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ORIGINAL ARTICLE

Automated multi-objective optimization for thin-walled plastic products using Taguchi, ANOVA, and hybrid ANN-MOGA

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Abstract

In this paper, an automated two-staged multi-objective optimization tool for plastic injection molding (PIM) is designed, implemented, and applied to industrial product. In the first stage, Taguchi method is utilized for design of experiments (DOE). Process parameters include mold temperature, melt temperature, flow rate, cooling time, and four parameters related to variable pressure profile. Quality characteristics of plastic product containing warpage, weld line, and clamp force are obtained by simulation experiments. ANOVA and S/N ratio are utilized for data analysis to identify the importance of factors, provide an initial optimal combination of process parameters, and obtain quantitative factor's contribution percentage. The number of process parameters is compressed from 8 to 5 considering factors' contribution percentage for reduction in time and computation cost. In the second stage, hybrid artificial neural network (ANN) and multi-objective genetic algorithm (MOGA) are utilized as further study to search for optimal solutions for synchronous reduction in three quality characteristics within compressed design space. Orthogonal array with Latin hypercube sampling (OA-LHS) is adopted for sampling with uniformity and stratification. ANN is utilized as a surrogate model to fit the surface between parameters and quality characteristics. MOGA is adopted to search the optimal solutions along the Pareto frontier. With the help of python, visual basic scripts, application programming interface (API) of Moldflow and DAKOTA, the two-stage optimization process is automated, which allows designers to study optimization for PIM, accurately and efficiently, without deep understanding of complicated optimization algorithms. The automated two-stage system is applied to an industrial plastic products and the result verifies that it is accurate and efficient in quality improvement.

Keywords Multi-objective optimization · PIM · Taguchi method · Hybrid ANN-MOGA · Automation

1 Introduction

Plastic injection molding (PIM) is becoming more and more important in plastic industry to generate thin-walled products because it owns outstanding advantages such as high surface quality, light weight, short product cycles, and good mechanical properties. The quality, quantity, and profitability of PIM are influenced by many factors including product design, molding design, material properties, and process parameters. Process parameters commonly considered include melt temperature, mold temperature, inject time, filling pressure, and packing pressure, and screw speed. Quality characteristics in PIM, including warpage, shrinkage, short shot, weld line, and sink marks, are strongly influenced by process parameters. In this study, the defects are reduced by optimization of parameters.

For thin-walled components, warpage is the most noteworthy defect which leads to unpredictable component shapes and poor assembly quality. Asymmetrical distribution in component thickness and improper cooling system would intensify warpage. Nian [1] studied local mold temperature setting for a cooling system to predict and reduce severe warpage. Lopez [2] analyzed and concluded that relationships between the process parameters and product weigh and pressure curves heavily relied on the geometry of the product and consequently, direct utilization of experimental result to new product may lead to wrong conclusions. Mohan [3] listed factors containing manufacturing process parameters, product design, and material that would influence shrinkage and warpage. Process parameters include barrel temperature, mold temperature, melt

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temperature, injection pressure, injection time, injection speed, hold time, back pressure, and cooling time. Moayyedian [4] evaluated short shot possibility considering process and geometric parameters. Process parameters included filling time, part cooling time, pressure holding time, and melt temperature. Gate type was selected as geometric parameters.

Design of experiment can increase the degree of accuracy and decrease the numbers of experiments compared with trial-and-error method. Taguchi techniques date back to 1987 by Taguchi and Konishi [5] and have been widely utilized in industry application to optimize the characters' performance within the combination of parameters. What's more, Taguchi together with analysis of variance (ANOVA) is an efficient and certified experimental approach in statistical analysis of PIM to reach a reduction in time and cost. Oliaei [6] studied the effect of material and all interaction effects of controlling parameters in PIM of plastic spoon parts. Mehat [7] represented ample reviews on Taguchi method which was comprised by orthogonal arrays (OA), signal to noise (S/N), and ANOVA. The Taguchi method is simple, robust, and has a relatively low-computational cost utilized to select parameter combination in limited parameter set.

More advanced algorithms together with the Taguchi method have been developed in searching for better process parameters in PIM. Optimization methods in PIM can be divided into two categories according to implicit or explicit functions are formulated, and approaches adopted to solve optimization problems include direct optimization and surrogate-based optimization methods. Hakimian [8] researched the effect of molding parameters such as packing time, cooling time, molding and melting temperature, packing and injection pressures, and their interactions on warpage and shrinkage of injection-molded micro gears assisted by the Taguchi method. An optimal injection molding condition for minimum shrinkage was conducted utilizing the Taguchi method, L_{27} experimental design, and ANOVA. Artificial neural network (ANN) was utilized as an efficient predictive tool for shrinkage in ref. [9]. Shi [10] utilized ANN together with the DOE method to build approximate relationship between warpage and process parameters. Back-propagation ANN (BPANN) was utilized in ref. [11] for cost estimation of plastic injection molding. ANN was utilized for pattern recognition and process optimization based on the Taguchi method in ref. [6]. An online system with ANN was designed by Everett [12] to accurately predict dynamic behavior of mold cavity surface temperature for mold cooling in PIM. Tripathy [13] adopted the Taguchi method combined with technique for order preference by similarity to ideal solution (TOPSIS) and grey relational analysis (GRA) to evaluate the effectiveness of optimization performance. Gong [14] applied the Taguchi-based six sigma approach in the study of elimination in defects to improve the process capability index Cp and Cpk in PIM process.

Surrogate methodology has been developed to replace time-consuming experiments or simulation to fit the surface of parameters and responses. A hybrid approach combining response surface methodology (RSM) with principle component analysis (PCA) and DOE was proposed by de Paivato [15] who study the robustness of parameters on multi-response dataset. ANOVA and F-test were utilized to determine the significance of parameters as a 95% confidence level. Xu [16] proposed hybrid method, which was called soft computing, combining of Taguchi's parameter design method, back-propagation neural network (BPNN), grey correlation analysis (GCA), particle swarm optimization (PSO), and multi-objective particle swarm optimization (MOPSO), to help solve complex task of optimization of process parameters. Oliaei [6] compared two different methods, Taguchi coupled with ANOVA and ANN analysis, and concluded that they were in good agreement with each other although with slight differences. Chen [17] proposed a two-stage optimization systems to find optimal process parameters utilizing Taguchi method combining with BPNN, genetic algorithm (GA), and a combination of particle swarm optimization genetic algorithm (PSO-GA). The two-stage method was proved to be more robust with a higher process capability index (Cpk). Tian [18] proposed a two-stage systematic optimization methodologies to implement process parameters optimization. In the first stage, Taguchi method was utilized to identify the significance of parameters and narrow the design space. In the second stage, Taguchi method together with NSGS-II was adopted for searching the optimal process parameter combination. Zhao [19] utilized IEGO algorithm to fit the non-linear relationship between process parameters and optimization objects and NSGA-II to search the optimal design solutions. In this paper, an automated two-stage system is proposed, where in the first stage, the Taguchi method is utilized for sampling and ANOVA is utilized for sensitivity analysis and design space compression, and in the second stage, ANN is utilized to fit the non-linear relationship and MOGA is utilized to search the optimal process parameters. Specially, the quantitative indicator, the total contribution (TC%) of each process parameter to all optimization objects guarantees the automation and efficiency of the design space compression procedure.

From the retrospect of the development of parameters optimization, it tells an emerging trend that synchronous reduction in multi-quality characteristics in PIM process is raising more and more attention and multi-objective optimization should be extensively utilized to make PIM a more efficient and energy-saving manufacture process. A multi-objective optimization, considering simultaneous decrease in volume shrinkage and clamping force, short shot as a constraint, was implemented by Kitayama [20, 21], utilizing sequential approximate optimization (SAO) together with radial basis function network to search the optimal parameters set. A multi-objective optimization of process parameters considering the valve gate open timing, the molding temperature, the melt temperature, the injection time, the packing pressure, the packing time, and the cooling time, taking warpage and clamping force as objectives was carried out by Zhang [22] utilizing optimal Latin hypercube design (OLHD), ellipsoidal basis function neural network (EBFNN), and multi-objective particle swarm optimization(MOPSO).

The real industrial application calls for robustness and reliability in optimization process. Kim [23] developed a robust optimal design methodology considering process variations as well as uncontrollable noise variables for reduction in weld line. Karasu [24] developed a fuzzy inference system to capture the high level of domain expertise for machine operators in changeover parameter setting in PIM considering uncontrollable or noise factors. The Lean Six Sigma- DMAIC (define, measure, analyze, improve, and control) has been widely utilized to make parameter optimization a robust application for improvement in quality and robustness of the injection molding process. Timans [25] and Desai [26] introduced a standardized approach by application of Six Sigma in small or medium manufacture unit to solve chronic problem in quality management and manufacture circle.

Optimization in PIM is computation-intensive and experiment-dependent task needing monotonous repetitive works. Simplification, standardization, and automation of optimization procedure can reduce the computation time and free the designers from the cumbersome procedures. Park [27] proposed an automated CAD/CAE integration tool together with metamodeling techniques including response surface methodology, and radial basis function for structural optimization process. Olofsson [28] applied design automation and injection molding simulation to structural optimization for injection molded parts.

Here lists the problems to be solved in this paper:

1. Injection process parameters have significant influence on plastic product characteristics. Mold temperature, melt temperature, flow rate, cooling time, and variable packing profile are taken into consideration for reduction in plastic product characteristic containing warpage, weld line, and clamp force. Sensitivity and significance of each factor should be identified.
2. Warpage is one of the major defects in PIM which should be minimized to reduce geometry distortion. Weld line should be decreased to avoid strength weakness and clamp force should be minimized to save energy and expand the range of machine selection. Synchronous reduction in warpage, weld line, and clamp force are not fully discussed in the literature.
3. Taguchi method is a conventional method for design of experiment (DOE) with robustness. S/N ratio and ANOVA are implemented to (a) provide a combination of parameters for quality characteristics based on Taguchi experiments, (b) quantification of contribution percentage for each parameter and identify the most important parameters which helps compress the design space. However, Taguchi together with S/N ratio and ANOVA method can only select simple combination of process parameters within discrete values. Further study should be made to search better solutions to obtain synchronous reduction in three objectives.
4. Simulation experiments are expensive in time consuming and computation cost. Surrogate model should be constructed to accelerate optimization process, and multi-objective method should be developed to search for optimal solutions with surrogate model.
5. Optimization of process parameters in PIM is complicated and needing monotonous repetitive manual works. Automation tool of the optimization process should be designed to free designers from complicated mathematical knowledge and repetitive work to innovative design work.

The rest of this paper is constructed as follows: overview of the optimization model and the proposed methodology is described in Section 2. In Section 3, Taguchi method together with S/N ratio and ANOVA is implemented. In Section 4, hybrid ANN-MOGA algorithm is implemented and optimal solutions are searched by the proposed algorithm. Conclusions are listed in Section 5.

2 Overview of optimization model and optimization methodology

2.1 Optimization model

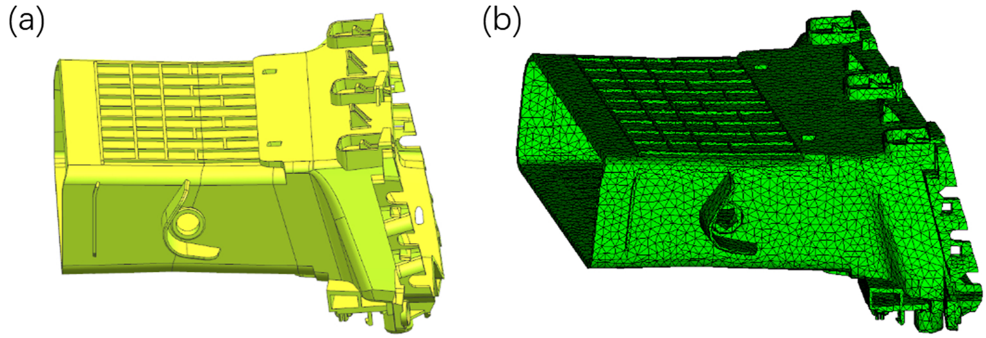
2.1.1 Simulation model

In this paper, a plastic product for automobile air conditional vent shown in Fig. 1 is considered. The 3D model and the mesh model of the vent are shown in Fig. 2a and b, respectively. The length of the vent is about 130 mm and the thickness is 2 mm.

The vent is made of ABS/PA (Acrylonitrile Butadiene Styrene/Polyamide). ABS/PA has advantages in processability, impact strength, stability, and appearance, which are utilized in many industrial fields such as automotive application including instrument panels and interior trim panels. The

Fig. 1 Plastic product

Fig. 2 **a** Nominal geometry and **b** mesh model



properties of ABS/PA are listed in Table 1. In this paper, warpage, weld line, and clamping force are the product characteristics. Severe warpage, approximately 1.5 mm, generated in manufacture process, shown in Fig. 4, leads to bad assembly condition which would result in fracture or shorter service life of the product. Decrease clamping force would broaden the choice of injection molding machine and save the energy. The initial simulated defects are listed in Fig. 3. The process parameters, including injection time, variable packing time and packing pressure, mold temperature, and melt temperature, are listed in Table 2. As shown in Figs. 1 and 4, the warpage generated by injection process is about 1.5 mm, and the simulation result is 1.496 mm with the same process parameters of ABS/PA, and weld line appears at the side wall of the vent, consistent with the simulation result shown in Fig. 5, which shows the efficiency of simulation model.

2.1.2 Injection molding process parameters

PIM process conditions have great influence on the quality of plastic product. This paper takes these parameters into consideration: mold temperature (A, Mold_T; unit, °C), melt temperature (B, Melt_T; unit, °C), flow rate (C, flow_rate; unit, cm^3/s), cooling time (D, Cool_t; unit, s), and variable packing profile–related parameters. Conventional constant packing pressure and packing time utilized during packing process are shown in Fig. 3a. Variable packing profile has been studied in Ref. [29–31] and proved to be effective to the quality of injection products. To get qualified products, variable packing profile instead of constant pressure is utilized. Consequently, packing profile–related parameters including packing time (E, t_{p1}; G, t_{p2}) and packing pressure (F, P_{p1}; H, P_{p2}; unit, MPa) are shown in Fig. 3b. The design variables are shown in Table 2.

Table 1 Property of ABS/PA

Material data	Value
Young's modulus (MPa)	1900
Shear modulus (MPa)	683.5
Poisson's ratio	0.39
Density (melt/solid) (g/cm^3)	0.9581/1.1073
Specific heat (liquid state) (J/Kg.K)	2257
Thermal conductivity (W/m.K)	0.17
Recommended melt temperature range (°C)	250-290
Recommended mold temperature (°C)	60-95

2.1.3 Optimization objectives

This work considers warpage and weld line as product quality characteristics. Clamp force, which works as an indicator for energy consumption, is taken into consideration as well. Warpage is defined as dimensional distortion between products and nominal geometry, which is caused by non-uniform change of internal stresses. The explanatory description for warpage is shown in Fig. 4. The desired warpage value is 0 mm as expected. Weld line generates when different flow fronts meet, which leads to weakness in the molded part. The injection location and the melt temperature are the main factors influencing the length of weld lines. In this work, total length of weld lines is considered. The description of weld line is shown in Fig. 5. Clamp force shown in Fig. 6 refers to the maximum force required during PIM process, which is an important indicator to select molding machine. Clamp force can be calculated by injection pressure and the projected area of the product [32], which is evaluated by numerical simulation commercial software Moldflow. The three quality characteristics are the smaller the better as expected. The values of warpage, weld line, and clamp force are up to 1.496 mm, 585 mm, and 251.5 tons, respectively.

2.2 Proposed two-step optimization process and automation

2.2.1 Two-stage optimization methodology

An automated two-stage multi-objective optimization method is proposed for PIM process, aiming to identify the most significant process parameters and obtain synchronous reduction in quality characteristics. Accordingly, this paper utilizes the integrated Taguchi method, ANOVA, and hybrid ANN-MOGA to provide the best combination of significant process

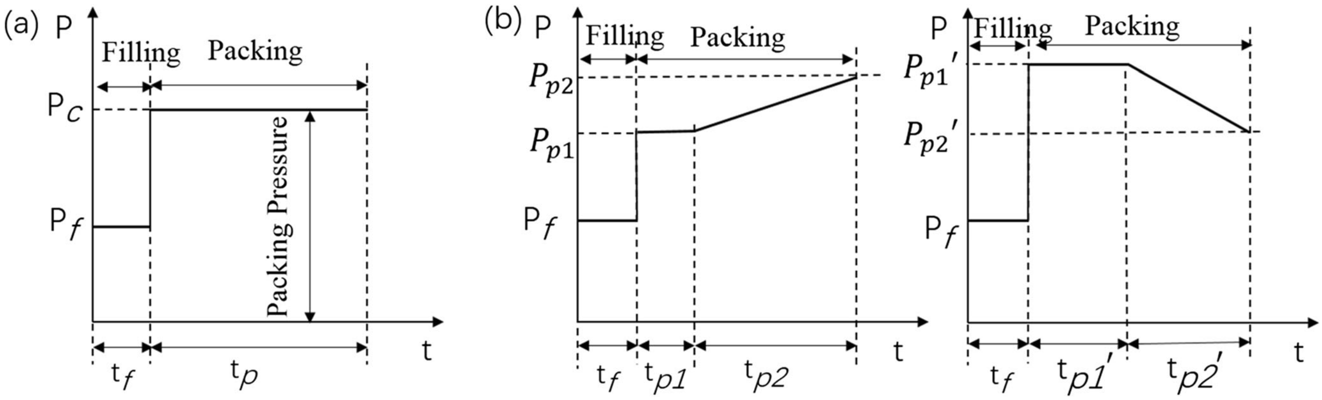


Fig. 3 Packing profile related parameters. **a** Constant packing time and packing pressure. **b** Proposed packing profile parameters at two different combination levels

parameters and search the global optimal solutions in design space. Firstly, the Taguchi method together with orthogonal array is utilized to arrange process parameters for simulation experiments. ANOVA and S/N ratio are implemented for data analysis to (1) identify the most significant process parameters, (2) provide best combination of parameters for each quality characteristic, (3) compress the process parameters design space to reduce time and computation cost for next stage. The initial design space contains 8 process parameters including mold temperature, melt temperature, cooling time, flow rate, and variable packing profile shown in Table 2 and the number is compressed into 5 by using contribution percentage calculated by Eq. (15). The first stage is introduced in detail in Section 3. Secondly, OA-LHS method is utilized to sample within compressed design space, ANN is utilized as surrogate model to fit highly non-linear relationship between response and process parameters, and MOGA is implemented to search the optimal point with ANN surrogate model to obtain synchronous reduction in quality indicators. The second stage is introduced in detail in Section 4. Fig. 7 depicts the two-staged optimization process.

2.2.2 Automation

Traditional optimization design for PIM is often implemented manually, which needs designers' deep understanding of PIM process, complicated optimization algorithm, and software skills. To free designers from monotonous repetitive manual tasks, an automated two-stage optimization tool is designed and implemented by using visual basic scripts, python, application programming interface (API) for Moldflow, Qt, and Dakota scripts. The design of experiments, data analysis, and optimization iterative process are implemented automatically without interaction with designers. The framework of the

Fig. 4 Illustrative example of warpage of the vent product (× 5)

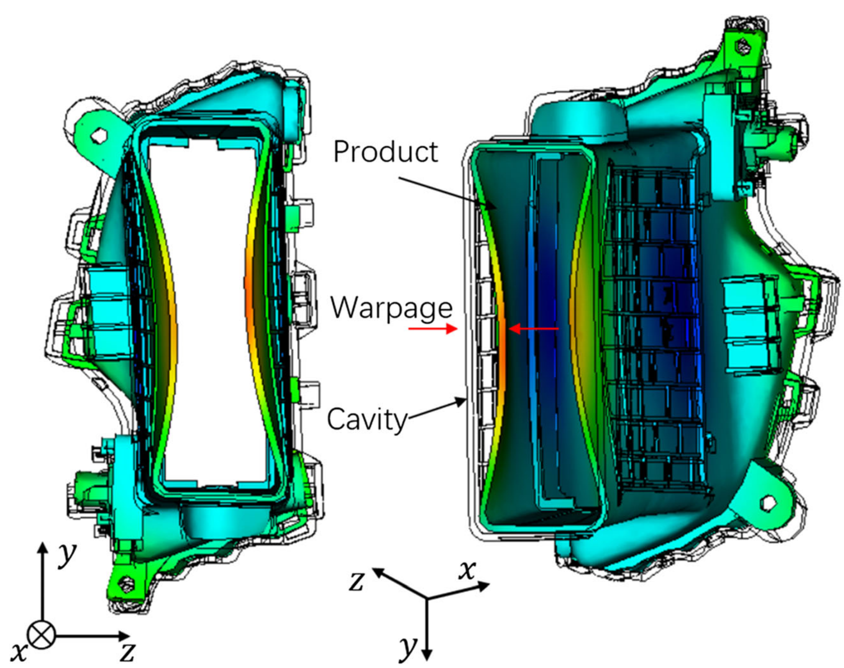


Table 2 Variable factors levels

Level	A, mold_T (°C)	B, melt_T (°C)	C, flow_rate (cm^3/s)	D, cool_t (s)	E, t_{p1} (s)	F, P_{p1} (MPa)	G, t_{p2} (s)	H, P_{p2} (MPa)
1	65	256	12	18	3	80	3	78
2	80	273	13.5	22	4	90	4	89
3	95	290	15	26	5	100	5	100

proposed automated tool is shown in Fig. 8. There are three parts shown in Fig. 8 i.e. the driver, the user interface, and the two-stage optimization process. The driver is responsible for configuration parser, data exchange, script generation, driving the two-stage optimization process, result extraction, and data analysis. The user interface is designed for users to interactively deploy configuration of optimization problem, including process parameter selection, the boundary of design parameters, sampling method, optimization objective selection, optimization algorithm selection, and compression rate. It is noteworthy that compression rate is important for design space compression which is introduced in Section 3.2. The driver reads the configuration and generates scripts to drive the two-stage optimization process automatically. The automated tool can accelerate optimization process for PIM with accuracy and efficiency.

3 First stage: Taguchi and ANOVA method

3.1 Taguchi orthogonal arrays for DOE

Taguchi method is an efficient DOE strategy to minimize the number of experiments. Orthogonal arrays are utilized to generate a small number of experiments with robustness and efficiency, which leads to reduction in time and cost. In this paper, $L_{27}(8^3)$ is utilized. Variable factors are shown in Table 2 and experiments set by the Taguchi method are shown in Table 3.

3.2 S/N ratio and ANOVA

S/N ratio and ANOVA data analyses are utilized to (1) identify the most significant parameter, (2) rank of importance of parameters using contribution percentage to reduce the design space, (3) provide a Taguchi optimal combination of parameters for the warpage, weld line, and clamp force.

3.2.1 S/N ratio

S/N ratio utilized in the Taguchi method is to measure the sensitivity of parameters considering uncontrollable factors. Since the targets of optimization objectives, warpage, weld line, and clamping force are to be minimized, the smaller-the-better is applied to calculate S/N ratio, by Eqs. (1) and (2) in dBi units:

$$\eta = -10\log_{10}(MSD) \tag{1}$$

$$MSD = \frac{1}{n}\left(\sum_{i=1}^{n} y_i^2\right) \tag{2}$$

where η represents the S/N ratio, MSD is the mean square deviation, y_i is the response in ith experiment, and n is the total number of experiments.

Fig. 9 shows the influence the process parameters have on quality characteristics. Fig. 9a, c, and e show the S/N ratio and Fig. 9b, d, and f show the mean value of each factor at each level for warpage, weld line, and clamping force, respectively. The larger the S/N ratio is, the better the process combination works. As depicted in Fig. 9, different factors have different influence on the three quality indications. Take Fig. 9a, b as a sample, melt temperature (B) and packing pressure (F) have a most important influence on warpage, and melt temperature (B) is the dominant factor. The best level for melt temperature for warpage is level 1, with a mean value of warpage equaling to 1.18 mm.

3.2.2 ANOVA

In order to distinguish the most important factors influencing the product quality quantificationally, ANOVA is implemented. Equations (3)–(7) are utilized to calculate the degree of freedoms, the sum of squares (SS) of each factor and total sum of squares (SS_T), and the contribution percentage of each factor. The calculation is represented for factor A as an example. Coupled with S/N ratio shown in Fig. 9, the results with ANOVA show the best combination of factors and levels. Table 4 lists the results of the eight factors of ANOVA for warpage, weld line, and clamping force.

Total degree of freedom, f:

$$f = N-1 \tag{3}$$

where N is the total number of experiments, here $N = 26$, and $f_T = 2 - 1 = 267$, and degree of freedom for single factor, take factor A for example, $f_A = k_A - 1 = 3 - 1 + 2$.

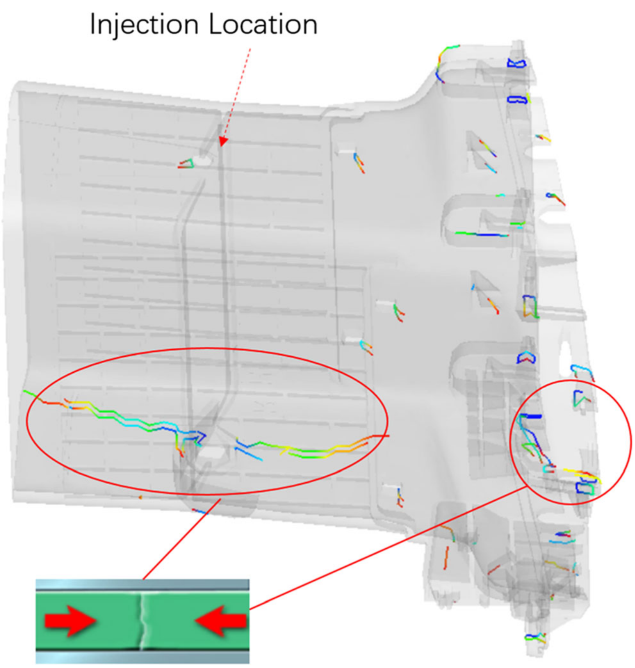


Fig. 5 Weld lines of the vent product

Sum of square, take factor A for example, SS_A:

$$SS_A = \frac{(\sum A_1)^2}{k_A} + \frac{(\sum A_2)^2}{k_A} + \frac{(\sum A_3)^2}{k_A} - \frac{(y_1 + y_2 + \cdots + y_N)^2}{N} \quad (4)$$

where $\sum A_i$ represents the sum of y_j when factor A is at the ith level.

Total sum of square, SS_T:

$$SS_T = \sum(SS_A + \cdots + SS_{error}) \quad (5)$$

Contribution for factor A: $C\%$

$$C\% = \frac{SS_A}{SS_T} \times 100\% \quad (6)$$

Total contribution of factor A: $TC\%$

$$TC\% = \frac{1}{3} * C\%_{warpage} + \frac{1}{3} * C\%_{wildline} \frac{1}{3} * C\%_{clampforce} \quad (7)$$

ANOVA results shown in

Table 4 identify significant factors and provide optimal combination of parameters. For warpage, melt temperature (B) with contribution of 45.29%, packing pressure (F) 23.47%, mold temperature (A) 11.94%, and cooling time (D) 5.19% play the most important role and among them, melt temperature is dominant. Variable packing profile influences warpage greatly with a sum contribution percentage of 28.12%. For weld line, flow rate (C) with contribution percentage of 34.53%, cooling time (D) 32.76%, and melt temperature (B) 28.18% are the most significant factors. Mold

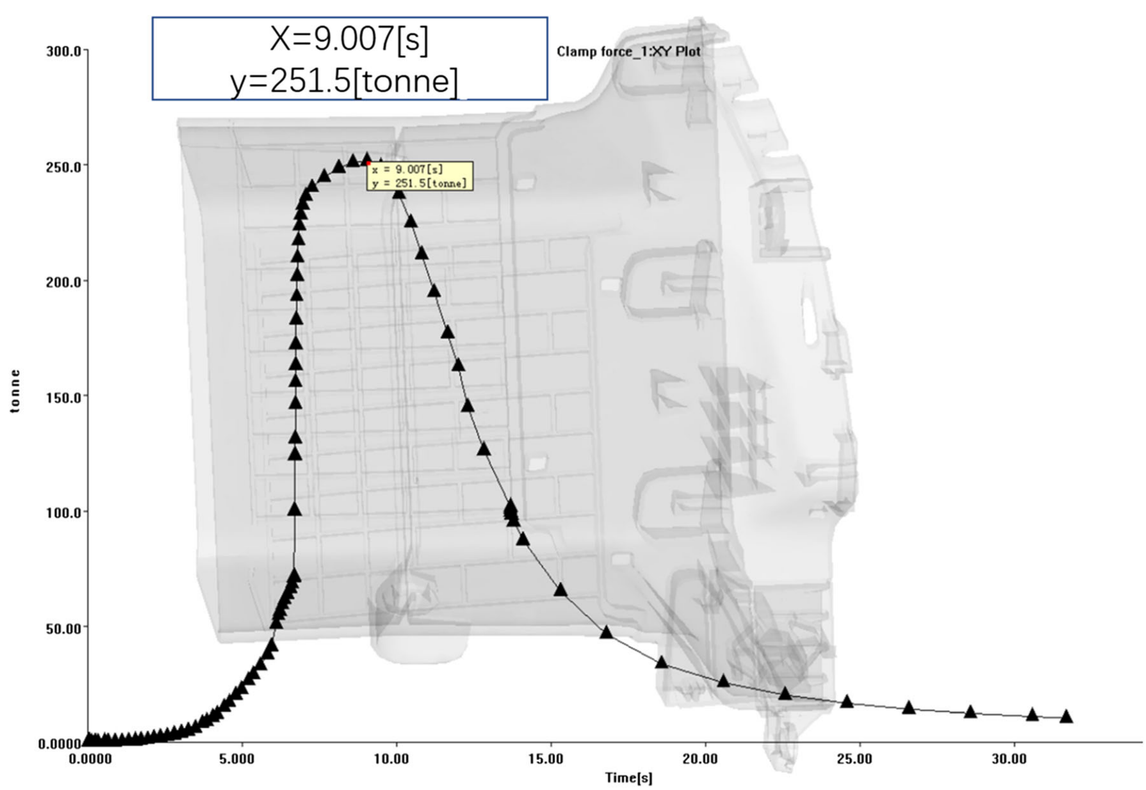


Fig. 6 Clamp force during PIM process

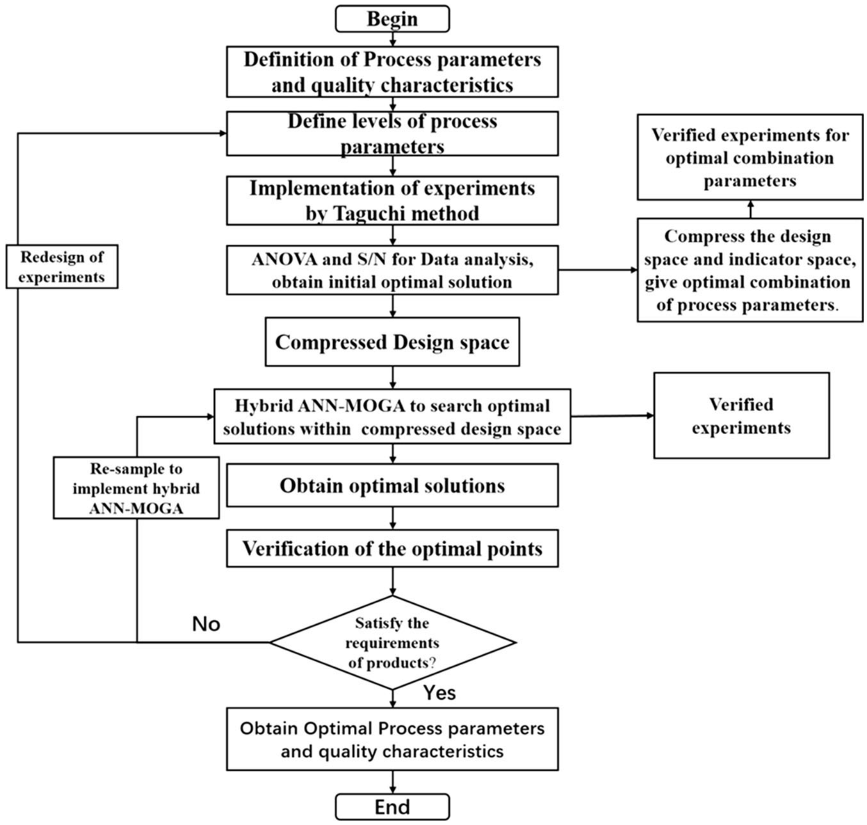


Fig. 7 Two-staged optimization process flowchart for PIM

temperature has a slight influence on it. For clamp force, melt temperature (B) is the most significant factor with contribution percentage equaling to 62.04%, and the other three are mold temperature (A) 12.22%, cooling time (D) 8.67%, and flow rate (C) 7.81%. The best level for each factor refers to the one that achieves the highest S/N ratio. The optimal parameter combinations provided by the Taguchi method are shown in Table 5. Total contribution (TC%) of each factor is calculated by Eq. (7). C% and TC% are pivotal parameters guaranteeing the automation of the procedure. In this work, compression rate is set to 90%, which means that design space is narrowed while the compressed design space can explain more than 90% of variation of responses. Considering accumulative C% and TC% value calculated in Eq. (8), mold temperature (A), melt temperature (B), flow rate(C), cooling time (D), and packing pressure (F) are chosen as control factors in the second stage of optimization. Packing time (E, H) and packing pressure (G) are set to constant value shown in Table 5.

$$\begin{aligned}
&ATC\% = 45.17\% + 15.71\% + 15.54\% + 9.99\% + 9.11\% = 95.52\% > 90\% \\
&AC\%_{warpage} = 45.29\% + 4.78\% + 5.19\% + 23.47\% + 11.94\% = 90.67\% > 90\% \\
&AC\%_{weldline} = 28.18\% + 34.53\% + 32.76\% + 0.34\% + 3.17\% = 98.98\% > 90\% \\
&AC\%_{clampforce} = 62.04\% + 7.81\% + 8.67\% + 6.16\% + 12.22\% = 96.9\% > 90\%
\end{aligned} \tag{8}$$

3.3 Result verification

Experiments have been done to verify the accuracy and efficiency of the Taguchi method and results are shown in Table 6. It can be concluded that Taguchi together with ANOVA method identifies the most significant process parameters and provides optimal combination of parameters for each quality characteristic. However, the Taguchi method has a limitation that it can only select a combination of process parameters with discrete values, which makes the initial optimal solution considering three objectives unsatisfactory. The second stage utilizing hybrid ANN-MOGA is necessary to be implemented to obtain synchronous reduction in warpage, weld line, and clamp force.

4 Second stage: multi-objective optimization using hybrid ANN-MOGA

In order to obtain synchronous reduction in warpage, weld line, and clamp force, hybrid ANN-MOGA is implemented to search optimal solutions within compressed design space provided by th Taguchi and ANOVA method. In the second

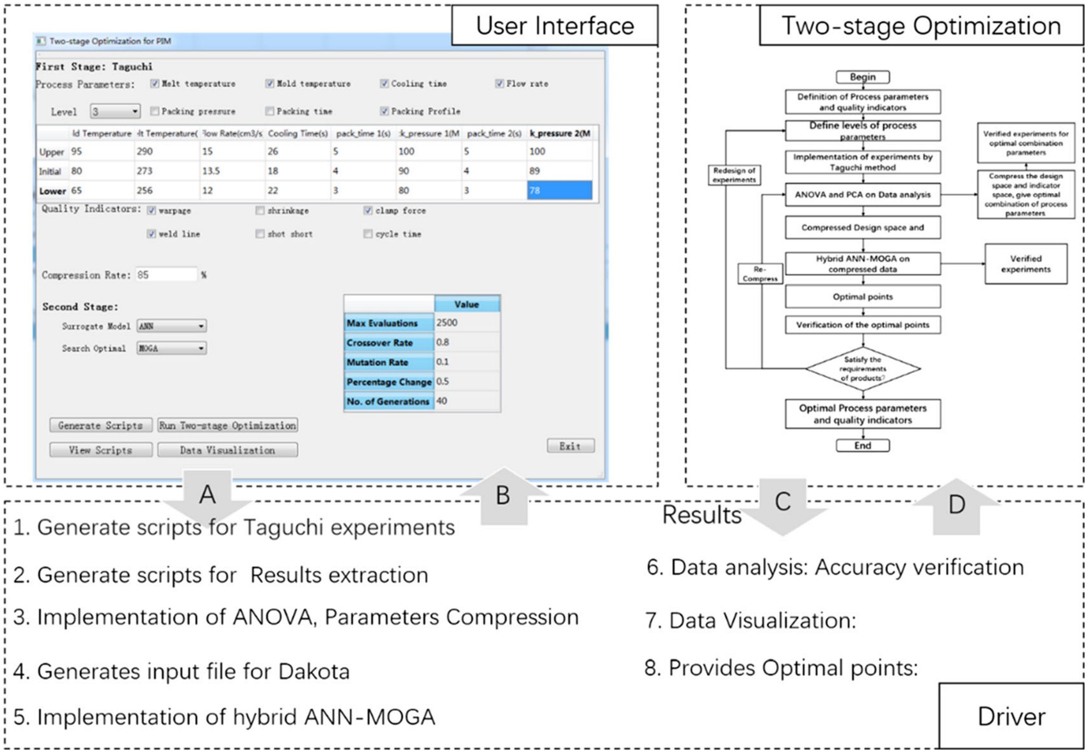


Fig. 8 The driver links user interface and proposed two-stage optimization process: A: Configuration parser, B: scripts and data visualization, **C**: response extraction, and D: driving the two-stage optimization process

stage, the variable parameters including mold temperature, melt temperature, flow rate, cooling time, cooling time, and packing pressure, and three objective functions, namely warpage, weld line, and clamp force, are taken into consideration. The optimization problem is listed as follows:

Table 3 Taguchi orthogonal array

Trial No.	Factors A	B	C	D	E	F	G	H	Trial No.	Factors A	B	C	D	E	F	G	H
1	1	1	1	1	1	1	1	1	15	2	2	3	1	3	1	2	1
2	1	1	1	1	2	2	2	2	16	2	3	1	2	1	2	3	3
3	1	1	1	1	3	3	3	3	17	2	3	1	2	2	3	1	1
4	1	2	2	2	1	1	1	2	18	2	3	1	2	3	1	2	2
5	1	2	2	2	2	2	2	3	19	3	1	3	2	1	3	2	1
6	1	2	2	2	3	3	3	1	20	3	1	3	2	2	1	3	2
7	1	3	3	3	1	1	1	3	21	3	1	3	2	3	2	1	3
8	1	3	3	3	2	2	2	1	22	3	2	1	3	1	3	2	2
9	1	3	3	3	3	3	3	2	23	3	2	1	3	2	1	3	3
10	2	1	2	3	1	2	3	1	24	3	2	1	3	3	2	1	1
11	2	1	2	3	2	3	1	2	25	3	3	2	1	1	3	2	3
12	2	1	2	3	3	1	2	3	26	3	3	2	1	2	1	3	1
13	2	2	3	1	1	2	3	2	27	3	3	2	1	3	2	1	2
14	2	2	3	1	2	3	1	3	-	-	-	-	-	-	-	-	-

$$
\begin{aligned}
&find : \mathbf{x} = \left[x_{mold\_T}, x_{melt\_T}, x_{flow\_rate}, x_{cooling\_time}, x_{pack\_pressure}\right] \\
&minimize : warpage(\mathbf{x}), weld_{line(\mathbf{x})}, clamp\_force(\mathbf{x}) \\
&s.j. : \quad 65°C < x_{mold\_T} < 95°C \\
&\qquad 256°C < x_{melt\_T} < 290°C \\
&\quad 12cm^3/s < x_{flow\_rate} < 15cm^3/s \\
&\qquad\quad 18s < x_{pack\_pressure} < 26s \\
&\quad 80MPA < x_{pack\_pressure} < 100MPa
\end{aligned}
$$

The other three parameters related to pressure profile are set to constant value as packing time (E) = 3.7 s, packing pressure time (F) = 4.3 s, and packing pressure (H) = 96.3 MPa.

4.1 Hybrid ANN-MOGA

4.1.1 OA-LHS for experiments

Orthogonal arrays combined with LHS are utilized to generate samples within design space. Compared with the LHS method, OA-LHS design owns the advantages of uniformity, orthogonality, and stratification of samples. Fig. 10 shows 25 sampling points, taking mold temperature and melt temperature as an example, obtained by OA-LHS and conventional LHS.

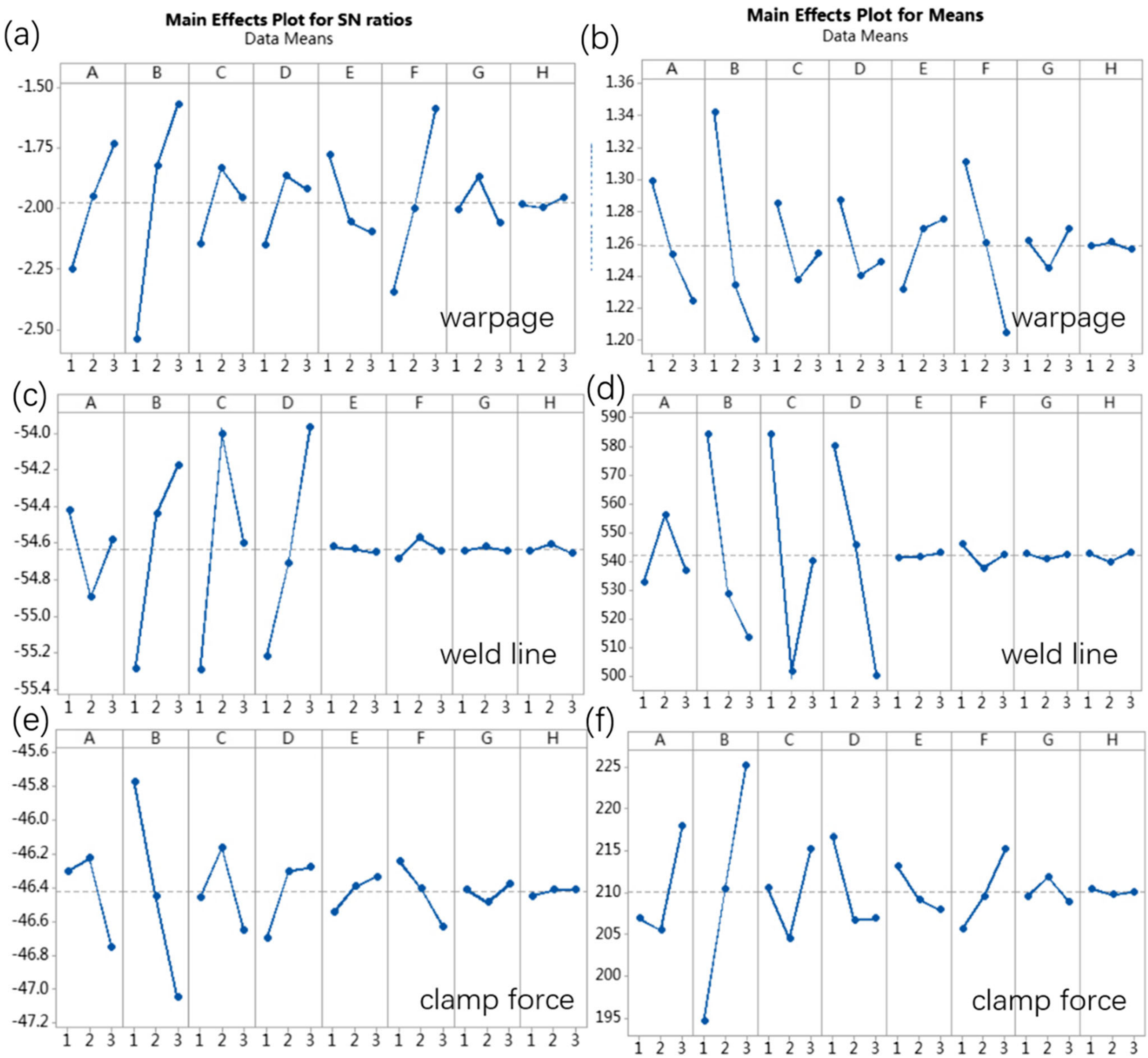


Fig. 9 S/N ratio of each factor at each level and their corresponding mean value: for warpage (**a**, **b**), for weld line (**c**, **d**), and for clamping force (**e**, **f**)

Table 4 ANOVA table for warpage, weld line, and clamping force

Factor		Warpage			Weld line			Clamp force			TC%
	f	SS	C%	Best	SS	C%	Best	SS	C%	Best	
A	2	0.025908	11.94	3	2804.112	3.17	1	827.8279	12.22	2	9.11
B	2	0.098287	45.29	3	24931.11	28.18	3	4201.394	62.04	1	45.17
C	2	0.010382	4.78	2	30547.22	34.53	2	528.7137	7.81	2	15.71
D	2	0.011264	5.19	2	28981.43	32.76	3	587.4967	8.67	3	15.54
E	2	0.010127	4.67	1	13.90766	0.02	1	134.7641	1.99	3	2.22
F	2	0.050937	23.47	3	302.2527	0.34	2	416.9726	6.16	1	9.99
G	2	0.002813	1.30	2	20.72786	0.02	2	43.55832	0.64	3	0.65
H	2	9.39E-05	0.04	3	60.75091	0.07	2	2.537474	0.04	3	0.05
Error	10	0.00719037	3.31	-	794.01754	0.90	-	29.336948	0.43	-	1.55
Total	26	0.21700141	1	-	88455.52	1	-	6743.26	1	-	1

Table 5 Optimal combination provided by the Taguchi method

	A (°C)	B (°C)	C (cm^3/s)	D (s)	E (s)	F (MPa)	G (s)	H (MPa)
Best for warpage	3	3	2	2	1	3	2	3
	95	290	13.5	22	3	100	4	100
Best for weld line	1	3	2	3	1	2	2	2
	65	290	13.5	26	3	90	4	89
Best for clamp force	2	1	2	3	3	1	3	3
	80	256	13.5	26	5	80	5	100
Optimal	80	278.7	13.5	24.7	3.7	90	4.3	96.3

4.1.2 Surrogate model—ANN

Artificial neural network (ANN) is a predictive, non-linear black-box modeling technique, which is commonly utilized in industrial application to replace high-computational-cost simulation or experiments by constructing a surrogate model with parameters and responses provided by experiments. ANN consists of a multilayered architecture including one input layer, one or more hidden layer(s), and one output layer. The processing units of layers are known as neurons, which are interconnected with variable weights ω_{ij} that need to be solved, shown in Eq. (9). ANN learns the relationship between input-output by summing a number of weighted inputs and passing the sum through a transfer function as Eq. (10).

$$net_j = \sum_{j=0}^{N} w_{ij}x_i + \mathbf{b}_j \tag{9}$$

$$\hat{\mathbf{y}} = f\left(net_j\right) \tag{10}$$

where $\hat{\mathbf{y}}$ is the predictive output data, $\mathbf{x} = [x_0, \ldots x_N]^T$ is the input vector, $\mathbf{b}$ is the bias weight, w_{ij} is the weight for processing from the ith neuron to the jth one, $f(\cdot)$ is the transfer function, and N is the number of inputs. Stochastic layered perceptron (SLP)-ANN [33] based on direct training approach is utilized which has a lower training cost than traditional BPANN. SLP-ANN model is in the form as Eq. (11):

$$\hat{f}(\mathbf{x}) = \tanh\Big(\tanh((\mathbf{x}A_0 + \theta_0)A_1 + \theta_1)\Big) \tag{11}$$

Table 6 Results of Optimal parameters combination provided by the Taguchi method

Experiments	Warpage (mm)	Weld line (mm)	Clamp force (t)
Best for warpage	1.063	529.8476	246.73
Best for weld line	1.278	497.0821	219.38
Best for clamp force	1.350	531.6959	185.43
Optimal of Taguchi	1.228	533.56	225.61

where $\mathbf{x}$ is points in design space and A_0, θ_0,A_1, and θ_1 are the matrices and vectors corresponding to the weights and bias of neurons. The non-linear characteristic allows ANN to be used to fit highly non-linear problem. The relationship between process parameters of PIM and quality indicators including warpage, weld lines, and clamp force is complicated and highly non-linear and consequently ANN is utilized to fit the relationship.

ANN architecture utilized in this work is shown in Fig. 11. The ANN consists of one input, stochastic hidden, and one output layers. The input neurons correspond to process parameters including mold temperature, melt temperature, flow rate, cooling time, and packing pressure. The output neurons correspond to warpage, weld line, and clamp force.

4.1.3 MOGA

Two or more objectives, often conflicting with each other, are to be optimized simultaneously in multi-objective optimization, where a set of points called the Pareto frontier are selected as the optimal designs. In this work, multi-objective genetic algorithm (MOGA) is utilized to search the optimal points along the Pareto frontier with ANN surrogate model. MOGA has four important components as *fitness evaluation* for survival probability, *niching* for diversity preservation, *crossover and mutation* for generating offspring to next generation, and *stopping criteria* for ending iterator process.

The procedure of MOGA is described as follows:

Step 1 N solutions are randomly generated to form the initial population P_0 at generation t_0.
Step 2 Calculate corresponding objectives.
Step 3 Assign rank by Eq. (12), assign fitness value by Eq. (13), calculate niche count by Eq. (14), and assign shared fitness by Eq. (15).

$$rank(x_i, t) = p_i(t) + 1 \tag{12}$$

$$f(\mathbf{x}, t) = N - \sum_{k=1}^{r(\mathbf{x},t)-1} n_k - 0.5 \times \left(n_{r(\mathbf{x},t)} - 1\right) \tag{13}$$

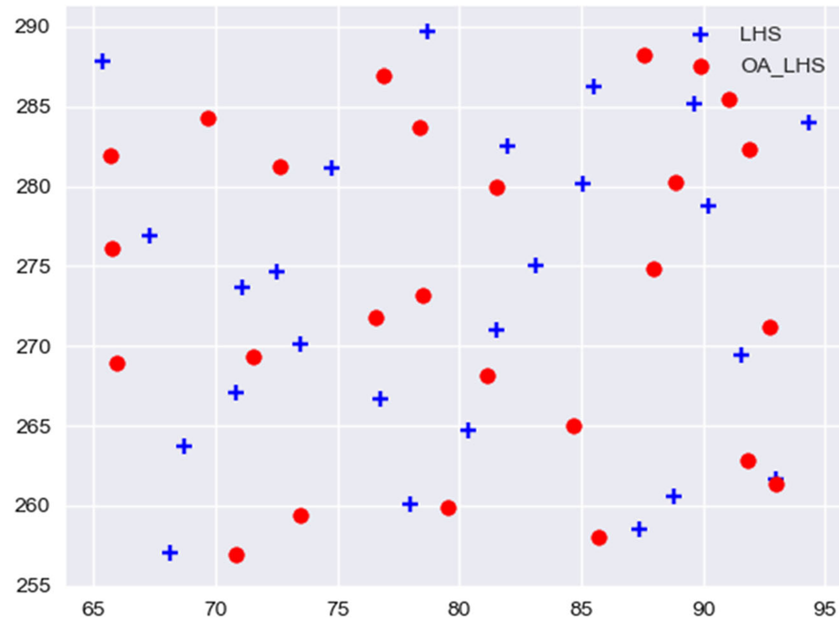


Fig. 10 Sampling points by OA-LHS

$$nc(\mathbf{x},t)=\sum_{y\in P,r(y,t)=r(\mathbf{x},t)}\max\left\{\frac{\sigma_{share}-dz(\mathbf{x},\mathbf{y})}{\sigma_{share}},0\right\} \tag{14}$$

$$f'(\mathbf{x},t)=f(\mathbf{x},t)/nc(\mathbf{x},t) \tag{15}$$

(σ_{share}, niche size; $dz(\mathbf{x}, \mathbf{y})$ is the Euclidean distance between solution **x** and **y**)

Step 4 If max iterators or stopping criteria is reached, return P_t.

Step 5 For $i = 1$ to generations

Select parents stochastically for implementation of crossover and mutation.

Calculate corresponding objectives.

Assign rank, assign fitness, calculate Niche Count and assign shared fitness.

Set $i = i + 1$

End for

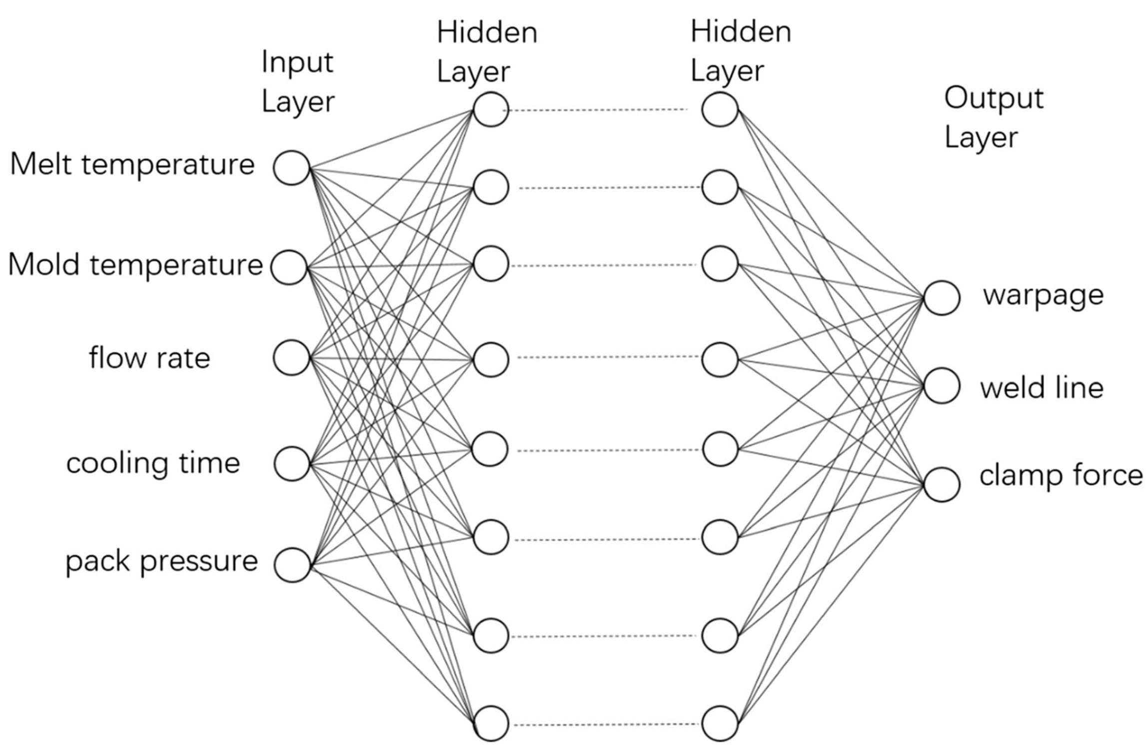


Fig. 11 Artificial neural network architecture

Table 7 Tuning parameters used in MOGA

Params Index	Value
Max evaluations	2500
Crossover rate	0.8
Mutation rate	0.1
Percentage change	0.5
No. of generations	40

The advantage of MOGA relies that it can search the Pareto frontier while maintaining diversity. Detailed information for MOGA can be found in ref. [34, 35] and ref. [36]. Parameters used in MOGA are shown in Table 7.

4.1.4 Implementation of hybrid ANN-MOGA

Generic algorithms always need thousands or more of points to obtain the optimal solutions, where surrogates can help to reduce the number of points needed. ANN is constructed over the sampling points and MOGA search the optimal solutions along the Pareto front on the ANN model. The procedure of hybrid ANN-MOGA used for optimization of PIM is described as:

1. OA-LHS is utilized to generate sampling points within design space, and corresponding responses are obtained by experiments.
2. ANN is utilized to construct the meta-model fitting sampling points and responses and MOGA is utilized to search optimal point along the Pareto frontier and then iteratively update the accuracy of ANN.
3. Stop if the max number of iterators or predefined accuracy is reached. The optimal points exist in the Pareto frontier of last iterator.
4. Implement experiments to verify the accuracy and efficiency of hybrid ANN-MOGA.
5. Data analysis is implemented for information mining and results explanation.

4.2 Data analysis

1. Accuracy verification

Twenty-five initial sampling points are generated to construct meta-model and 2500 points are added along the Pareto frontier to search the optimal points. Accuracy verification is implemented by randomly selecting 20 points predicted by hybrid ANN-MOGA. Results are shown in Fig. 12, from which it can be seen that the proposed algorithm is accurate enough to construct the response surface.

2. Sensitivity analysis

The heatmap of correlation coefficient between parameters and responses are shown in Fig. 13. The correlation coefficient is calculated with Eq. (16) as:

$$\rho_{\mathbf{X},\mathbf{Y}} = \frac{\mathrm{cov}(\mathbf{X},\mathbf{Y})}{\sigma_{\mathbf{X}}\sigma_{\mathbf{Y}}} = \frac{E((X-\mu_{\mathbf{X}})(\mathbf{Y}-\mu_{\mathbf{Y}}))}{\sigma_{\mathbf{X}}\sigma_{\mathbf{Y}}} \tag{16}$$

where cov is the covariance between two data sets, E is the expectation of data, μ is the mean value, and σ is the variance. The range of $\rho_{\mathbf{X},\mathbf{Y}}$ is $\rho_{\mathbf{X},\mathbf{Y}} \in (-1, 1)$. If $\rho_{\mathbf{X},\mathbf{Y}} = 0$, it means that there is no positive or negative relationship between X and Y, $\rho_{\mathbf{X},\mathbf{Y}} > 0$ means a positive relationship, and $\rho_{\mathbf{X},\mathbf{Y}} < 0$ means a negative relationship. As shown in Fig. 13, correlation coefficients between parameters shown in part 1 are near 0, which indicates the uniformity of sampling points. In part 2, it can be seen that warpage is strongly influenced by melt temperature and pack pressing which equals to − 0.75 and − 0.71, respectively. Clamp force is strongly influenced by melt temperature with positive $\rho_{\mathbf{X},\mathbf{Y}} = 0.91$. The results are consistent with ANOVA shown in Table 4 and Fig. 9. What is noteworthy is that the value of $\rho_{\mathbf{X},\mathbf{Y}}$ between warpage and clamp force is − 0.8, which shows a strongly negative relationship.

3. Pareto frontier

Pareto frontier of three objectives is shown in Fig. 14. It can be seen that warpage, weld line, and clamp force cannot reach

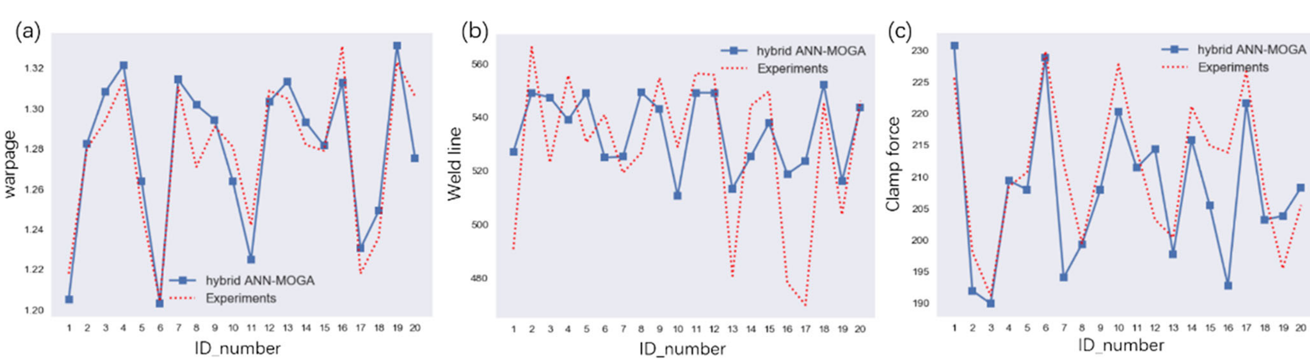


Fig. 12 Accuracy prediction of hybrid ANN-MOGA

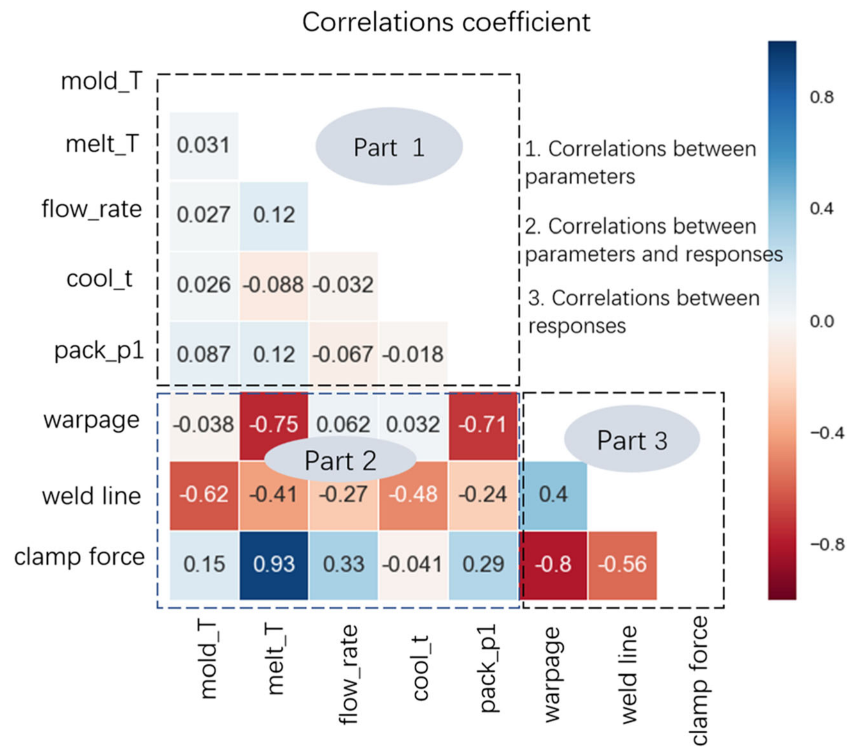


Fig. 13 Relationship between parameters and responses

the optimal synchronously where a compromise has to be made among them.

Triple-objective Pareto frontier is shown in Fig. 14a. For better understanding, pair-wise Pareto frontier of weld line and warpage, clamp force and weld line, and clamp force and warpage are represented in Fig. 9b, c, and d, respectively. As shown in Fig. 14(b), there is no significant trade-off between weld line and warpage along the Pareto frontier. There are design points to make weld line reach its minimum 510 mm and warpage near its minimum 1.06 mm.

As shown in Fig. 14(c), there is a significant trade-off between clamp force and weld line. When weld line reduces from 550 to 510 mm, clamp force increases from 210 to 252 ton. Considering Fig. 9 showing S/N ratio and

Table 4 showing ANOVA result, when melt temperature (B) increases, clamp force tends to be larger; meanwhile, weld line becomes smaller.

Remarkable negative linear relationship between clamp force and warpage can be seen from Fig. 14d, and the trend can be observed referring to Fig. 9,

Table 4, and Fig. 13 that melt temperature (B) has a very significant influence on both warpage and clamp force into different direction, which means that when melt temperature increases, warpage will decrease while clamp force increases. Packing pressure (F) has a similar effect to melt temperature (B) on warpage and clamp force.

It can be concluded that the Pareto frontier obtained by hybrid ANN-MOGA has good convergence with robustness. Designers can select optimal points along the Pareto front considering real quality requirements because of the trade-off among the three quality characteristics.

4.3 Result verification

Optimal points are selected along the Pareto frontier and experiments have been implemented to obtain responses for verification of the proposed method. As shown in Table 8, synchronous reduction in warpage, weld line, and clamp force are reached by optimal points obtained by hybrid ANN-MOGA compared with the results of Taguchi method shown in Table 6. The optimal solutions provided by Taguchi method and hybrid ANN-MOGA are shown in Table 9, which further validates the accuracy and effectiveness of the proposed two-stage method.

5 Conclusion

In this study, a two-stage multi-objective optimization methodology and corresponding automation tool have been designed, implemented, and applied to automobile air conditional vent. Warpage, weld line, and clamp force are considered as the objectives of optimization. Manufacture process parameters considered include mold temperature, melt temperature, flow rate, and variable packing profile parameters containing packing time and packing pressure. The Taguchi method together with ANOVA and hybrid ANN-MOGA has been utilized to analyze design space and synchronous reduction in optimization objectives. The results can be concluded as follows:

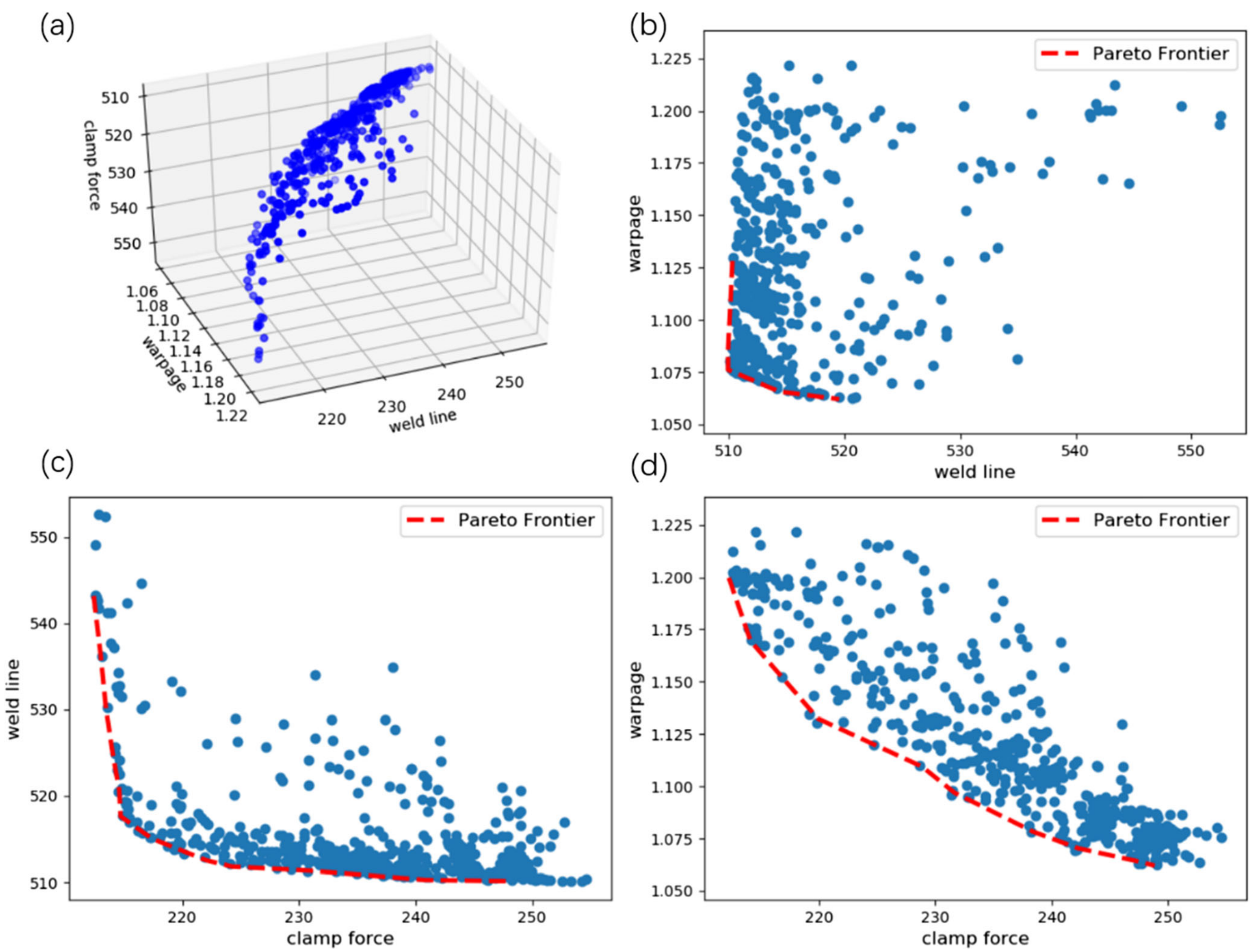


Fig. 14 Pareto frontier of three-objective optimization result

1. During the first stage, the Taguchi method together with S/N ratio and ANOVA is utilized to identify the significant process parameters, compress design space from 8 parameters to 5 ones, and provide initial optimal combination of process parameters. Optimal combination of process parameters for each quality characteristic is obtained efficiently.
2. To obtain synchronous reduction in warpage, weld line, and clamp force, hybrid ANN-MOGA is implemented in the second stage. OA-LHS is utilized for sampling to get unformal and stratified points. ANN is utilized to construct the surrogate model to fit the sampling points and response data to decrease the number of expensive experiments. MOGA, in this paper, is implemented to search the optimal point of the surrogate model along the Pareto frontier. The optimal solutions provided by hybrid ANN-MOGA are better than optimal solution provided by the Taguchi method considering three objectives.

Table 8 Optimal points provided by hybrid ANN-MOGA

	A (°C)	B (°C)	C (cm^3/s)	D (s)	F (MPa)		Warp (mm)	Weld (mm)	Clamp (t)
1	92.45	256.74	13.59	25.94	96.87	Predicted	1.187	512.51	216.16
						Exp	1.156	509.46	207.31
2	92.58	256.11	14.20	25.80	98.43	Predicted	1.198	515.92	226.74
						Exp	1.192	516.54	213.85
3	83.14	260.80	13.59	25.94	93.16	Predicted	1.188	518.83	219.82
						Exp	1.202	538.72	216.16

Table 9 Optimal solutions of Taguchi method and hybrid ANN-MOGA

Optimal points	Warp (mm)	Weld (mm)	Clamp (ton)
Taguchi method	1.228	533.56	225.61
Hybrid ANN-MOGA	1.156	509.46	207.31
Total reduction rate	5.9%	10.0%	8.1%

3. An automation tool is developed with the help of python, C++, API of Moldflow, Qt, and vbs, offering designers a friendly and interactive tool to implement the two-stage methodology, without deep understanding of complicated knowledge of optimization, or even without knowing the operation of related software. To demonstrate the efficiency of the proposed methodology and the automated tool, the system is applied to automobile air conditional vent and the result shows that the defects have reached a synchronous decrease compared with the arbitrary process parameters set by designers.

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