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Simulation of a regression-model and PCA based searching method developed for setting the robust injection molding parameters of multi-quality characteristics

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ABSTRACT

This article proposes an advanced searching method for setting the robust process parameters for injection molding based on the principal component analysis (PCA) and a regression model-based searching method. This method could effectively reduce the influence of environmental noise on molded parts' multi-quality characteristics in the injection molding process. Firstly, the PCA is utilized to construct a composite quality indicator to represent the quality loss function of multi-quality characteristics. The design of experiment and ANOVA methods are then used to choose the major parameters, which affect parts quality and are called as adjustment factors. Secondly, a two-level statistically designed experiment with the least squared error method was used to generate a regression model between part quality and adjustment factors. Based on this mathematical model, the steepest decent method is used to search for the optimal process parameters. To verify the performance, computer simulations and experiment of the light-guided plate molding were investigated in this work. By comparing the robust qualities using Taguchi method and our proposed method, it is found that our proposed method yields a better uniform production quality.

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1. Introduction

Robust process parameter setting plays a crucial role in ensuring the quality of molded parts prior to production. The traditional process parameter setting for injection molding is based on statistical and experiment, computer-aided simulations, or an operator's experience [1–7]. In the case that the setting result of producing the injection parts is close to the specification limits of the part quality, the production process will be easily affected by environmental noise and thus the defect rate will increase. Therefore, these parameters are inadequate and the production process is not robust. In addressing such problems, methods like fuzzy theory and artificial neural network have been proposed in recent years [8–11], but they require a large amount of datum in advance. In addition, with diverse materials and different designations of required products, such methods are difficultly applied in practical use. Other approaches, for example, Taguchi method and response surface method [12–15], targeting the parts quality by designing effective experiments to find out the optimal process parameters, have been developed [16–18]. Taguchi method is well known for its design in effective experiments, but the optimal process parameters are confined to the designed ranges of factor levels in experiments. The response surface method has no such limitation, although the design of experiments is inherently more complex.

The above experimental design methods are often used in the case of targeting one single quality characteristic to find the optimal process parameters at a time. In reality, seeking the ideal process parameters and focusing on multi-quality characteristics are difficult but generally required. Reddy et al. [19] attempted to find the ideal process parameters for three-quality characteristics through the optimization method. However, the calculations in these methods are rather complex and they are still not widely used.

In studying multi-quality characteristics, i.e., a large number of correlated quality characteristics, the information collected from experiments may be confused and data analysis may be difficult. The principal component analysis (PCA) allows data which contain information of multi-quality characteristics to be converted into several independent quality indicators. Part of these indicators is then selected to construct a composite quality indicator, which represents the mathematical function of the required multi-quality characteristics. If the PCA can be further integrated with Taguchi method, it becomes practical and efficient in solving problems of multi-quality characteristics [20,21]. In this paper, we adopt the regression-model based searching method to set the robust injection molding parameters [15], and utilize the PCA to generate a composite quality indicator. The DOE and ANOVA methods are then used to choose the major parameters as adjustment factors.

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Next, a two-level statistically designed experiment with the least squared error method is used to generate a regression model between part quality and adjustment factors. Based on this mathematical model, the steepest decent method is employed to search for the optimal process parameters of the LGP molding.

2. The advanced robust parameters searching method for multi-quality characteristics

Fig. 1 shows the advanced robust parameters searching method proposed in this study comprised of four phases: (1) setting the composite quality indicator, (2) executing 2^3 full factorial experiments, (3) searching for robust process parameters, and (4) adjusting the defective quality characteristics. The details of these four phases are discussed as follows.

2.1. Phase 1: Setting the composite quality indicator

Initially, the PCA was used in this phase to convert observed data which contain the information of multi-quality characteristics into several independent quality indicators. Some of these indicators were later selected to construct a composite quality indicator, which represents a mathematical model of multi-quality characteristics.

The observed data used for PCA are initially normalized to generate dimensionless values, which fall in the range between 0 and 1. If the quality requirements were different, the corresponding normalization could be different as well, as shown below:

Case 1: Larger-the-better. The target value of quality objectives was uncertain and was expected to have a large value in the end

$$Y^*_{ij} = \frac{L_{ij} - \min(L_j)}{\max(L_j) - \min(L_j)} \tag{1}$$

Case 2: Smaller-the-better. The target value of quality objectives was uncertain and was expected to have a small value in the end

$$Y^*_{ij} = \frac{\max(L_j) - L_{ij}}{\max(L_j) - \min(L_j)} \tag{2}$$

Case 3: Target-the-best. The target value of quality objectives was certain and was expected to reach it

$$Y^*_{ij} = 1 - \frac{|L_{ij} - O_b|}{\max\{\max(L_j) - O_b, O_b - \min(L_j)\}} \tag{3}$$

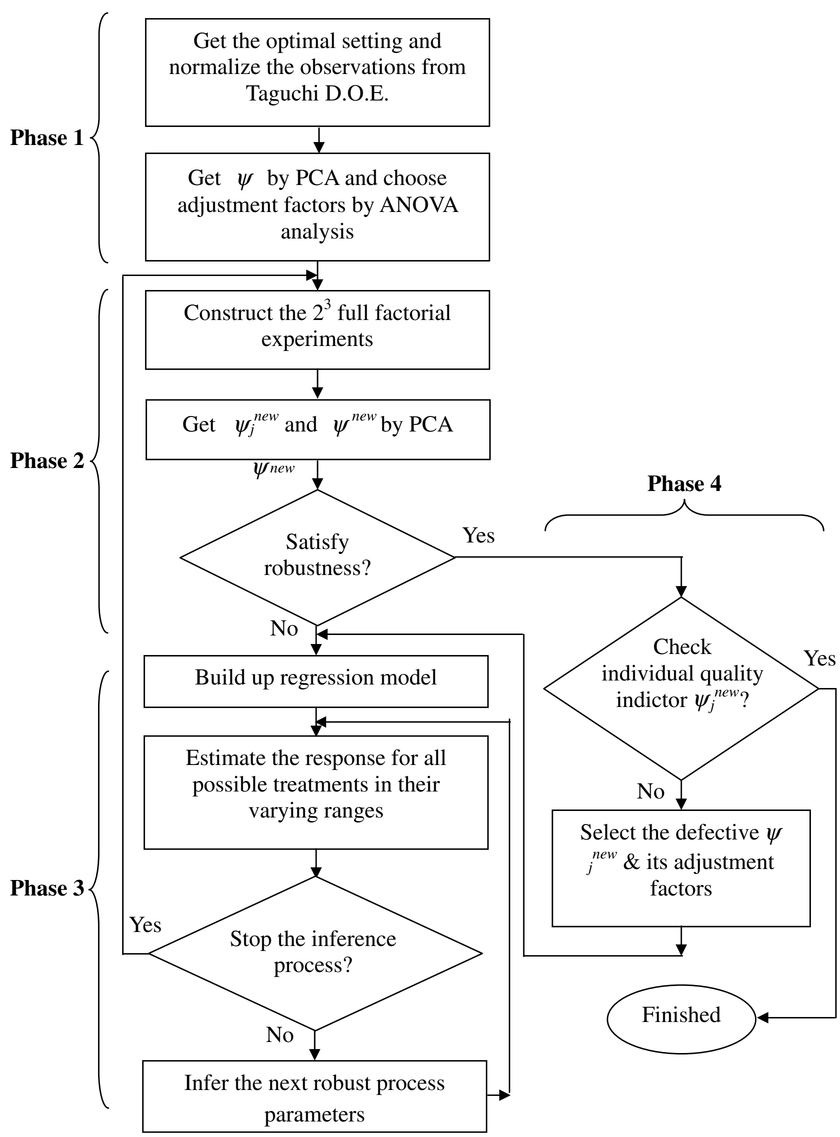

Fig. 1. Flowchart of the innovative robustness parameters searching method for multi-quality characteristics.

In which, L_{ij} and Y^*_{ij} represent the observed value and its normalized value for the ith experimental run and jth quality characteristics, respectively; $\max(L_j)$ and $\min(L_j)$ represent the maximum and the minimum observed values of the jth quality characteristics, respectively; O_b is the target value.

These normalized data were then used to construct a variance-covariance matrix '$\boldsymbol{A}$', which is illustrated as below:

$$\boldsymbol{A} = \begin{bmatrix} R_{1,1} & R_{1,2} & \dots & R_{1,n} \\ R_{2,1} & R_{2,2} & \dots & R_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ R_{m,1} & R_{m,2} & \cdots & R_{m,n} \end{bmatrix} \tag{4}$$

$$R_{k,l} = \frac{\mathrm{Cov}(Y^*_{i,k}, Y^*_{i,l})}{\sqrt{Var(Y^*_{i,k})\mathrm{Var}(Y^*_{i,l})}} \tag{5}$$

in which, 'n' stands for the number of quality characteristics and 'm' stands for the number of experimental runs. Then, eigenvectors and eigenvalues of matrix $\boldsymbol{A}$ could be computed, which are symbolized as $\boldsymbol{V}_j$ and λ_j, respectively.

In principal component analysis, the eigenvector $\boldsymbol{V}_j$ represents the weighting vector of j number of quality characteristics of the jth principal component. For example, if Q_j represents the jth quality characteristics, the jth principal component 'ψ_j' was treated as a quality indicator with the required quality characteristics:

$$\psi_j = V_{1j}Q_1 + V_{2j}Q_2 + \cdots + V_{jj}Q_j = \boldsymbol{V}'_j\mathbf{Q} \tag{6}$$

It should be noted that every principal component ψ_j represents a certain degree of explanation of the variation of quality characteristics, namely the accountability proportion (AP). When several principal components were accumulated, it increased the accountability proportion of quality characteristics. Such arrangements were called cumulative accountability proportion (CAP). In this study, the composite principal component ψ was defined as the sum of principal components with their individual eigenvalues greater than one. These specific components, ψ_j, were designated as individual quality indicators. The composite principal component represents the generalized indicator of parts quality characteristics, as shown below:

$$\psi = \sum_{j=1}^{K} \psi_j \tag{7}$$

If a quality characteristic Q_j strongly dominates in the jth principal component, this principal component becomes the major indicator of such a quality characteristic. It should be noted that one quality indicator may often represent all the multi-quality characteristics. In this work, the computation of PCA is executed by Minitab R14 software.

The selection of adjustment factors is based on the contribution percentage of experimental factors to the composite quality indicator,ψ, as analyzed by ANOVA method. The adjustment factors have two distinct characteristics: (1) a change of adjustment factors with the interference of environment will strongly affect the parts quality. If the adjustment factors are controlled, the production of qualified product will be assured. Through the varying of adjustment factors, this research discovered a process window to allow chosen factors to be altered within the window; the molded parts were able to meet their quality specifications. (2) When some of the parts that were molded with process parameters within the process window failed to reach the level of quality, alteration could be made on the range in order to meet the requirement.

In this phase, the composite quality indicator,ψ, may be generated by many quality indicators with different adjustment factors, but only the first three most important adjustment factors were selected in this work. They were used again in Phases 2, 3 and 4 to search for the optimal combination of process parameters. The steps in Phase 1 can be summarized as follows:

Step 1: Normalize the measurements: After performing the suggested Taguchi design experiment, normalize the observations of each quality characteristics by using the above Eqs. (1), (2) or (3).

Step 2: Determine ψ_j and ψ: By using PCA for the above normalized observations, the quality indicator ψ_j was determined with the criterion of the principal component's eigenvalue greater than one. Then, the composite principal component ψ was generated with the accumulated principal components ψ_j by using Eq. (7).

Step 3: Decide the three most significant adjustment factors: The composite quality indicator ψ was a linear combination of ψ_j. Therefore, selection of the adjustment factors depends on their level of contribution percentage to ψ through ANOVA analysis, should affect ψ_j, in which $j = 1,2,\ldots,K$ with respect to Eq. (7). Hence the adjustment factors could be found to have most significant experimental factors for ψ_j individually. These adjustment factors were used as the experimental factors of the 2^3 full factorial experiments in Phase 2.

2.2. Phase 2: Executing 2^3 full factorial experiments

As mentioned before, the quality of injection parts could vary with the interference of environmental noise. It was necessary to seek out a robust process window in which the adjustment factors were free to move around, if the quality characteristics could satisfy the quality specification limits. By varying the adjustment factors caused by environmental interference and carrying out the 2^3 full factorial experiments, a roust process window can be identified. The experimental runs were designed with a combination of the extreme points of three-dimension process window, as shown in Fig. 2. The cube in the figure is the intended robust process window. If a defect occurs at extreme points in the process window, a better region can be found by using the steepest decent method to search for a new location of parameters settings.

The steps in Phase 2 are as follows:

Step 1 : Design the 2^3 full factorial experiments: The experiments were designed according to the number and the possible ranges of adjustment factors. The initial central point for 2^3 full factorial experiment was referred to the optimal parameters setting of DOE suggested in Phase 1.

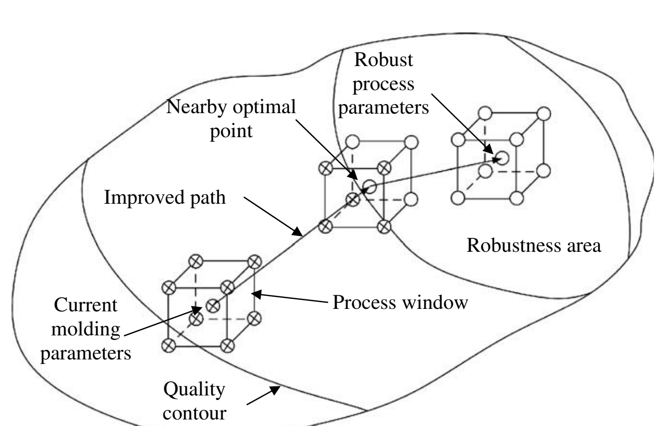

Fig. 2. Searching pattern for robustness parameters ('⊗': defective product; '○': qualified product).

Step 2 : Obtain the new ψ_j^{new} and ψ^{new}: By using PCA to the observations after normalization, the new quality indicators ψ_j^{new} and composite principal components ψ^{new} are obtained.

Step 3 : Check robustness: If all the ψ^{new} for running 2^3full factorial experiments meet the quality specification levels, this means that the set-points of the process parameters of this experimental group could be robust for the ψ^{new}. At this point we go to Phase 4 for further confirmation. Otherwise, the next step would be to repeat Phase 3 and search for another set of process parameters by employing the regression-model based robust parameters searching method.

2.3. Phase 3: Searching for robust process parameters [15]

Through setting up a regression model, based on the relationship between the process parameters and quality observations, the method of steepest decent was employed to determine the distance and direction to the target. It was assumed that a quality observation, y and k number of process parameters, have significant affects on the quality, such as $x_1, x_2, \ldots, x_k$. The sample datum of full factorial experiment in the previous phase could be used to fit the regression model. Therefore, the designed matrix of the experiment could be used to obtain the data sample, which fits the model. The matrix is shown by:

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{8}$$

$$\boldsymbol{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}; \quad \boldsymbol{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}; \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} \tag{9}$$

in which $\boldsymbol{Y}$ stands for the vector of observation which may be ψ_j^{new} or ψ^{new} here; $\boldsymbol{X}$ stands for the matrix of experimental runs; x_{nk} stands for the kth process parameter in the experimental run 'n'. $\boldsymbol{\beta}$ refers to the vector of estimated coefficients of the regression model, and $\boldsymbol{\varepsilon}$ stands for the random error vector.

The $\boldsymbol{\beta}$ vector can be estimated by the least squared error method as follows:

$$\boldsymbol{\beta} = \frac{1}{2}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Y} \tag{10}$$

Then, we determine the composite equation of the relationship between the process parameters and the product quality, and then convert $\boldsymbol{Y}$, and the matrix $\boldsymbol{X}$ in Eq. (9) into Eq. (10), to get the coefficient $\boldsymbol{\beta}$ in the regression model.

The steps in Phase 3 are as follows:

Step 1: Set up the regression model: Eq. (8) represents the relationship between process parameters and parts quality. And the $\boldsymbol{Y}$ and $\boldsymbol{X}$ in Eq. (9) can be substituted into the following equations:

$$\boldsymbol{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_8 \end{bmatrix}; \quad \boldsymbol{X} = \begin{bmatrix} 1 & -1 & -1 & -1 & 1 & 1 & 1 & -1 \\ 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 \\ 1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 \\ 1 & 1 & 1 & -1 & 1 & -1 & -1 & -1 \\ 1 & -1 & -1 & 1 & 1 & -1 & -1 & 1 \\ 1 & 1 & -1 & 1 & -1 & 1 & -1 & -1 \\ 1 & -1 & 1 & 1 & -1 & -1 & 1 & -1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{11}$$

The $\boldsymbol{X}$ matrix was constituted with two values, 1 and −1, which represent the upper and lower levels of each control factor, respectively. The second, third, and fourth columns represent the levels of x_1, x_2, and x_3 control factors, respectively. The fifth, sixth, and seventh columns represent the levels of interaction effects of x_1 to x_2, x_1 to x_3, and x_2 to x_3, respectively. The eighth column stands for the interaction effect among x_1, x_2, and x_3. Placing the vector $\boldsymbol{Y}$ and matrix $\boldsymbol{X}$ into Eq. (10), one obtains the coefficient vector of the regression model, $\boldsymbol{\beta}$.

Step 2: Estimate the responses for all possible treatments in the varying ranges: Use the set-point of the process parameters (or the predicted points of the robust molding parameters) and the least resolution of machine control as the basis to arrange all the possible treatments in the varying ranges. For example, if there are three adjustment factors and the upper and lower limits are five times the least resolution of the injection molding machine, the varying ranges of each adjustment factor could be divided into three groups and the number of treatments would be 5^3.

Step 3: Determine whether the inference process should be continued or not: This step determines whether the inference of the robust molding parameters should be stopped or not. By substituting all treatments to construct coefficient vectors of the regression model and to generate predicted values, stopping the inference process has two conditions: either all the predicted values meet the quality specification, or some of predicted values do. In the latter case, the set-point should be selected in the inference process, and then go to Step 4. For the former one, go to Phase 2 to check the robustness.

Step 4: Infer the next robust molding parameter: Set the search direction by means of the steepest decent method. The forward distance relies on the least resolution of the machine control. Go back to Step 2.

2.4. Phase 4: Adjusting the defective quality characteristic

When the composite quality indicator reaches the target value, and in the case that some of the individual quality indicators are out of the quality specification limits, they cannot always quickly reflect each individual defective quality, which may cause misjudgment of each individual defective quality. In other words, when the composite quality indicator fails to quickly reflect defective quality, it is necessary to improve the defective quality indicators. These indicators with the adjustment factors were put into Phase 3 to build a new regression model and then applied the regression-model based searching method to search for robust parameters. That is, modifying the adjustment factors make the inadequate quality to meet the requirement.

Step 1: Check for inadequate quality indicators: Make sure the individual quality characteristics all meet the quality specifications. If they do, the searching method is finished; otherwise, go to the next step.

Step 2: Select the inadequate quality indicators ψ_j^{new} and combine them to generate a composite quality indicator. Select the corresponding adjustment factors. Then, go to Phase 3.

3. Computer simulation and evaluation

In this work, the commercial simulation software Moldex3D was used to analyze the LGP molding conditions. This software is based on a three-dimension solid element model, which helps to promote precision, steadiness and efficiency in the simulation. It is well known that the meshing numbers of the finite element in the software may influence the convergence of simulation results. To verify the convergence, cases with different meshing numbers, with ranges from 81,600 to 96,760 increasing by 2,500, were initially tested with the same molding condition. The simulation results showed that the three-quality characteristics, maximal volumetric shrinkage rate, maximal warpage, and maximal shear stress tend to be stable when the meshing number was over 89,500. Thus, the simulation analysis used meshing elements over 89,500 in this study. The computer device used for the simulation was a Pentium 4 CPU, with 3 GHz speed, and 2 Gbyte RAM. It allowed a simulation run to be completed within 100 minutes. Fig. 3 shows a typical simulation of melt front, shear stress, total displacement, and shrinkage.

This study used a 2-inch width, 1 mm thickness light guide plate which had one cavity in each mold, as the molding object in the experiment. The sectional area of the sprue was round, increasing from 3 mm to 5 mm. The thickness of the designated fan gate was 2.5 mm descending to 0.7 mm. The cooling channels are shown as Fig. 4. The polymer materials were PMMA (KURARAY GH-1000 S) and the injection molding machine was Fanuc α-30i, which was made in Japan.

The designation of L_{18} ($2^1 \times 3^7$) Taguchi orthogonal arrays used for the simulation of LGP injection molding are shown in Table 1. The chosen experimental factors were cooling time, plastic temperature, mold temperature, filling speed, holding pressure, holding time, injection pressure, and screw stroke. The selected noise factors were materials viscosity with two similar values. As to the required quality characteristics, they contained the minimization of maximal shear stress, maximal warpage, and maximal volumetric shrinkage rate. The selection of experimental factor levels was referenced to the material features provided by the material supplier. The experiment was based on the adjustable region of the injection molding machine. In this study, the verification focused on the performance of optimal process parameters obtained by the innovative method described in this paper and Taguchi method, respectively. With regard to the efficiency of the simulation, the central and extreme values in the 3D process window were selected to form 27 combinations. The quality characteristics obtained from the Moldex3D simulation were further normalized by using Eq. (2). Table 2 lists the normalized and averaged values in columns 2, 3 and 4. They were used to form the variance-covariance matrix and then to calculate eigenvalues by PCA. Table 3

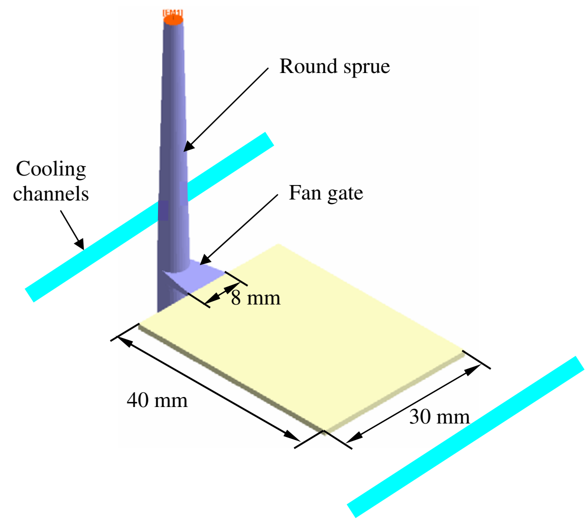

Fig. 4. Geometry of light-guided plate's injection mold.

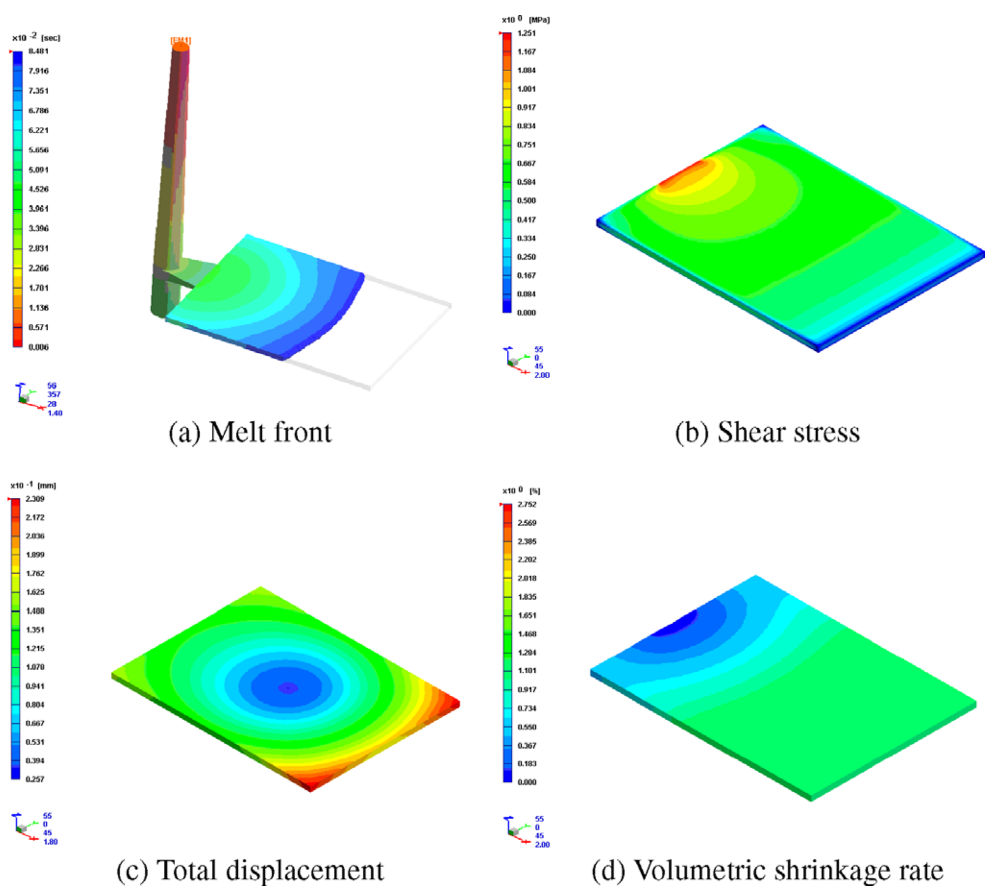

Fig. 3. Simulation of light-guided plate's melt front, shear stress, total displacement and volumetric shrinkage rate by Moldex3D software.

Table 1
Design of $L_{18}(2^1 \times 3^7)$ experiments and their simulation results

Exp. No.	Control factors								Observation					
	Cooling time (s)	Plastic temp. (°C)	Mold temp. (°C)	Filling speed (mm/s)	Holding pressure (MPa)	Holding time (s)	Filling pressure (MPa)	Screw stroke (mm)	Shear stress[a] (MPa)	Shear stress[b] (MPa)	Warpage[b] (μm)	Warpage[b] (μm)	Shrinkage[b] (%)	Shrinkage[b] (%)
1	10	240	60	70	50	3	90	8.8	1.87	1.80	1.7	1.7	1.22	1.22
2	10	240	70	80	60	4	100	9.0	1.96	1.89	1.8	1.7	1.13	1.13
3	10	240	80	90	70	5	110	9.2	2.02	1.94	2.0	2.0	1.20	1.20
4	10	250	60	70	60	4	110	9.2	1.52	1.47	1.5	1.5	0.97	0.97
5	10	250	70	80	70	5	90	8.8	1.57	1.52	1.7	1.7	1.02	1.02
6	10	250	80	90	50	3	100	9.0	1.64	1.58	2.3	2.3	1.53	1.53
7	10	260	60	80	50	5	100	9.2	1.28	1.24	1.3	1.3	0.87	0.86
8	10	260	70	90	60	3	110	8.8	1.33	1.29	2.1	2.1	1.39	1.39
9	10	260	80	70	70	4	90	9.0	1.24	1.20	2.1	2.1	1.33	1.33
10	20	240	60	90	70	4	100	8.8	2.00	1.93	1.4	1.4	0.95	0.95
11	20	240	70	70	50	5	110	9.0	1.87	1.81	1.7	1.7	1.02	1.02
12	20	240	80	80	60	3	90	9.2	1.96	1.87	2.3	2.3	1.51	1.51
13	20	250	60	80	70	3	110	9.0	1.58	1.52	3.1	3.0	1.20	1.20
14	20	250	70	90	50	4	90	9.2	1.63	1.58	1.8	1.8	1.15	1.15
15	20	250	80	70	60	5	100	8.8	1.52	1.47	2.1	2.1	1.21	1.21
16	20	260	60	90	60	5	90	9.0	1.33	1.29	1.3	1.3	0.85	0.85
17	20	260	70	70	70	3	100	9.2	1.24	1.20	2.1	2.1	1.39	1.39
18	20	260	80	80	50	4	110	8.8	1.29	1.25	2.1	2.1	1.33	1.33

[a,b] Generated with the variation of materials viscosity.

Table 2
Principal component analysis for L_{18} experimental observations

Exp. No.	Averaged normalized shear stress	Averaged normalized warpage	Averaged normalized shrinkage	ψ_1	ψ_2	ψ
1	0.23	0.76	0.46	0.85	0.28	1.13
2	0.12	0.77	0.59	0.96	0.18	1.14
3	0.05	0.60	0.48	0.76	0.10	0.85
4	0.64	0.94	0.83	1.21	0.72	1.92
5	0.58	0.80	0.75	1.06	0.64	1.70
6	0.50	0.43	0.00	0.27	0.52	0.79
7	0.92	1.00	0.97	1.34	1.01	2.34
8	0.87	0.57	0.21	0.49	0.90	1.40
9	0.97	0.57	0.29	0.55	1.01	1.56
10	0.07	0.94	0.85	1.26	0.15	1.41
11	0.22	0.79	0.75	1.08	0.29	1.36
12	0.13	0.45	0.04	0.34	0.16	0.49
13	0.57	0.01	0.49	0.31	0.59	0.91
14	0.51	0.75	0.56	0.89	0.56	1.46
15	0.64	0.58	0.47	0.71	0.68	1.39
16	0.87	1.00	1.00	1.36	0.95	2.31
17	0.97	0.56	0.21	0.49	1.01	1.49
18	0.91	0.55	0.30	0.54	0.95	1.49

ψ_1, the first principal component.
ψ_2, the second principal component.
ψ, the composite quality indicator, namely cumulative principal component generated by the sum of ψ_1 and ψ_2.

Table 3
Eigenvalues, eigenvectors, accountability proportion (AP), and cumulative accountability proportion (CAP) computed for the first three major quality indicators

	ψ_1	ψ_2	ψ_3
Eigenvalue	1.73	1.00	0.27
Eigenvector	$[-0.061\ 0.706\ 0.706]^T$	$[0.998\ 0.047\ 0.040]^T$	$[0.005\ -0.707\ 0.707]^T$
AP	0.58	0.33	0.09
CAP	0.58	0.91	1.00

presents the obtained eigenvalues, accountability proportions (AP), and eigenvectors.

Table 3 shows that the eigenvalue of the first principal component ψ_1 was 1.73 and AP was 0.58; the eigenvalue of the second principal component ψ_2 was 1.00 and AP was 0.33. The composite quality indicator ψ was the sum of individual quality indicators, in which their cumulative accountability proportion is normally set as greater than 0.8. In this case, the composite quality indicator ψ is the sum of ψ_1 and ψ_2, since the CAP of ψ_1 and ψ_2 was 0.91. In Table 3, the maximal shear stress, maximal warpage, and maximal volumetric shrinkage rate, with the corresponding weighting vector of the first principal component, was the eigenvector $[-0.061\ 0.706\ 0.706]^T$. This vector was substituted into Eq. (6) to calculate the first principal component ψ_1, and so was ψ_2. The quality observation obtained from Taguchi method was converted into ψ_1, ψ_2 and ψ using PCA, as shown in columns 5, 6 and 7 in Table 2. The warpage and the shrinkage weigh significantly in the first principal component, so the first principal component could be seen as the quality indicator of warpage and shrinkage. In this sense, the second principal component figure is that of shear stress.

Table 4 display the results of the ANOVA analysis carried out to examine the ψ value obtained by the L_{18} Taguchi method. The results show that plastic temperature, mold temperature, and holding time significantly affect the value of the composite principal component, so these three factors were selected as its adjustment factors. Table 5 shows that mold temperature and holding time have significant influence on ψ_1. Comparing Tables 4 and 5, mold temperature and holding time both had significant influence on

Table 4
ANOVA analysis for the composite quality indicator ψ

SV	DOF	SS	MS	F	PSS	CP (%)
Cooling time	1	0.02				
Plastic temp.	2	1.48	0.74	30.76	1.44	35.80
Mold temp.	2	1.00	0.50	20.70	0.95	23.70
Filling speed	2	0.06				
Holding pressure	2	0.05				
Holding time	2	1.26	0.63	26.16	1.21	30.27
Injection pressure	2	0.05				
Screw stroke	2	0.02				
Error	2	0.06				
Pooled error	(11)	(0.10)	(0.02)		0.41	10.23
Total	17	4.01				100.00

SV, source of variation; DOF, degrees of freedom; SS, sum of squares; MS, mean square; PSS, pure of sum squares; CP, contribution percentage; $F_{1,11,0.01} = 9.65$, $F_{2,11,0.01} = 7.2$.

Table 5
The ANOVA analysis for the first principal component ψ_1

SV	DOF	SS	MS	F	PSS	CP (%)
Cooling time	1	0.01				
Plastic temp.	2	0.05				
Mold temp.	2	0.84	0.42	22.04	0.80	36.00
Filling speed	2	0.02				
Holding pressure	2	0.04				
Holding time	2	1.13	0.57	29.89	1.10	49.45
Injection pressure	2	0.05				
Screw stroke	2	0.02				
Error	2	0.05				
Pooled error	(13)	(0.25)	(0.02)		0.32	14.55
Total	17	2.22				100.00

SV, source of variation; DOF, degrees of freedom; SS, sum of squares; MS, mean square; PSS, pure of sum squares; CP, contribution percentage; $F_{1,13,0.01}$ = 17.82, $F_{2,13,0.01}$ = 6.7.

ψ_1 and ψ, so plastic temperature should be the adjustment factor for the second principal component value.

Using these three adjustment factors in the full factorial experiment of multi-quality characteristics, the central point of the process window was the set-point of the current process parameters. According to Taguchi method, the optimal design of process parameters are plastic temperature at 260 °C, mold temperature at 60 °C, and holding time at 5 s. In the experiment, the ranges for the process window for mold temperature and plastic temperature were set at ±5 °C, and the holding time was set at ±0.5 s, which were five times of the resolution of the injection molding machine. The preferred quality characteristics were smaller-the-better, and the quality specifications were as follows: maximal shear stress less than 1.25 MPa, maximal warpage less than 1.5 μm, and maximal volumetric shrinkage rate less than 1%.

Table 6 demonstrates that results of using PCA to analyze the average value of the normalized quality characteristics andψ. It was observed that the ψ values in Runs 3 and 7 were less than the normalized lower specification limit 0.442 in the composite quality indicator. If the process parameters did not reach the desired levels of robustness, the experiment had to repeat Phase 3 to build a regression model used for searching for the set-point of robust process parameters. The set-point was found in the combination of plastic temperature at 263 °C, mold temperature at 57 °C, and holding time at 5.3 s. This combination was tested by the full factorial experiment and was analyzed by PCA. The average value of normalized quality characteristics was converted into ψ and ψ_2, as shown in Table 7.

In Table 7, all ψ values in the full factorial experiment were greater than the normalized lower specification limit 0.069. However, the average values of normalized shear stress in Run 1, Run 3, Run 5, and Run 7 were not greater than its normalized lower specification limit. Although the results satisfy the criterion of robustness in this phase, the individual quality observation did not meet the quality specification. Hence, the individual defective quality should be rectified in Phase 4.

According to PCA and ANOVA methods, the quality indicator of shear stress was ψ_2, and its adjustment factor was plastic temperature. After going through Phase 2 and Phase 3 to rectify the quality observations of the individual shear stress, the set-point of the robust process parameters was redefined as: plastic temperature at 266 °C, mold temperature and holding time the same. This set-point was again tested by the full factorial experiment and analyzed by PCA. The results shown in Table 8 indicate that the indi-

Table 6
Full-factorial experimental results and the principal component analysis for Taguchi method

Exp. No.	Initial central point			Averaged normalized shear stress	Averaged normalized warpage	Averaged normalized shrinkage	ψ
	Plastic temp. (260 °C)	Mold temp. (60 °C)	Holding time (5 s)	0.537	0.502	0.501	0.575
1	+5	+5	+0.5	0.088	0.846	0.678	1.336
2	−5	+5	+0.5	0.948	0.806	0.524	1.871
3	+5	−5	+0.5	0.103	0.017	0.082	0.159
4	−5	−5	+0.5	0.921	0.000	0.002	0.735
5	+5	+5	−0.5	0.088	0.987	0.972	1.681
6	−5	+5	−0.5	0.948	0.867	0.751	2.095
7	+5	−5	−0.5	0.103	0.065	0.395	0.434
8	−5	−5	−0.5	0.921	0.084	0.355	1.073
Normalized lower specification limit				≧0.395	≧0.117	≧0.029	≧0.442

Note: The eigenvector of the first principal component ψ_1 for shear stress, warpage and shrinkage is [−0.179 0.688 0.703], respectively. The eigenvector of the second principal component ψ_2 for shear stress, warpage and shrinkage is [0.976 0.212 0.040], respectively.

Table 7
Full-factorial experimental results and the principal component analysis for the first inference of robust parameters

Exp. No.	Initial central point			Averaged normalized shear stress	Averaged normalized warpage	Averaged normalized shrinkage	ψ	ψ_2
	Plastic temp. (263 °C)	Mold temp. (57 °C)	Holding time (5.3 s)	0.537	0.525	0.599	1.338	0.581
1	+5	+5	+0.5	0.166	0.826	0.634	1.267	0.250
2	−5	+5	+0.5	0.885	0.784	0.546	1.837	0.960
3	+5	−5	+0.5	0.149	0.012	0.218	0.296	0.144
4	−5	−5	+0.5	0.866	0.000	0.066	0.845	0.857
5	+5	+5	−0.5	0.166	0.907	0.905	1.519	0.252
6	−5	+5	−0.5	0.885	0.944	0.877	2.195	0.970
7	+5	−5	−0.5	0.149	0.040	0.444	0.472	0.141
8	−5	−5	−0.5	0.866	0.061	0.42586	1.140	0.855
Normalized lower specification limit				≧0.265	≧−0.176	≧−0.044	≧0.069	≧0.242

Note: The eigenvector of the first principal component ψ_1 for shear stress, warpage and shrinkage is [−0.068 0.703 0.708], respectively. The eigenvector of the second principal component ψ_2 for shear stress, warpage and shrinkage is [0.992 0.124 −0.028], respectively.

Table 8
Full-factorial experimental results and the principal component analysis for the second inference of robust parameters

Exp. No.	Initial central point			Averaged normalized shear stress	Averaged normalized warpage	Averaged normalized shrinkage	ψ_2
	Plastic temp. (266 °C)	Mold temp. (57 °C)	Holding time (5.3 s)	0.534	0.527	0.549	0.564
1	+5	+5	+0.5	0.154	0.819	0.562	0.204
2	−5	+5	+0.5	0.880	0.777	0.482	0.927
3	+5	−5	+0.5	0.144	0.015	0.104	0.143
4	−5	−5	+0.5	0.877	0.001	0.063	0.875
5	+5	+5	−0.5	0.154	0.920	0.887	0.208
6	−5	+5	−0.5	0.880	0.958	0.883	0.935
7	+5	−5	−0.5	0.144	0.051	0.367	0.143
8	−5	−5	−0.5	0.877	0.071	0.331	0.877
Normalized lower specification limit				≧0.010	≧−0.171	≧0.029	≧−0.002

Note: The eigenvector of the first principal component ψ_1 for shear stress, warpage and shrinkage is [−0.042 0.706 0.706], respectively. The eigenvector of the second principal component ψ_2 for shear stress, warpage and shrinkage is [0.998 0.069 −0.01], respectively.

vidual quality characteristic and ψ_2 were within the quality specification limits under the premise of ψ.

According to the results of searching for the optimal process parameters by Taguchi method, there were two sets that failed to meet the target when tested in the full factorial experiment. However, the optimal process parameters obtained from the proposed method in this study generated qualified products. This indicates that the innovative method proposed in this research is feasible for seeking optimal robust process parameters.

Verification of the results was carried out by comparing the performance of the optimal process parameters found by the proposed method and Taguchi method through computer simulation. In this simulation, the varying ranges of the adjustment factors were: plastic temperature and mold temperature at ±5 °C, and holding time varying at ±0.5 s. The robust process parameters found by Taguchi method were: plastic temperature at 260 °C, mold temperature at 60 °C, and holding time at 5 s. For those of the proposed method, the parameters setting were: plastic temperature at 266 °C, mold temperature at 57 °C, and holding time at 5.3 s. The experimental runs and simulation results are shown in Table 9.

Table 9 shows that the parts quality using Taguchi method for optimal parameters setting, contains 9 sets in the category of maximal shear stress over the target value, 1.25 MPa, 9 sets in maximal warpage over the target value, 1.5 μm; 1 set in maximal shrinkage was over the target value by 1%. However, all products produced by the innovative method were qualified. The normal distribution of utilizing three-quality characteristics in terms of probability density function is shown in Fig. 5. The dashed line and solid line stand for the optimal process parameters obtained by Taguchi method and the proposed method, respectively. These two lines show that the average value and standard deviation of parts quality were greatly improved by the innovative method. The number of experimental runs in this case study required 26 runs for the innovative method (including 3 set of full factorial experiments and 2 sets of predicting central point experiments), which was more than that of Taguchi method (19 runs). However, its performance in searching for the optimal process parameters generates 100% qualified products and was superior to that of Taguchi method, in which the yielding rate was only 44% with respect to the influence of environmental noise.

4. Experimental setup and results

To experimental evaluate the proposed robust parameters searching method of multi-quality characteristics, this study uses the injection of light guided plates (LGPs) as the tool and chooses the quality control of the replication ability in the micro-structure as the aims of the experiments. The dimensions of the injection product as shown in Fig. 6 are 40 mm length × 30 mm width × 1 mm depth of light guided plates. The micro-structure is a circular-shaped, electroformed stamper with 671 μm in diameter and 22.6 μm in height. The stamper for LGPs is clipped to the core of the mold and filled by a fan gate. The opening of the gate is 8 mm wide and 0.7 mm long. The mold has a single cavity and two cooling channels. The molding materials are made by PMMA Japan, and the molding machine is FANUC ROBOSHOT α-30iA. The molded micro-structure of LGP is measured by a 3D profiler and the measured points are shown in Fig. 7. The selected quality characteristics are maximizing the 9-point averaged height of the micro-structure and minimizing the deviation of 9-point measured heights. The specification for 9-point averaged heights of micro-structures is set above 80% (18.08 μm), which is acceptable in the industry.

The experiments in this paper are developed by Taguchi orthogonal arrays L_{18} to evaluate the robust process parameters on the replication ability of LGP. In terms of the quality of replication ability, the selected process parameters are: injection temperature,

Table 9
Qualities of robustness for Taguchi method and the proposed method

Exp. no.	Taguchi method						Proposed method					
	Plastic temp. (°C)	Mold temp. (°C)	Holding pressure (MPa)	Shear stress (MPa)	Warpage (μm)	Shrinkage (%)	Plastic temp. (°C)	Mold temp. (°C)	Holding pressure (MPa)	Shear stress (MPa)	Warpage (μm)	Shrinkage (%)
1	255	55	4.5	*1.36*	1.20	0.84	261	52	4.8	1.20	1.11	0.84
2	255	55	5.0	*1.36*	1.16	0.81	261	52	5.3	1.20	1.10	0.77
3	255	55	5.5	*1.36*	1.16	0.76	261	52	5.8	1.20	1.08	0.72
4	255	60	4.5	*1.36*	1.37	0.91	261	57	4.8	1.20	1.25	0.85
5	255	60	5.0	*1.36*	1.34	0.86	261	57	5.3	1.20	1.22	0.80
6	255	60	5.5	*1.36*	1.32	0.82	261	57	5.8	1.20	1.21	0.78
7	255	65	4.5	*1.36*	*1.54*	0.99	261	62	4.8	1.20	1.43	0.83
8	255	65	5.0	*1.36*	*1.52*	0.95	261	62	5.3	1.20	1.40	0.87
9	255	65	5.5	*1.36*	*1.56*	0.90	261	62	5.8	1.08	1.42	0.85
10	260	55	4.5	1.23	1.21	0.86	266	52	4.8	1.08	1.13	0.85
11	260	55	5.0	1.23	1.17	0.82	266	52	5.3	1.08	1.10	0.77
12	260	55	5.5	1.23	1.16	0.77	266	52	5.8	1.08	1.08	0.73
13	260	60	4.5	1.23	1.37	0.92	266	57	4.8	1.08	1.26	0.88
14	260	60	5.0	1.23	1.34	0.87	266	57	5.3	1.08	1.22	0.81
15	260	60	5.5	1.23	1.32	0.83	266	57	5.8	1.08	1.21	0.78
16	260	65	4.5	1.23	*1.54*	1.00	266	62	4.8	1.08	1.43	0.94
17	260	65	5.0	1.23	*1.57*	0.95	266	62	5.3	1.08	1.40	0.88
18	260	65	5.5	1.23	*1.52*	0.91	266	62	5.8	1.08	1.41	0.85
19	265	55	4.5	1.10	1.21	0.88	271	52	4.8	0.98	1.15	0.86
20	265	55	5.0	1.10	1.18	0.83	271	52	5.3	0.98	1.10	0.77
21	265	55	5.5	1.10	1.16	0.77	271	52	5.8	0.98	1.07	0.72
22	265	60	4.5	1.11	1.38	0.93	271	57	4.8	0.98	1.27	0.89
23	265	60	5.0	1.11	1.34	0.89	271	57	5.3	0.98	1.22	0.82
24	265	60	5.5	1.11	1.32	0.83	271	57	5.8	0.98	1.21	0.78
25	265	65	4.5	1.11	*1.55*	*1.01*	271	62	4.8	0.98	1.43	0.95
26	265	65	5.0	1.11	*1.52*	0.96	271	62	5.3	0.98	1.40	0.89
27	265	65	5.5	1.11	*1.51*	0.91	271	62	5.8	0.98	1.41	0.86

Italicized numbers mean unqualified parts.

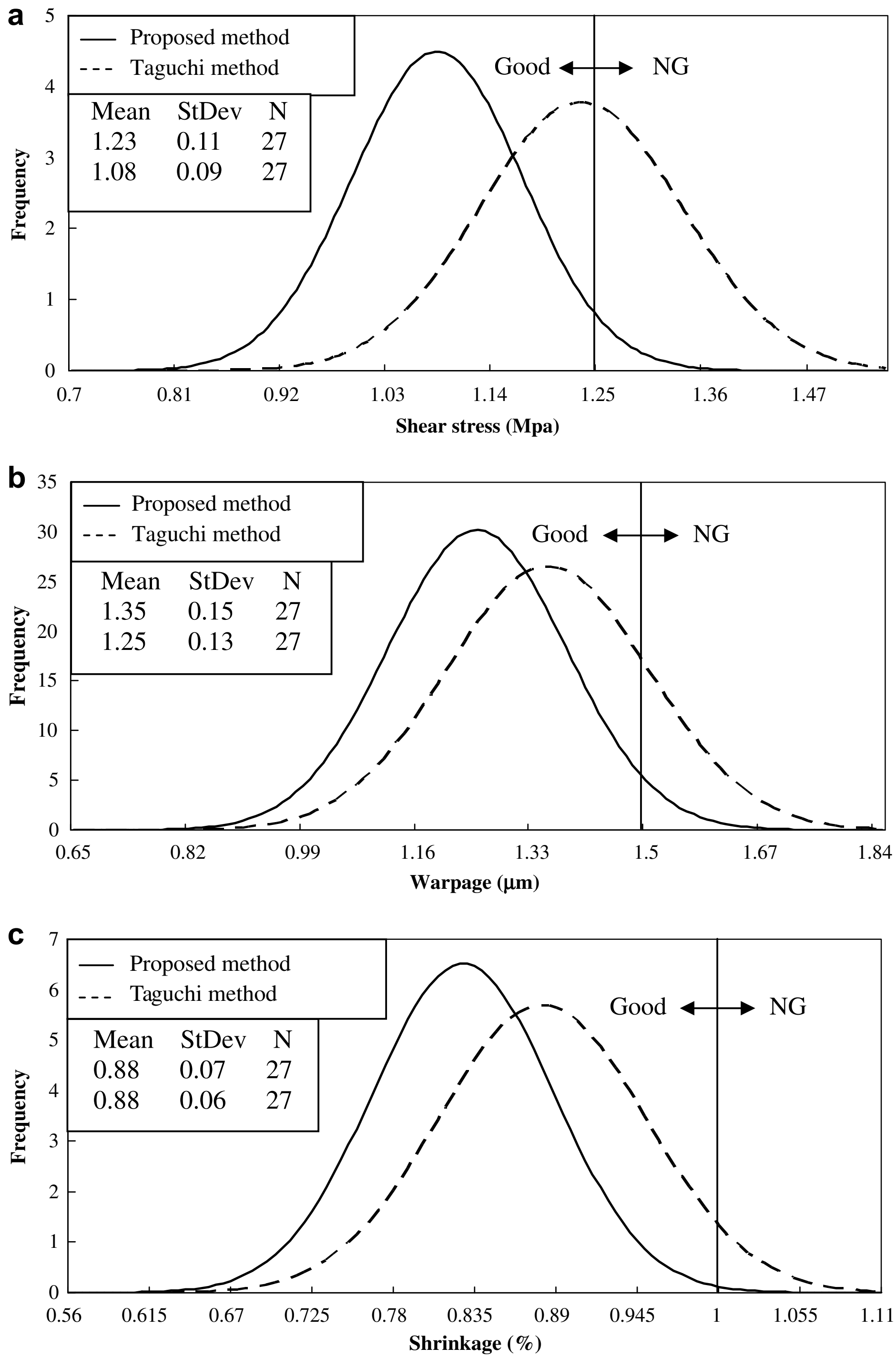

Fig. 5. Qualities of minimizing (a) shear stress, (b) warpage, and (c) volumetric shrinkage rate obtained by the proposed method and Taguchi method, respectively.

backing pressure and mold temperature. From the analysis of L_{18} experiment, the best combination is selected as the initial setting point consisting of 260 °C injection temperature, 80 kg/cm^2 packing pressure, and 70 °C mold temperature. To prove the setting point searched by the innovative method is indeed more robust than the initial setting point, these two setting points are used to inject 100 molds as the samples for measurement. Their results demonstrate whether the innovative method is superior to Taguchi method.

Twenty-one out of the 100 molds injected by the initial setting point are measured and their height of replicating the micro-structure is around 80%. Statistically, the experimental results are 20.25 μm high on average, with 89.6% of the microstructure 22.6 μm and a standard deviation of 2.646 μm. All 100 molds injected by the robust setting point are qualified to have height 20.53 μm on average, 95.3% of the microstructure 22.6 μm and standard deviation of 2.326 μm.

It can be seen that the Taguchi method can be improved by this innovative searching method: 21 deficient molds out of 100 samples are produced by Taguchi method, but zero deficient molds by the improved method. The reject rate is thus much reduced. In summary, the experimental results have shown that the proposed searching method is not only practical, but also performs better than the Taguchi method.

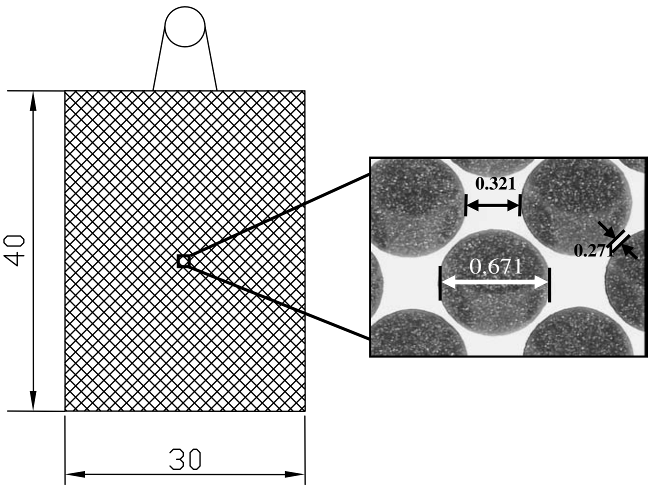

Fig. 6. The micro-structure of electroform stamper for light guided plates.

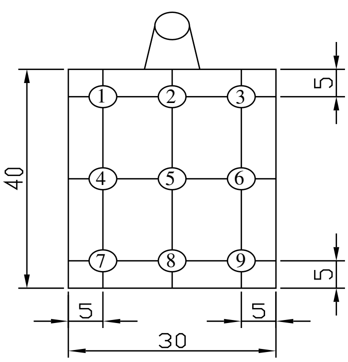

Fig. 7. The measured locations of replicated heights in LGP (unit:mm).

5. Conclusions

This work proposes an advanced searching method which effectively deals with the set-point of robust parameters in the injection molding process, to meet the requirements of multi-quality characteristics in molded parts. Computer simulations and experiment of the light-guided plate are performed to examine this method, and its performance is also compared with Taguchi method. The innovative searching method is based on: (1) principal component analysis to construct a composite quality indicator, which represents the mathematical model of multi-quality characteristics. (2) A regression model-based searching method can reflect variables to adjust the searching distance and direction. Our proposed method has advantages of fivefold:

(1) The operator does not used complex designs of experiments or related knowledge.
(2) The regression model for the description of mathematical relationship between part quality and process parameters is simple, and the inference of robust process parameters is efficient.
(3) The ratio of disqualified products due to unstable machines and non-uniform materials is decreased, and the effectiveness of the molding process can be improved.
(4) The treatment constructed in the full-factorial experiments can be checked in order to make sure whether the molding process is robust or not. Finally,
(5) The search for robust parameters is not restricted to the designed levels of controlled factors.

Also, the computer simulation and experiment of LGP molding conducted in this study shows that the performance of the proposed approach in searching for the optimal process parameters generates 100% qualified products and was superior to that of Taguchi method, with respect to the influence of environmental. In summary, the proposed innovative method has potential to effectively solve the problem of multi-quality characteristics and thus significantly improves the stability of molding process and raises its yield rate.

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