Journal of Applied Polymer Science

Offline Prediction of Process Windows for Robust Injection Molding

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ABSTRACT: Process parameters play a highly significant role in the final quality of parts produced using dynamic injection molding. Many researches have made great efforts in obtaining an optimum set of process parameters for improving molded part qualities with various optimization methods. However, this work has failed to provide sufficient information to adjust process parameters in the face of variable environmental conditions and various injection machines to ensure robust, high-quality injection moldings. Current conditions are too cumbersome and require technologists to perform repeated, detailed optimization procedures on the mass production plant floor. An offline method for prediction of process windows is proposed in this article. The process window is significant for robust manufacturing, and optimization of process parameters. Considering that it is an irregular region in a multi-dimensional space respecting to process parameters, numerical simulations based on DOE method were designed to offline build relationships between process parameters and part qualities. Then the simulation results were classified as positive or negative class, thereby yielding simulation sample data. Finally, the process window was verified using an SVM classifier and a set of simulation samples. Injection molding of an experimental production plate using various process parameters was conducted to verify the reliability of the predicted process window. The results show that, within tolerable deviations, the predicted window of experimental parts is in accordance with verification experiments. The proposed method demonstrates an ability to rapidly obtain a suitable set of process parameters for achieving consistency in part quality with low cost and high efficiency. © 2014 Wiley Periodicals, Inc. J. Appl. Polym. Sci. **2014**, *131*, 40804.

KEYWORDS: manufacturing; molding; theory and modeling

Received 20 January 2014; accepted 3 April 2014
DOI: 10.1002/app.40804

INTRODUCTION

Injection molding is by far the primary processing method for manufacturing plastic products. The quality of molded parts is directly dependent on material characteristics, mold designs, process parameters and the performances of the injection machine.[1] Determination of process parameters is the final step before the part is manufactured. At that point, it is too expensive to modify the mold, the material of choice cannot be altered and the chosen injection machine has been selected. In this case, there is still time to optimize the process parameters to ensure that the molded part is qualified, the production efficiency is maximized, and the manufacturing process is adequate.

However, the procedure for determining process parameters is an extraordinarily challenging task for two reasons. The first is that there are so many influencing factors to be considered, such as the structure of a mold, the rheology of a polymer melt, and the limits of the injection machine. The second can be generally attributed to the intricate and nonlinear relationships between the quality of a part and its corresponding process parameters. Unfortunately, determination of process parameters is still a skilled art on the production floor. This usually involves preliminary conjecture of a set of testing parameters on the basis of personal experience, followed by fabrication of a test molding of the desired part. Subsequently the quality of the product is evaluated to adjust the relevant process parameters, which leads to a second test molding. For example, a short shot might attribute to a slow injection velocity, or a low injection pressure. As a result, these two parameters would be moderately increased over those used in the previous molding. This trial and error method is repeated until the desired product can be routinely produced. Obviously, this approach is time-consuming and the quality of molded part depends primarily on the personal experiences of the particular molding engineer.

In the past decade, various optimization methods have been proposed to establish the best process parameters, including analytical and artificial intelligence methods.[2–11] Lucyshyn et al.[2] proposed a physical model for a quality control concept in injection molding based on theoretical derivation. Galantucci and Spina[3] and Chen et al.[4] optimized process parameters by combining simulation tools and DOE. Bozdana and Eyercioglu[5] constructed a frame-based, modular and interactive expert system. Chen et al.[6] established a soft computing model for optimizing multiple-input and multiple-output process variables working towards an optimization objective based on the product quality and dimensional precision. Yarlagadda and Khong[7] developed a hybrid neural network system to predict the injection time and pressure in injection molding. Petrova and Kazmer[8] integrated the neural networks and expert knowledge database to construct a hybrid neural network model for online controlling the molding quality. Zhou and Turng[9] presented an integrated simulation-based optimization system for implementing the iterative optimization of an injection molding process without artificial intervention, using a surrogate model based on the Gaussian process approach. Kwong et al.[10] designed a case based reasoning system to obtain proper molding parameters using expert systems. Shelesh-Nezhad and Siores[11] developed an intelligent system for obtaining the magnitude of process parameters by applying rule-based and case-based reasoning techniques.

These studies have focused on obtaining optimized process parameters to improve the quality control of injection molded parts. However, what is the objective of optimizing process parameters? What does an optimum set of process parameters mean for injection molding? In which production activities will these optimization methods help technologists? As is well known, the manufacturing process of injection molding is cyclical and characterized by high efficiency. Process parameters must be robust enough to ensure that the manufacturing process is not disrupted by fluctuation of environments (e.g. ambient temperature), injection machines, or materials. The concept of robust injection molding is now popular and is considered to be as important as quality control.[12] Thus the objective of optimizing process parameters should be not limited to the quality control of injection molded parts. An optimum set of process parameters means that the molded part is within acceptable tolerances, the production efficiency is maximized and the manufacturing process is robust. Previous research succeeded in finding online optimization methods for a few product parameters, such as dimension, weight and warpage. These can be optimized in a specific manufacturing environment. However, the aspect of robust manufacturing is ignored. Indeed, determining procedure of process parameters is required in all production activities of injection molding. When the mold is designed or fabricated, a set of process parameters must be found for performing a trial shot to test the mold. In a pilot plant, ranges of process parameters are evaluated for determining the optimum conditions. During mass productions, process parameters are optimized by minor adjustments to accommodate a particular injection machine and the environment. A close to optimum set of process parameters is required in the first two activities but must be further adjusted to accommodate varied environments and different injection machines. The aforementioned optimization method appears to be too exacting for the mass production stage, technicians are reluctant to perform repeated, demanding optimization procedure as the manufacturing environment varies, or the injection machine is changed.

Therefore, defining a suitable procedure for determining the best process parameters means (1) ascertaining ranges of process parameters that will create a robust, stable manufacturing process. And (2) seeking an optimum set of process parameters to accommodate a particular injection machine and environment. The first can be achieved using an offline prediction that employs simulation tools, a design of experiment method (DOE), fitting methods etc., which consider mold structures and material characteristics. The latter can be accomplished through a concise online optimization such as expert knowledge-based reasoning and optimization algorithm, according to manufacturing environment and injection machine's performance, taking advantage of offline prediction results. Huang and Lin[13] developed an innovative searching method for setting the robust process parameters based on a regression model. Kazmer et al.[14] derived a process window from quantitative process models using a novel multidimensional clipping algorithm. Kazmer and Mundhra[15] subsequently developed a new analytical procedure based on the extensive simplex method that derives the global process window for an arbitrary number of process parameters and quality specifications. Kulkarni proposed a method for obtaining the process window using contour plotting on DOE results.[12] Berti and Monti[16] proposed a new approach that enables a robust optimization of the injection molding process, based on the integration of numerical simulations. In these researches, the boundary in which the part can molded robustly has not been calculated or only represented by several linear planes.

Simulation tools have been proven to be useful for offline evaluation of a set of process parameters for a given mold.[17,18] Bourdon[17] developed a strategy to determine the optimum process parameters based on simulation calculations. Nagarsheth[18] combined a statistical and flow simulation technique to obtain permissible molding conditions. To ascertain the ranges of process parameters, we need a lot of simulation analyses. However, an accurate simulation requires the part be meshed into more than ten thousands elements, which means we need more time for simulation analysis. It is unacceptable.

This article focuses on the offline prediction of process parameters ranges that will produce a robust and stable manufacturing process. Design of experiment (DOE) is employed to reduce the number of simulation analyses. The process window is fitted using a support vector machine (SVM) classifier by evaluation of simulation results from a small quantity of analyses. Consequently, the process window, which is an irregular region, can be implicitly defined by the SVM classifier and simulation samples.

STRATEGIES FOR PREDICTING THE PROCESS WINDOW

For an experienced injection molding engineer, once the product material type and mold structure are confirmed, the optimized process parameters can be located in a zone where acceptable parts are molded without defects. The zone of

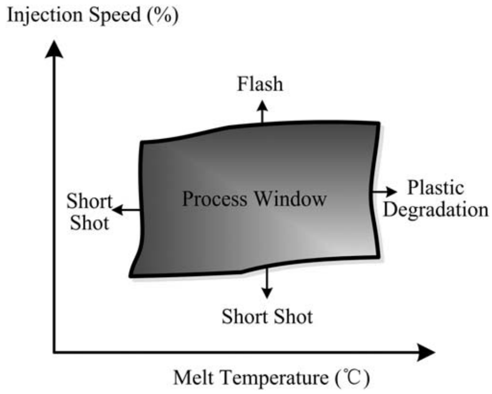

Figure 1. A typical process window (melt temperature vs. injection speed).

process parameters is called process window.[15,19,20] It is represented by a set of boundaries that define a window-like shape, as illustrated in Figure 1, in which injection speed and melt temperature are considered as process parameters. Outside of the illustrated process window, molded parts will be unacceptable due to defects such as sink, flash, or short shot. When the process parameters are close to the center of this window, the quality of the part will be less influenced by the variation of the shop floor environment, or fluctuations in the injection machine. Thus a robust and stable manufacturing process can be maintained. Kulkarni[12] further divided the process window into aesthetic, dimensional and control process windows and developed a procedure for determining the process window employing a DOE method.

The process window is significant for robust manufacturing, as well as the optimization of process parameters. There is little doubt that the potential optimum process parameters would be positioned in the process window. If the process window can be established prior to employing a process optimization method, the optimization procedure would be simplified. However, there are a large number of process parameters involved and intricate and nonlinear relationships exist between these and the quality of the molded part.[21] The process window is an irregular region in a multi-dimensional space of process parameters that presents a window-like shape. It is a difficult task to precisely describe such an irregular region using a mathematical or a descriptive form.

It is unrealistic to simultaneously consider all the parameters of every phase. Consequently, it is far more reasonable to establish an acceptable process window for a process stage, such as injection, or packing, rather than a full process window for all the process parameters.[20] In entire molding process, final product quality relies primarily on the filling and packing processes. The packing stage is considered in this article. Packing pressure, melt temperature and mold temperature are selected as the key parameters. These significantly affect the rheology of the polymer melt, pressure in the mold cavity, and the density distribution of the molded part. Thus, the process window is defined in a three-dimensional space of packing pressure, melt temperature and mold temperature.

The designed workflow of predicting a process window can be divided into following steps:

- STEP 1: Establishing initial ranges of process parameters. Initial ranges define the maximum boundary box of the process window and can be approximately estimated. An initial range for a typical process parameter is given according to the recommended values from the material supplier or from empirical values. For the packing stage, the initial range of packing pressure can be estimated from the maximum injection pressure, the weight of molded part, the size of gate and the family of the polymer. The initial ranges of melt and mold temperatures are usually provided by the polymer supplier.
- STEP 2: Performing a set of numerical simulations based on DOE. To decrease the number of process simulation analyses and simultaneously consider the coverage of the process parameters, several sets of process parameters are generated from the DOE, according to the initial range of process parameters. Following this, filling analyses with designed process parameters are performed using simulation tools.
- STEP 3: Evaluating simulation results and calculating qualitative indicators. Each set of designed process parameters is quantitative evaluated from the filling simulation results, such as flow front temperature, sheer stress and so on. The corresponding quality indices are selected as the constraint condition. If the simulation results satisfy all the above conditions, they are classed as positive samples. Otherwise, they are classed as negative samples. Thereby sample data can be obtained which will be applied to train a SVM classifier for establishing the process window.
- STEP 4: Training of a SVM classifier using sample data from evaluations of simulation results. Traditional fitting methods, such as artificial neural network (ANN), are unsuitable for the present situation, because the number of sample data from simulation is relatively small. Compared with ANN, the support vector machine is superior for this situation, because of the small sample classification and determination of the parameters of a predetermined nonlinear model based on the structural risk minimization principle.
- STEP 5: Establishing the boundary of the process window and optimized process parameters. Although the boundary of the process window can be obtained from calculation of the SVM classifier by interpolation of process parameters, it is recommended that the process window be represented by the SVM classifier and sample data. SVM directly predicts whether a set of process parameters is in the process window or not. The center point of the process window is thought to be robust for molding, and can be regarded as providing the optimized process parameters.

KEY ALGORITHMS

Simulation Analysis Based on DOE

DOE techniques have been employed to help molding technicians understand the injection molding process. Among the various DOE techniques, the Taguchi method has been widely used for injection molding. It is a method that employs an orthogonal table to arrange and analyze multifactor experiments. Taguchi parameter design obtains a random sample of future

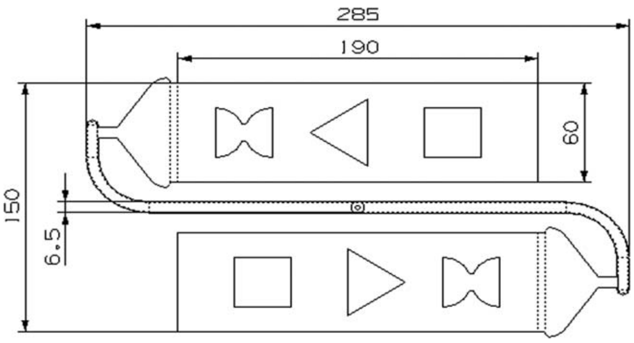

Figure 2. Dimensions of the plate part.

conditions with the orthogonal array. It has been used to uncover subtle interactions among process variables and determine optimal process parameters for injection molding with a minimum number of test runs and cost.[21]

In most applications, Taguchi parameter design helps one to better understand process characteristics and investigate how inputs affect responses. It is based on statistical backgrounds and an orthogonal array is representative of all inputs. Therefore, numerical experiments are performed with only process parameters in the scheduled orthogonal array, reducing the number of simulation analyses based on a statistical analysis.

It is conjectured that there are no interactions between injection factors, because the shear heat is negligible in the packing-holding phase and the mold temperature is influenced primarily by the coolant and cooling time. Thus the packing pressure, melt temperature and mold temperature are three factors considered in Taguchi parameter design and there is no interaction between them. The levels of melt temperature and mold temperature can be determined from the ranges recommended by the polymer material suppliers. The level of packing pressure is directly related to the weight of molded part, the rheology of polymer melt and the injection pressure and it can be determined from experience.

Subsequently, filling analyses with designed process parameters are performed using simulation tools. The flow of the polymer melt plays a very crucial role in the injection molding process. Filling simulation has been developed for decades so that it is relatively mature. There are several commercial software tools which can perform a filling simulation with a high accuracy. The filling simulation of injection molding process can be organized into three categories: mid-plane models, 2.5-dimensional models, which is also called surface models or dual domain models, and full three-dimensional models. In recent years, full three-dimensional simulations are available to be performed on a personal computer, attributing to the development of high performance computer and parallel computing technique. However, they still require a large-scale computation and the exacting restrictions on meshing. The 2.5D models based on the Hele-Shaw approximation are still a popular and effective solution to flow analysis for a part with a thin shell shape. Generally speaking, up to 75% of all plastic products are thin shell shaped. Filling analyses based on 2.5 models are employed in our study.

Evaluation of a Simulation Result

As previously mentioned, the process window is defined as a feasible process zone in which a part can be molded with a designated quality. The quality is usually defined as dimensional tolerance, mechanical property, and optical performance etc. Dependent variables, such as melt temperature, melt pressure, melt-front advancement, maximum shear stress etc., which depend on not only the process parameters but also the material and mold configuration used, can reflect the characteristics of the resin being processed. These variables, which are commonly referred to as process control variables for quality control, have been widely studied and reported in various publications.[22] Therefore, the quality of a molded part can be predicted or evaluated from these process control variables. On the other hand, these process control variables can be obtained directly from simulation results. Thus, the criteria of part quality based on process control variables can be derived from simulation results, defined as follows:

1. The maximum shear stress $\tau_{\max}$ should not exceed the permissible shear stress τ_{limit} of polymer melts, i.e., $\tau_{\max} < \tau_{\text{limit}}$
2. The maximum shear rate $\nu_{\max}$ should not exceed the permissible shear rate v_{limit} of polymer melts, i.e., $\text{v}_{\max} < \text{v}_{\text{limit}}$.
3. The temperature of flow front $T_{\text{front}}^{\text{ti}}$ should not be far below or far exceed the temperature T_{melt} of melt at the entrance, i.e., $T_{\text{melt}} - T_1 < T_{\text{front}}^{\text{ti}} < T_{\text{melt}} + T_2$, where T_{melt} is the temperature of melt at the entrance, $T_{\text{front}}^{\text{ti}}$ is the temperature of flow front at time t_i, T_1, and T_2 are temperature allowed tolerance between flow front and melt at the entrance. $T_1 = T_2 = 10°\text{C}$ is recommended for most applications.
4. Short shot is not allowed, thus the number of filled mesh elements N_{inj} is equal to the total number of mesh elements N_{total}, i.e., $N_{\text{inj}} = N_{\text{total}}$
5. The packing pressure P_{inj} should not exceed the ability $P_{\max}$ of the injection machine, i.e., $P_{\text{inj}} < P_{\max}$
6. The clamp force F_{clamp} should not exceed the permissible one $F_{\max}$, i.e., $F_{\text{clamp}} < F_{\max}$.

These evaluation criteria determine whether a set of selected process parameters is feasible. If a simulation result satisfies all of these conditions, it together with its corresponding process

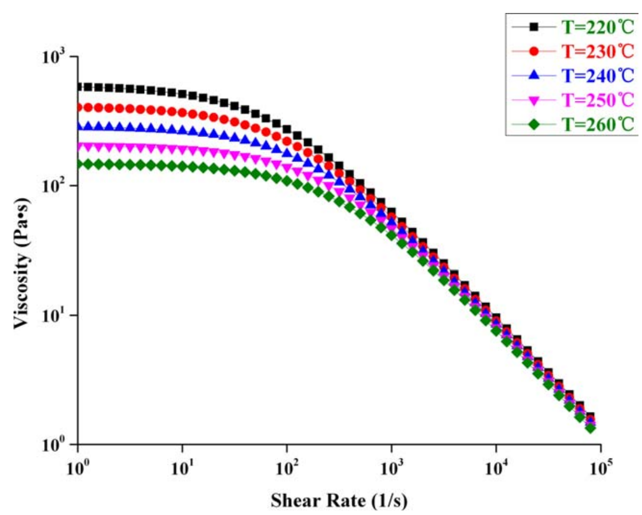

Figure 3. The measured rheology of PPH-T03. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Table I. Factors and Their Levels of the Orthogonal Array

Factor	Description	Level 1	Level 2	Level 3	Level 4	Level 5
A	Melt temperature (°C)	220 (A1)	230 (A2)	240 (A3)	250 (A4)	260 (A5)
B	Mold temperature (°C)	20 (B1)	30 (B2)	40 (B3)	50 (B4)	60 (B5)
C	Packing pressure (MPa)	15 (C1)	30 (C2)	45 (C3)	60 (C4)	75 (C5)

parameters is classed as a positive sample, with a rank +1. Otherwise, it is classed as a negative sample, with a rank −1.

It should be noted that quality criteria are not unique and depend on the definition of the process window. The process window, limited by the cited quality criteria, is defined as a feasible process zone in which a part is molded without flash, short shot, sinks, internal voids and burning mark. It is similar to the aesthetic process window defined in reference.[12]

Calculation of a Process Window

The process window can be obtained by calculating contour plots of qualitative indicators related to two factors,[12] or from a training of simulation samples. In most studies,[23,24] Artificial Neural Network (ANN) was used to predict how the quality was affected by process parameters. Although, ANN is a valuable machine learning modeling tool, providing sufficient, rich data for modeling the process' nonlinear relationships, it relies on empirical risk minimization.[25] Alternatively, SVM is motivated by statistical learning theory led to a class of algorithms characterized by the use of kernels, the absence of local minima, the sparseness of the solution and the capacity control obtained by acting on the margin. Recent research revealed that SVM had better performance than ANN when the sample data was small or untrustworthy.[26] Thus the SVM classifier is very suitable for predicting the process widows, owing to the non-linear relationships between process parameters and the quality of molded part, a lack of simulation samples, and influences by the accuracy of the simulation.

The problem of classification consists of estimating a function f: $R^N \rightarrow \{\pm 1\}$ using l independent and identical distributed input-output training data $(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_l, y_l), \in R^N \times \{\pm 1\}$. $\boldsymbol{x}$ is a vector of process parameters, namely packing pressure, melt temperature and mold temperature. +1 represent the quality of molded part is acceptable, conversely −1 means unacceptable.

The SVM classifier can fit noise and outliers leading to poor generalization, thus a hard margin classifier is no longer adequate. C-SVM classifier, in which a penalty term has been introduced to generate a soft margin, is employed. The classifier attempts to separate the data by minimizing the objective function:

$$\begin{gathered} \text{Minimize} \sum_{j=1}^{l} \alpha_j - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j) \\ \text{Subject to} \sum_{i=1}^{l} \alpha_i y_i = 0 \\ \text{and } C \geq \alpha_i \geq 0, i=1, \ldots, l. \end{gathered} \tag{1}$$

where α_i is a non-negative Lagrange multiplier. C is a penalty parameter. K represents a kernel function which is positive define function $R^N \times R^N$ to R^N that defines an embedding of input patterns into feature vectors.

The nonlinear decision function is:

$$f(\boldsymbol{x}) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i^* y_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b^*\right), \tag{2}$$

where $\boldsymbol{x}$ is a set of process parameters needed to be predicted whether it is in the process window or not.

Radial basis kernel function (RBF) is employed as the kernel function. RBF is defined as:

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\gamma \|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2\right) \ \gamma > 0, \tag{3}$$

where γ is a kernel parameter.

It should be noted that the penalty parameter C represents the importance of the inputs, while the kernel parameter γ reflects linear mapping from input parameters into the feature vectors. C and γ can be independently searched with an exponential interval ($C = 2^{-10}, 2^{-9}, \ldots 2^{10}$, $\gamma = 2^{-10}, 2^{-9}, \ldots 2^{10}$). $C = 1024$ and $\gamma = 0.0625$ in our study.

Once the SVM classifier is trained with simulation samples, the quality of the molded part can be predicted by a given set of process parameters. The boundary of the process window can be obtained from calculation of the SVM classifier by interpolation of process parameters. There are many methods that can be used to find the best process parameters if relationships between process parameters and part quality are known. These include genetic algorithm (GA), particle swarm optimization

Table II. Classifications of Simulation Samples

No.	Factor and level $\boldsymbol{x}_i$	Class y_i	No.	Factor and level $\boldsymbol{x}_i$	Class y_i
1	A1B1C1	−1	14	A3B4C1	−1
2	A1B2C2	+1	15	A3B5C2	+1
3	A1B3C3	+1	16	A4B1C4	+1
4	A1B4C4	−1	17	A4B2C5	−1
5	A1B5C5	−1	18	A4B3C1	+1
6	A2B1C2	−1	19	A4B4C2	+1
7	A2B2C3	+1	20	A4B5C3	+1
8	A2B3C4	+1	21	A5B1C5	−1
9	A2B4C5	−1	22	A5B2C1	+1
10	A2B5C1	−1	23	A5B3C2	+1
11	A3B1C3	+1	24	A5B4C3	+1
12	A3B2C4	+1	25	A5B5C4	−1
13	A3B3C5	−1			

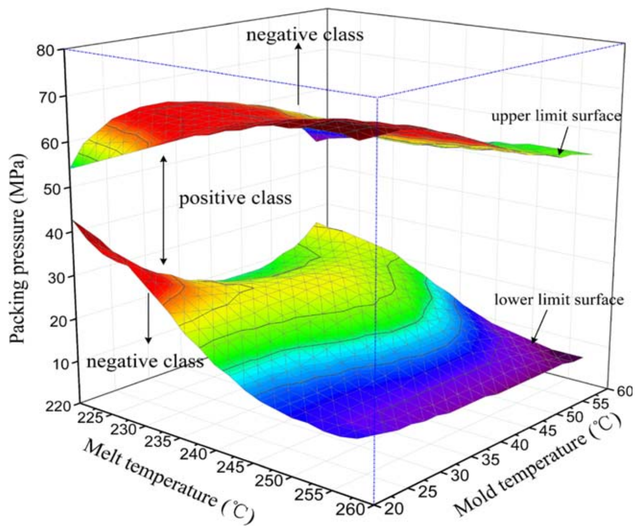

Figure 4. The predicted process window. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

algorithm (PSO).[24,27] We argue that the center point of the process window is a reasonable choice, because confidence level of the predicted window cannot be confirmed until an actual molding of a part is produced. This is because there are too many uncertainties concerning the polymer material, mold, injection material and environment.

A CASE STUDY

To demonstrate the procedure and algorithms for predicting the process window, a case study is presented in this section. A plate part with a thickness of 3 mm was prepared, as shown in Figure 2. It was designed with a varied cross section in the flow length direction in order to obtain a variation in injection pressure. A fan gate is located at one end of the plate and the mold has two symmetrical cavities. The resin used in the experiment was a general polypropylene branded as PPH-T03 produced by China Petroleum Chemical Industry Co., Ltd. The recommended range of melt temperature and mold temperature were 220 to 260°C, 20 to 60°C, respectively. The weight of molded plate was estimated to be 65 g, and the range of packing pressure was from 1 MPa to 90 MPa determined from experience.

The rheology property of a polymer has a great influence on its filling behavior and the accuracy of a filling analysis depends on facticity of the rheological parameter. The rheology of a polymer is complicated and its viscosity varies dramatically with shear rate and temperature. Two materials belonging to the same class as the subject polymer, but from different manufacturers might produce a profound discrepancy in their rheology properties. Thus, the viscosity of the material used in this case was measured and rectified before the numerical simulation was performed. The rheology of PPH-T03 was measured using a capillary rheometer, as shown in Figure 3. It can be seen that viscosity of PPH-T03 is more sensitive to shear rate than temperature, and the sensitivity to temperature decreases while shear rate increases.

As previously mentioned in Strategies for Predicting the Process Window section, packing pressure, melt temperature and mold temperature are considered as process parameters for the packing stage. The injection speed, packing time and cooling time were 35%, 25 s and 20 s, respectively. The switchover position from injection to packing was set at the position where the melt volume reached 95% of the whole cavity.

Initially, an orthogonal array $L_{25}(5^3)$ with three factors and five levels was employed, as listed in Table I. The levels of the factors were determined according to estimated ranges of the three process parameters, and they are encoded for convenience of expression, for example, B3 denotes the level 3 of factor B, i.e. mold temperature of 40°C.

Subsequently, 25 filling analyses with different process parameters were carried out using the simulation tool, according to the orthogonal array $L_{25}(5^3)$, as listed in Table II. For example, A4B3C1 indicates a filling analysis with a melt temperature of 250°C, a mold temperature of 40°C and a packing pressure of 15 MPa. All filling analyses were accomplished in 7.8 min on a personal computer with an Intel (R) Core (TM) i7-2600 3.4 GHz processor and 8 GB RAM.

Analytical results were evaluated using the established criteria of part quality, which are described in Section "Evaluation of a Simulation Result." If the results of an analysis satisfied all criteria, the corresponding row in the orthogonal array is a positive sample marked as $+1$; otherwise is negative one marked as -1. As a result, a total of 25 samples were obtained, including 14 positive samples and 11 negative samples. Classifications of the simulated samples are listed in Table II.

Then, samples from simulation results could be trained by a SVM classifier. The input-output training data were $(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_{25}, y_{25}), \in R^3 \times \{\pm 1\}$. $\boldsymbol{x}_i$ is the vector of i-th normalized packing pressure, melt temperature and mold temperature in Table II, y_i is the class from evaluation of corresponding simulation results. The penalty parameter C and the kernel parameter γ were set to 1024 and 0.0625 respectively by a search with an exponential interval. The accuracy of cross-validation reached up to 96% and the prediction accuracy was 80% for 20 independent testing samples, which means the achieved classification hyperplane trained by the SVM can classify the test samples as positive or negative with a high reliability.

To give an intuitive glance at the process window, the boundaries of the process window have been obtained from calculations using the SVM classifier by interpolation of process parameters, as shown in Figure 4. The process window is depicted as a zone in a three dimensional space relative to packing pressure, mold temperature and melt temperature. It denotes the space including all positive samples and represents a collection of process parameters which can be used to successfully mold the desired part. The boundary of the process window has been smoothed for a clear display. An upper and a lower limit surfaces of packing pressure relative to the mold and melt temperatures are obtained. The space of positive samples is located between the upper and lower limit surfaces. The space of negative samples is separated by the process window.

It can be seen that packing pressure has a great effect on the quality of the molded part while mold temperature and melt

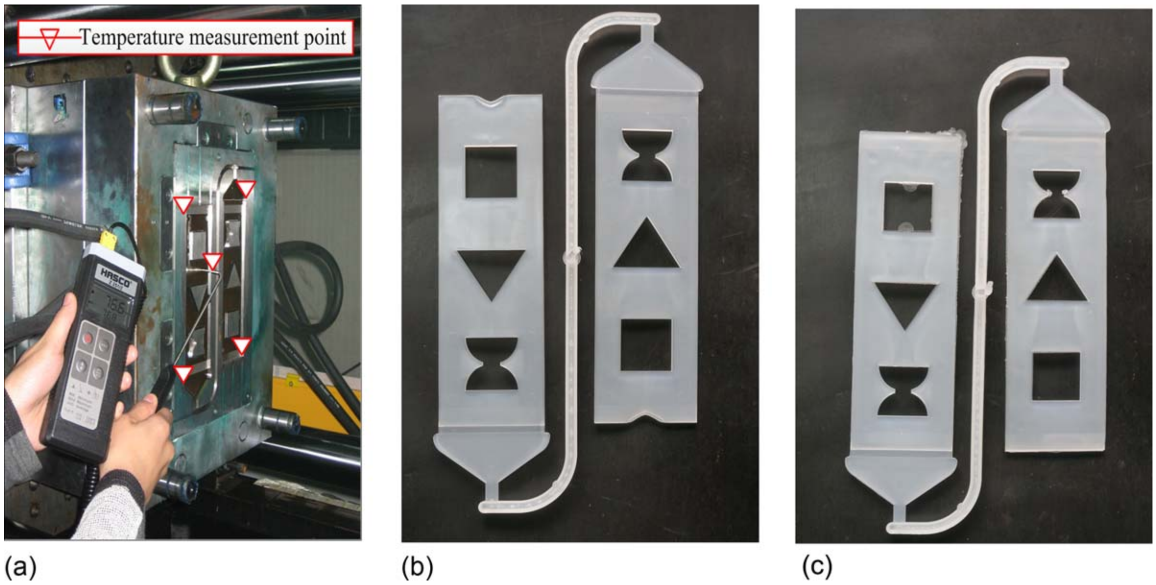

Figure 5. Verification experiment: (a) mold temperature measurement; (b) a part with short shot molded at a packing pressure beneath the lower limit; (c) a part with flash shot molded at a packing pressure beyond the upper limit. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

temperature play relatively small roles. This also can be intuitively concluded from the rheological properties of polypropylene, as shown in Figure 3. An exceeded clamp force or a flash might be encountered when the packing pressure is beyond the upper limit. Conversely, a short shot might occur when the packing pressure is less than the lower limit. It appears that the process window is an irregular region in a multidimensional space relative to the process parameters in injection molding and attributed to the rheology of polymer melt and complex structures of mold cavity. It is obvious that the two limit surfaces are curved and they are difficult to be described in a mathematical or a descriptive form. Therefore, it is recommended that the process window is directly represented by a SVM classifier and simulation samples. Once the process window is determined, the range of a parameter can be acquired while holding the other two constant. For example, the range of feasible packing pressure is 9.9 to 69.4MPa when the melt temperature is 260°C and mold temperature is 30°C. Thereby the range of feasible packing pressure can be predicted while melt temperature and mold temperature are defined in the trained SVM classifier.

VERIFICATION AND DISCUSSION

In order to verify the reliability of the predicted process window, the plate part was molded with different melt temperature, mold temperature and packing pressure. The injection machine was a BSIII-150 with a maximum clamp force 150 ton, manufactured by Borch machinery Co., Ltd. The mold temperature was controlled by a temperature controller STM-910-W, manufactured by ShiNi plastic technologies, Inc. The actual melt temperature and mold temperature were measured using a handheld temperature meter Z251/2, manufactured by Hasco Hasenclever GmbH Co.

A sequence of injection moldings was carried out to find the feasible ranges of packing pressure while mold temperature and melt temperature were held constant. A part with any aesthetic defect, such as short shot, sink mark, or flash, was regarded as unacceptable. The process parameters adapted to mold this part were considered to be out of the process window. The implementation details of the experiments were as follows. First, the melt temperature and mold temperature were set to specific values respectively, and their actual values were then measured using the handheld temperature meter. The melt temperature was the average value of three mold shots. The mold temperature was an average value of measured temperatures from five points on the mold surface, as marked in Figure 5(a). The temperatures were considered to be stable until the actual mold temperature and melt temperature attained the set values within a tolerance of ±0.5°C respectively. The injection velocity, *V*/*P* switch point and cooling time were in accordance with simulations. Then we set the packing pressure to a small value and began molding. The packing pressure was increased in a small increment and recorded at points where the cosmetically acceptable part was molded, without any shorts or sinks. The recorded pressure was the lower limit of packing pressure. The packing pressure continued to be increased and was recorded at the point where there was evidence of an unacceptable molded part with defects of flashes or burn marks. This recorded pressure was the upper limit of packing pressure. The lower and upper limit bracketed the feasible range of packing pressure on the precondition of a given melt and mold temperature. The melt and mold temperature were modified according to Table III, and the previously mentioned molding steps were repeated. The verification experiment was continued until all the combinations of the melt and mold temperatures listed in Table III were used. A part with short shot at a packing pressure beneath the lower limit, and the other one with flash shot molded at a packing pressure beyond the upper limit, both were shown in Figure 5(b,c) respectively.

Twelve ranges of packing pressure contrasting with the predicted ranges of packing pressure were obtained from the

Table III. Comparisons of Packing Pressure Range by Prediction and by Experiment

No.	Melt temp. (° C)	Mold temp. (°C)	Feasible range of packing pressure by experiment (MPa)	Feasible range of packing pressure by prediction (MPa)
1	220	30	28-66	25.3-64.5
2	220	50	23-61	19-56.8
3	230	20	33-63	33-61
4	230	40	23-62	23.9-63.1
5	230	60	21-57	23.9-49.1
6	240	30	24-63	20.4-66.6
7	240	50	22-56	20.4-56.1
8	250	20	17-67	12.7-71.5
9	250	40	15-58	14.8-63.1
10	250	60	13-54	7.8-54.7
11	260	30	13-62	9.9-69.4
12	260	50	11-57	7.8-58.2

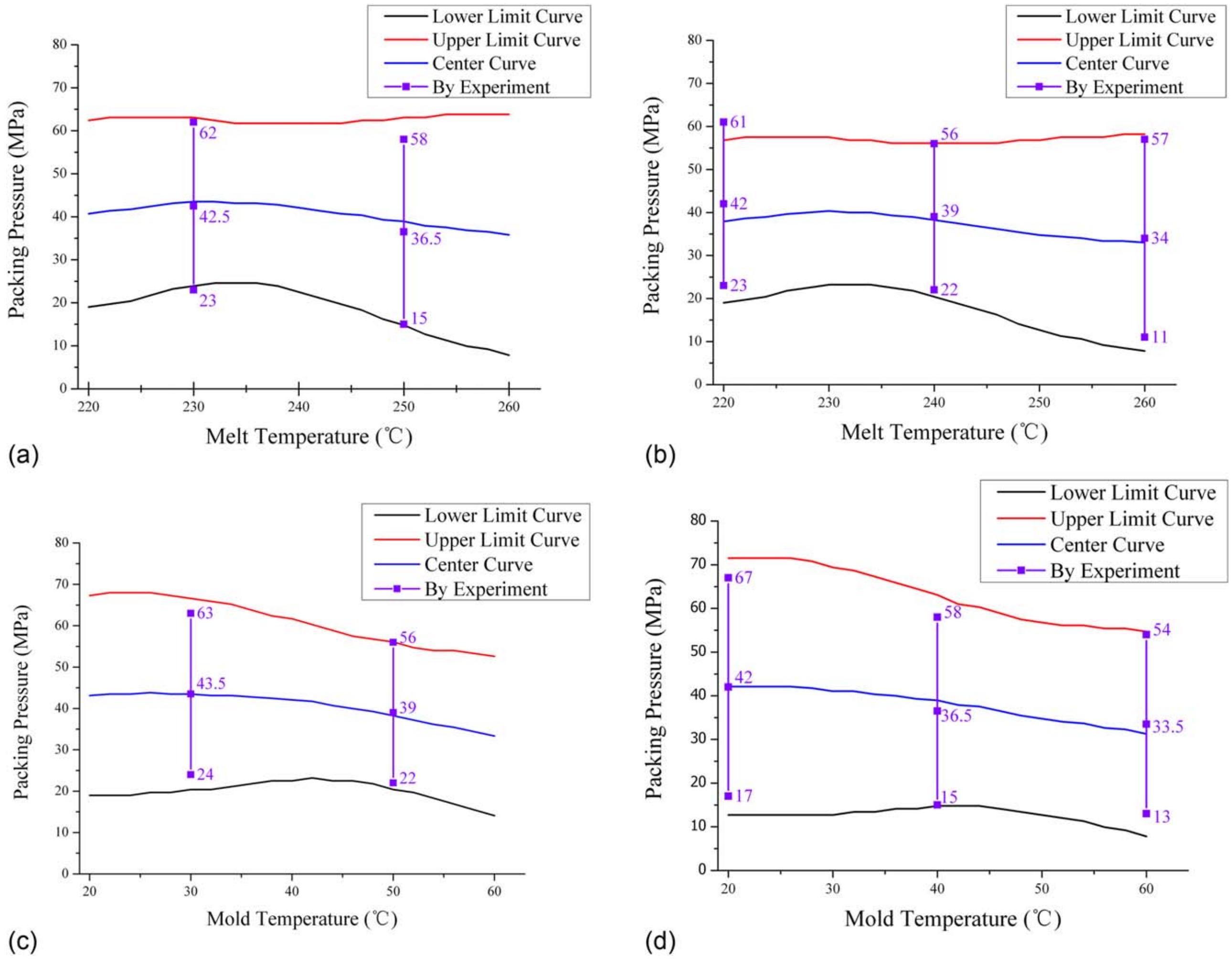

Figure 6. Comparison of feasible packing pressure range by prediction and experiment: (a) mold temperature = 40°C; (b) mold temperature = 50°C; (c) melt temperature = 240°C; (d) Melt temperature = 250°C. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

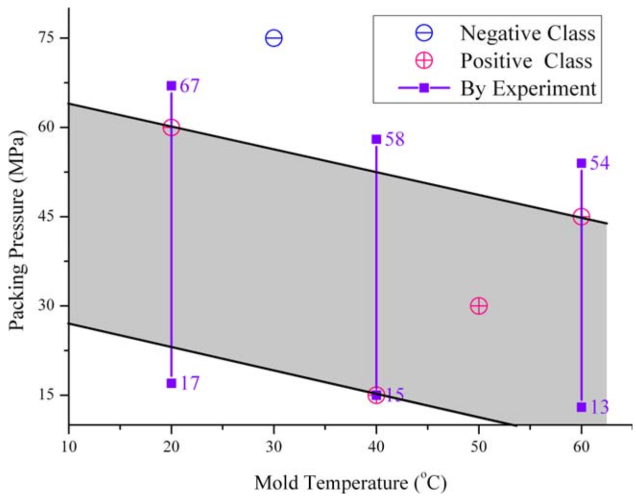

Figure 7. Comparison of feasible packing pressure range by contour plotting and experiment, melt temperature = 250°C. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

verification experiments as listed in Table III. The predicted ranges of packing pressures were calculated by substituting the corresponding melt temperatures and mold temperatures into the trained SVM classifier. At the same time, slices of the predicted process window in Figure 4 were made at the given melt or mold temperature. The intersecting curves between cut planes and the upper/lower limit surface were plotted, as well as the feasible ranges of the packing pressure from the experiments, as shown in Figure 6.

As shown in Table III and Figure 6, the upper limit and lower limits of the packing pressure, obtained either from the experiments or by the prediction calculations, slightly descend with increments of melt or mold temperature. This can be attributed to the lower viscosity and a better fluidity of the polymer melt when the melt or mold temperature increases. The predicted upper and lower boundaries of the packing pressure are close to the experimental results. The maximum deviation between the predicted and experimental upper boundary is 7.9 MPa when the melt and mold temperature are 230°C and 60°C respectively. And the maximum deviation between the predicted and experimental lower boundary is 5.2 MPa when the melt and mold temperature are 250°C and 60°C, respectively. The mean absolute errors of the predicted upper and lower boundary are 3.3 MPa and 2.6 MPa, respectively. These deviations might be due primarily to the accuracy of the simulation tools. There are many hypotheses in filling numerical simulations, such as the homogeneity of the polymer melts, no flow resistance existed between the mold wall and polymer melts. These can be substantiated from the evidence that the predicted ranges are all lower than the experimental ranges. This might be attributed to a lower pressure drop resulting from simulated calculations rather than the actual injection molding. In addition, the number of simulation samples, the fitting precision of the SVM classifier, and the discrepancies between actual cosmetic defects and criteria of part quality based on process control variables all contribute to these deviations.

Nevertheless, these deviations are relatively small and are tolerable for engineering applications. The predicted process window is useful for determining the actual optimum process parameters. For example, for robust injection molding, a reasonable choice is to set the process parameters to values as near as possible to the center curve obtained by prediction, as shown in Figure 6. The upper limit and lower limit can also be used as a reference in adjustment of the parameters.

Kulkarni proposed a method for obtaining the process window using contour plotting on DOE results.[12] In a contrast, a two dimensional process window respecting to mold temperature and packing pressure is obtained using this method, as shown in Figure 7. The dark area denotes the process window. The upper limit is a line which passes two DOE points marked with a positive class, and the lower limit is another parallel line which only passes one DOE point with a positive class. The melt temperature is 250°C, as same as in Figure 6(d). The feasible ranges of packing pressure are compared with the experimental results listed in Table III. Compared with Figure 6(d), the boundary of this process window is straight and it does not well in coincidence with the nonlinear boundary obtained by the experiment. Errors between the prediction and the experiment are rather too larger than that in Figure 6(d). This might be caused by that the three referenced points for contour plotting are limited to a slice plane where the melt temperature is 250°C and other DOE points at different mold temperatures are out of consideration. As a result, only several process windows on which slice planes existed DOE points can be obtained by this method.

A statistical experiment had been performed to verify robustness of the predicted process window. The weight variation of parts was selected as an assessment of robust injection, defined as:

$$\delta = \frac{\sqrt{(1/(n-1))\sum_{i=1}^{n}(w_i-\bar{w})^2}}{\bar{w}} \times 100\%, \tag{4}$$

where δ, w_i, $\bar{w}$ and n are the weight variation, the weight of the i-th part, the average weight and the number of molded parts respectively. All parts were molded with a melt temperature 240°C and a mold temperature 30°C. Five packing pressures were chosen in a range of 23.9 MPa to 63.1 MPa, which is from boundaries of the predicted process window, as listed in Table IV.

Table IV. Statistical Results of Part Weights with Different Packing Pressures

Packing pressure (MP)	Mean weight (g)	Max. weight (g)	Min. weight (g)	St. dev. (g)	Weight variation (%)
23.9	62.36408	62.65	62.18	0.140146	0.225
33.7	63.4849	63.72	63.31	0.113767	0.179
43.5	64.18653	64.34	64.08	0.077792	0.121
53.3	66.34571	66.56	66.15	0.110678	0.167
63.1	71.75429	72.14	71.16	0.16761	0.234

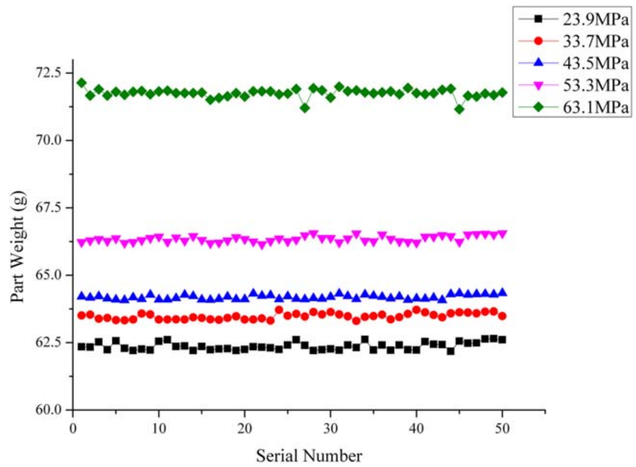

Figure 8. Weight distributions of part molded with different packing pressures. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Fifty parts were molded with each packing pressure and then measured by a PL202-S electronic balance with precision of 0.01 g manufactured by METTLER TOLEDO Co., Ltd. The weight distributions of all molded parts are shown in Figure 8, and the statistical results are listed in Table IV and depicted in Figure 9.

It is not unexpected that the average part weight grows with increasing packing pressure, because more melts are packed into the cavity with a higher pressure. However, the weight variation of parts is neither monotonically decreasing nor monotonically ascending with increasing packing pressure. It first decreases and then ascends, and reaches a minimum value while the packing pressure is 43.5 MPa, which locates at the center of the predicted process window. The weight variation of parts becomes great when the packing pressure is set closer to the upper/lower limit. For example, it reaches 0.234% when packing pressure is 63.1 MPa, increased by 46.22% in contrast to 43.5 MPa. Therefore, it might be helpful for maintaining a robust injection molding to select a set of parameters near the center of the predicted process window.

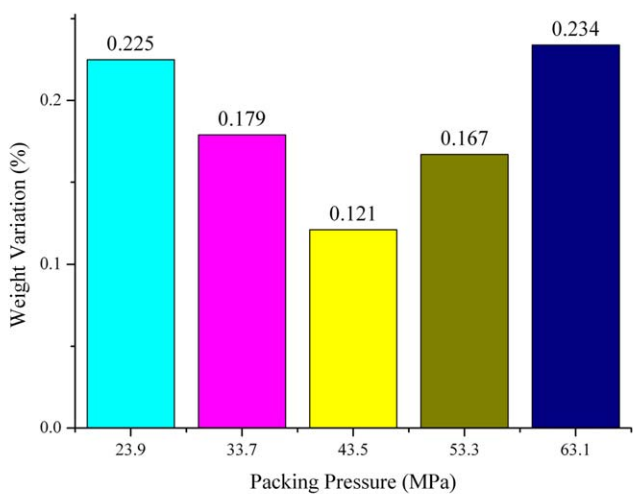

Figure 9. Weight variation of molded parts with different packing pressures. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

CONCLUSIONS

The development of a process window determines the feasible ranges of process parameters and is meaningful for robust injection molding. The process window is an irregular region in a multi-dimensional space of process parameters. It is a difficult task to precisely describe and calculate such an irregular region in a mathematical or a descriptive form. In this study, a novel methodology was proposed for predicting a process window. Numerical simulations based on a DOE method were designed to build relationships between a set of process parameters and part qualities. The process window was predicted using a SVM classifier and a set of simulation samples, simultaneously fulfilling computational efficiency and prediction accuracy. Injection molding of experimental plate with various process parameters was carried out to verify the reliability of the predicted process window.

The results of the verification experiment showed that simulation tools can be used for offline evaluation of a part by qualities process control variables from simulation results. A combination of DOE and simulations improves computation efficiency. The nonlinear and multidimensional process window can be accurately described by a SVM classifier and a set of simulation samples. The predicted window of an experimental part is in accordance with verification experiments within tolerable deviations. The presented method for prediction of process windows shows a potential ability to help in determination of process parameters. For instance, the center curves of a predicted process window can be a reasonable choice for robust injection molding, and the boundaries can also be used as references for adjustment of process parameters.

In contrast to barely obtaining an optimum set of process parameters by various optimization methods in many studies, this work demonstrates the development of a successful offline prediction of process windows for robust injection molding. The proposed method shows an ability to help technologists rapidly obtain a suitable set of process parameters for achieving consistency in part quality with low cost and high efficiency. This is, especially useful in variable environments with fluctuating injection machines on the plant floor. Further work is needed to improve the confidence of the predicted process windows by increasing the simulation accuracy and elaborating on the quality criteria for simulation results.

ACKNOWLEDGMENTS

The authors acknowledge financial support from the National Natural Science Foundation Council of China (Grant No. 51105152, 51125021, 512101052), National Program on Key Basic Research Project (Grant No. 2012CB025903, 2013CB035805), National Key Technology Support Program (Grant No. 2013BAF03B01), and "NC generation" Specific Foundation Project of Guangdong Province for Innovation and Applications in Mechanical Products (Grant No. 20120119).

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