An Integrated Approach to Decision-Making that Maximizes the Plastic Injection Molding Process

Luis Pérez-Domínguez, David Luviano-Cruz, Jesús Israel Hernández-Hernández, Delia J. Valles-Rosales, Dynhora-Danheyda Ramírez-Ochoa, and Diana Ortiz-Muñoz

Abstract This research addresses the intricate challenge of optimizing plastic injection molding processes with multiple objectives. Unlike multi-objective optimization, which often has a clear strategy for determining optimal solutions, many-objective optimization lacks a universally accepted approach to identifying ideal outcomes. In our study, we utilize a many-objective decision-making methodology that involves iterative selection of potential solutions based on experimental design techniques. In this mode, this approach ensures gradual progress toward a direction set by the user. In addition, the focus is on improving both the quality and efficiency of the injection molding process by linking design variables to process parameters. The optimization problem, characterized by four objectives, features a specific plastic fan as a case study in two different scenarios. The findings validate the effectiveness

L. Pérez-Domínguez (✉) · D. Luviano-Cruz · D. Ortiz-Muñoz
Departamento de Ingenieria Industrial y Manufactura, Universidad Autónoma de Ciudad Juárez, Henry Dunant 4612, Juárez 32315, Chihuahua, México
e-mail: luis.dominguez@uacj.mx

D. Luviano-Cruz
e-mail: david.luviano@uacj.mx

D. Ortiz-Muñoz
e-mail: diana.ortiz@uacj.mx

J. I. Hernández-Hernández
Departamento de Ingeniería Eléctrica y Computación, Universidad Autónoma de Ciudad Juárez, Av. del Charro, Juárez 32315, Chihuahua, México
e-mail: israel.hernandez@uacj.mx

D. J. Valles-Rosales
Department Chair-Industrial Management and Technology, Texas A&M University-Kingsville, W Ave B, Kingsville, TX 78363, USA
e-mail: delia.rosales@tamuk.edu

D.-D. Ramírez-Ochoa
Universidad Tecnólogica de Chihuahua, Av. Montes Americanos, Sector 35, Chihuahua 31216, Chihuahua, México
e-mail: dramirez@utch.edu.mx

E. León-Castro et al. (eds.), *Systems and Decision Processes in Management, Innovation and Sustainability*, Studies in Systems, Decision and Control 562,
https://doi.org/10.1007/978-3-031-69382-3_19

of our proposed method as a robust mechanism for managing the complexities of many-objective optimization in plastic injection molding processes.

Keywords Decision Making · Optimization · Many Objective Optimization

1 Introduction

Plastic injection molding is a common manufacturing method used in numerous industries, including the electronics, automotive, and packaging sectors. The following, method requires numerous input parameters and produces multiple output features, making it a multiple input, multiple output (MIMO) system. Because various aspects must be considered simultaneously, plastic injection molding presents itself as a multi-objective optimization problem, requiring multiple objectives to be maximized at the same time. If two or three objectives $1 < k3$ are considered, the issue is referred to as a multi-objective optimization problem (MOP) [1, 2]. If more than three objectives $1 < k > 3$ are included, the problem is referred to as many objective optimization problems (MaOP) [3, 4]. Although many-objective problems (MaOPs) and multi-objective problems (MOPs) share a similar theoretical definition, they differ significantly [5–9]. The Pareto set and Pareto front, which are the solution sets for MOPs, can be precisely approximated [10]. However, for MaOPs, this is not the case, given that the Pareto sets and Pareto fronts typically constitute k 1 -dimensional entities, where k denotes the total objectives, achieving accurate approximations in MaOPs is more challenging [11–13].

In addition, the production of high-quality about the Powder Injection Molding (PIM) parts poses significant challenges [14–16]. It requires extensive optimization and analysis, which can be time-intensive and expensive. Ensuring part quality necessitates the proper integration and fine-tuning of various aspects, which encompasses the part and mold design, material selection, and setting of process parameters. This integration and coordination of multiple factors are crucial for obtaining high-quality PIM parts efficiently. Besides, the setting of process parameters appears to be the most practical step toward producing high-quality parts quickly and affordably. To determine the ideal values for process parameters, academics and engineers have used a variety of approaches, including expert systems, data fitting models, optimization algorithms, and reasoning based on previous cases. Comprehensively improving these parameter settings across many methodologies has been made easier and more comprehensive thanks to computer-aided engineering tools and simulations. Statistical sampling techniques have shown to be helpful in obtaining improved optimization outcomes with reduced computational or simulation expenses, in addition to utilizing Computer-Aided Engineering (CAE) tools [17–19]. Using experimental design methodologies, these sampling techniques carefully select data points or parameter values within the practical search space. Compared to exhaustive approaches, these methods offer more effective optimization and faster arrival at better solutions by strategically sampling from the feasible region. Beyond the use of CAE tools, the employment of statistical methodologies such as sampling has enabled the achievement of enhanced outcomes within shorter durations of execution or simulation periods. Sampling involves the collection of data, predominantly through strategies of experimental design, at specific values within a viable search domain, $x \in D$ [20]. In tackling the intricate issue of optimizing settings for process parameters, researchers and engineers in the PIM domain have widely adopted a holistic strategy that merges statistical methods, smart algorithms, and CAE simulations. By amalgamating these complementary technologies and strategies, they have pinpointed the optimal parameter configurations for PIM processes, thereby securing superior results.

2 Basic Concepts

2.1 Plastic Injection Molding

Subsequent paragraphs, however, are indented. This section offers a summary of the process variables and goals reviewed in this investigation. Further details and an extensive outline of the PIM process can be found in references [21–25]. The main attention is on process parameters such as melt temperature (Tmelt), mold temperature (Tmold), packing time (tpack), packing pressure (Ppack), and cooling time (tcool), which have frequently been considered in prior research. These process parameters are described as follows:

x_1: : Melt temperature (Tmelt):This refers to the temperature reached by the platic melt when it enters the mold.

- x_2: Mold temperature (Tmold): It signifies the mold's temperature.
- x_3: Packing time (tpack): The duration for injecting additional plastic into the mold cavity to counteract shrinkage inherent in the injection molding process.
- x_4: Packing pressure (Ppack): Pressure exerted on the melt during the packing phase is defined here. In this case, Ppack represents the packing pressure distributed throughout the effective packing duration $t1 = 0.5\ t$pack as illustrated in a pressure profile. Figure 1 shows an example of a pressure profile.

- x_5: Mold Cooling Time (tcool): Following the packing of material into the mold, the duration for which the part is kept inside the closed mold to cool before ejection. This cooling phase can represent half of the overall cycle length.

The objectives are linked to enhancing the quality and efficiency of the PIM process. Both functional and aesthetic qualities are used to gauge its quality, including residual stressors such as the Von Mises stress and product warpage. In this sense, the following objectives are described in detail:

f_1 : Warping (mm): This deviation from the intended shape is caused by inconsistent shrinkage rates within the plastic product. Thermal gradients existing between

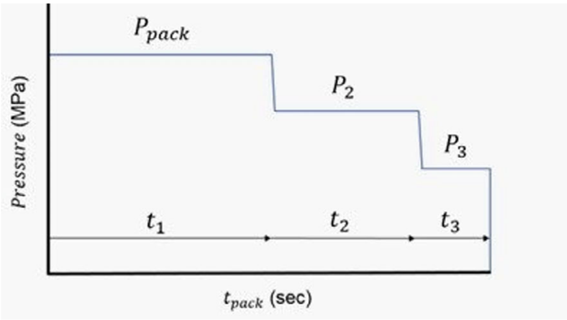


Fig. 1 Mapping of compressive loads during packing

different sections of the mold cavity are responsible for this effect. Likewise, it is well known like warpage conditions.

f_2 : Maximum Mold Closure Force (Tons): Supplied by the machine's clamping mechanism, this force represents the highest level of clamping pressure applied to resist the internal cavity pressure generated during injection and packing phases. Judicious utilization of this force presents opportunities for energy efficiency improvements.

f_3: : Cycle time (seconds): Details the complete duration of the process, encompassing the filling, mold opening, packing, and cooling stages. The duration is influenced by the packing and cooling times, which may constitute as much as 70% of the total cycle time.

f_4: : Residual Von Mises Stress (MPa): This metric evaluates the thermal stresses that remain in the ejected part once it has cooled to room temperature, using the Von Mises stress formulation.

2.2 Multi-Objective Optimization (MOP)

$$\begin{aligned} &\mathrm{Minimizar\,F(x)} \\ &\mathrm{Sujeto\,a:} \\ &\mathrm{g(x)} \leq 0 \\ &\mathrm{h(x)} = 0 \\ &\mathrm{x} \in \mathrm{R^n} \end{aligned} \tag{1}$$

F is a function that maps from R^n to R^k, , where F(x) is a vector comprising k objective functions f1(x), …, fk(x). The constraints include inequality constraints represented by the vector $g_1(x) = (g_1(x), ..., g_m(x))^T$, and equality constraints represente by the vector vector $h_1(x) = (h_1(x), ..., h_p(x))^T$. The concept of dominance defines the idea of optimality in a multi-objective optimization problem.

Definition 1. Consider vectors x and y in R. The vector x is considered smaller than y (denoted $x < y_p$) if for every component i from 1 to k, x_i is less than y_i. Similarly, the relation $\leq p$ is defined.

– A vector y within set D is said to be dominated by a vector x also in D (denoted $x < y$) in accordance with rule (1).
– If $F(x) \leq p$ and F(y) $\neq F(x)$ hold true. Otherwise, y is considered nondominated by x.
– A point x within the set D is termed (Pareto) optimal or a Pareto point when no other point y in D dominates x.
– The collection P_D consisting of all Pareto optimal solutions is known as the Pareto set, and its corresponding image $F(P_D)$ is referred to as the Pareto front.

There are many approaches that use Pareto dominance as the underlying criterion to distinguish solutions, which directs their search for MOPs and MaOPs.

2.3 Movement in Objective Space

The method for finding a solution through cooperative efforts with one or more users or decision-makers is described below.

The procedure starts with a first solution, x, which is chosen from the set D using an experimental design method. Then, for each i between 1 and$N$, a series of potential solutions, xi, are generated, with each solution denoting a movement in the user-specified direction. The method relies on the idea that the user has a preferred direction or vector, represented as dk which is a k-dimensional real vector, in the space of objective functions or criteria being optimized. In this mode, starting from an initial solution $\times$ 0, the user wants to choose solutions xi whose objective function values or outputs are described by the following Eq. 2:

$$F(x(i+1)) \approx F(x(i)) + \tau(i)d(k) \tag{2}$$

where:

- F represents a function
- $x(i)$ and $x(i+1)$ represent consecutive iterations or steps
- $\tau(i)$ is typically a step size or learning rate at iteration i
- $d(k)$ represents a direction or update vector (Eq. 3).

$$\mathrm{d}^1 = \begin{cases} -1 \\ 0 \end{cases} \tag{3}$$

The discussion is focused, without losing broader relevance, on a situation where there are two objective functions to be optimized. For example, let's examine a scenario where the user wants to reduce the value of $f\,1$, even if that means sacrificing.

$f2$, since $f1$ is considered twice as important as $f2$. In this case, the user can set the following:

$$d^1 = \begin{cases} -1 \\ 0 \end{cases} \tag{4}$$

In this mode, it is highly improbable that the dataset contains a point x_i where the equality condition in (2) is precisely satisfied. Therefore, we must calculate a "closest approximation," which we determine through the following approach in equation.

$$Z_i := F(x_0) + \tau d := Z_{\{i-1\}} + \tau d \tag{5}$$

In the equation, τ represents a fixed step size, which is based on the specific problem. The objective is to identify the closest solution within the dataset $T = \{x_1, y_1, ..., x_n, y_n\}^T$ to the reference pointZ_i. To achieve this, we utilize the enhanced weighted Tchebycheff scalarization function as described by [26], which is defined as follows in Eq. 6:

$$\min_{x \in D_k} \max_{i=i,...,n} \{w_i |fi(x) - Z_i|\} + \rho \sum_{i}^{k} w_i(f_i(x) - Z_i) \tag{6}$$

In the equation, Z_i represents the i-th reference point $w_i = (w_1, ..., w_k)^T$ is a vector of weights, where each weight w_i is a positive number for $w_i > 0$, $i = 1, ..., k$, and ρ. The parameter ρ is termed the augmentation coefficient and is required to be a small positive value. This approach allows us to generate a sequence of potential solutions that move the corresponding image sequence along the vector d_k. This method's pseudocode is shown in Algorithm 1.

Algorithm 1 Move in Objective Space.

1	Requirement: initial point $\mathbf{x}_0$ direction $\mathbf{d_k}$ within the objective space
2	Guarantee: a sequence (x_i) of potential solutions
3	for $i = 1, 2, ...,$ do
4	choose $i \in R^+$
5	set $Z_i = Z_{(i-1)} + \tau d_k$
6	solve (6) starting with x_0 to obtain x_i
7	Terminate

The Fig. 2 depicts a sample situation of a bi-objective problem to help with visualization. In this scenario, the reference point Z_1 is considered infeasible for the beginning position x_0. As a result, the solution x_1 obtained from Eq. 6 indicates the closest feasible solution to the stated reference point.

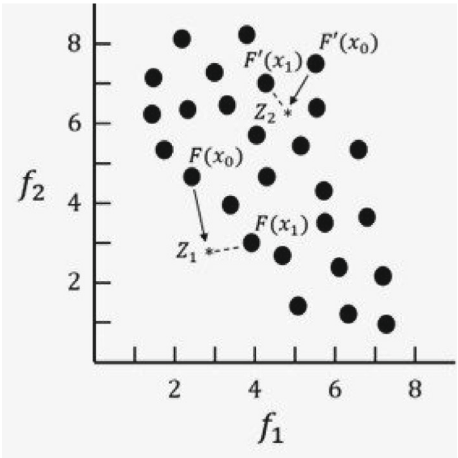


Fig. 2 Example of spatial mobility on a bi-objective situation

3 Illustrative Case

We suggest a case study focused on the design of a particular plastic fan. In this sense, the Fig. 3 displays the selected plastic fan, which measures 60 × 60 × 47.8 mm.

Figure 4 presents a schematic of the molding die, runner system, and cooling channels.

Using MOLDEX3D R15 2018 (moldex3d.com), a finite element (FE) model with 34,538 elements is created to simulate the injection molding process. The material under study is a polypropylene (PP) variety offered by A. Schulman under the trade name POLYFLAM RPP 374ND CS1. Also, the attributes of Materials Polypropylene are presented as following.

- Density: 1.35 g per cubic centimeter.
- Release temperature: 90 degrees Celsius.
- Thermal conductivity: 35,000 ergs per second per centimeter per degree Celsius.

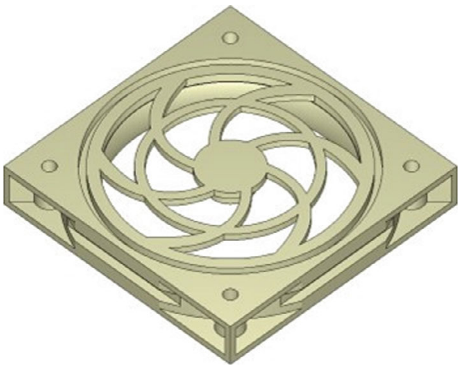


Fig. 3 Synthetic ventilation device

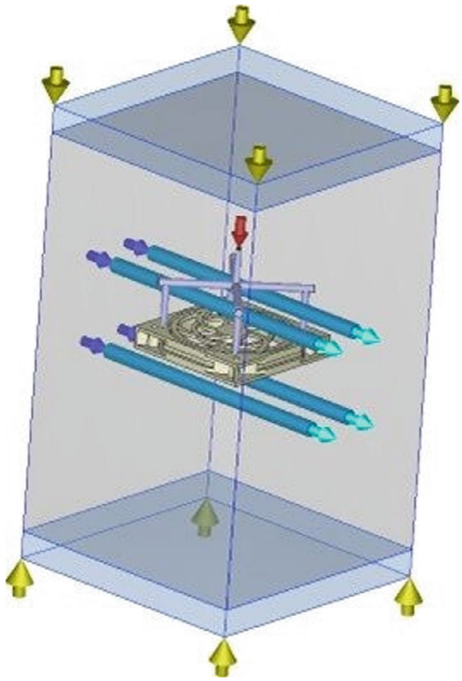


Fig. 4 Overview of the molding die, runner network, and cooling channels

- Elastic modulus: 3 × 10 to the power of 10 dynes per square centimeter.
- Poisson's ratio: 0.38.
- Heat capacity: 1.5 × 10 to the power of 7 ergs per gram per degree Celsius.
- Melting temperature range: 200 to 220 degrees Celsius.
- Mold temperature range: 40 to 80 degrees Celsius.

Then, here is a list of the process parameters, their units, and the ranges that were taken into consideration during the investigation.

- x1. Melt Temperature (°C), Range: 200–250
- x2: Mold Temperature (°C), Range: 40–80
- x3: Packing Time (sec), Range: 3.5–5.5
- x4: Compaction Pressure (MPa) Range: 50–90
- x5: Cooling Time (sec), Range: 10–15

Figure 5 shows a representation of the warpage scale within the modeling software. In this study, we gathered 360 samples for specified values of $x \in D$.

$$D := \left\{ x \in R^4 \begin{array}{ccccc} 200 & \leq & x1 & \leq & 250 \\ 40 & \leq & x2 & \leq & 80 \\ 3.5 & \leq & x3 & \leq & 5.5 \\ 50 & \leq & x4 & \leq & 90 \\ 10 & \leq & x5 & \leq & 15 \end{array} \right\} \tag{7}$$

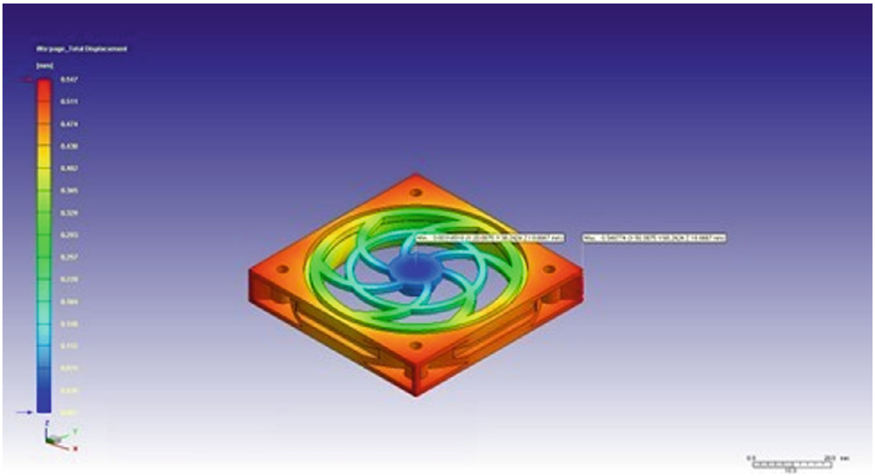


Fig. 5 Deformation in the synthetic fan

To evaluate $y \in R^4$ using full factorial, 3^5 and stochastic design of tests methods [27].

4 Results

This section outlines the results from applying the strategy described in subsection 2.3 to the case study addressed earlier. In this mode, with the collected information$T = (x_1, y_1, \ldots, x_{360}, y_{360})$ and the prior knowledge of the problem, the initial solution x_0 with the normalized objective vector $F(x_0) = Z_0 = [0.00, 1.00, 1.00, 0.39]$ was selected.

Also, the additional parameters evaluated in the numerical simulation; Occupancy time (0.81 s), Highest-pressure device (155 MPa), Quantity of injection, Magnitude of injection (16.16 cc), VP Change by Magnitude Filling (98.0%), Molding Empty Time (5.0 s), Melt Temp (90.8 °C), The temperature of the air (25.0 °C).

Figure 6 depicts the data about the metrics for the process.

In addition, Fig. 7 represents the information about packing rate.

Consequently, the features of each function are the following:

- The warpage deformation (in mm) represents the function $f1$ and should be minimized.
- The clamping force (in tons) represents the function $f2$ and should be minimized.
- The cycle time (in seconds) represents the function $f3$ and should be minimized.
- The Von Mises stress (in MPa) is represented as $f4$ and should be minimized.

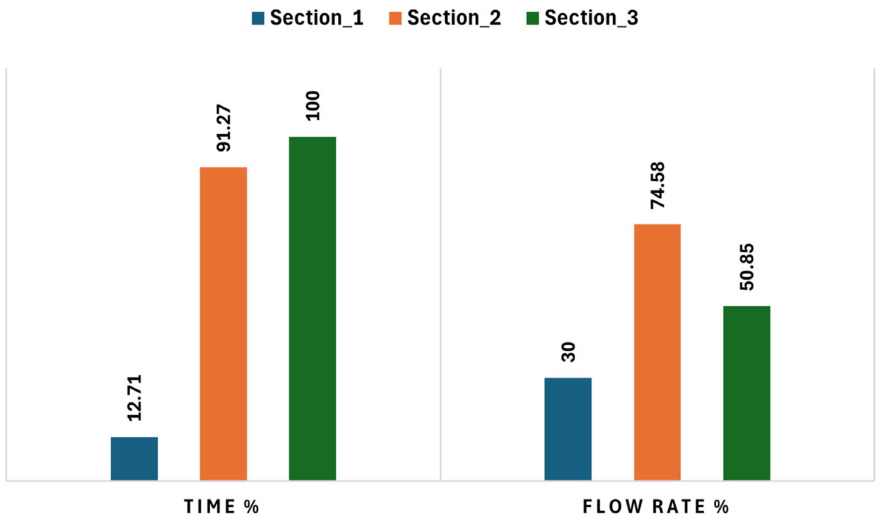


Fig. 6 Metrics for the process

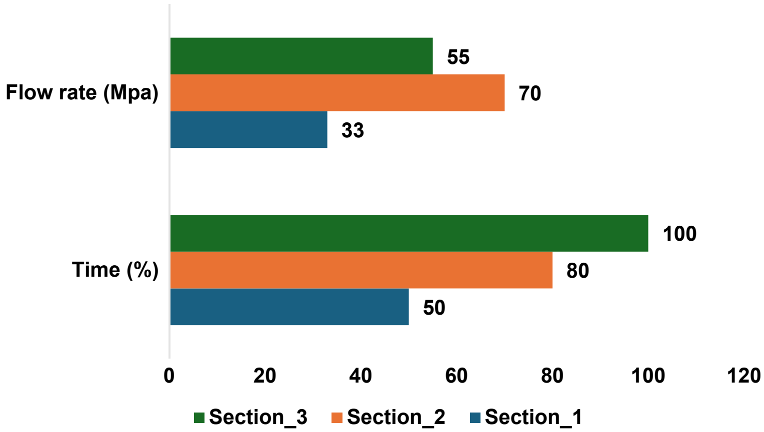


Fig. 7 Details on the packing rate

4.1 Results First Scenario

Establish $f\,2$ and $f\,3$ by making a sacrifice in relation to $f\,1$'s value, which results in the direction d = [2, -1, -1, 0] and $\tau = 0.02$.

$$Z_i := Z_{i-1} + 0.02\begin{pmatrix} -2 \\ -1 \\ -1 \\ 0 \end{pmatrix}, \ldots, 20 \tag{9}$$

The normalized results obtained by utilizing the radar chart are displayed in Fig. 8 to illustrate the objective requirements.

The Fig. 9 depicts a visual representation of the same findings, with the x-axis showing the iteration number and the y-axis displaying the normalized values of the objectives.

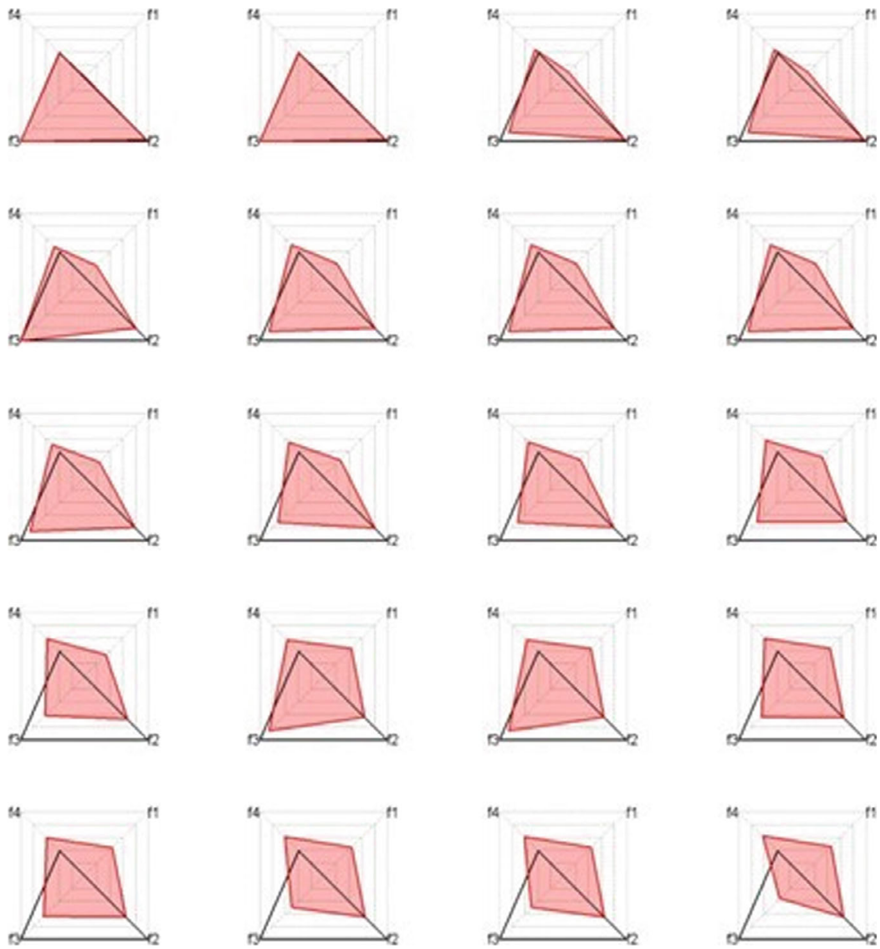


Fig. 8 The findings corresponding to the first scenario

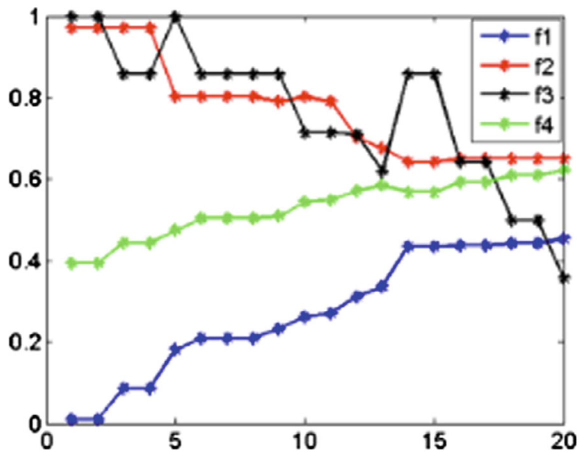


Fig. 9 The outcomes of the initial scenario are depicted using a line graph

Additionally, the comparison carried out using an integrated method with the preference selection index (PSI) and multi-objective optimization based on ratio analysis called PSI-MOORA, as reported by [27]. In this sense, Fig. 10 demonstrates the results for $f3$ with the best ranking to be chosen.

The normalized objective function values of four chosen solutions, consistent with the direction determined by the decision-maker, are shown in Table 1.

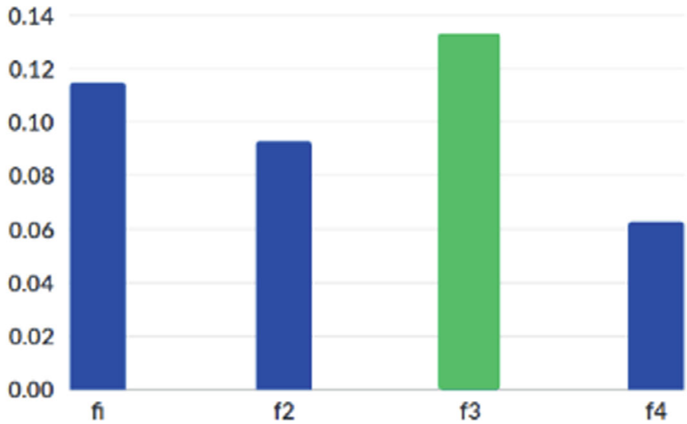


Fig. 10 The PSI-MOORA method is used to analyze the data for the second scenario

Table 1 Normalized objective values identified for the first scenario

Point	f1	f2	f3	f4
F(0)	0	1	1	0.39
F(×5)	0.18	0.8	1	0.47
F(×10)	0.26	0.79	0.71	0.54
F(×20)	0.45	0.65	0.35	0.62

4.2 Results of the Second Scenario

In the subsequent scenario under consideration, we start with the normalized objective $F(x_0) = Z_0 = [0.88, 0.04, 0.00, 1.00]$, and we select the direction vector $f_d = [-2, 1, 1, 0]$ along with a step length of $\tau = 0.01$. The designated direction entails a diminution of the first objective function, concomitant with the acceptance of sacrifices in the second and third objective functions.

$$\mathrm{Z_i} := \mathrm{Z_{i-1}} + 0.01\begin{pmatrix} -2 \\ 1 \\ 1 \\ 0 \end{pmatrix}, \ldots, 20 \tag{9}$$

The chosen normalized objective values for the second scenario under consideration, corresponding to the solutions obtained at iterations 0, 5, 10, and 20, are presented in Table 2.

The findings are visually represented in Fig. 11.

Furthermore, a line graph depicting the outcomes of the second scenario is shown in Fig. 12.

According to the PSI-MOORA method, the best ranking presented in Fig. 13 belongs to the function $f1$.

The combination of MaOP and the PSI-MOORA method allows for more informed and accurate decision making in the context of the PIM problem. Using MaOP ensures that multiple objectives are considered simultaneously, which is crucial in situations where a single criterion cannot be optimized without negatively affecting others. The PSI-MOORA method, for its part, provides a clear and objective structure to evaluate and compare different alternatives, facilitating the selection

Table 2 Specified normalized objective values picked for the second scenario

Point	f1	f2	f3	f4
F(×0)	0.88	0.04	0	1
F(×5)	0.29	0.78	0	0.58
F(×10)	0.08	0.64	0.28	0.62
F(×20)	0.03	0.96	0.28	0.45

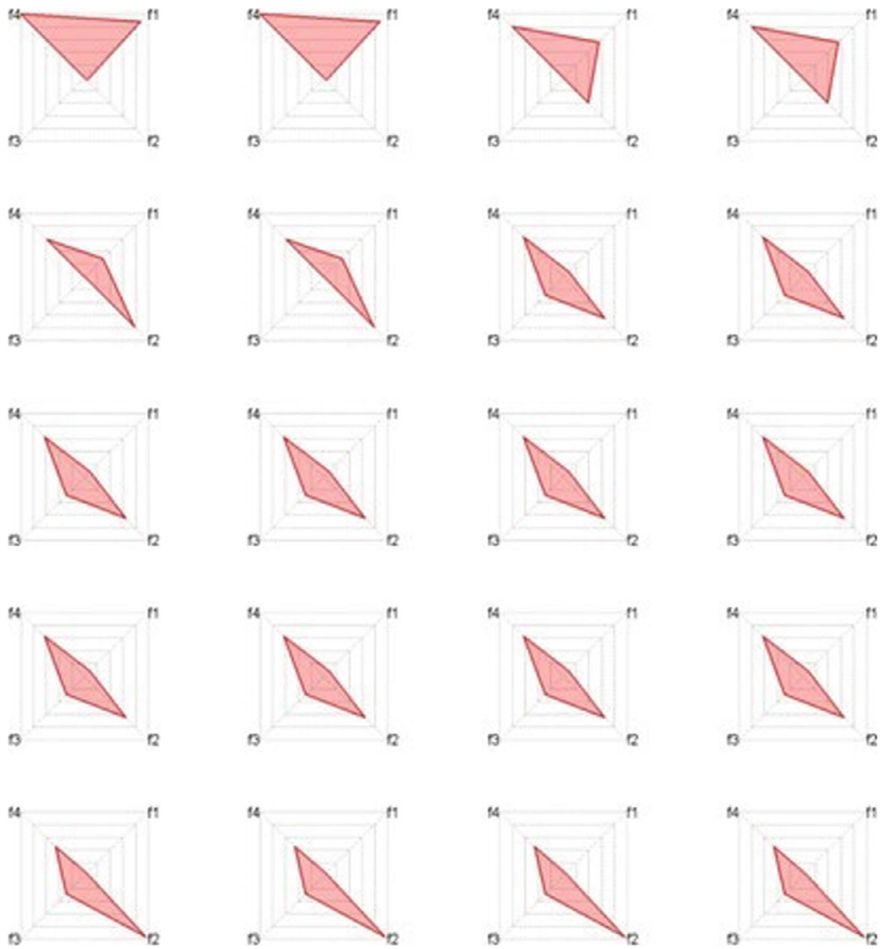
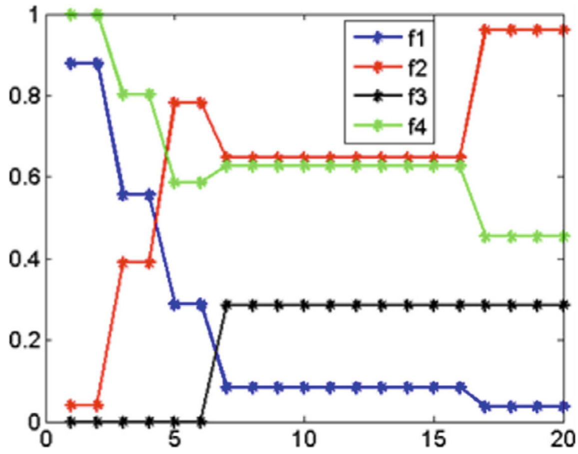


Fig. 11 Results for second scenario

of the best available option. Finally, the findings indicate that MaOP is a potential method for the PIM problem. Consequently, the PSI-MOORA method confirms the best function in order to make a decision.

Fig. 12 The data for the second scenario is visualized using a line graph



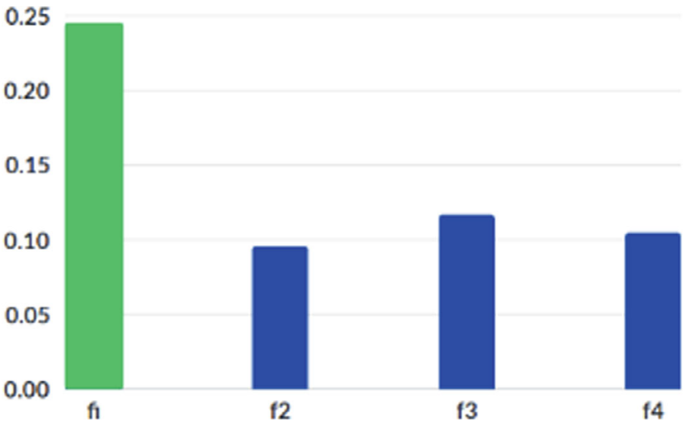


Fig. 13 Visualization of the data for the second scenario using the PSI-MOORA method

5 Conclusion

This document concentrates on the multi-objective optimization involved in the plastic injection molding process. A decision-making approach is proposed to address a model comprising four objectives, each of which can significantly influence the effectiveness of the plastic injection molding (PIM) process.

A decision-making methodology has been proposed for a model with four objectives, each of which has the ability to significantly affect how well the PIM process performs.

The distinctive characteristic of a multi-agent optimization problem (MaOP) is that their solution sets typically form (k-1)-dimensional objects, making it impractical to compute appropriate approximations of such sets.

The case study demonstrated that the applied strategy iteratively selects candidate solutions from the data set based on the user's preferences. Two distinct scenarios were examined, and in each case, a shift from the initial solution towards the targeted search direction was noted. Thus, the proposed method can be utilized as a tool for multi-objective optimization in the plastic injection molding process.

The findings suggest that MaOP is an effective method for solving complex problem identification and management problems. LIkewise, integrating it with the PSI-MOORA method, a robust decision-making tool is obtained, confirming the best function and ensuring that decisions are based on a comprehensive and balanced analysis of all relevant criteria.

Upcoming research efforts should concentrate on developing approaches that can accommodate a larger number of design variables. Additionally, this approach has the potential to be extended to handle movements within the decision variable space.

References

1. Cui, Y., Geng, Z., Zhu, Q., Han, Y.: Multi-objective optimization methods and application in energy saving. Energy **125**, 681–704 (2017). https://doi.org/10.1016/j.energy.2017.02.174
2. Zhou, H., Zhang, S., Wang, Z.: Multi-objective optimization of process parameters in plastic injection molding using a differential sensitivity fusion method. Int. J. Adv. Manuf. Technol. **114**, 423–449 (2021). https://doi.org/10.1007/s00170-021-06762-8
3. Zou, X., Chen, Y., Liu, M., Kang, L.: A new evolutionary algorithm for solving many-objective optimization problems," IEEE Transactions on Systems, Man, and Cybernetics. Part B (Cybernetics) **38**, 1402–1412 (2008). https://doi.org/10.1109/TSMCB.2008.926329
4. He, C., Zhang, Y., Gong, D., Ji, X.: A review of surrogate-assisted evolutionary algorithms for expensive optimization problems. Expert Syst. Appl. **217**, 119495 (2023). https://doi.org/10.1016/j.eswa.2022.119495
5. Zhang, Y., Tian, Y., Zhang, X.: Improved SparseEA for sparse large-scale multi-objective optimization problems. Complex & Intell. Syst. **9**, 1127–1142 (2023). https://doi.org/10.1007/s40747-021-00553-0
6. Tanabe, R., Ishibuchi, H.: An easy-to-use real-world multi-objective optimization problem suite. Appl. Soft Comput. **89**, 106078 (2020). https://doi.org/10.1016/j.asoc.2020.106078
7. Gunantara, N.: A review of multi-objective optimization: Methods and its applications. Cogent Engineering **5**, 1502242 (2018). https://doi.org/10.1080/23311916.2018.1502242
8. Dosantos, P., Bouchet, A., Mariñas-Collado, I. Montes, S.: OPSBC: A method to sort Pareto-optimal sets of solutions in multi-objective problems. Expert. Syst. Appl., 123803 (2024). https://doi.org/10.1016/j.eswa.2022.119495
9. Li, W., Wang, R., Zhang, T., Ming, M., Li, K.: Reinvestigation of evolutionary many-objective optimization: Focus on the Pareto knee front. Inf. Sci. **522**, 193–213 (2020). https://doi.org/10.1016/j.ins.2020.03.007
10. Schütze, O., Cuate, O., Martín, A., Peitz, S., Dellnitz, M.: Pareto explorer: a global/local exploration tool for many-objective optimization problems. Eng. Optim. (2019). https://doi.org/10.1080/0305215X.2019.1617286
11. Bai, H., Zheng, J., Yu, G., Yang, S., Zou, J.: A Pareto-based many-objective evolutionary algorithm using space partitioning selection and angle-based truncation. Inf. Sci. **478**, 186–207 (2019). https://doi.org/10.1016/j.ins.2018.10.027
12. Wang, S., Wang, H., Wei, Z., Wang, F., Zhu, Q., Zhao, J., Cui, Z.: A Pareto dominance relation based on reference vectors for evolutionary many-objective optimization. Appl. Soft Comput. 111505 (2024). https://doi.org/10.1016/j.asoc.2024.111505

13. Yang, L., Zhang, Y., Cao, J., Li, K., Wang, D.: A many-objective evolutionary algorithm based on reference vector guided selection and two diversity and convergence enhancement strategies. Appl. Soft Comput. 111369 (2024). https://doi.org/10.1016/j.asoc.2024.111369
14. Desai, D., Prajapati, B.: Competitive advantage through Six Sigma at plastic injection molded parts manufacturing unit: A case study. Int. J. Lean Six Sigma **8**, 411–435 (2017). https://doi.org/10.1108/IJLSS-06-2016-0022
15. Chen, W., Tai, P., Wang, M., Deng, W., Chen, C.: A neural network-based approach for dynamic quality prediction in a plastic injection molding process. Expert Syst. Appl. **35**, 843–849 (2008). https://doi.org/10.1016/j.eswa.2007.07.037
16. Gim, J., Lin, C., Turng, L.: In-mold condition-centered and explainable artificial intelligence-based (IMC-XAI) process optimization for injection molding. J. Manuf. Syst. **72**, 196–213 (2024). https://doi.org/10.1016/j.jmsy.2023.11.013
17. Parente, B., Miranda, D., Freiras, E., Silva, G., Martins, L., Rocha, A.: Production of an injection mold: analysis and improvements identification in the manufacturing process. Procedia Comput. Sci. **219**, 115–120 (2023). https://doi.org/10.1016/j.procs.2023.01.271
18. Matin, I., Hadzistevic, M., Hodolic, J., Vukelic, D., Lukic, D.: A CAD/CAE-integrated injection mold design system for plastic products. Int. J. Adv. Manuf. Technol. **63**, 595–607 (2012). https://doi.org/10.1007/s00170-012-3926-5
19. Cui, S., Huang, Z., Zhang, Y.: System design and implementation of an integrated CAE system for injection molding. Polym.-Plast. Technol. Eng. **47**, 458–465 (2008). https://doi.org/10.1080/03602550801946799
20. Henz, B., Mohan, R., Shires, D.: A hybrid global–local approach for optimization of injection gate locations in liquid composite molding process simulations. Compos. A Appl. Sci. Manuf. **38**, 1932–1946 (2007). https://doi.org/10.1016/j.compositesa.2007.03.005
21. Dang, X.: General frameworks for optimization of plastic injection molding process parameters. Simul. Model. Pract. Theory **41**, 15–27 (2014). https://doi.org/10.1016/j.simpat.2013.11.003
22. Zhao, N., Lian, J., Wang, P., Xu, Z.: Recent progress in minimizing the warpage and shrinkage deformations by the optimization of process parameters in plastic injection molding: A review. Int. J. Adv. Manuf. Technol. **120**, 85–101 (2022). https://doi.org/10.1007/s00170-022-08859-0
23. Masato, D., Piccolo, L., Lucchetta, G., Sorgato, M.: Texturing technologies for plastics injection molding: a review. Micromachines **13**, 1211 (2022). https://doi.org/10.1007/s00170-022-08859-0
24. Finkeldey, F., Volke, J., Zarges, J., Heim, H., Wiederkehr, P.: Learning quality characteristics for plastic injection molding processes using a combination of simulated and measured data. J. Manuf. Process. **60**, 134–143 (2020). https://doi.org/10.1016/j.jmapro.2020.10.028
25. Lee, L., Young, W., Lin, R.: Mold filling and cure modeling of RTM and SRIM processes. Compos. Struct. **27**, 109–120 (1994). https://doi.org/10.1016/0263-8223(94)90072-8
26. Steuer, R., Choo, E.: An interactive weighted Tchebycheff procedure for multiple objective programming. Math. Program. **26**, 326–344 (1983). https://doi.org/10.1007/BF02591870
27. Kumari, A., Acherjee, B., Kumar, K.: Gear Material Selection Using an Integrated PSI-MOORA Method. In: Handbook of Formal Optimization, A.J. Kulkarni and A.H. Gandomi (Eds.) Singapore: Springer, pp. 1–12 (2023). https://doi.org/10.1007/978-981-19-8851-6_23-1