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A principal component analysis model-based predictive controller for controlling part warpage in plastic injection molding

Songtao Zhang, Rickey Dubay *, Meaghan Charest

Laboratory of Advanced Controls and Intelligent Sensors, Department of Mechanical Engineering, University of New Brunswick, 15 Dineen Drive, P.O. Box 4400, Fredericton, New Brunswick E3B 5A3, Canada

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ABSTRACT

Quality control is an important aspect of manufacturing processes. Product quality of injection molded parts is influenced by the injection molding process. In this study statistical tools were used to develop a model that relates injection molding process variables to part quality. A statistically based model predictive control algorithm was developed for controlling part quality with manipulated variables coolant flow rate and coolant temperature. This approach replaces the need of off-line quality measurement and provides real-time injection modeling quality control.

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1. Introduction

Injection molding (IM) has been widely used to produce plastic parts at an economical price. The IM process has proven to be suitable for molding thin walled parts with complex geometries where a degree of precision is required. This is feasible because the IM process can be adapted to the characteristics of the molding material so the desired quality and repeatability can be maintained (Wang, Zeng, Xiaoxin, & Yuejun, 2013b).

Research concerning IM parameters that effect part quality is an ongoing field of study. An example of a quality feature is warpage, the main cause of undesirable warpage in an IM product is the imbalance of thermal residual stresses. These are caused by a non-uniform temperature distribution through the thickness of the moldings resulting from varying cross sections, part geometries, and temperature differences between the mold surfaces, etc. (Akay, Ozden, & Tansey, 1996). A variety of measures based on optimization techniques have emerged to improve IM process parameter settings, injection mold design, and IM machine performance with the objective of improving part quality. Optimization can be achieved in simulation or experimentally using classical design of experiment tools such as orthogonal experiments and the Taguchi method (Altan, 2010; Nie, Zhang, & Niu, 2013). Simulation tools and expert systems such as Moldflow Plastics Xpert(MPX) (Jauregui-Beckera, Tosellob, van Houtena, & Hansen, 2013; Stanek, Manas, Manas, & Suba, 2011), and neural-network techniques (Fei, Huajie, Lin, Wei, & Maosheng, 2011) outline the trend to integrate IM process prediction and IM parameter monitoring into the quality improvement.

Process control is an important aspect of the IM machine performance. Various modern control techniques have been applied to the IM process, such as adaptive control, model predictive control (MPC), and other intelligent control algorithms. This results in more segments of the IM process being controlled and helps maintain part quality (Wang & Mao, 2012). Examples of these include the reported study and design of a barrel temperature controller (Diduch, Dubay, & Li, 2004; Dubay, Diduch, & Li, 2004). The work sought to reduce the melt temperature fluctuations during start-up of the injection molding machine (IMM) and during continuous part molding. The focus centered on a single parameter without considering other process parameter interaction, which are important for the part quality. In another investigation, a temperature-independent adaptive controller was proposed for injection velocity during the filling phase (Dubay & Lakhram, 2004). They developed a controller which is immune to variations of processing condition such as melt temperature fluctuations in order to ensure consistent cavity pressure profiles and hence consistent part quality. Again, the interactions of process parameters are not being considered.

Despite the efforts of controlling the many parameters that effect final part quality periodic off-line quality inspection is necessary. Min showed that the quality of IM parts is dependent on both mold design and processing conditions (Min, 2003). Various factors including individual IM process settings and variations that relate the final IM product quality have been investigated in detail and various control methods have been proposed for the IM process.

* Corresponding author.
E-mail addresses: Songtao.Zhang@unb.ca (S. Zhang), dubayr@unb.ca (R. Dubay), charest.meaghan@unb.ca (M. Charest).

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Controlling combinations of key process parameters is therefore a reasonable idea for comprehensive IM quality improvement.

Collecting and analyzing large amounts of data to identify and understand key information is becoming more prominent in industry (Gandini, Lombardi, & Vaccarino, 2011). An example of this is the relation of production cost to a variety of injection molding production factors using artificial neural networks (Wang, Wang, & Wang, 2013a). In this investigation process parameter data was collected and analyzed since it express process information and can be used to identify the quality and control models necessary for quality based model. Extracting the correct information from the large amount of process data comprised of unavoidable noise is the key point for this approach. Principal component analysis (PCA) was used to construct a quality based regression model. This model combined with independent component analysis (ICA) is used to develop a Dynamic Matrix Control Scheme. This makes it possible to maintain product quality on-line during production.

Recently, implementing powerful statistical tools and data mining techniques has been gaining popularity in industry (Gandini et al., 2011). When large amounts of data can be collected and analyzed, it becomes possible to identify and understand trends in the data. An example of this is the relation of production cost to a variety of injection molding production factors using artificial neural networks (Wang et al., 2013a). In another study, a less complex method was used, a principal component analysis (PCA) based pattern matching method was applied to process monitoring and fault detection using independent component analysis (ICA). This showed the importance of PCA and ICA technique as data mining tools (Chen et al., 2013).

In this investigation process parameter data was collected and analyzed in order to identify the quality and control models necessary for quality based MPC. Extracting the correct information from the large amount of process data collected that included unavoidable noise was a key point for this approach. Principal component analysis was used to construct a quality based regression model. This model combined with ICA was used to develop a MPC scheme. The unique combination of PCA, ICA, and MPC make it possible to automatically affect part quality on-line while varying key process parameters. This novel methodology demonstrates good performance.

2. Background

In order to directly control part quality with on-line process data (cavity pressure, cavity temperature, etc.), an accurate model to estimate part quality is built in two steps:

1. Identifying the important components of the IM process using PCA.
2. Using the principal components obtained as predictors to build a regression analysis model to evaluate part quality.

The background theory required to obtain the model is described in this section.

2.1. PCA based quality model

Principal component analysis is a well known statistical method and has been widely used in data analysis and compression. For example consider the vector $\vec{\boldsymbol{Z}}$ which represents the injection molding process output as

$$\vec{\boldsymbol{Z}} = [z_1, z_2 \dots z_n]^T \tag{1}$$

where z_i with $i = 1, 2 \dots n$ are sensor outputs with noise and its expectation of $\vec{\boldsymbol{Z}}$ denoted by

$$\vec{\boldsymbol{\mu}}_{\boldsymbol{Z}} = E(\vec{\boldsymbol{Z}}) = [E(z_1), E(z_2), \dots, E(z_n)]^T \tag{2}$$

its covariance matrix is

$$\boldsymbol{C}_{\boldsymbol{Z}} = E((\vec{\boldsymbol{Z}} - \vec{\boldsymbol{\mu}}_{\boldsymbol{Z}})(\vec{\boldsymbol{Z}} - \vec{\boldsymbol{\mu}}_{\boldsymbol{Z}})^T) \tag{3}$$

The variance of a component of $\vec{\boldsymbol{Z}}$ indicates the spread of the possible values of outputs z_i around its mean value $E(z_i)$. If two components z_i and z_j of the data are un-correlated, their covariance is zero. The covariance matrix is, by definition, always symmetric.

From a set of sample vectors of $\vec{\boldsymbol{Z}} : \vec{\boldsymbol{Z}}_{\boldsymbol{1}} \dots \vec{\boldsymbol{Z}}_{\boldsymbol{M}}$, the sample expectation and the sample covariance matrix can be calculated as the estimates of the real expectation and the covariance matrix of $\vec{\boldsymbol{Z}}$. Each sample of $\vec{\boldsymbol{Z}}$ represents the cavity pressure and cavity temperature data from one injection molding cycle. From a symmetric matrix such as the covariance matrix, a set of orthogonal basis can be determined by finding the eigenvalues and eigenvectors of the covariance matrix. The eigenvectors $\vec{\boldsymbol{e}}_{\boldsymbol{i}}$ and the corresponding eigenvalues λ_i^* are the solutions of the equation

$$C_Z \vec{\boldsymbol{e}}_{\boldsymbol{i}} = \lambda_i^* \vec{\boldsymbol{e}}_{\boldsymbol{i}}, \quad i = 1, 2 \dots n \tag{4}$$

Ordering the eigenvectors in the descending order of eigenvalues (i.e., largest first), an ordered orthogonal basis can be created in which the first eigenvector relates to the direction of largest variance of $\vec{\boldsymbol{Z}}$. Suppose there exists a data set of which the sample mean and the covariance matrix have been calculated. Let $\boldsymbol{A}$ be a matrix consisting of eigenvectors of the covariance matrix (the eigenvectors are the row vectors of $\boldsymbol{A}$). The relation of vector $\vec{\boldsymbol{Z}}$ and the vector $\vec{\boldsymbol{X}}$ can be expressed as

$$\vec{\boldsymbol{X}} = \boldsymbol{A}(\vec{\boldsymbol{Z}} - \vec{\mu}_{\boldsymbol{Z}}) \tag{5}$$

which is a point in the orthogonal coordinate system space defined by the eigenvector. Components of $\vec{\boldsymbol{X}}$ can be seen as the coordinates of the orthogonal base.

Using all the eigenvectors of the covariance matrix is not necessary, the output data can be approximated using some of the vectors from the orthogonal basis. If the matrix having the first K (significant) eigenvectors as rows is denoted by $\boldsymbol{A}_K$, a similar expression can be created as

$$\vec{\boldsymbol{X}} = \boldsymbol{A}_K(\vec{\boldsymbol{Z}} - \vec{\mu}_{\boldsymbol{Z}}) \tag{6}$$

The vector of the original data has then been projected on the coordinate system having dimension K and the resulting vector can be expressed by linear combination of the basis vectors to its original value. This transformation minimizes the mean squared error (MSE) between the process output data and its approximation. Thus, by selecting a given number of eigenvectors with the largest eigenvalues, PCA offers a convenient way to control the trade-off between loosing information and reducing the size of $\vec{\boldsymbol{Z}}$. More details of PCA can be seen in Jollife (2002), MacGregor and Kourti (1995) and Burnham and Viveros (1996). Based on the K principle components obtained, a linear regression method can be applied to build a prediction model of IM product quality.

2.2. Independent component analysis

Once the PCA has transformed the high dimension IM process output into an orthogonal coordinated system in which the principle components of the data are un-correlated, the principle components can be viewed as a combination of independent events in the IM process. As an example, the event can be triggered by the machine operator who adjusts settings such as the coolant flowrate (as the manipulated variables). To identify or separate these events, ICA is applied on the principal component subspace X.

As the Central Limit Theorem indicates, the distribution of a sum of independent random variables tends toward a Gaussian

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