Int J Adv Manuf Technol (2018) 94:357–370
DOI 10.1007/s00170-017-0812-1

ORIGINAL ARTICLE

Process parameters optimization using a novel classification model for plastic injection molding

Huang Gao [1] · Yun Zhang [1] · Yang Fu [1] · Ting Mao [1] · Huamin Zhou [1] · Dequn Li [1]

Received: 10 October 2016 / Accepted: 17 July 2017 / Published online: 11 August 2017

Abstract Intelligent technology is widely used to optimize process parameters for injection molding. Traditional process parameter optimization methods for esthetic defects suffer from convergence and stability problems. This paper proposes a novel optimization method, utilizing the fact that the feasible parameter domain is usually sandwiched between two opposite defects when a parameter increases from a low level to a high level. By maximizing the margin between the opposite defects of the samples, optimized parameters are obtained by choosing the parameter combination that is furthest away from both types of defects. Background data is introduced for the initialization of the model. Two practical product experiments are conducted to verify the proposed method, and comparisons are made with the fuzzy reasoning method. The results show that the proposed optimization method has more stable convergence performance and does not suffer from the oscillation problem compared with the fuzzy reasoning method. The injection process under the optimized injection parameters obtained from the proposed method provides a much more stable product quality than traditional methods, with only half the standard deviation and a process capability index eight times higher. This method can also be used for other industry applications that share similar solution distribution characteristics.

Keywords Parameter optimization · Classification · Background data · Injection molding

✉ Yun Zhang
marblezy@hust.edu.cn

[1] State Key Laboratory of Material Processing and Die & Mold Technology, Huazhong University of Science and Technology, Wuhan 430074, People's Republic of China

1 Introduction

Injection molding is one of the most important processing methods in the plastics industry [1–3]. The quality of plastic injection-molded parts depends on the material, mold design, injection molding machine, and process parameters required to manufacture them [4, 5]. Since the material, the mold, and the injection molding machine are usually determined in the initial stage of product development, the most important task is to systematically determine the optimal process parameters. Traditionally, the injection-molding process parameters are determined through trial-and-error [6, 7] approaches by experienced molding personnel rather than through theoretical and analytical approaches. First, the personnel find a set of tentative parameters by recalling similar molded parts in their previous work. The tentative parameters are used as initial parameters for a mold trial. Subsequently, the tentative parameters are iteratively adjusted and modified according to the operator's intuition and experience until the quality of the part is found to be satisfactory. The trial-and-error process is time consuming and costly because the efficiency depends on the experience of the operator [8, 9].

Over the past decades, experimental design and optimization approaches have been widely applied to determine process parameters for plastic injection molding [10]. The main method framework includes two steps: *model fitting* and *optimization. The model fitting step aims at establishing a relationship model between the process parameters and the product quality.* The practical approach includes the response surface method (RSM), artificial neural network (ANN), radial basis function (RBF), Kriging surrogate modeling, etc. Chuang et al. [11] applied RSM to determine the optimum process parameters for thin-shell plastic parts. Shi et al. [12] proposed ANN to optimize the injection molding process of minimizing the warpage of injection-molded parts. Li et al.

[13] applied RBF to optimize the packing profile of the injection molding process. Gao et al. [14–17] developed an adaptive optimization method based on the Kriging surrogate model to minimize the warpage of injection-molded parts. *Based on the well-fitted model, the optimization method is introduced to determine the optimal parameter set to produce the best-quality product*. The practical approach is the optimizing algorithm, including the genetic algorithm (GA), particle swarm optimization (PSO), and simulated annealing (SA). Kim et al. [18] used GA to optimize the molding conditions, which consist of the mold temperature, the melt temperature, and the filling time, based on the results from flow simulation. Guo et al. [19] used GA to optimize the processing parameters to minimize the sink mark depth. Increasingly, researchers have combined fitting-based methods with optimization-based methods to obtain the optimized process parameters. Kurtaran et al. [20] combined ANN with GA to determine the best injection-molding process parameters to minimize the warpage of a bus ceiling lamp base. Tsai and Luo [21] combined ANN with GA to establish an inverse model of injection molding for optical lens to achieve improved accuracy. Chen et al. [22] adopted hybrid PSO-GA methods to determine the optimal process parameters for product length and warpage. Iniesta et al. [23] presented a hybrid of ANN and the artificial bee colony algorithm to optimize the injection-molding process parameters to minimize warpage of the plastic products. In short, by estimating the relationship model between the product qualities and process parameters, the experimental design and optimization approach has achieved great success in optimizing the process parameters.

However, the experimental design and optimization approach requires the product quality to be quantifiable. In fact, the quality of an injected part is usually defined by both quantitative features (like dimensional defects, warpage, dimensions, weight) and qualitative features (like esthetic defects, short shot, flash, sink marks, burn). Esthetic defects are determined by visual inspection, usually by the operator standing in front of the injection machine. The operator decides at that time whether the part is acceptable or not. Because esthetic defects can hardly be quantified, the relationship between the molded part defects and the process parameters can be hardly modeled using the aforementioned modeling method. Knowledge-based or expert system approaches are likely the most promising methods to address this problem [24]. Pandelidis and Kao [25] presented a knowledge-based system for the diagnosis of multiple defects in injection molding. Jan and O'Brien [26] developed an expert system for the injection molding of engineering thermoplastics, and the system offers corrective action for part defects. Shelesh-Nezhad and Siores [27] proposed the idea of using rule-based reasoning to eliminate part defects. These methods were successful in some circumstances. However, due to their incomplete integration of qualitative and quantitative reasoning, a typical symbolic knowledge-based or expert system can only provide the parameter types and associated correction direction. No range of correction or crisp value is given.

To overcome shortcomings of the existing knowledge-based or expert system approaches, He et al. [24, 28] presented a fuzzy-neural approach to automatically predict the process parameter resetting and achieve better product quality. Zhou et al. [9, 29] proposed a fuzzy reasoning model to prevent esthetic defects. In their study, the seriousness of each defect is described naturally using a linguistic term set, such as {slight, medium, serious}, and the process parameter correction range was determined by the seriousness of the defects. Fuzzy reasoning can provide not only the correction direction of process parameters but also the crisp value of process parameters.

Although the fuzzy reasoning-based method provides feasible solutions that can automatically set process parameters to eliminate esthetic defects, two key issues still need to be considered. *First, there is no discussion on whether the process parameters are robust enough to ensure stability of product qualities*. Because the process of injection molding is cyclical and repetitive, the process parameters should be robust enough to overcome variations in material properties, variations in the machine, and changes in the manufacturing circumstances [6]. Consequently, the product quality stability is thought to be an important indicator for evaluating process parameter settings [30, 31]. The fuzzy reasoning-based method provides a logical reasoning framework aiming for the removal of esthetic defects, though there is no guarantee that the final process parameters are robust enough. *Second, the fuzzy reasoning-based method suffers from the convergence problem, because the input membership functions used in fuzzy reasoning applications are not fitted to the process window* [32]. This will lead to unstable production processes when the process parameters are located at the edge of the process window. In some circumstances, qualified parts can hardly be obtained when the process window is small. In particular, computer, communication, and consumer electronic (3C) products, such as portable computers and cell phones, are widely applied throughout the world. The designs of those 3C products have a tendency to be light, thin, short, and small [33, 34]. Plastic injection molding (PIM) is frequently applied to produce parts with thin-wall features in different fields. The process window of such parts is continually decreasing.

To solve the aforementioned convergence and stability problem, a novel classification model-based optimization method is proposed in this study to obtain the optimal process parameters. After describing in detail the model theory, comprehensive injection-molding experiments are conducted to exhibit the superiority, and comparisons are made with the fuzzy reasoning-based method.

2 Optimization model

2.1 Method framework

There is a feasible process zone for injection molding. This defect-free process zone is always referred to as the process window [29, 35]. Take the injection pressure and melt temperature as examples, as shown in Fig. 1. If the melt temperature is too low, a higher injection pressure is required to deliver the melt polymer into the cavities. If the melt temperature is too high, burn may occur. On the other hand, if the injection pressure is too low, a short shot may occur, while high injection pressure may cause flash. The proper process window is important for robust and stable manufacturing as well as for the optimization of process parameters [36].

The process window is usually a closed area in high dimensional space, because the number of parameters is far more than three. The process window shown in Fig. 1 is just for demonstration in the case of two parameters, and it can be established by finding four corners through dozens of mold trials. However, detecting a full set of process windows would be very difficult because of a large number of process parameters involved and complicated interactions among them. It is difficult to exactly describe such an irregular region in a multidimensional space of process parameters into a mathematical or a descriptive form. Therefore, construction of the high dimensional process window would be a very time-consuming task, in which, by finding the exact boundaries of the process window by fitting using hundreds of mold trials. Sometimes, it is even almost impossible in practice.

Based on the above reasons, the molding personnel usually seek feasible process parameters based on opposing defects rather than determining the entire process window. Short shot, flash, shrinkage, air bubbles, burn, and bump white are the most frequent esthetic defects in injection molding. Among these defects, some are caused by small process parameter values, while others are caused by large process parameter values. Taking the injection velocity, packing pressure, and packing time as examples, when the values of the injection velocity, packing pressure, and packing time are small, the mold parts will suffer from short shot, shrinkage, air bubbles, and so on. With an increase in these process parameters, the defects will disappear. However, if these process parameters continue to increase, burn, flash, and bump white may appear. Thus, product defects can be divided into two opposing categories. Short shot, air bubbles, shrinkage, etc., caused by low process parameter values can be classified into one category, labeled “+1.” On the other hand, burn, flash, bump white, etc., caused by high process parameter values can be classified into the opposite category, labeled “−1,” as shown in Fig. 2. The margin border can be regarded as the process window border, and the defect-free process zone between the process window border is the process window. The optimal process parameter set is more probably located in the center of the process window. We try to find the center of the process window by means of approximation only using few mold trials, rather than finding the exact boundaries of the process window by fitting using hundreds of mold trials.

Generally, the whole process can be divided into two steps. First, the molding personnel set up a series of process parameters based on theirr experience or intuition, and then, defective products are produced. The influence of the process parameters on the product quality will be reflected in the form of product defects. Second, by analyzing the internal relationship between the process parameters and product defects, the molding personnel constantly adjust the process parameters, eliminating the product defects and finally obtaining the qualified products.

Corresponding to the previous two steps, the proposed optimization model mainly consists of sampling and parameter correction, as shown in Fig. 3. The process of sampling is to

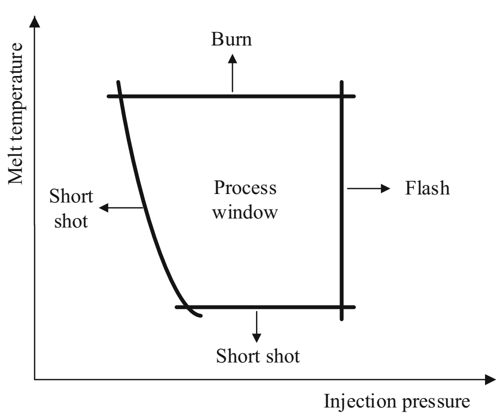


Fig. 1 Illustration of the process window with two parameters: injection pressure and melt temperature

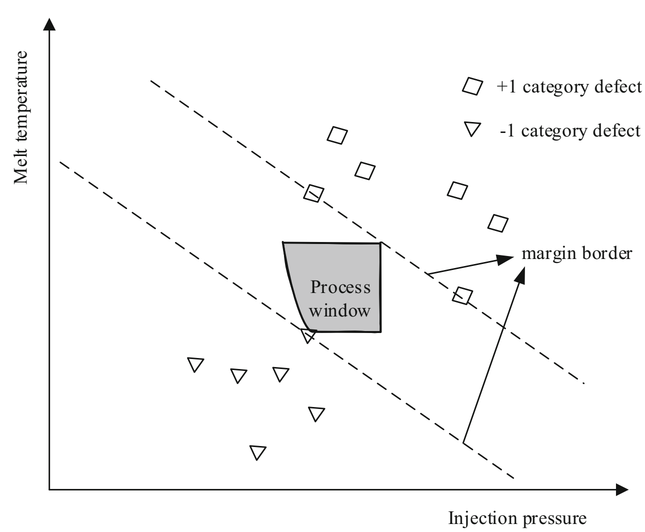


Fig. 2 The process window using opposite defects

collect sample data during mold trials. Each sample data set consists of two parts: the process parameters and their corresponding product defect category. The process of parameter correction is to obtain the optimal process parameters using a novel classification model based on sample data. The parameter correction procedure is repeated until a fully successful part, without any defects, is obtained.

2.2 Sampling

2.2.1 Sample data

During the mold trials, a series of defective products will be produced. The product defect category and the corresponding process parameter set constitute the sample data, defined as

$$S=\{S_1,S_2,\cdots,S_i,\cdots,S_l\}$$
$$=\{(x_1,y_1),(x_2,y_2),\cdots,(x_i,y_i),\cdots,(x_l,y_l)\} \tag{1}$$

$$x_i=\left\{a_i^1,a_i^2,\cdots,a_i^n\right\},\quad y_i\in\{-1,+1\} \tag{2}$$

where S represents the sample data set, $S_1, S_2, \cdots, S_i, \cdots, S_l$ are the sample data, x_i is the process parameter set, and a_i^1, $a_i^2, \cdots, a_i^n$ denote the process parameters. $y_i \in \{-1,+1\}$ represents the product defect category. l denotes the number of sample data points. The sample data is obtained by mold trials.

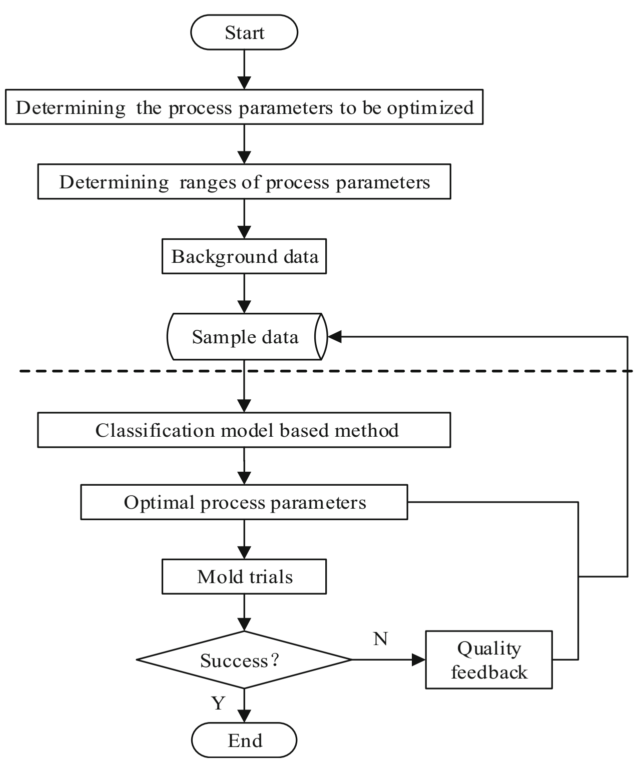


Fig. 3 The framework of the proposed optimization model

Considering the fact that varying process parameter ranges differ greatly from each other due to their diversity, the sample data is normalized by Eq. (3), and the optimal process parameters are un-normalized by Eq. (4)

$$x^{'}=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \tag{3}$$

$$x=x^{'}\times(x_{\max}-x_{\min})+x_{\min} \tag{4}$$

where x is the original data, $x^{'}$ is the normalized data, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of x.

Sample data is obtained by the actual mold trials, which first requires changing the corresponding process parameters, followed by a mold trial and finally observing the product quality. Thus, the acquisition of sample data is a time-consuming process. In particular, some process parameters, such as the nozzle temperature and barrel temperature, are easy to increase but take a long time to decrease.

2.2.2 Background data

In the beginning, there is no sample data, and instead, background data are applied. Background data is a kind of exaggerated data comprised of prior knowledge of defect correction rules. Background data is equivalent to the implicit representation of these rules. Background data has universal applicability, which is suitable for different materials, molds, and machines. Background data has two main effects. First, in the absence of sample data, background data is used as sample data. Second, background data is used to construct the extreme process parameter adjustment direction. Background data is determined by the operators. Taking the injection velocity, packing pressure, and packing time as examples, if the values of the injection velocity, packing pressure, and packing time are very low, parts with +1 category defects will be produced. To obtain qualified parts, these process parameters should be increased. In contrast, high injection velocities, packing pressures, and packing times will lead to −1 category

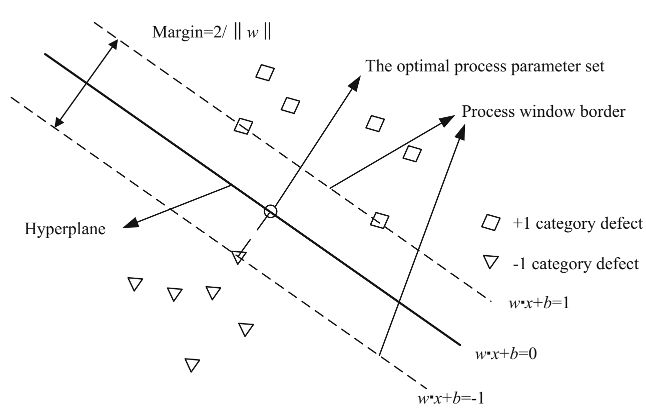
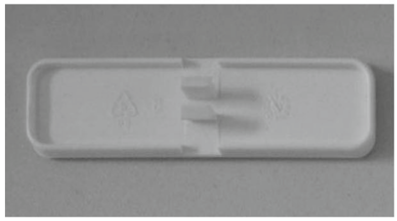


Fig. 4 The schematic diagram of the maximum process window border

Table 1 The part geometry and experimental setup for the two parts

Property	Buckle	Mobile phone shell
Parts cavity geometry		
Plastic material	PS	PC/ABS
Molding machine	JSW J110ADC-180H	
Optimized process parameters	injection velocity packing pressure packing time	injection velocity packing pressure packing time back pressure screw rotation speed

defect parts. These process parameters should be decreased to obtain qualified parts. When collecting background data, +1 category and −1 category data are both required.

Background data is artificially constructed and thus does not need actual mold trials and is easily obtained. Background data is particularly useful when there is no sample data, and the molding personnel have no experience and do not know how to obtain sample data. Thus, background data can not only reduce the number of mold trials but can also reduce the required molding personnel experience.

2.3 Parameter corrections based on the classification model

2.3.1 Maximum process window border method

Given a set of l sample data $\{(x_1, y_1), (x_2, y_2), \cdots, (x_l, y_l)\}$, where $x_i = \left\{a_i^1, a_i^2, \cdots, a_i^n\right\}$ and $y_i \in \{-1, +1\}$, the goal is to find a plane that separates the positive and negative sample data without error [37]. There are various planes that can separate the positive and negative sample data. The maximum process window border method consists of finding the hyperplane that correctly separates the sample data and maximizes the distance between the closest sample data and the hyperplane. The distance between the process window borders is known as the margin, as shown in Fig. 4. The larger the margin, the wider the process window, and the more robust the process will be.

The hyperplane equation can be expressed as

$$w \bullet x + b = 0 \tag{5}$$

where w is an n-dimensional row vector and b is a bias.

The decision function is

$$f(x) = \mathrm{sign}[w \bullet x + b] \tag{6}$$

Without loss of generality, it is appropriate to consider a canonical hyperplane, where the parameters w and b are constrained by

$$\min_i |w \bullet x_i + b| = 1 \tag{7}$$

The distance of a sample data point to the hyperplane is

$$d(w, b; x) = \frac{|w \bullet x + b|}{||w||} \tag{8}$$

The optimal hyperplane is given by maximizing the margin, subject to the constraints of Eq. (8). The margin is given by

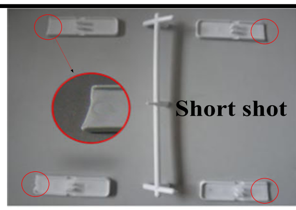
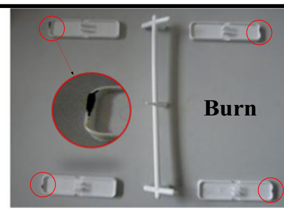
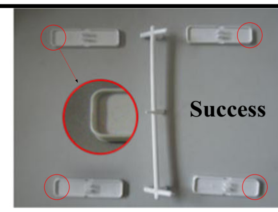
$$\begin{aligned} \text{margin} &= \min_{x_i : y_i = -1} d(w, b; x_i) + \min_{x_i : y_i = 1} d(w, b; x_i) \\ &= \min_{x_i : y_i = -1} \frac{|w \bullet x_i + b|}{||w||} + \min_{x_i : y_i = 1} \frac{|w \bullet x_i + b|}{||w||} \\ &= \frac{1}{||w||} \left(\min_{x_i : y_i = -1} |w \bullet x_i + b| + \min_{x_i : y_i = 1} |w \bullet x_i + b| \right) \\ &= \frac{2}{||w||} \end{aligned} \tag{9}$$

Thus, the process window border expressions are $w \bullet x + b = +1$ and $w \bullet x + b = -1$. The area between the process window borders is the molding area. The area outside the

Table 2 Constraints of the process parameters

Process parameter	Lower limit	Upper limit
Injection velocity (mm/s)	0	350
Packing pressure (MPa)	0	240
Packing time (s)	0.02	2

Table 3 Optimization of the process parameters for the buckle

Trial no.	First	Second	Third
Defects			
Training data	Background data	Background data, S_1	Background data, S_1, S_2
Process parameter set	$x_1 = (175, 130.5, 1.1)$	$x_2 = (240, 178, 1.38)$	$x_3 = (210, 150.3, 1.25)$
Feedback	$y_1 = +1$	$y_2 = -1$	Success

process window borders consists of the −1 category defect area and the +1 category defect area, as shown in Fig. 4. Formally, the constructed hyperplane must satisfy the following constraints:

$$\begin{cases} w \bullet x_i + b \geq +1 \;\; for \;\; y_i = +1 \\ w \bullet x_i + b \leq -1 \;\; for \;\; y_i = -1 \end{cases} \tag{10}$$

where x_i denotes a vector of the process parameters, y_i represents the product defect category, and l is the number of sample data points.

Maximizing $\frac{2}{||w||}$ means minimizing $\frac{1}{2}||w|^2$. Thus, the problem of determining the maximum process window border can be converted into a convex optimization problem:

$$\begin{cases} \min\limits_{w,b} \;\; \frac{1}{2}||w|^2 \\ s.t. \;\; y_i\left(w^T \bullet x_i + \mathrm{b}\right) \geq 1, \;\; i = 1, \cdots, l. \end{cases} \tag{11}$$

The Lagrangian is given by

$$L(w, b, \lambda) = \frac{1}{2}||w|^2 - \sum_{i=1}^{l} \lambda_i \left[y_i\left(w^T \bullet x_i + \mathrm{b}\right) - 1\right] \tag{12}$$

where λ_i represents a non-negative Lagrangian multiplier. It is well known from optimization theory that the solution is characterized by the saddle point of the Lagrangian:

$$\max_{\lambda} \min_{w,b} L(w, b, \lambda) \tag{13}$$

One obtains

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \rightarrow w = \sum\limits_{i=1}^{l} \lambda_i y_i x_i \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum\limits_{i=1}^{l} \lambda_i y_i = 0 \end{cases} \tag{14}$$

By replacing w in the Lagrangian, the following dual problem is obtained:

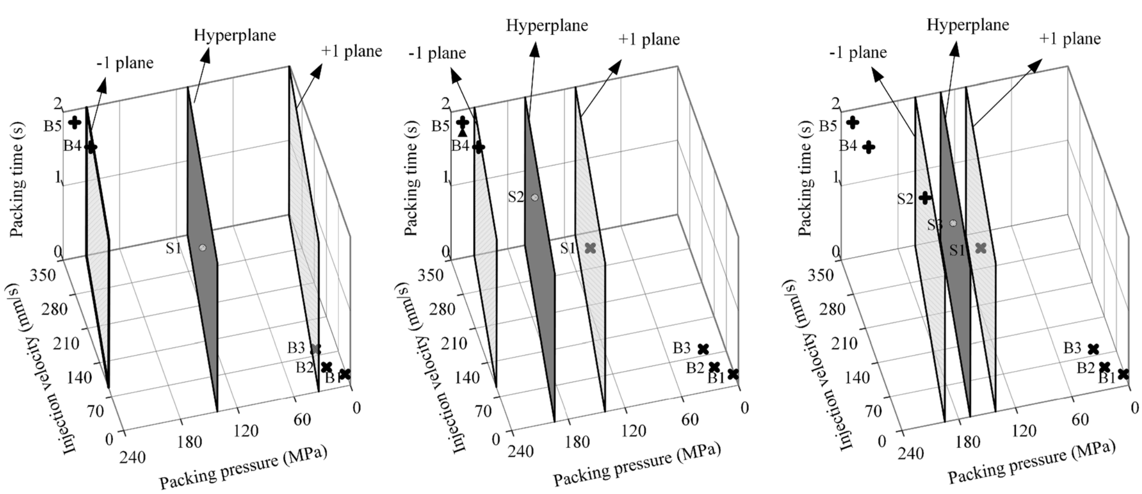


Fig. 5 The process window of **a** the first trial run, **b** the second trial run, and **c** the third trial run

Fig. 6 Molded parts (mobile phone shell) using a large adjustment range: **a** the first trial run, **b** the second trial run, **c** the third trial run, **d** the fourth trial run, and **e** the fifth trial run

$$\begin{cases} \min \ \frac{1}{2} \sum_{h=1}^{l} \sum_{i=1}^{l} y_h y_i \lambda_h \lambda_i (x_h x_i) - \sum_{h=1}^{l} \lambda_h \\ s.t. \quad \sum_{i=1}^{l} y_i \lambda_i = 0 \end{cases} \tag{15}$$

where λ_i and λ_h represent non-negative Lagrangian multipliers.

The optimal value set is

$$\lambda^* = \left(\lambda^*{}_1, \ldots\ldots, \lambda^*{}_l\right)^T \tag{16}$$

Thus,

$$w = \sum_{i=1}^{l} y_i \lambda^*{}_i x_i \tag{17}$$

$$b = y_d - \sum_{i=1}^{l} y_i \lambda^*{}_i (x_i \cdot x_d) \tag{18}$$

where λ_d^* is a non-zero value of set λ^*, x_d represents the process parameter combination corresponding to λ_d^*, and y_d denotes the defect category corresponding to λ_d^*. Thus, the hyperplane equation is obtained.

2.3.2 Parameter correction using the maximum process window border

Once the hyperplane is determined, the following most important task is to determine the sample data closest to the hyperplane. The projection point of the sample data on the hyperplane is the point at which the optimal process parameter set is located.

The distance s_i for each sample data set to the hyperplane is

$$s_i = \frac{|w \bullet x_i + b|}{||w||}, i = 1, \cdots, l \tag{19}$$

Then, the value of $|s_i|$ is compared to determine the value of $s_{\min}$. Next, the process parameter set $x_{\min}$ for the minimum distance is obtained.

$$s_{\min} = \min||s_i||, i = 1, \cdots, l \tag{20}$$

$$x_{\min} = \left\{a_{\min}^1, a_{\min}^2, \cdots, a_{\min}^n\right\} \tag{21}$$

where $a_{\min}^1, a_{\min}^2, \cdots, a_{\min}^n$ are the process parameters of the minimum distance.

The optimal process parameter set $x_{opt} = \left\{\alpha_{opt}^1, \alpha_{opt}^2, \cdots, \alpha_{opt}^n\right\}$ denotes the projection point of $x_{\min}$ on the hyperplane.

$$\alpha_{opt}^i = \alpha_{\min}^i - \frac{|w_i|}{w_i \sum_{i=1}^{n} |w_i|} s_{\min}; i = 1, \ldots, n \tag{22}$$

where $a_{opt}^1, a_{opt}^2, \cdots, a_{opt}^n$ are the optimal process parameters.

The recommended optimal process parameter set is located on the hyperplane. The maximum process window border

Table 4 The main process parameters and their adjustments in the mold trials for the mobile phone shell

Trial no.		First	Second	Third	Fourth	Fifth	Sixth	…
Feedback			Short shot, Serious	Short shot, Serious	Short shot, Slight	Flash, Slight	Short shot, Slight	…
Process parameters	Injection velocity (mm/s)	90	+60	+60	+20	−20	+20	…
	Packing pressure (MPa)	88.2	+24	+24	+8	−8	+8	…
	Packing time (s)	0.1	+0.4	+0.4	+0.13	−0.13	+0.13	…
	Screw rotation speed (rpm)	156	+40	+40	+13	−13	+13	…
	Back pressure (MPa)	5.6	+6	+6	+2	−2	+2	…

(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 7 Molded parts (mobile phone shell) using a small adjustment range: **a** the first trial run, **b** the second trial run, **c** the third trial run, **d** the fourth trial run, **e** the fifth trial run, **f** the sixth trial run, **g** the seventh trial run, **h** the eighth trial run, and **i** the ninth trial run

method ensures the farthest distance between the recommended process parameters and the defect areas, which guarantees that the recommended process parameters are optimal.

3 Experimental setup

All experiments were carried out on a JSW J110ADC-180H electric precision injection-molding machine, which is well known for its high repeat accuracy and excellent stability. The main technical details of the machine are listed in Table 9. The device to measure part weight is METTLER TOLEDO ME 204 with a precision of 0.0001 g.

Two parts in practical production were used to verify the feasibility and effectiveness of the proposed method. Part geometry and experimental setup for the two parts are listed in Table 1. To reduce the influence of the previous process parameters on the molding process and to ensure the reliability of the results, each batch of process parameters was repeated five times, and the last time was selected as the experimental results. To obtain qualified parts, the process parameters' need to be adjusted were determined according to part characteristics. The esthetic defects of the parts were judged by the molding personnel and the stability of the part was measured by the weight deviation.

In the experiment, the buckle was thought to be easily molded and has a very big process window. A successful part can be obtained by adjusting a small number of process parameters. Through experiments and product feature analysis, qualified parts can be obtained by adjusting the injection velocity, packing pressure, and packing time. Thus, the injection velocity, packing pressure, and packing time were selected as the optimized process parameters. The mobile phone shell was thought to be a thin-wall plastic product and has very high demand for esthetic. It would be hard to mold and has a very small process window. For this part, the injection velocity, packing pressure, packing time, screw rotation speed, and back pressure were selected as the optimized process parameters.

4 Results and discussions

4.1 Verification and validation

The optimization of the process parameters by the proposed method was first verified and validated for the buckle, and the injection velocity, packing pressure, and packing time were selected as the optimized process parameters. The constraints on the process parameter set $x_i = \left(\alpha_i^1, \alpha_i^2, \alpha_i^3\right)$ are listed in Table 2, where α_i^1 represents the injection velocity, α_i^2 denotes the packing pressure, and α_i^3 is the packing time. Other major process parameters are listed in Table 10. The background data is listed in Table 11.

Table 5 The main process parameters and their adjustments in the mold trials for the mobile phone shell

Trial no.		First	Second	Third	Fourth	Fifth	Sixth	Seventh	Eighth	Ninth
Feedback			Short shot, serious	Short shot, serious	Short shot, serious	Short shot, serious	Short shot, serious	Short shot, serious	Short shot, serious	Sink, slight
Process parameters	Injection velocity (mm/s)	90	+18	+18	+18	+18	+18	+18	+18	+0
	Packing pressure (MPa)	88.2	+7.2	+7.2	+7.2	+7.2	+7.2	+7.2	+7.2	+2.4
	Packing time (s)	0.1	+0.12	+0.12	+0.12	+0.12	+0.12	+0.12	+0.12	+0.04
	Screw rotation speed (rpm)	156	+12	+12	+12	+12	+12	+12	+12	+0
	Back pressure (MPa)	5.6	+1.8	+1.8	+1.8	+1.8	+1.8	+1.8	+1.8	+0.6

Table 6 The main process parameters and their adjustments in the mold trials for the proposed method

	Trial no.	First	Second	Third	Fourth
	Defects				
	Training data	Background data 1	Background data 1, S_1	Background data 1, S_1, S_2	Background data 1, S_1, S_2, S_3
Process parameters	Injection velocity (mm/s)	232	-131	+105	+12
	Packing pressure (MPa)	149.9	-97.7	+81.3	+6.7
	Packing time (s)	1.03	-0.58	+0.46	+0.07
	Screw rotation speed (rpm)	237	-58	+46	+6
	Back pressure (MPa)	20.2	-12.3	+10.7	+1
	Feedback	$y_1 = -1$	$y_2 = +1$	$y_3 = +1$	Success

The optimization process of the process parameters for the buckle is listed in Table 3. The first optimized process parameter set x_1 was obtained by constructing the maximum process window border based on background data. These process parameters were then applied to the injection-molding machine for a mold trial. A part with short shot defects was obtained. At the same time, a new sample data set $S_1 = (x_1, y_1)$ was formed. The second optimized process parameter set x_2 was obtained by constructing the maximum process window border based on the new sample data set S_1 and the background data. These parameters were then applied to the injection-molding machine for the next mold trial. In this case, a part with burn defects was obtained. Similarly, the third process parameter set x_3 was obtained, and the third mold trial was carried out, which produced a fully successful part without any defects. Thus, the optimized process parameters were obtained in a very short time.

To provide a more intuitive view of the proposed method, the process window of the process parameters for each mold trial is displayed in the form of graphics, as shown in Fig. 5. The leftmost planes are −1 planes. The upper left area of the −1 plane is the −1 category defect area. The sample data located in the upper left of the −1 plane belongs to the −1 category. The rightmost planes are +1 planes. The bottom right area of the +1 plane is the +1 category defect area. The sample data located in the bottom right of the +1 plane belongs to the +1 category. The area between the +1 plane and the −1 plane is the molding area. The hyperplane is the gray plane located in the middle of the molding area. The recommended optimized process parameter set is located on the hyperplane. From Fig. 5a to c, it can be seen that the optimal process parameter set was located in the center of the process window, far from the process window border. Thus, the

Fig. 8 Adjustment process of the **a** injection velocity, **b** packing pressure, **c** packing time, **d** screw rotation speed, and **e** back pressure

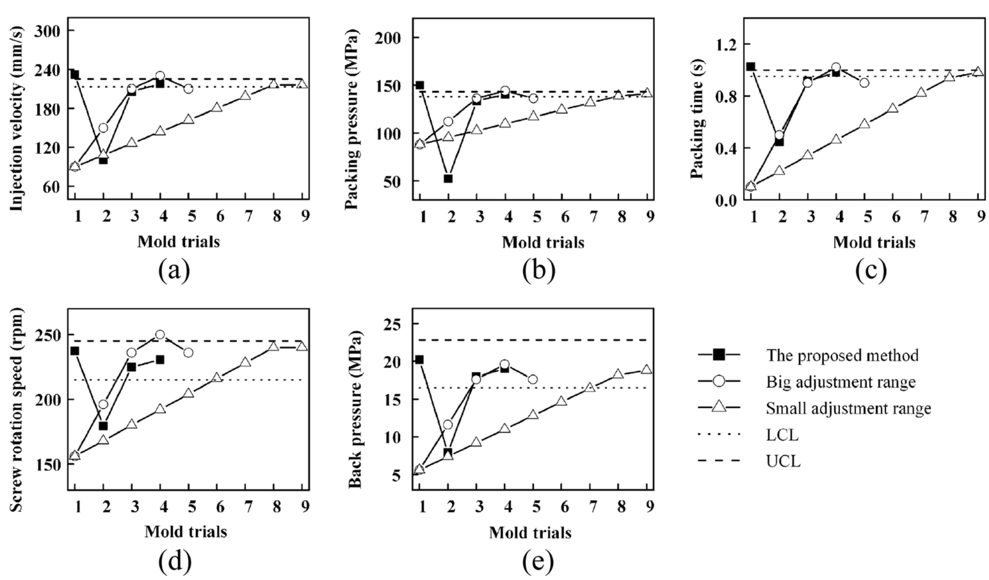


Table 7 The optimal process parameters for the confirmation experiment

	Injection velocity (mm/s)	Packing pressure (MPa)	Packing time (s)	Screw rotation speed (rpm)	Back pressure (MPa)
Background data 1	218	140.2	0.98	231	19
Background data 2	220	140.4	0.97	228	18.8

stability of the product quality is well guaranteed. In addition, the proposed method is a history-based method, for which, each mold trial data set was used as the sample data for the next mold trial. With an increase in the number of mold trials, the molding area decreases, and the adjustment ranges of the process parameters constantly converge until qualified products are produced, which is especially critical for the parts that are difficult to manufacture and have a narrow process window.

4.2 Convergence analysis

The convergence of the proposed method was examined for the mobile phone shell. For this part, the injection velocity, packing pressure, packing time, screw rotation speed, and back pressure were selected as the optimized process parameters. A convergence comparison is made with the fuzzy reasoning-based method of Zhou et al. [9].

In the fuzzy reasoning-based method, the main initial process parameters of the mobile phone shell were determined by the preliminary optimization and simplified model. These parameters were then applied to the injection-molding machine for the next mold trial. The molded part from the first trial run is shown in Fig. 6a, which had a serious short shot defect. This defect and its degree were fed back to the system by the operator. The process parameters were then adjusted by the fuzzy system for the first time, and these adjusted parameters were applied to the injection-molding machine for the next mold trial. This time, the degree of short shot was reduced, as shown in Fig. 6b. Repeating the process, the fuzzy reasoning-based method failed to produce a successful part, as shown in Fig. 6c. The main process parameters and their adjustments are listed in Table 4. As seen from the table, the adjustment range of the process parameters is determined by the defect type and defect degree and no convergence. If the adjustment range of the process parameters is too large and the process window is too small, a qualified part cannot be obtained, as occurred in this experiment. To verify this phenomenon, the adjustment of the process parameters was reduced to three tenths of the original. This time, a qualified part was produced after nine mold trials, as shown in Fig. 7. The main process parameters and their adjustments are listed in Table 5.

For the proposed method, the constraints on these five process parameters are listed in Table 12. The other major process parameters were the same as those determined by the fuzzy reasoning-based method. Background data 1 is listed in Table 13. The main process parameters and their adjustments in the mold trials for the proposed method are listed in Table 6. As seen from Table 6, the adjustment ranges of the process parameters are determined by the background data and the historical mold trial data. As the

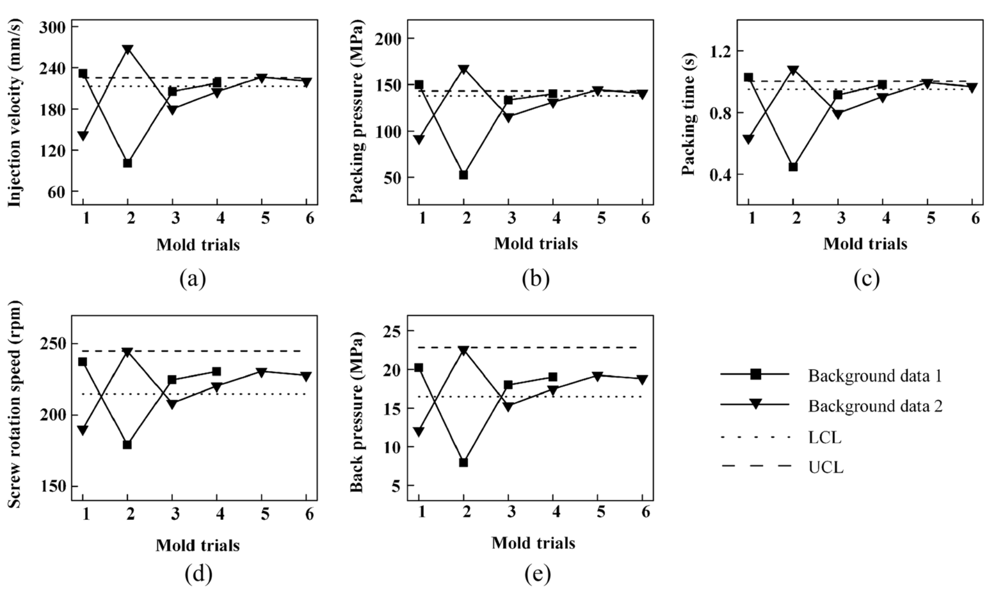


Fig. 9 Adjustment process for different background data for the **a** injection velocity, **b** packing pressure, **c** packing time, **d** screw rotation speed, and **e** back pressure

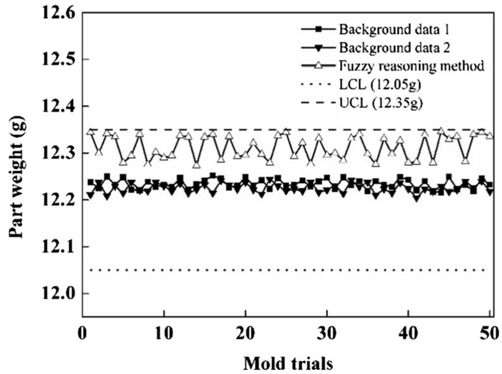


Fig. 10 Comparison of the part weights from the proposed method and the fuzzy reasoning method

mold trial progressed, the adjustment of the process parameters continued convergence, and a qualified part was obtained after four mold trials. In addition, in the fuzzy reasoning process, the defect type and the seriousness of each defect are fed back into the system. However, it should be noted that the seriousness of each defect is evaluated by the operator without uniform standards, which may lead to bias for different operators. On the other hand, the proposed method only focuses on the type of defects and not the seriousness of each defect. Thus, there is no operator bias for the proposed method.

To further illustrate the convergence of the proposed method, the process window borders of the process parameters were determined by experiment, as shown in Fig. 8. LCL and UCL are the process window borders of the process parameters. Taking the packing pressure for example, the LCL value is 138 MPa, the UCL value is 143.1 MPa, and the process window width is 5.1 MPa. In the fuzzy reasoning-based method, the adjustment ranges of the process parameters are determined by the defect type, defect degree, and adjustment range value setting. If the adjustment range is too large, as listed in Table 4, the minimum adjustment range of the packing pressure is 8 MPa, which is larger than the process window width. Thus, qualified parts cannot be obtained. By reducing the adjustment range to one third of the original values, as listed in Table 5, the minimum adjustment range of the packing pressure is 2.4 MPa, which is smaller than the process window width. This time, a successful part was obtained. However, the mold trial number was greatly increased, which greatly increased the mold trial time and material consumption. For the proposed method, with an increase in the number of mold trials, the molding area decreases, and the adjustment ranges of the process parameters constantly converge until qualified products are produced, which is especially critical for parts that are difficult to manufacture and have a narrow process window.

4.3 Stability analysis

The purpose of this section is to verify the stability of the proposed method. The stability verification is divided into two parts: the stability of the different background data and the stability of the production process. Both experiments were carried out on the mobile phone shell.

4.3.1 Stability of different background data

To illustrate the stability of the proposed method for different background data, a new background data set, called background data 2, was used in a comparative experiment, as listed in Table 14. The final optimized process parameters for background data 1 and background data 2 are listed in Table 7. The optimization processes for the different background data sets are shown in Fig. 9. LCL and UCL are the process window borders of the process parameters. It can be seen that the background data has some impact on the correction history but does not affect the final result. Taking the packing pressure for example, as shown in Fig. 9b, the process window of the packing pressure is very narrow, between 138 and 143.1 MPa. For background data 1, after four mold trials, the packing pressure converges to 140.2 MPa, which is located in the middle of the process window. For background data 2, although six mold trials were needed, the packing pressure also converged to 140.4 MPa, which is also located in the middle of the process window. Thus, the proposed method has very good stability for different background data.

4.3.2 Stability of the production process

Injection molding is a cyclical and repetitive process. Even if the process parameters are properly adjusted, the part quality cannot be consistent due to variabilities in the production process. To illustrate the stability of the proposed method for the

Table 8 Comparison of part weight statistics

		Average weight (g)	Standard deviation	C_{pk}
Proposed method	Background data 1	12.2343	0.0102	3.78
	Background data 2	12.2253	0.0101	4.12
Fuzzy reasoning method		12.3121	0.0242	0.52

production process, three confirmation experiments were performed. One experiment utilizes the optimal process parameters obtained from the fuzzy reasoning-based method. The other two experiments utilize the optimal process parameters obtained from the proposed method for background data 1 and background data 2.

The part weight was selected as the indicator to evaluate the process stability for the following reasons. First, this parameter has a close relationship with other quality properties (e.g., esthetic properties, dimensional properties, and mechanical properties). Second, it is a good indicator of process stability. Furthermore, it can be quantitatively measured easily with high precision [38, 39]. The target value of the part weight was 12.20 g.

To demonstrate the stability of the proposed method, 50 product samples were produced and weighed for each experiment. The statistical averages and standard deviations of the three sets of process parameters are compared to judge the superiority of the approach for determining the final optimal process parameters. In addition, the process capability index was also compared.

The process capability index is a statistical measure of the process capability and is an important indicator to assess the process stability.

$$C_{pk} = \min\left(\frac{UCL-\mu}{3\sigma}, \frac{\mu-LCL}{3\sigma}\right) \tag{23}$$

where C_{pk} is the process capability index, μ represents the average weight, σ denotes the standard deviation, and UCL and LCL are the upper limit and lower limit of the part weight, respectively. Usually, the practical minimum C_{pk} in many manufacturing processes is 1.33 [40, 41]. Engineers always devote great effort to determine a reasonable process parameter design for a product's production to achieve a superior C_{pk} value. Therefore, this research utilized C_{pk} as the major comparison criterion for evaluating the performances of the different approaches.

Comparisons of the part weight for the three sets of process parameters are shown in Fig. 10. The optimized part weights of the proposed method using different background data were closer to the target value, while the part weight from the fuzzy reasoning-based method was located on the edge of the acceptable part weight range. According to the results listed in Table 8, the standard deviation of the proposed method was 0.0102 and 0.0101, which was half of that of the fuzzy reasoning-based method. The C_{pk} values of the proposed method using different background data were 3.78 and 4.12, which are more than seven times that of the fuzzy reasoning-based method. All of these observations indicate that the proposed method has better stability than the fuzzy reasoning-based method. The reason for this situation is that the proposed method not only takes the process window into account but also determines the optimized process parameters located in the center of the process window. Thus, the proposed method is an effective method for process parameter optimization for injection molding.

5 Conclusions

The process parameters critically influence productivity, quality, and production costs in the plastic injection-molding industry. Stability and convergence are two important issues for determining the proper injection-molding process parameters. To solve these two issues, a novel classification model-based optimization method is proposed. The advantage of the proposed method can be concluded as follows:

1) The proposed method shows very good convergence. With an increase in the number of mold trials, the process window decreases, and the adjustment ranges of the process parameters constantly converge until qualified products are produced, which is especially critical for parts that are difficult to manufacture and have a narrow process window. The fuzzy reasoning-based method cannot solve this problem.
2) The proposed method has better product quality stability than the fuzzy reasoning-based method. The optimal process parameters obtained by the proposed method are located in the center of the process window. Thus, the proposed method is more robust and is able to overcome variabilities in the production process.
3) The proposed method has better learning and generalization capability. It is a history-based method, in which each mold trial data set is used as the sample data for the following mold trial. The method learns from the sample data and overcomes the difficulties of rule expression and organization.
4) There is no operator bias in the proposed method. The proposed method only considers the type of defects and does not consider the seriousness of each defect. Thus, the defect feedback is the same for different operators.

Acknowledgements The authors would like to acknowledge financial support from the National Natural Science Foundation Council of China (Grant No. 51675199, 51635006) and the National Program on Key Basic Research Project (Grant No. 2013CB035805).

Appendix

Table 9 Properties of the injection machine

Machine properties	Value
Clamp force (t)	110
Screw diameter (mm)	35
Maximum injection pressure (MPa)	260
Maximum packing pressure (MPa)	240
Maximum injection velocity (mm/s)	350

Table 10 Main process parameters employed in the mold trial

Process parameters	Value
Melt temperature (°C)	200
Mold temperature (°C)	70
Injection pressure (MPa)	230
Injection time (s)	2
Packing velocity (mm/s)	20
Cooling time (s)	15
Screw rotational speed (rpm)	150

Table 11 Background data

No.	Injection velocity (mm/s)	Packing pressure (MPa)	Packing time (s)	Category
B1	20	2	0.02	+1
B2	30	20	0.1	+1
B3	40	30	0.3	+1
B4	300	220	1.8	−1
B5	340	230	1.9	−1

Table 12 Constraints of the process parameters

Process parameter	Lower limit	Upper limit
Injection velocity (mm/s)	0	350
Packing pressure (MPa)	0	240
Packing time (s)	0	1.5
Screw rotation speed (rpm)	130	300
Back pressure (MPa)	0	30

Table 13 Background data 1

No	Injection velocity (mm/s)	Packing pressure (MPa)	Packing time (s)	Screw rotation speed (rpm)	Back pressure (MPa)	Category
1	10	1	0.02	131	0.1	+1
2	20	1.5	0.1	140	1	+1
3	340	218	1.49	290	29.5	−1
4	330	219	1.5	295	29.9	−1

Table 14 Background data 2

No	Injection velocity (mm/s)	Packing pressure (MPa)	Packing time (s)	Screw rotation speed (rpm)	Back pressure (MPa)	Category
1	50	4	0.1	135	2	+1
2	60	40	0.28	150	5	+1
3	320	200	1.3	270	27	−1
4	330	210	1.35	280	28	−1

References

1. Tang SH, Tan YJ, Sapuan SM, Sulaiman S, Ismail N, Samin R (2006) The use of Taguchi method in the design of plastic injection mould for reducing warpage. J Mater Process Technol 182(1–3):418–426. doi:10.1016/j.jmatprotec.2006.08.025
2. Kuo C-FJ, Dewantoro G, Huang C-C (2015) Optimization of injection-molded light guide plate with microstructures by using reciprocal comparisons. J Intell Manuf 26(4):677–690. doi:10.1007/s10845-013-0826-y
3. Zhao P, Zhou HM, He Y, Cai K, Fu JZ (2014) A nondestructive online method for monitoring the injection molding process by collecting and analyzing machine running data. Int J Adv Manuf Technol 72(5–8):765–777. doi:10.1007/s00170-014-5711-0
4. Zhao J, Cheng G (2015) An innovative surrogate-based searching method for reducing warpage and cycle time in injection molding. Adv Polym Technol 35:288–297. doi:10.1002/adv.21554
5. Chen W-C, Nguyen M-H, Chiu W-H, Chen T-N, Tai P-H (2016) Optimization of the plastic injection molding process using the Taguchi method, RSM, and hybrid GA-PSO. Int J Adv Manuf Technol 83(9):1873–1886. doi:10.1007/s00170-015-7683-0
6. Chen Z, Turng L-S (2005) A review of current developments in process and quality control for injection molding. Adv Polym Technol 24(3):165–182. doi:10.1002/adv.20046

7. Cheng J, Liu Z, Tan J (2013) Multiobjective optimization of injection molding parameters based on soft computing and variable complexity method. Int J Adv Manuf Technol 66(5–8):907–916. doi:10.1007/s00170-012-4376-9
8. Chen WC, Kurniawan D (2014) Process parameters optimization for multiple quality characteristics in plastic injection molding using Taguchi method, BPNN, GA, and hybrid PSO-GA. Int J Precis Eng Manuf 15(8):1583–1593. doi:10.1007/s12541-014-0507-6
9. Zhou HM, Zhao P, Feng W (2007) An integrated intelligent system for injection molding process determination. Adv Polym Technol 26(3):191–205. doi:10.1002/adv.20097
10. Kashyap S, Datta D (2015) Process parameter optimization of plastic injection molding: a review. Int J Plast Technol 19(1):1–18. doi:10.1007/s12588-015-9115-2
11. Chuang M-T, Yang Y-K, Hsiao Y-H (2009) Modeling and optimization of injection molding process parameters for thin-shell plastic parts. Polym-Plast Technol Eng 48(7):745–753. doi:10.1080/03602550902824630
12. Shi HZ, 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(9–12):955–962. doi:10.1007/s00170-009-2346-7
13. Li C, Wang F-L, Chang Y-Q, Liu Y (2010) A modified global optimization method based on surrogate model and its application in packing profile optimization of injection molding process. Int J Adv Manuf Technol 48(5–8):505–511. doi:10.1007/s00170-009-2302-6
14. Gao Y, Wang X (2009) Surrogate-based process optimization for reducing warpage in injection molding. J Mater Process Technol 209(3):1302–1309. doi:10.1016/j.jmatprotec.2008.03.048
15. Gao Y, Wang X (2008) An effective warpage optimization method in injection molding based on the Kriging model. Int J Adv Manuf Technol 37(9–10):953–960. doi:10.1007/s00170-007-1044-6
16. Gao Y, Turng L-S, Wang X (2008) Process optimization and effects of material properties on numerical prediction of warpage for injection molding. Adv Polym Technol 27(4):199–216. doi:10.1002/adv.20138
17. Gao Y, Turng L-S, Wang X (2008) Adaptive geometry and process optimization for injection molding using the kriging surrogate model trained by numerical simulation. Adv Polym Technol 27(1):1–16. doi:10.1002/adv.20116
18. Kim SJ, Lee KI, Kim YI (1996) Optimization of injection-molding conditions using genetic algorithm. In. pp 173–180
19. Guo W, Hua L, Mao HJ (2014) Minimization of sink mark depth in injection-molded thermoplastic through design of experiments and genetic algorithm. Int J Adv Manuf Technol 72(1–4):365–375. doi:10.1007/s00170-013-5603-8
20. Kurtaran H, Ozcelik B, Erzurumlu T (2005) Warpage optimization of a bus ceiling lamp base using neural network model and genetic algorithm. J Mater Process Technol 169(2):314–319. doi:10.1016/j.jmatprotec.2005.03.013
21. Tsai K-M, Luo H-J (2014) An inverse model for injection molding of optical lens using artificial neural network coupled with genetic algorithm. J Intell Manuf 28:1–15. doi:10.1007/s10845-014-0999-z
22. 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(9–12):1465–1474. doi:10.1007/s00170-014-5941-1
23. Iniesta AA, Alcaraz JLG, Borbon MIR (2013) Optimization of injection molding process parameters by a hybrid of artificial neural network and artificial bee colony algorithm. Rev Fac Ing-Univ Antioquia 67:43–51
24. He W, Zhang YF, Lee KS, Liu TI (2001) Development of a fuzzy-neuro system for parameter resetting of injection molding. J Manuf Sci Eng 123(1):110. doi:10.1115/1.1286732
25. Pandelidis I, Kao J-F (1990) DETECTOR: a knowledge-based system for injection molding diagnostics. J Intell Manuf 1(1):49–58. doi:10.1007/bf01471341
26. Jan T-C, O'Brien K (1993) A user-friendly, interactive expert system for the injection moulding of engineering thermoplastics. Int J Adv Manuf Technol 8(1):42–51. doi:10.1007/bf01756636
27. Shelesh-Nezhad K, Siores E (1997) An intelligent system for plastic injection molding process design. J Mater Process Technol 63(1):458–462
28. He W, Zhang YF, Lee KS, Fuh JYH, Nee AYC (1998) Automated process parameter resetting for injection moulding: a fuzzy-neuro approach. J Intell Manuf 9(1):17–27. doi:10.1023/a:1008843207417
29. Li DQ, Zhou HM, Zhao P, Li Y (2009) A real-time process optimization system for injection molding. Polym Eng Sci 49(10):2031–2040. doi:10.1002/pen.21444
30. Kazmer DO, Westerdale S (2009) A model-based methodology for on-line quality control. Int J Adv Manuf Technol 42(3–4):280–292
31. Sun C-H, Chen J-H, Sheu L-J (2010) Quality control of the injection molding process using an EWMA predictor and minimum–variance controller. Int J Adv Manuf Technol 48(1–4):63–70. doi:10.1007/s00170-009-2278-2
32. Chaves ML, Vizán A, Márquez JJ, Ríos J (2010) Inspection model and correlation functions to assist in the correction of qualitative defects of injected parts. Polym Eng Sci 50(6):1268–1279
33. Chiang K-T, Chang F-P (2006) Analysis of shrinkage and warpage in an injection-molded part with a thin shell feature using the response surface methodology. Int J Adv Manuf Technol 35(5):468–479. doi:10.1007/s00170-006-0739-4
34. Chen CC, Su PL, Lin YC (2009) Analysis and modeling of effective parameters for dimension shrinkage variation of injection molded part with thin shell feature using response surface methodology. Int J Adv Manuf Technol 45(11–12):1087–1095. doi:10.1007/s00170-009-2045-4
35. Mok SL, Kwong CK, Lau WS (1999) Review of research in the determination of process parameters for plastic injection molding. Adv Polym Technol 18(3):225–236. doi:10.1002/(sici)1098-2329(199923)18:3%3C225::aid-adv3%3E3.0.co;2-3
36. Yu SR, Zhang Y, Yang D, Zhou HM, Li JC (2014) Offline prediction of process windows for robust injection molding. J Appl Polym Sci 131 (18). doi:10.1002/app.40804
37. Pontil M, Rifkin R, Evgeniou T From regression to classification in support vector machines. In: Proceedings of ESANN'99. 7th European Symposium on Artificial Neural Networks, 21–23 April 1999, Brussels, Belgium, 1999. 7th European Symposium on Artificial Neural Networks. ESANN'99. Proceedings. D-Facto, pp 225–230
38. Chen W-C, Tai P-H, Wang M-W, Deng W-J, Chen C-T (2008) A neural network-based approach for dynamic quality prediction in a plastic injection molding process. Expert Syst Appl 35(3):843–849. doi:10.1016/j.eswa.2007.07.037
39. Yang Y, Gao F (2006) Injection molding product weight: online prediction and control based on a nonlinear principal component regression model. Polym Eng Sci 46(4):540–548. doi:10.1002/pen.20522
40. Takahashi T (2003) Robust design for mass production. J Mater Process Technol 143–144:786–791. doi:10.1016/S0924-0136(03)00377-7
41. Dudek-Burlikowska M (2005) Quality estimation of process with usage control charts type X-R and quality capability of process Cp, Cpk. J Mater Process Technol 162–163:736–743. doi:10.1016/j.jmatprotec.2005.02.210