LIGHTWEIGHT DESIGN OF MOVING-PLATE FOR INJECTION MOULDING MACHINE BASED ON MULTI-OBJECTIVE OPTIMIZATION SCHEME MINING

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To address the trade-offs between mechanical performance and lightweight effects in moving-plate, this study proposes a lightweight design approach that combines approximate modelling, multi-objective optimization, and optimal solution mining. Using this, a Pareto solution for lightweight structures meeting multiple criteria was established. An interval vague set-based decision method was developed, integrating both subjective and objective data for optimal solution evaluation. Applying our approach to a two-plate injection moulding machine's moving-plate, we achieved an optimized design under three operational conditions. The validity and practicality of the method could be verified by comparing the results of this scheme to those based solely on subjective or objective information.

Keywords: Moving-plate of injection moulding machine, multiple working conditions, lightweight design, multi-objective decision making, optimal solution mining.

1. Introduction

The moving-plate, which is one of the critical parts of the die closing mechanism of injection moulding machines, performs die mounting, fixing, and motion guidance, and its mass accounts for approximately 70% of the overall weight. To meet the requirements of the rigid strength of the injection moulding machines under different working conditions while reducing the mass, inertia, and impact in the process of opening and closing the mould and improving the stability of high-speed and high-precision large injection moulding equipment, there is an urgent need to solve practical engineering problems.

Consequently, some researchers have used finite element analysis and structural optimization techniques to rationally design the plate. Sun [1] introduced a self-organizing approach for the topology optimization of a stationary plate to

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reduce the deformation of the moving-plate under die-closing conditions. Based on finite element analysis (FEA), Zuo et al. [2] parameterized the dimensions of the key parts of the stationary plate and conducted a finite element analysis to identify the critical factors on the deformation of the plate through orthogonal tests. Ling et al. [3] parameterized the reconstructed model after topological optimization of the plate and constructed a dual-objective optimization model, which the volume of the plate and plate deformation during die-closing are minimized. And the Pareto optimal solution set was obtained using a multi-objective genetic algorithm. Using Kriging model, Li et al. [4] designed an experiment for shape-size optimization of the reconstructed model of the plate and predicted a more accurate optimizing space with fewer experimental trials.

Although some progress has been reported in the aforementioned studies, structural optimization considering a single work condition can barely guarantee other condition specifications. Multi-objective optimization can solve multi-condition problems. However, the optimized result often turns out to be a Pareto solution set, which was not able to meet engineering practice requirement of a definite set of optimization parameters. Hence, researchers have proposed the use of a multi-objective decision-making approach to obtain satisfactory solutions.

Wang et al. [5] proposed a fuzzy multi-objective decision-making approach based on a vague set, wherein the decision matrix was non-dimensionalised to obtain the objective-grade-membership matrix. The schemes were sorted by computing the support, opposition, and neutral vague value using a scoring function. Yi et al. [6] proposed an optimization method based on the entropy weight vague set, analyzed the sensitivity of the objective function under individual conditions through information entropy, used a vague set to describe the extent to which each scheme meets the design requirements, and finally quantified how each condition fits the applicable scheme using the scoring function. Wang et al. [7] proposed an entropy weight grey correlation analysis method, obtained the weight applicable to each objective function using the entropy weight method, and computed the grey correlation of each scheme to mine the optimal solution of the multi-objective optimization results. Liu et al. [8] proposed an alternative for identifying the membership function based on data variance and fuzzy thresholds, and the subjective and objective information were considered for the evaluation of the scheme.

Regarding the lightweight design problem of the moving-plate of a two-plate injection moulding machine, an alternative coupling of approximate modelling and multi-objective optimization with optimal solution mining was performed. In the first step, a mathematical model for the parameter optimization of the moving-plate was constructed, and multi-objective parameter optimization was carried out in conjunction with approximate modelling. Further, a multi-objective decision method based on the interval vague set was proposed and applied to the multi-objective lightweight scheme decision of the moving-plate structure to obtain a model with the optimal comprehensive performance of the moving-plate.

2. Multi-objective Parametric Optimization of Moving-plate

2.1 Description of moving-plate model and conditions

This study focuses on a 1/4 scale model of a lightweight moving-plate structure for a specific model of a two-plate injection moulding machine (Fig. 1), with the principal properties presented in Table 1.

Table 1

Principal properties of the moving-plate

Modulus of elasticity/(N·m-2)	Poisson's ratio	Density/(Kg·m-3)	Volume length x width x thickness (mm)
1.69E11	0.275	7200	2200×2100×700

The plate can accommodate dies of different sizes in a practical work, and the maximum die size that can be accommodated is limited by the tie-bar pitch. As shown in Fig. 2, the tie bar pitch ($H \times V$) reflects the maximum projected area between the die holding space and moulded product, which is the preferred parameter for determining the die. The tie bar pitch of the injection molding machine was 1550×1450 mm. The rectangular loading face ($H' \times V'$) was configured in according to specific requirements of die size. The three loading faces, loading, and their corresponding predetermined performance requirements for the moving plate are presented in Table 2. The smallest die loading face was defined at a pitch ratio of 0.7×0.7 (Condition 1), while the largest die loading face was defined at pitch ratios of 1×0.7 (Condition 2) and 0.7×1 (Condition 3).

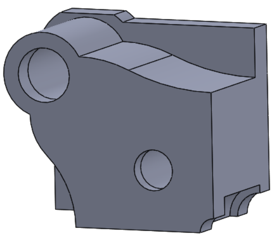


Fig. 1. Prototype of the moving-plate

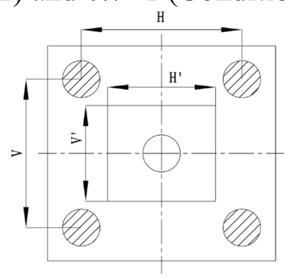


Fig. 2. Schematic of the loading face and tie bar hole pitch

Table 2

Three loading conditions of the moving-plate

Working Conditions	Loading face ($H' \times V'$) / mm-mm	Loading/ kN	Specified deformation level/ mm	Specified stress level/ MPa
1	1085×1015		≤0.6225	
2	1550×1015	16000	≤0.5727	≤100
3	1085×1450		≤0.5727	

The model was subjected to a static analysis in ANSYS, and the simulation results are presented in Table 3. In the context of the study, *V* denotes the maximum equivalent stress, *D* represents the maximum deformation, and *M* stands for mass.

Table 3

Simulation results of the lightweight structure of the moving-plate under the three working conditions

Working Conditions	*V* (MPa)	The predetermined value of *V* (MPa)	*D* (mm/m)	The predetermined value of *D* (mm/m)	*M* (kg)
1	96.60		0.6261	0.6225	
2	99.72	100	0.5821	0.5727	3681.3
3	92.90		0.5607	0.5727	

As shown in Table 3, the equivalent stresses of the proposed model under the three conditions conformed to the predetermined specifications. The deformation values under Condition 2 exceeded the predetermined specifications. Hence, it is necessary to further optimize the design.

2.2 Multi-objective parametric optimization mathematical model of moving-plate

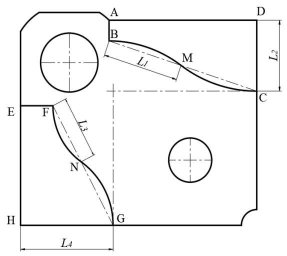


Fig. 3: Profile of the material removed from the direction of the tie-bar in the moving-plate

The mass *M* of the moving-plate, the maximum deformations D_1, D_2, D_3 and the maximum equivalent stresses V_1, V_2, V_3 under the three conditions are considered as the objective function in the paper.

To achieve a lightweight design, the material is removed from the direction of the tie-bar holes in the moving-plate as depicted in Figure 3. The cutting profile on its left and upper sides, designated as ABCD and EFGH, are similar. As shown in the Fig.3, the AB, AD, and DC are linear segment respectively, while the curved BC segment consists of two arcs of arc BM and MC. To ensure structural smoothness and continuity, the tangent arcs of arc BM and MC are employed as the tangent-point is M.

The length of the segments AB and AD is kept as unchanged due to their extreme position located. As the C point is pre-defined, a horizontal auxiliary line is drawn through point C and then the arc CM can be derived. Through point M, an arc MB is drawn tangent to arc MC. At this point, the size and shape of the profile ABCD are determined by the positions of points M and C. The profile EFGH can be determined as the same pattern is followed.

Mathematially, the chord lengths of arcs BM and FN, as well as the lengths of segments DC and GH, are denoted as L_1, L_2, L_3, and L_4, respectively. By analyzing the extreme positions of the moving-plate structure, the value ranges for L_1 to L_4 are deduced as:

$$0 \le L_1 \le A_1,\ L^1_{\min} \le L_2 \le L^1_{\max},\ 0 \le L_3 \le A_2,\ L^2_{\min} \le L_4 \le L^2_{\max}$$

Here, A_1 and A_2 respectively represent the lengths of BC and FG. $L^1_{\min}$ and $L^2_{\min}$ denote the lengths of AB and EF, while $L^1_{\max}$ and $L^2_{\max}$ characterize the lengths of CD and GH when at their limit positions (i.e., when curves BMC and FNG intersect the mold mounting holes).

From the aforementioned value ranges, a coupling between A_1, A_2 and L_2, L_4 respectively is evident, which can lead to potential erroneous sample points in subsequent experimental designs. Hence, this study the variable A_1 is employed as a design variable and a new design variable s_1 is introduced , which is defined as $s_1 = L_1 / A_1 \in [0,1]$. Consequently, $L_1 = s_1 \times A_1 \le A_1$. Similarly, the A_2 is defined as a design variable and a new variable $s_2 = L_3 / A_2 \in [0,1]$, leading to $L_3 = s_2 \times A_2 \le A_2$.

During the parameter optimization process, the presence of design variable ranges that are either excessively large or small negatively will impact the optimization scheme. Through iterative modeling and simulations, the value ranges for the design variables are fixed as: $A_1 \in [722, 784]$, $s_1 \in [0.3, 0.7]$, $A_2 \in [570, 630]$, $s_2 \in [0.3, 0.7]$.

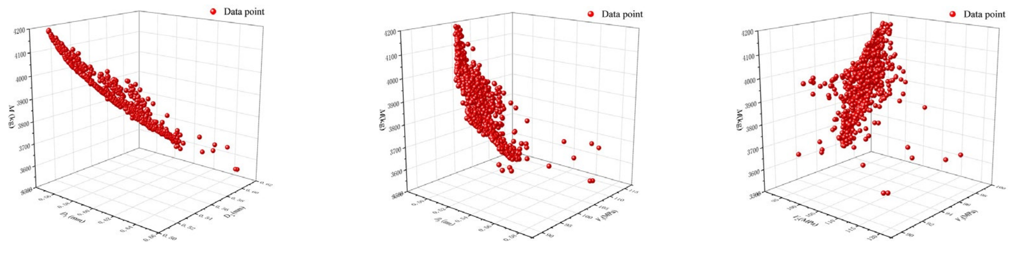
In summary, the mathematical model for the multi-objective parametric optimization of the moving-plate is defined as:

$$\begin{aligned} &\text{Find } X = [A_1, s_1, A_2, s_2]^T \\ &\text{Min} f(x) = \{M, D_1, D_2, D_3, V_1, V_2, V_3\} \\ &\text{s.t. } 722mm \le A_1 \le 784mm \\ &570mm \le A_2 \le 630mm \\ &0.3 \le s_1 \le 0.7 \\ &0.3 \le s_2 \le 0.7 \end{aligned} \tag{1}$$

2.3 Approximate model and multi-objective parametric optimization

The optimal Latin hypercube method [9] was used to generate 60 sets of sample points, and the response surface, radial basis function, orthogonal polynomial, and Kriging models [4] regarding the multi-objective parametric optimization of the moving-plate were constructed separately. The approximate model with the highest R^2 value for the coefficient of correlation in each response was selected to make up the design space as part of the moving-plate optimization problem. In this study, the mapping relationships between the design variables and M, D_1, D_2, D_3 and V_3 were fitted using the orthogonal polynomial method, and those between the design variables and V_1 and V_2 were fitted using the Kriging method.

The optimization process was performed using the NSGA-II algorithm [10] in the approximate model design space of the moving-plate multi-objective optimization problem. A total of 384 sets of Pareto-optimal solutions were derived using 1000 iterations. Using M as an example, 384 sets of Pareto-optimal solutions derived from these iterations are shown in Fig.4.



(**a**) (**b**) (c)

Fig. 4: Pareto solution sets for the moving-plate multi-objective optimization problem: (a) Pareto solution sets of M with respect to D_1 and D_2 (b) Pareto solution sets of M with respect to D_3 and V_1 (c) Pareto solution sets of M with respect to V_2 and V_3

As aforementioned in the optimization results, no solution was obtained from the Pareto solution set of the moving-plate multi-objective optimization problem that would result in the seven objective functions M, D_1, D_2, D_3, V_1, V_2 and V_3 being optimal, while the improved performance of an objective function would result in performance degradation of the other objective functions at varying degrees of impact. Hence, the designer could not select the solution with the best overall performance. Conventional purely subjective or objective decision-making methods have certain shortcomings because they ignore the real reflection of the objective data on the performance of the solution, cannot exclude subjective instability, are limited to data, and cannot guide subjective experience. Hence, it is necessary to consider the effect of each objective function on the performance of a scheme based on experience.

3. Lightweight Scheme Decision Based on Interval Vague Set

Regarding the evaluation of the 384 groups of schemes in the Pareto solution set and its optimal solution mining problem, a decision-making method considering the objective specifications of each objective function and the subjective preferences of the decision-maker was proposed with reference to the multi-objective decision and theory of vague sets. The subjective/objective information contained in each objective function in the scheme was represented in the form of vague values and converted into evaluation values to rank all the schemes in order.

3.1. Interval Vague sets

To make vague sets [11] more capable of expressing uncertain data, the values of true and false membership functions are represented using interval values, and the concept of interval-valued vague sets [12] is proposed accordingly.

Let U be the theoretical domain; let us refer to the vague set $A=\left\{\left(\left[t_A(x), f_A(x)\right]\right) \middle| x\in U\right\}$ as an interval-valued vague set and denote $t_A\left(x\right)$ and $f_A\left(x\right)$ as the true and false membership degrees of $x\in A$, respectively, where

$$t_A\left(x\right)=\left[t_A^-(x), t_A^+(x)\right]\subseteq\left[0,1\right] \tag{2}$$

$$f_A\left(x\right)=\left[f_A^-(x), f_A^+(x)\right]\subseteq\left[0,1\right] \tag{3}$$

$t_A^-(x)$, $t_A^+(x)$, $f_A^-(x)$ and $f_A^+(x)$ are the true and false membership degrees applicable to the subintervals of the interval [0,1], respectively, with each conforming to $0\le t_A^-(x)+f_A^-(x)\le 1$ and $0\le t_A^+(x)+f_A^+(x)\le 1$.

Let $\pi_A(x)$ denote the hesitancy or uncertainty (neutrality) of $\pi_A(x)$, expressed as

$$\pi_A(x)=\left[\pi_A^-(\mathrm{x}), \pi_A^+(\mathrm{x})\right] \tag{4}$$

where $\pi_A^-(x)=1-t_A^-(x)-f_A^-(x)$; $\pi_A^+(x)=1-t_A^+(x)-f_A^+(x)$

Compared with the vague set, the interval vague set can effectively deal with ambiguity and uncertainty among different evaluation indicators and has a better applicability to multi-criteria scheme decisions.

3.2. Modified multi-objective decision-making based on the interval Vague set

3.2.1. Multi-objective decision model

In this study, the information contained in each scheme was converted into an evaluation value based on the characteristics of the vague set, and all the schemes were ranked orderly. However, because vague set itself lack precise quantization and comparison criteria, they cannot be used to rank schemes in a direct manner. Researchers often use fuzzy multi-objective decision-making methods[5] to calculate the satisfaction level of a solution for each objective function by setting upper and lower bounds of satisfaction. Practically, objective functions may vary depending on the condition of the application, preferences of the decision maker, and other factors. If the upper and lower satisfaction bounds are shared, the decision results may be vulnerable to missing information or irrational decisions. Hence, in this study, the upper and lower bounds for the satisfaction of each objective function in a specific problem were set separately, and the improved multi-objective decision model is expressed as follows:

Let F be the objective set in the multi-objective decision-making, $F=\left\{f_1^*, f_2^*, \cdots, f_m^*\right\}$ (for distinguishing $f_A\left(x\right)$ in Section 3.1), X the set of schemes, and $X=\left\{x_1, x_2, \cdots, x_n\right\}$. f_{ij}^* is the ith objective value of the scheme x_j, that is, $f_{ij}^* = f_i^*(x_j)$, where i=1,2,…,m; j=1,2,…,n. To eliminate the incommensurability among the objective values, each data point must be normalised to convert f_{ij}^* to relative superiority [13] μ_{ij}. Hence, the decision matrix μ, which treats objective-grade membership as an element, can be expressed as follows:

$$\mu = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \mu_{m1} & \mu_{m2} & \cdots & \mu_{mn} \end{bmatrix} \tag{5}$$

Definition 1: For a given λ^{L_i} (the lower bound of the degree of satisfaction for the i_{th} objective function that the decision maker may accept), λ^{U_i} (the upper bound of the dissatisfaction degree for the i_{th} objective function that the decision maker may accept) if

(1) $\mu_{ij} > \lambda^{L_i}$, the j_{th} scheme supports the i_{th} objective function.

(2) $\mu_{ij} < \lambda^{U_i}$, the j_{th} scheme opposes the i_{th} objective function.

(3) $\lambda^{L_i} \le \mu_{ij} \le \lambda^{U_i}$ calls the j_{th} scheme neutral as regards the i_{th} objective function.

Definition 2: Let conformity to $F_j = \left\{f_i \in f \left| \mu_{ij} > \lambda^{L_i}\right.\right\}$ be the set of the support objectives for the j_{th} solution, conformity to $A_j = \left\{f_i \in f \left| \mu_{ij} < \lambda^{U_i}\right.\right\}$ be the set of opposing objectives for the j_{th} solution, and conformity to $N_j = \left\{f_i \in f \left| \lambda^{U_i} \le \mu_{ij} \le \lambda^{L_i}\right.\right\}$ be the set of neutral objectives for the j_{th} solution.

3.2.2. Multi-objective decision-making based on the interval Vague set

A decision process that merely considers the objective or subjective information or a simple weighting of objective and subjective information makes the decision process incomplete and nonstandard. In this regard, a multi-objective decision-making method based on an interval vague set is proposed. The proposed method, which combines the theory of the interval vague set to the modified multi-objective decision model described in Section 3.2.1, uses weights to denote objective and subjective information as contained in the decision problem and ranks the decision results by the scoring the function size of each scheme. The multi-objective decision model based on the vague interval set is defined as follows:

Definition 3: Let the subjective weight vector of the objective be $w' = \left(w_{11}, w_{21}, \cdots, w_{m1}\right)$, the objective weight vector be $w'' = \left(w_{12}, w_{22}, \cdots, w_{m2}\right)$, and the interval weight vector of the objective be expressed as

$$w = \left(\left[w_{11}, w_{12}\right], \left[w_{21}, w_{22}\right], \cdots, \left[w_{m1}, w_{m2}\right]\right) \tag{6}$$

Definition 4: Regarding any scheme $x_j \in X$, the information of its support, opposition, and neutral objectives set on *m* objectives can be expressed in vague terms as

$$V\left(x_j\right) = \left[t\left(x_j\right), f\left(x_j\right), \pi\left(x_j\right)\right] \tag{7}$$

Where:

$t\left(x_j\right) = \left[t_1\left(x_j\right), t_2\left(x_j\right)\right]$; $f\left(x_j\right) = \left[f_1\left(x_j\right), f_2\left(x_j\right)\right]$; $\pi\left(x_j\right) = \left[\pi_1\left(x_j\right), \pi_2\left(x_j\right)\right]$

$t_1\left(x_j\right) = \sum_{i \in J_{1j}} w_{i1}$; $t_2\left(x_j\right) = \sum_{i \in J_{1j}} w_{i2}$; where $J_{1j} = \left\{i \middle| f_i \in F_j\right\}$

$f_1\left(x_j\right) = \sum_{i \in J_{2j}} w_{i1}$; $f_2\left(x_j\right) = \sum_{i \in J_{2j}} w_{i2}$; where $J_{2j} = \left\{i \middle| f_i \in A_j\right\}$

$\pi_1\left(x_j\right) = \sum_{i \in J_{3j}} w_{i1}$; $\pi_2\left(x_j\right) = \sum_{i \in J_{3j}} w_{i2}$; where $J_{3j} = \left\{i \middle| f_i \in N_j\right\}$

Definition 5: Let the portion of the neutral objective set inclined to support the objective set be $t\left(x_j\right)\pi\left(x_j\right)$. Therefore, the scoring function for the scheme x_j containing more support information can be expressed as

$$S(x_j) = \frac{t_1(x_j) + t_1(x_j)\pi_1(x_j)}{2} + \frac{t_2(x_j) + t_2(x_j)\pi_2(x_j)}{2} \tag{8}$$

In summary, a multi-objective decision based on an interval vague set involves the following steps:

Step 1: Construct a decision matrix for an objective solution based on a specific problem.

Step 2: The decision matrix is converted into an objective grade membership matrix via normalisation.

Step 3: Consider the subjective and objective weights of the objectives and present them both in the form of interval weight vectors of the objectives.

Step 4: Calculate the interval vague value applicable to each scheme.

Step 5: Define the scoring function and rank all the solutions until the optimal scheme is obtained.

3.3. Selection of multi-objective light weight scheme for moving-plate

To obtain the optimal result of the overall lightweight performance of the moving-plate, a modified multi-objective decision method based on the interval vague set was used for scheme selection from 384 sets of Pareto solutions, as described in Section 2.3, using the following specific steps:

a. Construct a decision matrix *F* of seven rows and 384 columns based on the multi-objective parametric optimization results of the moving-plate, as described in Section 2.3.

b. Convert F into the objective superiority matrix μ using the linear scale method.

c. Calculate the subjective weight *w*' = (0.546, 0.206, 0.103, 0.103, 0.021, 0.0105, 0.0105) of seven objective functions using the AHP [14] and the objective weight *w*''= (0.213, 0.176, 0.199, 0.179, 0.107, 0.101, 0.025) of each objective function using the entropy weight method [14]. Thus, the interval weight vector is *w* = ([0.546,0.213], [0.206,0.176], [0.103,0.199], [0.103,0.179], [0.021,0.107], [0.0105,0.101], [0.0105,0.025]).

d. Given the lower bound of the degree of satisfaction for the mass of the moving-plate $\lambda^{U_1} = 0.98$, the upper bound of the dissatisfaction degree $\lambda^{L_1} = 0.97$; lower bound of the satisfaction degree for the maximum deformation of the moving-plate $\lambda^{U_2} = \lambda^{U_3} = \lambda^{U_4} = 0.92$, the upper bound of the dissatisfaction degree $\lambda^{L_2} = \lambda^{L_3} = \lambda^{L_4} = 0.91$; lower bound of the satisfaction degree for the maximum equivalent stress of the moving-plate $\lambda^{U_5} = \lambda^{U_6} = \lambda^{U_7} = 0.95$, and upper bound of dissatisfaction degree $\lambda^{L_5} = \lambda^{L_6} = \lambda^{L_7} = 0.94$, the vague value of each scheme was obtained from Definition 4.

e. Calculate the scoring function applicable to each scheme from Definition 5.

Table 4 presents the results of the support set, opposition set, and scoring function values for the 384 sets of the Pareto solutions. Figure 5 shows the scoring function values of all the Pareto solutions.

Table 4

Calculation results of the support set, opposition set, and scoring function

No.	t_1	t_2	f_1	f_2	π_1	π_2	$S(x_j)$
1	0.454	0.787	0.546	0.213	0	0	0.6205
2	0.4225	0.579	0.5775	0.421	0	0	0.5008
3	0.4225	0..579	0.567	0.32	0.0105	0.101	0.5322
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
384	0.5565	0.238	0.103	0.179	0.3405	0.583	0.5614

As shown in Fig. 5, the scoring function values of the Pareto solutions of groups 65, 95, 100, and 105 are the largest, thereby showing that these four groups of schemes meet the decision requirements best. The corresponding structural parameters of the moving-plate are shown in Table 5.

As shown in Table 5, the differences between the four sets of the Pareto solutions corresponding with the design variables are negligible, implying that they are a similar set of solutions (denoted as Scheme G^*).

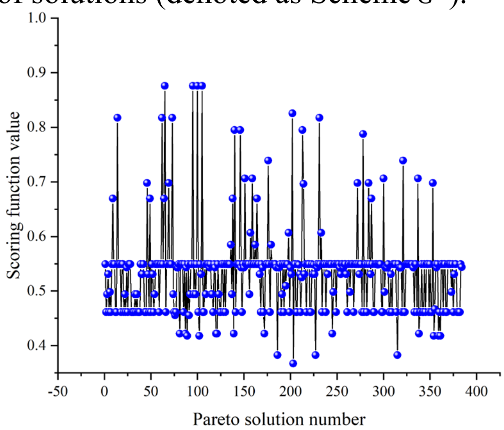


Fig. 5. Scoring function value of the Pareto optimal solution

Table 5

Design variables corresponding with the Pareto optimal solutions with the largest scoring function values

No.	A_1/mm	s_1	A_2/mm	s_2
65	738.0399554	0.375058593	617.1678973	0.359676773
95	738.0399554	0.375058593	617.1678973	0.359676773
100	738.0399554	0.375058593	617.1678973	0.359355344
105	738.0399554	0.375058593	618.0575718	0.359676773

The size parameters were assigned to the moving-plate model, and the corresponding performance parameters were obtained. With the other conditions remaining consistent, the scoring functions that only considered the subjective and objective weights were calculated and ranked using the scheme associated with the maximum value of the scoring function, denoted as G_1, G_2. Table 6 summarises the moving-plate performance values for the different weights.

As seen in Table 6, regarding the multi-objective decision problem with the parametric optimization results of the moving-plate, the moving-plate was determined with the smallest mass and poorest mechanical performance if only the subjective weights (Scheme G_1) were considered. The best mechanical performance and the largest mass was found if only the objective weights (Scheme G_2) were considered. In the case of the modified multi-objective decision method based on the interval Vague set (Scheme G^*), the moving-plate was determined with the mass and mechanical performance at a level between Scheme G_1 and G_2, which in turn validates the optimal performance of the scheme considers the subjective preference of the decision-maker (experience) and the objective information of the decision.

Table 6

Performance of the moving-plate corresponding with the maximum value of the scoring function under different weights

Scheme	M/Kg	D_1/mm	D_2/mm	D_3/mm	V_1/MPa	V_2/MPa	V_3/MPa
G_1	3784	0.5985	0.5985	0.5361	96.81	98.78	95.52
G_2	3827	0.5918	0.5510	0.5298	93.42	96.28	95.79
G^*	3789	0.5964	0.5553	0.5342	95.76	98.78	94.36

3.4. Simulation of decision results

In line with the process specifications, the parameters as contained in Scheme G^* were rounded, with the design variables subject to the parametric optimization expressed as follows:

$$X^* = [738, 0.375, 618, 0.360]$$

Reassigning all the parameters contained in X^* to the parameterised model of the moving-plate, a finite element simulation analysis was performed under three conditions. Table 7 presents a performance comparison of the moving-plate before and after the parametric optimization.

Table 7

Mass and performance responses of the moving-plate

Performance of the moving-plate	M/Kg	D_1/mm	D_2/mm	D_3/mm	V_1/MPa	V_2/MPa	V_3/MPa
Predetermined value	-	0.6225	0.5727	0.5727	100	100	100
Simulation results before the parametric optimization	3681	0.6261	0.5821	0.5607	96.60	99.72	92.90
Optimal Pareto solutions	3789	0.5964	0.5553	0.5342	95.76	98.78	94.36
Simulation results after the parametric optimization	3754	0.5980	0.5570	0.5358	95.32	97.59	93.34
Forecast error	-0.93%	0.27%	0.31%	0.30%	-0.46%	-1.20%	-1.08%
Ratio of optimization	1.98%	-4.49%	-4.31%	-4.44%	-1.33%	-2.14%	0.47%

The forecast error, as shown in Table 7 is defined as the relevant difference between predicted values under scheme G^* and simulation results after parametric optimization. A maximum discrepancy of -1.20% can be found. This finding shows the dependable predictive accuracy of the approximate model constructed in Section 2.3 agree well with simulated results. The last row in Table 7, shows that comparison of simulation results before and after parametric optimization in a relevant difference. It can be observed that the maximum overall deformation levels of the moving-plate subject to parameterized optimization were reduced under all three conditions, thereby fulfilling the predetermined requirements. The mass increased at a ratio of 1.98%. Except for the maximum equivalent forces under Condition 3 (increased at a ratio of 0.47%), the remaining mechanical properties were enhanced to some extent, thereby fulfilling the predetermined requirements.

4. Conclusion

Using a two-plate injection-moulding machine, the moving-plate was subjected to multi-objective parametric optimization and lightweight scheme selection. The main research findings are as follows:

(1) In this study, the topologically reconstructed model of a two-plate injection moulding machine was parameterized, and an optimized mathematical model was constructed using the mass, maximum deformation, and maximum equivalent stress under three conditions as the objective functions. The optimal Latin hypercube method was used to design the test scheme and construct the approximate model, while the orthogonal polynomial-Kriging with the highest forecast accuracy was selected to construct the approximate model. The optimizing process was performed using the NSGA-II algorithm until 384 sets of qualified Pareto solutions were obtained.

(2) A multi-objective decision method based on the interval Vague set was raised for certain problems, including information lost and irrational decision in the conventional fuzzy multi-objective decision making. The multi-objective lightweight scheme was selected for the parametric optimization results of the moving-plate, wherein the subjective and objective information were derived from the hierarchical analysis and the entropy weight method. Here, all the Pareto solutions were ranked by defining a new scoring function, until the comprehensive optimal solution of the moving-plate multi-objective parametric optimization problem was obtained. As revealed in the simulation analysis, the performance levels of the optimization model under the three conditions qualify the predetermined specifications, which in turn validates the effectiveness of the decision method that considers the subjective preferences of the decision maker (experience) and the objective information contained in the objective function.

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