Int J Adv Manuf Technol (2017) 89:241–254
DOI 10.1007/s00170-016-9065-7

ORIGINAL ARTICLE

Multi-objective optimization of injection molding process parameters in two stages for multiple quality characteristics and energy efficiency using Taguchi method and NSGA-II

Maosheng Tian[1] · Xiaoyun Gong[2] · Ling Yin[3] · Haizhou Li[1] · Wuyi Ming[2] · Zhen Zhang[4] · Jihong Chen[1]

Received: 23 February 2016 / Accepted: 15 June 2016 / Published online: 28 June 2016

Abstract In this paper, the parameters optimization of plastic injection molding (PIM) process was obtained in systematic optimization methodologies by two stages. In the first stage, the parameters, such as melt temperature, injection velocity, packing pressure, packing time, and cooling time, were selected by simulation method in widely range. The simulation experiment was performed under Taguchi method, and the quality characteristics (product length and warpage) of PIM process were obtained by the computer aided engineering (CAE) method. Then, the Taguchi method was utilized for the simulation experiments and data analysis, followed by the S/N ratio method and ANOVA, which were used to identify the most significant process parameters for the initial optimal combinations. Therefore, the range of these parameters can be narrowed for the second stage by this analysis. The Taguchi orthogonal array table was also arranged in the second stage. And, the Taguchi method was utilized for the experiments and data analysis. The experimental data formed the basis for the RSM analysis via the multi regression models and combined with NSGS-II to determine the optimal process parameter combinations in compliance with multi-objective product quality characteristics and energy efficiency. The confirmation results show that the proposed model not only enhances the stability in the injection molding process, including the quality in product length deviation, but also reduces the product weight and energy consuming in the PIM process. It is an emerging trend that the multi-objective optimization of product length deviation and warpage, product weight, and energy efficiency should be emphasized for green manufacturing.

Keywords Multi-objective optimization · Injection molding · Quality characteristics · Energy efficiency · Taguchi method · NSGA-II · Process modeling

✉ Zhen Zhang
jameszhang198808@gmail.com

1 State Engineering Research Center of Numerical Control System, Huazhong University of Science & Technology, 430074 Wuhan, China

2 Department of Electromechanical Science and Engineering, Zhengzhou University of Light Industry, 450002 Zhengzhou, China

3 School of Mechanical Engineering, DongGuan University of Technology, 523808 Dongguan, China

4 State Key Lab of Digital Manufacturing Equipment & Technology, School of Mechanical Science and Engineering, Huazhong University of Science & Technology, Wuhan 430074, China

1 Introduction

Plastic injection molding (PIM) can quickly manufacture high-grade plastic parts with complex configuration at a single time. Because of versatility in mold and process design, it has been widely used in manufacturing plastic products, which process is actually one of the intricate systems. The quality of plastic injection molding parts depends on the choice of materials, mold design, and determination of process parameter settings. The choice of materials and mold design is usually decided before producing parts, which cannot be easily changed. Defects in the products, including warp, shrinkage, sink marks, and contour distortions, can be reduced by optimizing process parameter settings. Therefore, to search for optimal process parameter settings is recognized as the most feasible method and crucial step in plastic injection molding so as to obtain high quality products efficiently and economically.

Many researchers have been devoted to the conventional process parameter optimization which method relies on experience and trial-and-error [1]. Although these conventional methods including the design of experiments (DOE) method are costly and time-consuming, it is important to evaluate design parameters and objectives through utilizing the results of design of experiment and expert knowledge at first. A design of experiment is used to establish the parameter levels [2]. Sahu [3] employed design of experiments and modified complex method to optimize process conditions for reducing warpage. Ozcelik [4] also employed this method to choose design objective parameters and used Taguchi method to acquire the orthogonal parameter arrays. In order to investigate the optimal process parameters, the Taguchi approach is used in injection molding [5]. Tang [6] introduced the Taguchi method to improve product quality in manufacturing processes. It can solve the quality problems of products efficiently. However, Taguchi's parameter design method can only select the better combination of specified process parameter level which includes discrete values. To improve conventional Taguchi parameter design, Fei [7] combined analysis of variance (ANOVA) with Taguchi method to obtain the effect of injection molding process parameter and optimal settings.

To search for the important optimal process parameters, a series of simulation methods also had been introduced. Computer-aided engineering (CAE) is widely used in PIM to find the optimal process parameters [8–12]. In addition, many researchers have focused on finding surrogate models, such as artificial neural network (ANN), support vector regression (SVR), and response surface method (RSM). These surrogate models are regarded as a mathematical approximation instead of the actual simulation analyses. Mathivanan [13, 14] minimized the sink depths in injection-molded thermoplastic components by integrating finite element flow analysis with central composite design (CCD) of experiments and genetic algorithm (GA). The results confirmed that this proposed methodology could be effective. Shi [15, 16] optimized process conditions to minimize the warpage of the injection molding parts by using ANN model. To obtain an optimal parameter setting with a better control, Shie [17] employed a radial basis neural network (RBN) over the contour distortions of polypropylene composite components. Xu [18] integrated a back-propagation neural network (BPNN) with particle swarm optimization (PSO) to help engineers identify optimal process conditions. BPNN can be utilized to efficiently optimize PIM multiple objectives including part weight, flash, or volumetric shrinkage, present trade-off behaviors [19]. Zhou [20] studied optimization of process parameters using the SVR and GA. Chen [21] presented an integrated optimization system to determine the optimal parameter settings of multi-input multi-output (MIMO) plastic injection molding process using BPNN and GA. Kurtaran [22] made reduction in warpage in thin shell plastic parts using response surface method (RSM) and ANN. To further improve part quality, a novel methodology integrating variable complexity methods (VCM), constrained non-dominated sorted genetic algorithm (CNSGA), BPNN, and Moldflow analyses was put forward to locate the optimal solutions to the constrained multi-objective optimization problem [23]. Moldflow can be employed to obtain relevant data regarding warpage and weld lines and evaluate the corresponding designs [24]. Wang [25] employed a combination of the Moldflow software and ANN to understand the relationship between plastic injection molding process parameters and shrinkage. The simulation results can state the most important process parameter affecting shrinkage.

The multi-objective optimization approached have become a new trend in recent research in optimizing machining process parameters. As a novel multi-objective optimization method, non-dominated sorting genetic algorithm (NSGA-II) is used to get good welding parameters (such as welding speed, wire feed rate and rap), and errors can be controlled within 3.97 % [26]. To select parameters in machining process significantly affects quality, productivity, and cost of a component, NSGA-II was used to solve the multi-objective optimization problem [27]. In order to find the best process parameter combination that optimizes simultaneously the performance characteristics of hard turning behavior of AISI 52100 bearing steel, Bouacha et al. [28] compared the performance of non-dominated sorting genetic algorithm (NSGA-II) and particle swarm optimization-based neural network(PSO-NN). It was found that NSGA-II exhibits better performance than the PSO-NN methodology. Zhang and Ming [29, 30] successfully applied NSGA-II to optimize the process parameters of wire electrical discharge machine (WEDM) and obtained the optimal parameter combinations that results in high surface quality and good material removal rate (MRR).

In addition to modifying the warp, shrinkage, sink marks, and contour distortions of PIM, product weight and energy-consuming can also be optimized while adjusting the injection molding process parameter settings. Hsu [31] presented an integrated scheme to optimize parameter design problems with multiple responses. Castro [32] employed an approach comprising CAE, ANN, and data envelopment analysis to determine the proper operating conditions for finding the best compromise among several conflicting performance measures. It is well known that the PIM process consumes high energy. The hydraulic system consumes most of the energy consume of the injection molding machine. Thus, control precision and energy-saving are desired tendencies of the injection molding industry. Peng [33] employed neuro-dynamic optimization to control an injection molding process. The simulation results showed that the proposed method can solve the high energy consumption. Lu [34] studied the trade-off between product quality and energy consumption in injection molding. The energy consumption can be significantly reduced in laboratory scale tests, and at the same time, the product quality can meet the pre-determined requirements.

Although the above mentioned researches have achieved various levels of success, more efforts should be taken to search an intelligent optimization strategy for efficiently optimizing the PIM parameters when multiple objectives are involved. DOE method and computer aided engineering (CAE) method have their merits and shortcomings, respectively. In a widely range of process parameters, the precision of prediction by DOE method cannot satisfy with the engineering application. However, the prediction of CAE method cannot always agree with the special PIM equipment. In addition, the product weight and energy consumption also could not solve by CAE method. Therefore, the multi-objective optimization of injection molding process parameters was put forward by two stages in this paper, and the multiple quality characteristics and energy efficiency are concerned using Taguchi method and NSGA-II. In the first stage, the CAE method was taken in order to determine the significant factors and narrow the range of them. In the second stage, experimental data formed the basis for the RSM analysis via the multi regression models and combined with NSGS-II to determine the optimal process parameter combinations. An additional reason that the multi-objective optimization of product length deviation and warpage, product weight, and energy efficiency is a new trend for green manufacturing that should be emphasized.

The following structure of this paper is arranged as below. The optimization method and experimental setup are drawn in Section 2. In Section 3, the simulation results are shown and the analysis of them is obtained for the first stage optimization. And the experimental regression model is built and the multi-objective optimization is obtained by NSGA-II for the second stage optimization in Section 4. Then, the discussions and conclusions are drawn in Section 5 and Section 6, respectively.

2 Optimization method and experimental setup

2.1 Optimization method

In this paper, the optimization of PIM was obtained by two stages. In the first stage, the parameters, such as melt temperature, injection velocity, packing pressure, packing time, and cooling time, were selected by simulation method in widely range. The simulation experiment was performed under Taguchi method, and the quality characteristics (product length and warpage) of PIM were obtained by the Moldflow commercial software. Then, the Taguchi method was utilized for the simulation experiments and data analysis, followed by the S/N ratio method and ANOVA, which were used to identify the most significant process parameters for the initial optimal combinations. Also, it can narrow the range of these parameters for the second stage by this analysis.

Since the injection-molded pieces used in this study were pieces of plastic, the quality characteristics and energy efficiency are concerned. The Taguchi orthogonal array table was also arranged in the second stage. Then, the Taguchi method was utilized for the experiments and data analysis. The experimental data formed the basis for the RSM analysis via the multi-quality regression models and combined with NSGS-II to determine the optimal process parameter combinations in compliance with multi-objective product quality characteristics and energy efficiency.

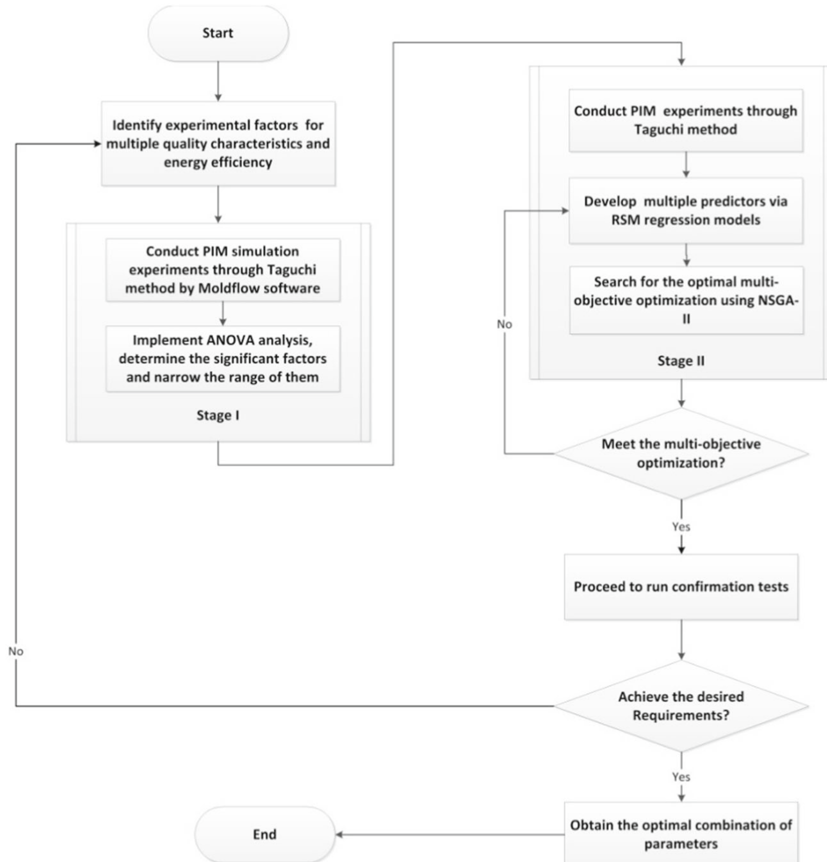
In this way, the achieved process parameter combinations were expected not only to enhance the stability of the injection molding process and ensure that the product length met the specifications but also to effectively reduce product weight and energy consume. The flowchart of the proposed method is shown in Fig. 1.

2.2 Experimental setup

In the second stage, the injection molding experiments were done by the JM55-ECO machine, which is manufactured by Hsong Holdings Limited. PP-4025 plastic material was chosen due to its characteristics of high hardness, low shrinkage, and greater resistance to high temperature. The product nominal length was 150.00 mm, and the desired warpage value was 0 mm as expected. The experimental mold and the finished product are shown in Figs. 2 and 3, respectively. The sketch of up and down deviations of length and warpage is shown as Fig. 3b, c. The workpiece is divided into two parts under the geometric center point in the MoldFlow software. Then, the up and down length deviation is defined as the deviation of parts of up and down, respectively. Similarity, the up and down warpage is also defined by this rule. Product length was measured using a three-coordinate measuring machine (Corma 564) with a range of 500 mm and precision of 0.005 mm. Weight was measured using the precise analytical balance (Setra BL120) with a precision of 0.001 g. Energy consume was measured by energy meter (Heng-Ping FA2104S) with a precision of 0.1W.h.

Both in the first stage and in the second stage, the Taguchi method was employed to conduct the experiments. For the first stage, an L_{25} (5^5) orthogonal array experiment was arranged under Taguchi parameter standard setting values,

Fig. 1 Flowchart of the proposed method

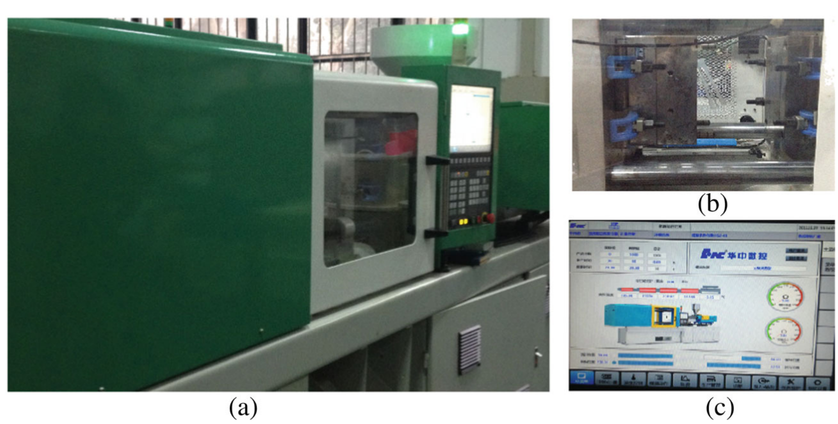


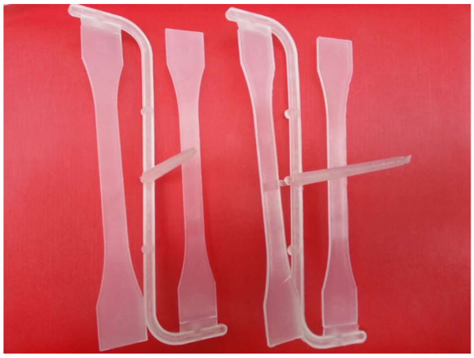
in which no. 1 to no. 25 were Taguchi experimental data. Accordingly, the control factor's range was given five levels, as depicted in Table 1. For the second stage, it is similar to that of the first stage. An L_{25} (5^5) orthogonal array experiment was also utilized to perform the PIM process. The multiple quality characteristics and energy efficiency are the performance of injection molding process. Accordingly, the control factor's range was given five levels, as depicted in Table 2. Overall, the range of factors in Table 2 covered the optima parameters under CAE simulation. However, some parameters are the boundary of high or low limitation, such as melt temperature, injection velocity, and packing time. Then, the range of the second stage optimization is nearly shrunk to half, comparing to the first stage optimization.

3 Simulation results and analysis for the first stage of optimization

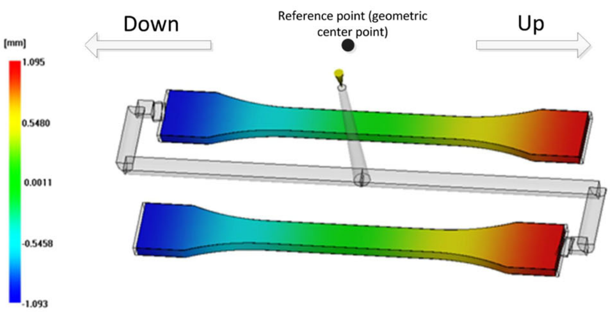
In this section, the L_{25} (5^5) orthogonal array is applied by Moldflow simulation with assign five factors into rows. Melt temperature (MT), injection velocity (IV), packing

Fig. 2 Experimental mold. **a** Overview of machine. **b** Injection mold. **c** Control system

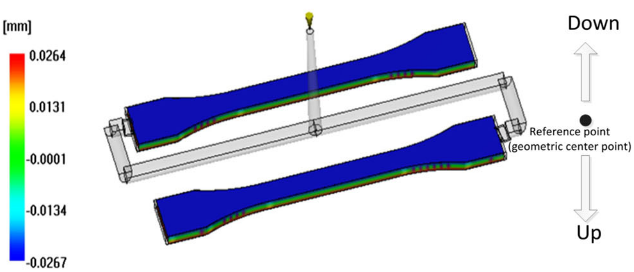




(a) Finished experimental product



(b) The sketch of up and down length deviations



(c) The sketch of up and down warpage deviations

Fig. 3 Finished experimental product and sketch of up and down deviations

pressure(PP), and packing time (PT), and cooling time (CT) are control factors and are assigned to variable A, B, C, D, and E, respectively. Therefore, the significant PIM process parameters are determined by ANOVA and DOE screening experiments via these simulations. In total, 50 data samples are collected. From the experimental treatments with two replications (up and down deviation) and the S/N ratio of two quality characteristics, length deviation and warpage, are shown in Table 3.

Table 4 shows the ANOVA results of product length deviation and indicates that A and D are very significant, since the *P* values of them are no more than 0.01. It can also be concluded that the effects of C and E are not significant, since the *P* values of them are more than 0.05. Table 5 also reveals that A is significant for warpage, and the others are not significant. Therefore, the control factors in the second stage could narrow the range of melt temperature and packing time.

Since the responses of the experiment are length deviation and warpage, the desired target product length deviation and warpage are both 0 mm, and the smaller-the-better is applied to calculate S/N ratio for each treatment. In quality engineering, the S/N ratio could be an effective utilization to obtain the significant parameter from those controlling parameters by evaluating the minimum variance. For smaller-the-better, the definition of the S/N ratio is listed in Eq. 1, in which η is the S/N ratio, y_i is the response, and n is the number of replications.

$$\eta = -10 \times \lg\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \tag{1}$$

The η values of length deviation and of warpage are presented in Tables 6 and 7, respectively. The largest value of η depicts the optimal condition. The define of delta listed in Tables 6 and 7 is drawn as Eq. 2.

$$Delta = X_{max} - X_{min},\ X = A, B, C, D, and E \tag{2}$$

The Taguchi optimal parameters are the average of that of length deviation and that of warpage. According to the process parameter combinations of highest S/N ratio under different responses in Tables 6 and 7 and the ANOVA results in Tables 4 and 5, the initial process parameter settings obtained from the Taguchi method and ANOVA are melt temperature = 230, injection velocity = 90, injection pressure = 80, packing time = 4, and cooling time = 18 for the

Table 1 Control factors and the standard settings of levels in the first stage

	Melt temperature (°C)	Injection velocity (mm/s)	Packing pressure(MPa)	Packing time (s)	Cooling time (s)
Level 1	190	30	40	1	10
Level 2	200	45	50	2	12
Level 3	210	60	60	3	14
Level 4	220	75	70	4	16
Level 5	230	90	80	5	18

Table 2 Control factors and the standard settings of levels in the second stage

	Melt temperature (°C)	Injection velocity (mm/s)	Packing pressure(MPa)	Packing time (s)	Cooling time (s)
Level 1	210	50	50	2.5	14
Level 2	215	60	55	3	15
Level 3	220	70	60	3.5	16
Level 4	225	80	65	4	17
Level 5	230	90	70	4.5	18

length deviation optimization. Similarity, the initial process parameter settings are melt temperature = 230, injection velocity = 90, injection pressure = 50, packing time = 5, and cooling time = 12 for the warpage optimization. Therefore, the initial process parameter settings for Taguchi optimization are melt temperature = 230, injection velocity = 90, injection pressure = 65, packing time = 4.5, and cooling time = 15. The result is listed in Table 8 for the first stage optimization. The confirmation tests of Taguchi optimization are conduced by CAE simulations. Then, the up and down of length deviation are 0.9779 and −0.9762, respectively; the up and down of warpage are 0.0264 and −0.0266, respectively. These data of CAE simulation is also shown as Fig. 4. Compared to Table 3, the performance of optimized control parameters is better than that of previous settings. Then, the feasibility of optimization method is confirmed.

In addition, Minitab 17 statistical software is utilized for data analysis. Figures 5 and 6 draw the main effect of factors on the S/N ratio of product length deviation and

Table 3 Experimental design, response statistics, and S/N ratio under CAE simulation

No.	Control parameters					Length deviation (mm)			Warpage (mm)		
	A	B	C	D	E	Up	Down	S/N ratio	Up	Down	S/N ratio
1	190	30	40	1	10	1.095	−1.093	−0.7803	0.0297	−0.0298	24.5096
2	190	45	50	2	12	1.086	−1.084	−0.7085	0.0298	−0.03	24.4659
3	190	60	60	3	14	1.076	−1.074	−0.6281	0.0296	−0.0298	24.5242
4	190	75	70	4	16	1.067	−1.065	−0.5551	0.0294	−0.0298	24.5533
5	190	90	80	5	18	1.058	−1.056	−0.4815	0.0292	−0.0296	24.6122
6	200	30	50	3	16	1.058	−1.056	−0.4815	0.0288	−0.029	24.7613
7	200	45	60	4	18	1.05	−1.048	−0.4155	0.0289	−0.0291	24.7313
8	200	60	70	5	10	1.042	−1.04	−0.3490	0.0287	−0.029	24.7763
9	200	75	80	1	12	1.067	−1.065	−0.5551	0.0288	−0.0289	24.7764
10	200	90	40	2	14	1.057	−1.055	−0.4732	0.0286	−0.0288	24.8217
11	210	30	60	5	12	1.027	−1.025	−0.2229	0.0281	−0.0283	24.9743
12	210	45	70	1	14	1.044	−1.042	−0.3656	0.0284	0.0284	24.9130
13	210	60	80	2	16	1.037	−1.034	−0.3030	0.0281	−0.0283	24.9743
14	210	75	40	3	18	1.029	−1.027	−0.2398	0.0279	−0.0282	25.0206
15	210	90	50	4	10	1.021	−1.019	−0.1720	0.0275	−0.0278	25.1453
16	220	30	70	2	18	1.017	−1.015	−0.1378	0.0276	−0.0277	25.1454
17	220	45	80	3	10	1.011	−1.008	−0.0821	0.0275	−0.0277	25.1611
18	220	60	40	4	12	1.004	−1.001	−0.0216	0.0271	−0.0273	25.2879
19	220	75	50	5	14	0.9978	−0.996	0.0282	0.027	−0.0272	25.3199
20	220	90	60	1	16	1.019	−1.017	−0.1549	0.0273	−0.0274	25.2402
21	230	30	80	4	14	0.9875	−0.985	0.1184	0.0269	−0.027	25.3682
22	230	45	40	5	16	0.982	−0.98	0.1666	0.0267	−0.0269	25.4166
23	230	60	50	1	18	0.9975	−0.995	0.0308	0.0268	−0.0269	25.4004
24	230	75	60	2	10	0.991	−0.989	0.0877	0.0266	−0.0267	25.4654
25	230	90	70	3	12	0.9846	−0.983	0.1440	0.0264	−0.0266	25.5144

Table 4 ANOVA for product length deviation

Source	DOF	Adj SS	Adj MS	F-Value	P-Value
A	4	1.73355	0.433386	2537.28	0.000
B	4	0.01675	0.004188	24.52	0.004
C	4	0.00086	0.000215	1.26	0.415
D	4	0.11804	0.029509	172.76	0.000
E	4	0.00159	0.000398	2.33	0.216
Error	4	0.00068	0.000171		
Total	24	1.87147			

warpage, respectively. It is noted that the data mean is utilized to determine factor effects. With this figure, the factor effects can be visually observed. It shows that melt temperature (A) has the extremely important effect on both S/N ratio of product length deviation and warpage. There is a clear linear relationship between melt temperature and the product length deviation and warpage, respectively; the product length deviation and warpage decrease significantly by increasing melt temperature. This is because that better fluidity can be obtained when the melt temperature is high. Figure 5 also shows the effect of injection velocity (B), packing pressure (C), packing time (D), and cooling time (E) on the S/N ratio of product length deviation. As it is depicted, melt temperature and packing time have an extremely important effect on the S/N ratio of product length deviation, and especially melt temperature is a dominant factor on product length deviation. The same procedure is used for the main effect of factors on the S/N ratio of product warpage. As it is depicted in Fig. 6, none of the factors has an extremely important effect on the S/N ratio of product warpage except for melt temperature (A). The trend of Fig. 6 is similar to the Fig. 5. Therefore, the product length deviation is selected as the indicator of quality characteristics in the optimization of process parameters in the second stage. Considering the above analysis, the control factors and the standard settings of levels in the second stage are listed in Table 2.

Table 5 ANOVA for product warpage

Source	DOF	Adj SS	Adj MS	F-Value	P-Value
A	4	2.55057	0.637643	495.32	0.000
B	4	0.05675	0.014189	11.02	0.020
C	4	0.00684	0.001710	1.33	0.395
D	4	0.01132	0.002831	2.20	0.232
E	4	0.00293	0.000732	0.57	0.701
Error	4	0.00515	0.001287		
Total	24	2.63357			

Table 6 η value of product length deviation (in S/N ratio)

Level	A	B	C	D	E
1	−3.1537	−1.5041	−1.8252	−1.3485	−1.8252
2	−2.2744	−1.4053	−1.535	−1.3029	−1.535
3	−1.3035	−1.271	−1.2876	−1.3338	−1.2876
4	−0.3684	−1.2341	−1.0458	−1.2636	−1.0458
5	0.5477	−1.1376	−0.8585	−1.3033	−0.8585
Delta	3.7014	0.3665	0.9667	0.0849	0.9667

4 Experimental regression models and multi-objective optimization in the second stage

4.1 Experimental results

In this section, the L_{25} (5^5) orthogonal array is also applied by experiment with assign five factors into rows. The range of these factors is determined in the first stage of optimization. In total, 25 data samples are collected. From the experimental treatments, length deviation, product weight and energy consume are shown in Table 9.

4.2 Regression models

In the process of PIM, the response statistics changes drastically with the control parameters. Hence, it is very difficult to obtain an analytical model based on the physics of process. To solve this problem, one way is to build its controllable parameters to the response statistics based on regression analysis. In this subsection, general second order models for prediction of length deviation ($\boldsymbol{L_d}$), product weight ($\boldsymbol{P_w}$), and energy consume ($\boldsymbol{E_c}$) are utilized during the PIM. The models[35] can be drawn as the following equation:

$$Y = b_0 + \sum_{i=1}^{k} b_i x_{in} + \sum_{i=1}^{k} b_{ii} x_{in}^2 + \sum_{i=2}^{k} \sum_{j=1}^{i-1} b_{ij} x_{in} x_{jn}, \quad (3)$$

where $\boldsymbol{Y}$ is the cutting performance ($\boldsymbol{L_d}$,$\boldsymbol{P_w}$ or $\boldsymbol{E_c}$); b_0, b_i, b_{ii}, and b_{ij} are the coefficients; x_{in} and x_{jn} are the control parameters, n is the sequence number of experiment (1–25)

Table 7 η value of product warpage (in S/N ratio)

Level	A	B	C	D	E
1	122.6654	124.759	125.0565	124.8398	125.0579
2	123.8673	124.6881	125.0931	124.8729	125.0191
3	125.0277	124.9634	124.9356	124.9818	124.9471
4	126.1548	125.1358	124.9026	125.0862	124.946
5	127.1652	125.3339	124.8924	125.0995	124.91
Delta	4.4998	0.6458	0.2007	0.2597	0.9667

Table 8 Taguchi experimental optimal parameters under confirmed CAE simulation

	Melt temperature (°C)	Injection velocity (mm/s)	Packing pressure(MPa)	Packing time (s)	Cooling time (s)
Length deviation	230	90	80	4	18
Warpage	230	90	50	5	12
Taguchi optimal parameters	230	90	65	4.5	15

for both materials; k is the factor number (1–5); x_{in}^2 is the second order term of variable and $x_{in}\ x_{jn}$ is the interaction terms.

The regression models are developed by the software MINITAB 17, which is commercial software for statistical analysis. The models of PIM for $\boldsymbol{L_d}$, $\boldsymbol{P_w}$ and $\boldsymbol{E_c}$ are given as Equation (4) to Equation (6).

$$\begin{aligned} L_d = &-39.4 + 0.1635A - 0.0489B + 0.839C \\ &-0.0398D - 0.0239E + 0.000614B \times B \\ &-0.001776C \times C - 0.002733A \times C \\ &-0.000711B \times C \end{aligned} \tag{4}$$

$$\begin{aligned} P_w = &\ 5.292 + 0.000343A - 0.000380B - 0.0763C \\ &+0.0679D - 0.00054E + 0.000768C \times C \\ &-0.001237C \times D \end{aligned} \tag{5}$$

$$\begin{aligned} E_c = &\ 60.2 - 0.2281A + 0.00142B - 0.669C \\ &-1.071D + 0.1202E + 0.001011C \times C \\ &+0.1839D \times D + 0.00268A \times C \end{aligned} \tag{6}$$

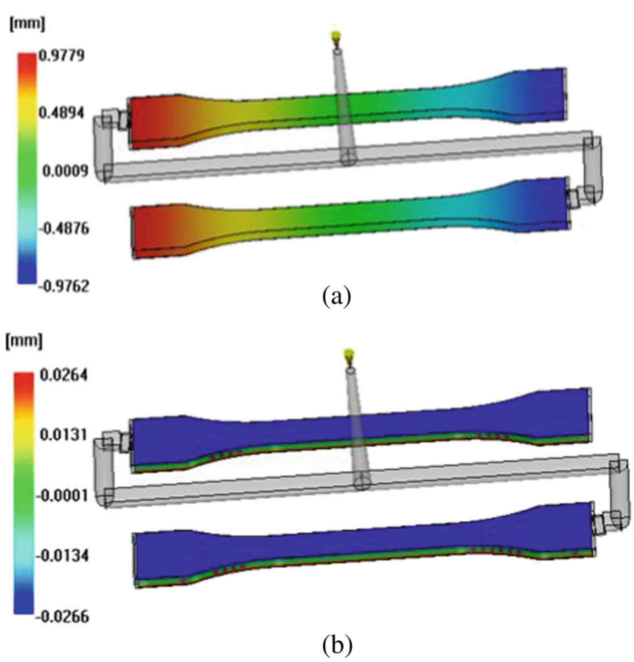


Fig. 4 The performance confirmed by CAE simulation (melt temperature = 230, injection velocity = 90, injection pressure = 65, packing time = 4.5, and cooling time = 15). **a** Length deviation. **b** Warpage

Based on Student's t test at 95 % confidence level, there are some coefficients omitted in above equations for $\boldsymbol{L_d}$,$\boldsymbol{P_w}$ and $\boldsymbol{E_c}$, respectively. Therefore, it is very important to verify the adequacy of the proposed models. Then, the verification is done by the R^2 (coefficients of multiple determinations) and ANOVA test, and Tables 10, 11, and 12 show the test results. R^2 for them are 82.46, 96.04, and 94.90 %, respectively. The adjusted R-squared of three regression models are 72, 92.34, and 94.42 %, respectively. So the regression models for $\boldsymbol{L_d}$,$\boldsymbol{P_w}$ and $\boldsymbol{E_c}$ can be accepted as far as $R^2$are concerned.

4.3 Multi-objective optimization

NSGA-II was first proposed by Deb [36] to conduct the elite-preserving and a phenotype crowd comparison operator to keep the diversity and reduce the computational complexity; therefore, this evolutionary algorithm has an excellent competency in exploring the set of Pareto-optimal solutions to handle constrained multi-objective optimization problems. The mathematic predictive models for length deviation, energy consuming and product weight are optimized using NSGA-II which has the capacity of finding the optimal solution of multi-objective (two and three objectives) problem. Length deviation and energy consuming are the two main performances of PIM with natural conflict; thus, they are regarded as two optimized objectives. By using the NSGA-II for two-objective optimization, the optimal process parameter settings with the primary goals of minimum length deviation and minimum energy consuming

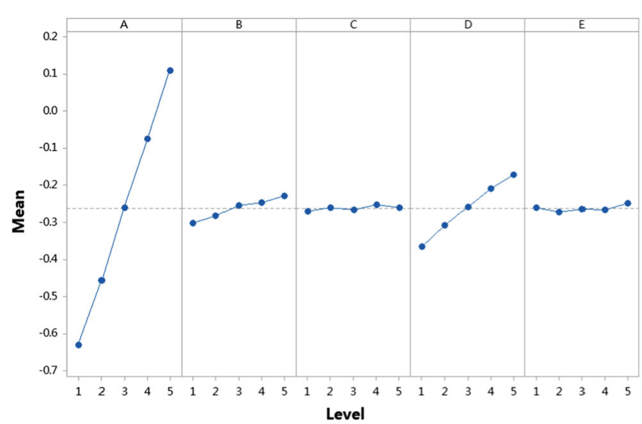


Fig. 5 Main effects plot for S/N ratio of product length deviation

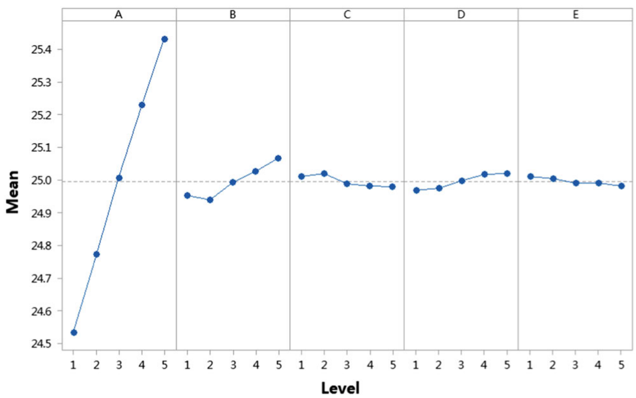


Fig. 6 Main effects plot for S/N ratio of product warpage

were obtained respectively. For sake of the synchronous optimal of two goals, the objective functions are given as follows:

Objective 1 = length deviation;
Objective 2 = energy consuming;

The following parameters of NSGA-II were listed according to the study of obtaining optimal solutions with the high efficiency:

(1). Population size = 150
(2). Maximum number of generations = 500
(3). Mutation probability = 0.25
(4). Crossover probability = 0.8

The Pareto-optimal front of two objectives (Length deviation and Energy consuming) is shown in Fig. 7a, which means the formation of the Pareto front results in the final solution set. From Fig. 7a, it can be observed that the values of the optimal sets were no bias towards too high or too low due to NSGA-II allowing the all non-dominated fronts to co-exist in the population. When the values of length deviation increase from 0.1 to 0.87 mm, the energy consuming decreases gradually. However, when the length deviation continues increasing, the energy consuming is hardly reduced and almost keeps the same. On the other hand, in order to study the relationship of energy consuming and product weight, the same operational

Table 9 Experimental design and response statistics under PIM

No.	Control parameters					Length deviation (mm)	Product weight(g)	Energy consume(W.h)
	A	B	C	D	E			
1	210	50	50	2.5	14	0.572	3.465	9.7
2	210	60	55	3	15	0.718	3.47	10.1
3	210	70	60	3.5	16	0.35	3.507	10.3
4	210	80	65	4	17	0.49	3.55	10.5
5	210	90	70	4.5	18	0.165	3.651	11.1
6	215	50	55	3.5	17	0.711	3.477	9.5
7	215	60	60	4	18	0.562	3.496	9.8
8	215	70	65	4.5	14	0.481	3.546	10
9	215	80	70	2.5	15	0.382	3.693	9.9
10	215	90	50	3	16	0.76	3.434	9.6
11	220	50	60	4.5	15	0.98	3.506	9.8
12	220	60	65	2.5	16	0.455	3.567	9.7
13	220	60	70	3	17	0.031	3.758	10.1
14	220	70	50	3.5	18	0.721	3.447	9.4
15	220	90	55	4	14	0.661	3.476	9.2
16	225	50	65	3	18	0.849	3.556	9.7
17	225	60	70	3.5	14	0.149	3.682	9.4
18	225	70	50	4	15	0.825	3.445	8.5
19	225	80	55	4.5	16	0.729	3.462	9.3
20	225	90	60	2.5	17	0.706	3.492	9
21	230	50	70	4	16	0.204	3.704	9.7
22	230	60	50	4.5	17	0.787	3.472	8.8
23	230	70	55	2.5	18	0.611	3.476	8.7
24	230	80	60	3	14	0.504	3.499	8.5
25	230	90	65	3.5	15	0.391	3.578	9.1

Table 10 Test results of analysis of ANOVA for L_d in PIM

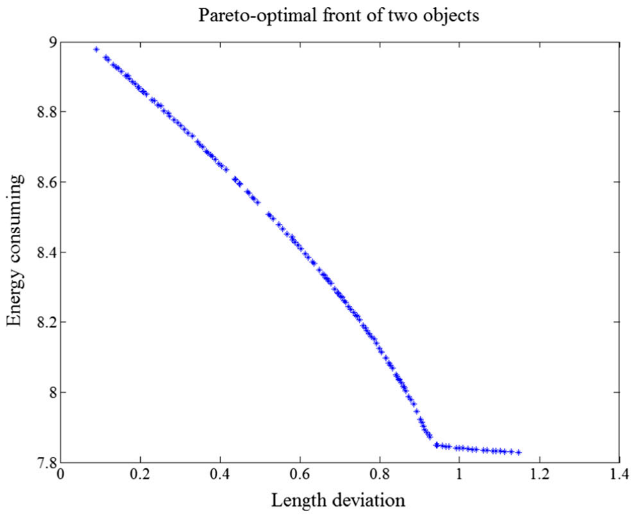
Source	DOF	Adj SS	Adj MS	F-value	P value
Regression	9	1.16901	0.12989	7.84	0
A	1	0.14802	0.14802	8.93	0.009
B	1	0.05089	0.05089	3.07	0.1
C	1	0.22159	0.22159	13.37	0.002
D	1	0.01414	0.01414	0.85	0.37
E	1	0.02043	0.02043	1.23	0.284
B*B	1	0.16855	0.16855	10.17	0.006
C*C	1	0.138	0.138	8.32	0.011
A*C	1	0.14472	0.14472	8.73	0.01
B*C	1	0.07617	0.07617	4.59	0.049
Error	15	0.24865	0.01658		
Total	24	1.41766			

Table 11 Test results of analysis of ANOVA for P_w in PIM

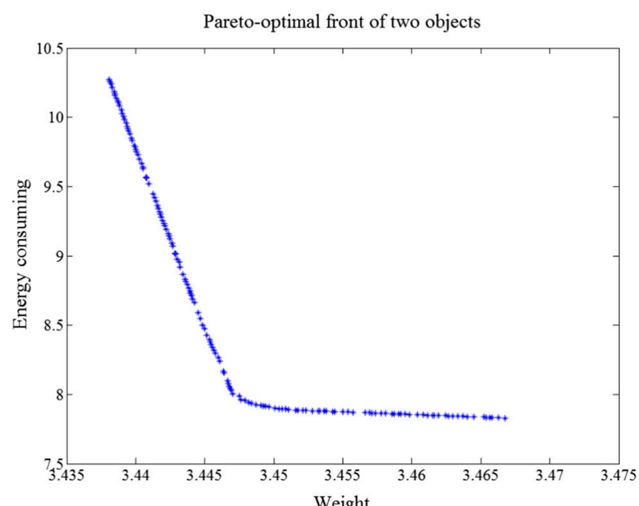
Source	DOF	Adj SS	Adj MS	F-value	P value
Regression	7	0.194988	0.027855	58.97	0
A	1	0.000129	0.000129	0.27	0.609
B	1	0.000722	0.000722	1.53	0.233
C	1	0.016518	0.016518	34.97	0
D	1	0.000691	0.000691	1.46	0.243
E	1	0.000015	0.000015	0.03	0.863
C*C	1	0.025805	0.025805	54.63	0
D*C	1	0.000836	0.000836	1.77	0.201
Total	17	0.00803	0.000472		
Error	24	0.203018			

Table 12 Test results of analysis of ANOVA for E_c in PIM

Source	DOF	Adj SS	Adj MS	F-value	P value
Regression	8	8.80819	1.10102	37.19	0
A	1	0.40398	0.40398	13.64	0.002
B	1	0.00784	0.00784	0.26	0.614
C	1	0.21851	0.21851	7.38	0.015
D	1	0.07632	0.07632	2.58	0.128
E	1	0.56494	0.56494	19.08	0
C*C	1	0.04476	0.04476	1.51	0.237
D*D	1	0.10657	0.10657	3.6	0.076
A*C	1	0.20268	0.20268	6.85	0.019
Error	16	0.47372	0.02961		
Total	24	9.2819			



(a) Pareto-optimal front of two objects for energy consuming versus length deviation



(b) Pareto-optimal front of two objects for energy consuming versus product weight

Fig. 7 Pareto-optimal front of two objectives

method and parameter setting were applied to optimize the two objectives (energy consuming and product weight). Then, their Pareto-optimal front with the solution set is presented in Fig. 7b. Although energy consuming is gradually decreasing as well as length deviation and product weight both rise up on the whole, the energy consuming turns to fall slowly and change a little after it goes through the critical point. It means that length deviation and weight become undesirability with the decrease of energy consuming. On the contrary, high quality (low length deviation and small weight) has to pay the price for energy consuming.

What is more, length deviation, energy consuming and product weight are all regarded as three optimization goals using NSGA-II, and the optimization models with the operational parameters were set as follows:

(1). Min f(x) = {length deviation, energy consuming, product weight}.
(2). Population size = 200
(3). Maximum number of generations = 600
(4). Mutation probability = 0.25
(5). Crossover probability = 0.8

Nine better Pareto-optimal solutions from the whole solutions are obtained at the end of NSGA-II operation and shown in Table 13, and Pareto-optimal front of three-objective optimization is shown in Fig. 8. It can be found that length deviation, energy consuming and product weight cannot come to the best simultaneously, and thus they should make a compromise that length deviation and weight are as small as possible under acceptable energy consuming. Considering the actual requirements of processing, the black circle presents the best optimal solutions for PIM. The Pareto-optimal solutions in the black circle can keep the balance between high quality and low energy consuming.

Table 13 Nine better Pareto-optimal solutions for three optimization goals in PIM

No.	Control parameters					Length deviation (mm)	Product weight(g)	Energy consume(W.h)
	A	B	C	D	E			
1	210.0	90.0	51.7	2.5	18.0	0.626	3.438	10.274
2	216.8	87.3	51.4	2.5	17.5	0.725	3.442	9.599
3	227.7	88.9	51.4	2.6	14.9	1.074	3.447	8.291
4	226.8	88.2	53.0	2.5	15.0	0.988	3.448	8.463
5	229.2	89.0	54.1	2.5	14.1	1.027	3.452	8.207
6	230.0	63.2	50.1	2.8	14.1	0.952	3.461	7.860
7	229.0	74.6	64.4	4.4	18.0	0.148	3.552	9.738
8	227.3	75.8	65.3	4.4	17.8	0.111	3.568	9.859
9	230.0	79.6	66.4	3.0	14.0	0.132	3.609	8.943

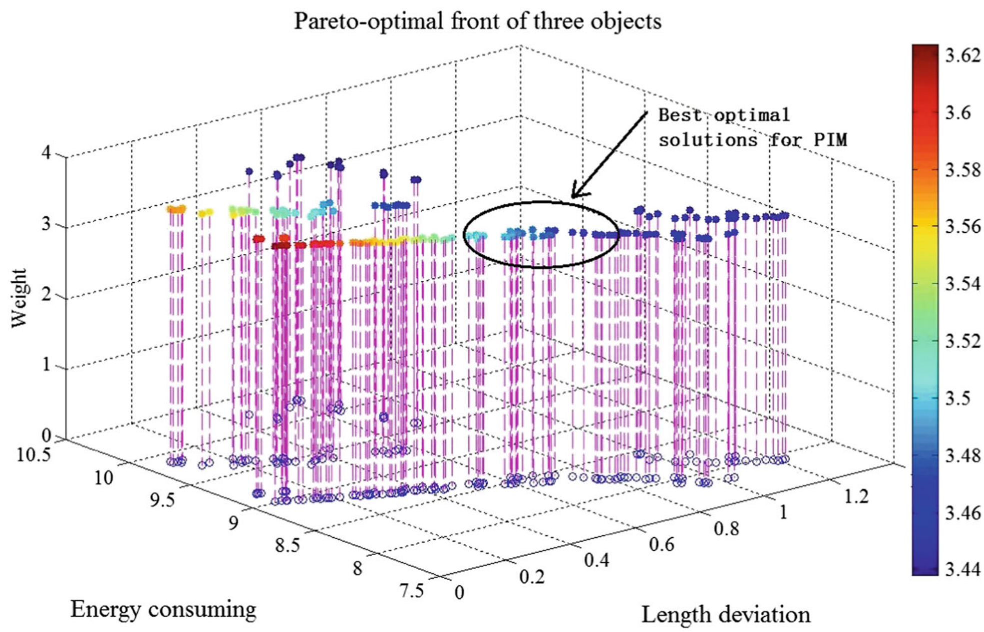


Fig. 8 Pareto-optimal front of three objectives

4.4 Confirm experiment

In order to validate the Pareto-optimal front of three objectives, some verification experiment were done, which is listed in the Table 14.The mean prediction error (MPE) is given by the following Equation

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\frac{abs(Y_i - Y_i^*)}{Y_i} \times 100 \tag{7}$$

where, the n is the total number of testing pattern, the Y_i is the experimental result of i^{th} testing pattern, and the Y_i^* is the prediction result of i^{th} testing pattern. It can be concluded that the combination of optimized process parameters is meet to the prediction accuracy, since the mean prediction errors of all are no more than 15 %.

5 Discussions

Injection molding parameter settings are affected by the cost of production. According to previous studies, in premanufacturing, the parameter setting combinations are generally determined based on the engineers' practical field related experiences or through empirical methods, trial-and-error methods, and experimental designs. These methods tend to be costly in terms of both time and money, and the obtained process parameters are not usually optimal. Therefore, the multi-objective optimization of injection molding process parameters are put forward by two stages in this paper, and the multiple quality characteristics and energy efficiency are concerned using Taguchi method and NSGA-II.

In the first stage, the parameters, such as melt temperature, injection velocity, packing pressure, packing time, and cooling time, are selected by simulation method in widely range. By the S/N ratio method and ANOVA analysis, it

Table 14 Verification experimental results for Pareto-optimal front of three objectives in PIM

No.	Control parameters					Experimental result			Optimized result			Prediction error		
	A	B	C	D	E	Length deviation (mm)	Product weight (g)	Energy consume (W.h)	Length deviation (mm)	Product weight (g)	Energy consume (W.h)	Length deviation (%)	Product weight (%)	Energy consume (%)
1	216.8	87.3	51.4	2.5	17.5	0.724	3.513	9.8	0.725	3.442	9.599	0.14	2.02	2.05
2	226.8	88.2	53.0	2.5	15.0	0.853	3.573	9.2	0.988	3.448	8.463	15.83	3.50	8.01
3	230.0	63.2	50.1	2.8	14.1	0.815	3.505	8.8	0.952	3.461	7.860	16.81	1.26	10.68
Mean												10.93	2.26	6.91

shows that melt temperature has the extremely important effect on both S/N ratio of product length deviation and warpage. Then, the most significant process parameters can be identified for the initial optimal combinations in PIM. In addition, the range of these parameters can be narrowed for the second stage. Therefore, the precision of regression models in the second stage can obtain better than that of without CAE simulation.

In the second stage, the experimental data form the basis for the RSM analysis via the multi regression models and combine with NSGS-II to determine the optimal process parameter combinations in compliance with multi-objective product quality characteristics and energy efficiency. By this way, the achieved process parameter combinations are expected not only to enhance the stability of the injection molding process and ensure that the product length meet the specifications but also to effectively reduce product weight and energy consume. It is an emerging trend that the multi-objective optimization of product length deviation and warpage, product weight, and energy efficiency should be emphasized for green manufacturing.

As it is shown in this paper, the merits of both DOE method and CAE method have been enhanced. By this method, the parameter setting combinations can be selected under the Pareto solutions of multi-objective optimization. The choice is not only for the two objects optimizations but also for the three objects optimizations.

6 Conclusions

In this investigation, the multi-objective optimization of injection molding process parameters was put forward by two stages, and the multiple quality characteristics and energy efficiency are concerned using Taguchi method and NSGA-II. The obtained results are summarized as follows:

(1) It shows that the melt temperature has an extremely important effect on both S/N ratio of product length deviation and warpage in CAE simulation. And the optimal parameters for them are melt temperature = 230 °C, injection velocity = 90 mm/s, packing pressure = 65Mpa, packing time = 4.5s, and cooling time =5s.

(2) To obtain the multi-objective optimization in the second stage, the regression models for $\boldsymbol{L}_d$,$\boldsymbol{P}_w$ and $\boldsymbol{E}_c$ can be accepted as far as $R^2$are concerned, in which R^2 for them are 82.46, 96.04, and 94.9 %, respectively.

(3) Using NSGA-II algorithm, the two-objective and three-objective optimizations can offer the optimal parameter settings with minimum length deviation, product weight and energy consuming, in which the mean prediction errors of all are no more than 15 %. And the most suitable process parameter combinations can be obtained from Pareto-optimal solutions according to the requirement of the manufacturing engineer.

Acknowledgments This research is supported by the National Science and Technology Supporting Plan under Grant No. 2013 BAF03B01. In addition, this work is supported by National Natural Science Foundation of China (NSFC) under Grant No. 51505084 and by the Natural Science Foundation of Hubei Province of China under Grant No. 2013CFB063.

References

1. Kashyap S, Datta D (2015) Process parameter optimization of plastic injection molding: a review[J]. Int. J. Plast. Technol. doi:10.1007/s12588-015-9115-2
2. Michael P, Christian G, Wan K (2015) Micro injection moulding process parameter tuning. 9th CIRP Conference on Intelligent Computation in Manufacturing Engineering-CIRP ICME ’14 Procedia CIRP 33:400–405
3. Sahu R, Yao DG, Kim B (1997) Optimal mold design methodology to minimize warpage in injection molded parts. Technical papers of the 55th SPE ANTEC Annual Technical Conference 3:3308–3312
4. Ozcelik B, Erzurumlu T (2006) Comparison of the warpage optimization in the plastic injection molding usingANOVA, neural network model and genetic algorithm. J Mater Process Tech 171(3):437–445
5. Wu CH, Chen WS (2006) Injection molding and injection compression molding of three-beam grating of DVD pickup lens. Sensors Actuators A Phys 125(2):367–375
6. Tang SH, Tan YJ, Sapuan SM, Sulaiman S, Ismail N, Samin R (2007) The use of Taguchi method in the design of plastic injection mould for reducing warpage. J Mater Process Technol 182(1–3):418–426
7. Fei NC, Kamaruddin S, Siddiquee AN, Khan ZA (2011) Experimental investigation on the recycled HDPE and optimization of injection moulding process parameters via Taguchi method. Int J Mech Mater Eng 6(1):81–91
8. Lam YC, Deng YM, Au CK (2006) A GA/gradient hybrid approach for injection moulding conditions optimization. Engineering with Computers 21(3):193–202
9. Ozcelik B, Erzurumlu T (2006) Comparison of the warpage optimization in the plastic injection molding using ANOVA, neural network model and genetic algorithm. Mater Process Technol 171(3):437–445
10. Farshi B, Gheshmi S, Miandoabchi E (2011) Optimization of injection molding process parameters using sequential simplex algorithm. Mater Des 32(1):414–423
11. Gao YH, Wang XC (2009) Surrogate-based process optimization for reducing warpage in injection molding. J Mater Process Technol 209(3):1302–1309
12. Chen WC, Liu KP, Liu B, Lai TT (2013) Optimization of optical design for developing an LED lens module. Neural Comput Applic 22(3–4):811–823
13. Mathivanan D, Parthasarathy NS (2009) Sink-mark minimization in injection molding through response surface regression modeling and genetic algorithm[J]. Int J Adv Manuf Technol 45(45):867–874

14. Mathivanan D, Parthasarathy NS (2009) Prediction of sink depths using nonlinear modeling of injection molding variables. Int J Adv Manuf Technol 43:654–663
15. Shi HC, Gao YH, Wang XC (2010) Optimization of injection molding process parameters using integrated artificial neural network model and expected improvement function method. Int J Adv Manuf Technol 48:955–962
16. Shi HC, Xie SM, Wang XC (2013) A warpage optimization method for injection molding using artificial neural network with parametric sampling evaluation strategy. Int J Adv Manuf Technol 65:343–353
17. Shie JR (2008) Optimization of injection molding process for contour distortions of polypropylene composite components by a radial basis neural network. Int J Adv Manuf Technol 36:1091–1103
18. Gang X, Yang ZT, Long GD (2012) Multi-objective optimization of MIMO plastic injection molding process conditions based on particle swarm optimization. Int J Adv Manuf Technol 58:521–531
19. Gang X, Yang ZT (2015) Multi-objective optimization of process parameters for plastic injection molding via soft computing and grey correlation analysis. Int J Adv Manuf Technol 78:525–536
20. Zhou J, Turng LS, Kramschuster A (2006) Single and multi-objective optimization for injection molding using numerical simulation with surrogate models and genetic algorithm. Int Polym Process 21:509–520
21. Chen WC, Liou PH, Chou SC (2014) An integrated parameter optimization system for MIMO plastic injection molding using soft computing. Int J Adv Manuf Technol 73:1465–1474
22. Kurtaran H, Erzurumlu T (2006) Effective warpage optimization of thin shell plastic parts using response surface methodology and genetic algorithm. Int J Adv Manuf Technol 27:468–472
23. Cheng J, Liu ZY, Tan JR (2013) Multiobjective optimization of injection molding parameters based on soft computing and variable complexity method. Int J Adv Manuf Technol 66:907–916
24. Wu CY, Ku CC, Pai HY (2011) Injection molding optimization with weld line design constraint using distributed multi-population genetic algorithm. Int J Adv Manuf Technol 52:131–141
25. Wang R, Zeng J, Feng X, Xia Y (2013) Evaluation of effect of plastic injection molding process parameters on shrinkage based on neural network simulation. J Macromol Sci B 52(1):206–221
26. Rong YM, Zhou Q, Huang Y, Chang Y, Zhang GJ, Shao XY (2015) Multi-objective optimization of laser brazing with the crimping joint using ANN and NSGA-II. Int J Adv Manuf Technol 04:1–9
27. Gholami MH, Azizi MR (2014) Constrained grinding optimization for time, cost, and surface roughness using NSGA-II. Int J Adv Manuf Technol 73:981–988
28. Bouacha K, Terrab A (2016) Hard turning behavior improvement using NSGA-II and PSO-NN hybrid model. Int J Adv Manuf Technol 15:1–20
29. Zhang G, Zhang Z, Ming W, Guo J, Huang Y, Shao X (2014) The multi-objective optimization of medium-speed WEDM process parameters for machining SKD11 steel by the hybrid method of RSM and NSGA-II. Int J Adv Manuf Technol 70(9–12):2097–2109
30. Ming W, Zhang Z, Zhang G, Huang Y, Guo J, Chen Y (2014) Multi-objective optimization of 3D-surface topography of machining YG15 in WEDM. Mater Manuf Process 29(5):514–525
31. Hsu CM, Su CT, Liao D (2003) A novel approach for optimizing the optical performance of the broadband tap coupler. Int J Syst Sci 34(3):215–226
32. Castro C, Cabrera-Rios M, Lilly B, Castro J, Mount-Campbell C (2005) Simultaneous optimization of mold design and processing conditions in injection molding. J Polym Eng 25(6):459–485
33. Peng YG, Wang J, Wei W (2014) Model predictive control of servo motor driven constant pump hydraulic system in injection molding process based on neuro dynamic optimization. J Zhejiang Univ-Sci C (Computers & Electronics) 15(2):139–146
34. Lu NY, Gong GX, Yang Y, Lu JH (2012) Multi-objective process parameter optimization for energy saving in injection molding process. J Zhejiang Univ-Sci A (Appl Phys & Eng) 13(5):382–394
35. Montgomery DC, Runger GC (2010) Applied statistics and probability for engineers [M]. Wiley
36. Deb K, Pratap A, Agarwal S, Meyarivan T (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 6(2):182–197