.08.250

Balachandran, G. (2018). Challenges in special steel making. *IOP Conference Series: Materials Science and Engineering, 314*, Article 012016. https://doi.org/10.1088/1757-899X/314/1/012016

Binesh, B., & Aghaie-Khafri, M. (2017). Modelling and optimization of semi-solid processing of 7075 Al alloy. *Materials Research Express, 4*, Article 096502. https://doi.org/10.1088/2053-1591/aa8272

Brezocnik, M., & Župerl, U. (2021). Optimization of the continuous casting process of hypoeutectoid steel grades using multiple linear regression and genetic programming - An industrial study. *Metals, 11*(6), Article 972. https://doi.org/10.3390/met11060972

Britto, A., & Pozo, A. (2012). Using archiving methods to control convergence and diversity for many-objective problems in particle swarm optimization. In *2012 IEEE Congress on Evolutionary Computation* (pp. 1-8). IEEE Publishing. https://doi.org/10.1109/CEC.2012.6256149

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation, 6*(2), 182-197.

El-Ashmawi, W. H., Ali, A. F., & Slowik, A. (2020). An improved Jaya algorithm with a modified swap operator for solving team formation problem. *Soft Computing, 24*, 16627-16641. https://doi.org/10.1007/s00500-020-04965-x

Esonye, C., Onukwuli, O. D., Anadebe, V. C., Ezeugo, J. N. O., & Ogbodo, N. J. (2021). Application of soft-computing techniques for statistical modeling and optimization of *Dyacrodes edulis* seed oil extraction using polar and non-polar solvents. *Heliyon, 7*(3), Article e06342. https://doi.org/10.1016/j.heliyon.2021.e06342

Fadaee, M., Mahdavi-Meymand, A., & Zounemat-Kermani, M. (2022). Suspended sediment prediction using integrative soft computing models: On the analogy between the butterfly optimization and genetic algorithms. *Geocarto International, 37*(4), 961-977. https://doi.org/10.1080/10106049.2020.1753821

Feng, Q., & Zhou, X. (2019). Automated and robust multi-objective optimal design of thin-walled product injection process based on hybrid RBF-MOGA. *The International Journal of Advanced Manufacturing Technology, 101*, 2217-2231. https://doi.org/10.1007/s00170-018-3084-5

Feng, Y., Lu, R., Gao, Y., Zheng, H., Wang, Y., & Mo, W. (2018). Multi-objective optimization of VBHF in sheet metal deep-drawing using Kriging, MOABC, and set pair analysis. *The International Journal of Advanced Manufacturing Technology, 96*, 3127-3138. https://doi.org/10.1007/s00170-017-1506-4

Ganesh, N., Shankar, R., Kalita, K., Jangir, P., Oliva, D., & Pérez-Cisneros, M. (2023). A novel decomposition-based multi-objective symbiotic organism search optimization algorithm. *Mathematics, 11*(8), Article 1898. https://doi.org/10.3390/math11081898

Goudos, S. K., Deruyck, M., Plets, D., Martens, L., Psannis, K. E., Sarigiannidis, P., & Joseph, W. (2019). A novel design approach for 5G massive MIMO and NB-IoT green networks using a hybrid jaya-differential evolution algorithm. *IEEE Access, 7*, 105687-105700. https://doi.org/10.1109/ACCESS.2019.2932042

Guo, Y., Liu, W., Sun, M., Xu, B., & Li, D. (2018). A method based on semi-solid forming for eliminating coarse dendrites and shrinkage porosity of H13 tool steel. *Metals, 8*(4), Article 277. https://doi.org/10.3390/met8040277

Jangir, P., Buch, H., Mirjalili, S., & Manoharan, P. (2023). MOMPA: Multi-objective marine predator algorithm for solving multi-objective optimization problems. *Evolutionary Intelligence, 16*, 169-195. https://doi.org/10.1007/s12065-021-00649-z

Ji, Z., & Xie, Z. (2008). Multi-objective optimization of continuous casting billet based on ant colony system algorithm. In *2008 IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application* (Vol. 1, pp. 262-266). IEEE Publishing. https://doi.org/10.1109/PACIIA.2008.28

Jian, X., & Weng, Z. (2020). A logistic chaotic JAYA algorithm for parameters identification of photovoltaic cell and module models. *Optik*, *203*, Article 164041. https://doi.org/10.1016/j.ijleo.2019.164041

Khosravi, H., Eslami-Farsani, R., & Askari-Paykani, M. (2014). Modeling and optimization of cooling slope process parameters for semi-solid casting of A356 Al alloy. *Transactions of Nonferrous Metals Society of China (English Edition), 24*(4), 961-968. https://doi.org/10.1016/S1003-6326(14)63149-6

Kor, J., Chen, X., Sun, Z., & Hu, H. (2011). Casting design through multi-objective optimization. *IFAC Proceedings, 44*(1), 11642-11647. https://doi.org/10.3182/20110828-6-IT-1002.01726

Kumar, S., Jangir, P., Tejani, G. G., Premkumar, M., & Alhelou, H. H. (2021). MOPGO: A new physics-based multi-objective plasma generation optimizer for solving structural optimization problems. *IEEE Access, 9*, 84982-85016. https://doi.org/10.1109/ACCESS.2021.3087739

Kumar, S. D., Mandal, A., & Chakraborty, M. (2014). Cooling slope casting process of semi-solid aluminum alloys: A review. *International Journal of Engineering Research & Technology (IJERT), 3*(7), 269-283.

Kumar, S. B., Idris, M. H., Farah, N. F. N., & Kamal, R. (2013). Investigation of mechanical properties of AZ91D magnesium alloy by gravity die casting process. *Jurnal Mekanikal, 36*, 1-9.

Li, K., Chen, R., Fu, G., & Yao, X. (2019). Two-archive evolutionary algorithm for constrained multiobjective optimization. *IEEE Transactions on Evolutionary Computation, 23*(2), 303-315. https://doi.org/10.1109/TEVC.2018.2855411

Li, S., Fan, X., Huang, H., & Cao, Y. (2020). Multi-objective optimization of injection molding parameters, based on the Gkriging-NSGA-vague method. *Journal of Applied Polymer Science, 137*(19), Article 48659. https://doi.org/10.1002/app.48659

Mishra, P., & Sahu, A. (2018). Manufacturing process optimization using pso by optimal machine combination on cluster level. *Materials Today: Proceedings, 5*(9), 19200-19208. https://doi.org/10.1016/j.matpr.2018.06.275

Nafisi, S., & Ghomashchi, R. (2019). Semi-solid processing of alloys and composites. *Metals, 9*(5), Article 526. https://doi.org/10.3390/met9050526

Narayanan, R. C., Ganesh, N., Čep, R., Jangir, P., Chohan, J. S., & Kalita, K. (2023). A novel many-objective sine-cosine algorithm (MaOSCA) for engineering applications. *Mathematics, 11*(10), Article 2301. https://doi.org/10.3390/math11102301

Onifade, M., Lawal, A. I., Aladejare, A. E., Bada, S., & Idris, M. A. (2022). Prediction of gross calorific value of solid fuels from their proximate analysis using soft computing and regression analysis. *International Journal of Coal Preparation and Utilization, 42*(4), 1170-1184. https://doi.org/10.1080/19392699.2019.1695605

Pandya, S. B., Visumathi, J., Mahdal, M., Mahanta, T. K., & Jangir, P. (2022). A novel MOGNDO algorithm for security-constrained optimal power flow problems. *Electronics, 11*(22), Article 3825. https://doi.org/10.3390/electronics11223825

Patel, G. C. M., Krishna, P., Vundavilli, P. R., & Parappagoudar, M. B. (2016a). Multi-objective optimization of squeeze casting process using genetic algorithm and particle swarm optimization. *Archives of Foundry Engineering, 16*(3), 172-186. https://doi.org/10.1515/afe-2016-0073

Patel, G. C. M., Krishna, P., & Parappagoudar, M. B. (2016b). Modelling and multi-objective optimisation of squeeze casting process using regression analysis and genetic algorithm. *Australian Journal of Mechanical Engineering, 14*(3), 182-198. https://doi.org/10.1080/14484846.2015.1093231

Patel, G. C. M., Krishna, P., & Parappagoudar, M. B. (2015). Modelling of squeeze casting process using design of experiments and response surface methodology. *International Journal of Cast Metals Research, 28*(3), 167-180. https://doi.org/10.1179/1743133614Y.0000000144

Premkumar, M., Jangir, P., Sowmya, R., Elavarasan, R. M., & Kumar, B. S. (2021). Enhanced chaotic JAYA algorithm for parameter estimation of photovoltaic cell/modules. *ISA Transactions, 116*, 139-166. https://doi.org/10.1016/j.isatra.2021.01.045

Premkumar, M., Jangir, P., Kumar, B. S., Alqudah, M. A., & Nisar, K. S. (2022). Multi-objective grey wolf optimization algorithm for solving real-world BLDC motor design problem. *Computers, Materials & Continua*, *70*(2), 2435-2452. https://doi.org/10.32604/cmc.2022.016488

Raed, A. Z., Mohammed, Z., Al, A., Awadallah, M. A., Doush, I. A., & Assaleh, K. (2022). An intensive and comprehensive overview of JAYA Algorithm, its versions and applications. *Archives of Computational Methods in Engineering, 29*(2), 763-792. https://doi.org/10.1007/s11831-021-09585-8

Rao, R. V. (2011). *Advanced modeling and optimization of manufacturing processes*. Springer. https://doi.org/10.1007/978-0-85729-015-1

Rao, R. V., Rai, D. P., Ramkumar, J., & Balic, J. (2016). A new multi-objective Jaya algorithm for optimization of modern machining processes. *Advances in Production Engineering & Management*, *11*(4), 271-286. http://dx.doi.org/10.14743/apem2016.4.226

Rao, R. Venkata, Keesari, H. S., Oclon, P., & Taler, J. (2019). Improved multi-objective Jaya optimization algorithm for a solar dish Stirling engine. *Journal of Renewable and Sustainable Energy*, *11*(2), Article 025903. https://doi.org/10.1063/1.5083142

Rao, R. V. (2018). *Jaya: An advanced optimization algorithm and its engineering applications.* Springer. https://doi.org/10.1007/978-3-319-78922-4

Said, R. M., Sallehuddin, R., Mohd Radzi, N. H., & Mohd Kamal, M. R. (2021). Jaya algorithm for optimization of cooling slope casting process parameters. *Journal of Physics: Conference Series*, *2129*(1), Article 012042. https://doi.org/10.1088/1742-6596/2129/1/012042

Singh, A., Singh, R. M., Kumar, A. R. S., Kumar, A., Hanwat, S., & Tripathi, V. K. (2021). Evaluation of soft computing and regression-based techniques for the estimation of evaporation. *Journal of Water and Climate Change, 12*(1), 32-43. https://doi.org/10.2166/wcc.2019.101

Son, Y. G., Jung, S. S., Park, Y. H., & Lee, Y. C. (2021). Effect of semi-solid processing on the microstructure and mechanical properties of aluminum alloy chips with eutectic Mg2Si intermetallics. *Metals, 11*(9), Article 1414. https://doi.org/10.3390/met11091414

Tanvir, M. H., Hussain, A., Rahman, M. M. T., & Ishraq, S, Zishan, K., Rahul, S. T., & Habib, M. A. (2020). Multi-objective optimization of turning operation of stainless steel using a hybrid whale optimization algorithm. *Journal of Manufacturing and Materials Processing, 4*(3), Article 64. https://doi.org/10.3390/jmmp4030064

Tavakolpour-Saleh, A. R., Zare, S. H., & Badjian, H. (2017). Multi-objective optimization of stirling heat engine using gray wolf optimization algorithm. *International Journal of Engineering, 30*(6), 150-160.

Tugiman, T., Thayab, A., Ariani, F., Sitorus, T., Suhandi, S., & Rizki, R. (2019). The effect of cooling slope on mechanical properties of aluminum-8.5wt.% Si alloy produced by gravity casting. In *Proceedings of the 2nd Annual Conference of Engineering and Implementation on Vocational Education (ACEIVE 2018)* (pp. 1-7). EAI Publishing. https://doi.org/10.4108/eai.3-11-2018.2285718

Vinh, L., & Nguyen, N. S. (2020). Parameters extraction of solar cells using modified JAYA algorithm. *Optik, 203*, Article 164034. https://doi.org/10.1016/j.ijleo.2019.164034

Warid, W., Hizam, H., Mariun, N., & Wahab, N. I. A. (2018). A novel quasi-oppositional modified Jaya algorithm for multi-objective optimal power flow solution. *Applied Soft Computing, 65*, 360-373. https://doi.org/10.1016/j.asoc.2018.01.039

Wu, C., & He, Y. (2020). Solving the set-union knapsack problem by a novel hybrid Jaya algorithm. *Soft Computing, 24*, 1883-1902. https://doi.org/10.1007/s00500-019-04021-3

Wu, H., Yang, X., Cao, G., Zhao, L., & Yang, L. (2021). Design and optimisation of die casting process for heavy-duty automatic transmission oil circuit board. *International Journal of Cast Metals Research, 31*(2), 88-96. https://doi.org/10.1080/13640461.2021.1904673

Zamli, K., Alsewari, A., & S. Ahmed, B. (2018). Multi-start jaya algorithm for software module clustering problem. *Azerbaijan Journal of High Performance Computing, 1*(1), 87-112.

Zheng, K., Lin, Y., Chen, W., & Liu, L. (2020). Numerical simulation and optimization of casting process of copper alloy water-meter shell. *Advances in Mechanical Engineering, 12*(5), 1-12. https://doi.org/10.1177/1687814020923450

Zhenghao, Li, J., & Hao, H. (2020). Non-probabilistic method to consider uncertainties in structural damage identification based on hybrid Jaya and tree seeds algorithm. *Engineering Structures, 220*, Article 110925. https://doi.org/10.1016/j.engstruct.2020.110925

Zhou, D., Kang, Z., Yang, C., Su, X., & Chen, C. C. (2022). A novel approach to model and optimize qualities of castings produced by differential pressure casting process. *International Journal of Metalcasting, 16*, 259-277. https://doi.org/10.1007/s40962-021-00596-6

Zitzler, E., Deb, K., & Thiele, L. (1999). Comparison of multiobjective evolutionary algorithms: empirical results. *Evolutionary Computation, 8*(2), 173-195. https://doi.org/10.1162/106365600568202