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Monitoring and dynamic control of quality stability for injection molding process

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ABSTRACT

Stability control of production is an important aspect of injection molding. However, challenges continue to exist with respect to improving product quality stability to achieve a faster forming speed and a higher automation for injection molding because the injection process is usually disturbed by several inevitable variations. The difficulty in overcoming the fore-mentioned inevitable disturbances and achieving dynamic control of product quality is related to establishing a quantitative relationship between product quality and process variables. In this study, a quality prediction model based on polymer melt properties is established to monitor product weight variation online. A pressure integral (*PI*) based on the prediction model is proposed as an effective process variable to predict product weight variation. Additionally, a dynamic control method is proposed to improve product quality stability. The experimental results indicate that *PI* presents advantages of consistency and stability in monitoring product weight variation when compared with models proposed by extant studies. The proposed control method results in a decrease in product weight variation from 0.16% to 0.02% in the case of varying mold temperature and the number of cycles to return stability decreases from 11 to 5 in with respect to variations in the melt temperature.

1. Introduction

Injection molding is an extremely important method in producing plastic products in manufacturing industries, and it possesses several advantages including short molding periods, high dimensional precision, and easy realization of automation. However, challenges persist in increasing product quality stability to achieve a faster forming speed and a higher automation for injection molding because an injection process is typically disturbed by various inevitable variations such as polymer melt properties, machine operations, and mold temperature. Several studies focus on disturbances to product quality stability including non-uniform melt properties because of variations in back pressure and screw rotation speed in the plasticizing stage (Tanoue et al., 2006) and mold temperature variation because of variations in the time taken by a manual or robot picker (Kurt et al., 2009). Therefore, stability control of product quality is a critical issue in injection molding.

In the last decade, various statistical methods were developed to monitor quality stability in injection molding. The fore-mentioned statistical methods do not require prior process knowledge, supervise all variables of whole control trajectories, and monitor abnormal situations (Kazmer et al., 2008). For example, (Lu and Gao, 2005) proposed a process analysis and quality prediction scheme based on a stage-based partial least square model, and (Wang et al., 2012) proposed a phase separation method based on multiway principle component analysis for monitoring the injection molding process. Zhang et al. (2015) proposed a statistical quality monitoring method to automatically extract statistical variables, and results indicated that the extracted variables were significant and representative with respect to product quality. Although the above methods were effective in process monitoring and rapid detection of an abnormal situation, they are ineffective in dynamically controlling product quality because of the lack of a quantitative relationship between product quality and process variables in the statistical methods.

Difficulty in overcoming the fore-mentioned inevitable disturbances and achieving dynamic control of product quality involves establishing a quantitative relationship between product quality and process variables. Process variables in injection molding involve large time-delays, time-variations, nonlinearity, and are multivariable, and thus a mathematical approximation algorithms are considered the most appropriate method to establish the aforementioned relationship. A basic approach involves collecting the sample data of the monitored process variables and product quality and subsequently fitting the approximate relationship through an appropriate mathematical approximation

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algorithm. Common mathematical approximation algorithms include Artificial Neural Networks (ANNs), Partial Least Squares Regression (PLS), Support Vector Regression (SVR), and Gaussian Process (GP). For example, (Chen et al., 2014) employed ANNs to construct a quality predictor between warpage and process variables. Zhao et al. (2008) developed a quality prediction method based on a PLS regression model with a simpler structure by using phase specific average process trajectory. Gao et al. (2014) developed a data-driven model based on SVR to quantify the relationship between quality characteristics and sensor data. Xia et al. (2011) proposed an optimization approach based on a GP surrogate model to determine process parameters and improve quality control for injection molding. An advantage of a mathematical approximation algorithm is that it possesses wide applicability and is suitable for almost any quantifiable quality prediction. Its disadvantage is that several samples are required to fit the approximate relationship. Therefore, this method is generally applicable in the optimization of process parameters and is not suitable for dynamic process control.

Conversely, a few studies demonstrated that product quality is characterized by injected polymer melt properties and flow states although the complexity of the injection molding makes it difficult to directly establish quantitative relationships between product quality and process variables (Chen and Turng, 2005). For example, (Wang, 2012) proposed a PVT diagram of a polymer melt describing the specific volume change with respect to melt temperature and pressure as the foundation for constant quality with the same degree of orientation, residual stresses, and shrinkage. Chen and Gao (2006) recommended that a uniform melt front velocity throughout the filling of a mold cavity can minimize non-uniformity of the molded parts. Additionally, various sensor technologies were applied to measure polymer melt properties and the flow state within an injection molding process. For example, (Wang et al., 2009) developed an online testing PVT equipment based on cavity pressure and temperature sensors to realize melt pressure and temperature measurement in real time. Wong et al. (2008) employed a capacitive transducer to detect start/end of mold filling and subsequently controlled velocity-to-pressure switchover. Gao et al. (2014) established an online product quality monitoring system through in-process measurement. Nguyen Thi et al. (2015) measured fiber orientation distribution in injection-molded parts by using X-ray computed tomography. The development of sensor technology can lead to the feasibility of dynamically controlling product quality by adjusting appropriate control variables based on the online monitoring of polymer melt properties and the flow state.

This study focuses on a dynamic control method of quality stability for injection molding based on the online monitoring of variation in melt properties. A quality prediction model based on polymer melt properties is established to monitor product weight variation online, and a dynamic control method is proposed to improve product quality stability.

2. Quality prediction model and control method

2.1. Representation of stability

The concept of product quality is ambiguous and there are several product quality definitions that can be classified into the following three categories: (a) dimensional properties (for e.g., weight, length, and thickness), (b) surface properties represented by the appearance of surface defects (for e.g., sink marks and jetting), and (c) mechanical or optical properties (for e.g., tensile and impact strength). Yang and Gao (2006) claimed that the performance of a manufacturing process and its quality control are monitored through product weight because quality is inversely proportional to variability and this is reflected in the product weight variation while product weight is closely related to other quality properties. For example, (Harry, 1991) suggested that a strong linear correlation exists between product length and weight, and (Min, 2003) indicated a strong correlation between product shrinkage and weight. Therefore, product weight is a good indicator of process stability.

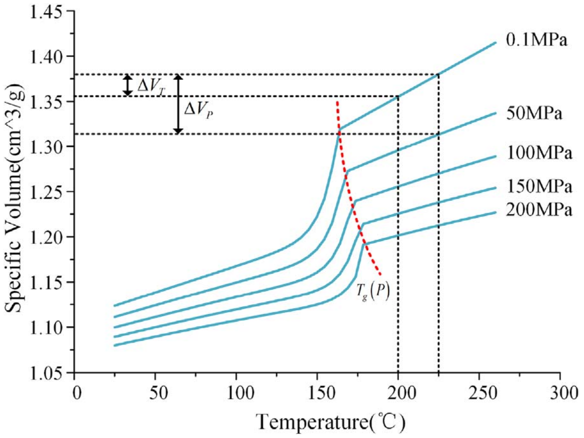

Fig. 1. A PVT diagram of polypropylene (PP-1215C) obtained from the Moldflow material database.

2.2. Quality variation analysis

In injection molding, a plasticized polymer melt is first injected into a closed mold cavity and is subsequently held to compensate for polymer shrinkage. This is followed by cooling it down to obtain the desired product. The volume of the mold cavity is constant, and thus the product weight changes with variations in melt specific volume. Fig. 1 shows a PVT diagram of polypropylene obtained from the Moldflow material database, and this demonstrates the relationship between melt specific volume with respect to temperature and pressure. For example, a decrease in temperature from 225 °C to 200 °C decreases specific volume to approximately 0.025 cm^3/g. Similarly, pressure increases from 0.1 MPa to 50 MPa, and this decreases the specific volume to approximately 0.7 cm^3/g.

The causes of the variation in melt specific volume can be classified into the following three categories: (a) Initial melt pressure that is potentially influenced by inconsistent material supply such as incomplete drying or material from different production batches. (b) Initial melt temperature that is potentially influenced by barrel heating and shear heat due to screw rotation. (c) Flow resistance that is potentially influenced by the mold temperature due to inconsistent cycle time and causes different melt compression while filling the cavity.

The control of melt specific volume consists of an injection stage and a holding stage. A melt is injected and compressed to fill a closed mold cavity during the injection stage and is then held to compensate for the polymer shrinkage during holding stage. The injection stage is simplified as an isothermal process for it is reasonable to ignore the variation in melt temperature (Michaeli and Schreiber, 2009) because the injection time is short (usually less than 2 s) and the thermal conductivity of the polymer melt is poor (less than 1% that of metal). Based on this simplification, the melt specific volume is mainly affected by the melt pressure during the injection stage. Fig. 2 illustrates the polymer melt extruded in the chamber during the injection process by the driving force from screw movement, and this results in a variation in melt pressure. The melt pressure profile in the chamber is divided into three sections corresponding to the three sub-stages of the injection stage, namely (a) initial filling, (b) stable filling, and (c) melt compression. With respect to the initial filling, the melt pressure depends on the resistance of the melt flowing through the runner. Generally, a higher initial melt pressure or a lower initial melt temperature increases melt viscosity and requires a higher melt pressure to overcome resistance through the runner. With respect to the stable filling, the melt pressure depends on the flow resistance of the melt filling the cavity. For example, a higher mold temperature increases melt flowability and