IMPROVED FAULT DETECTION APPROACH FOR INJECTION MOLDING

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Abstract

Statistical process control (SPC) for injection molding typically consists of setting alarm limits on a few important molding variables for real-time part containment. A new multivariate statistical process control (MSPC) method is presented that utilizes the measurement of process variable relationships to achieve a more robust quality control system. This approach not only detects process outliers outside of an allowable alarm range but can detect changes in correlation structure between multiple dependent variables, which often is the cause for out of spec parts.

Introduction

In today’s advanced injection molding processes, high levels of process characterization, process understanding, process monitoring, and process control are needed to achieve automatic quality assurance and process automation. Improved process automation provides many significant benefits to a molder, some of which includes improved process consistency, improved process productivity, reduced operator interference, and reduced labor costs [1]. Automatic quality assurance, however, has continuously proven to be the main barrier when trying to automate the molding process. This paper investigates an alternative and more effective approach to achieving automatic quality assurance in the injection molding process.

Automatic quality assurance is not only in demand for most applications, but sometimes is required, such as in specific medical applications where constant part sampling is either impossible or very difficult to do or when part contamination issues prevent an operator from inspecting the quality of parts. The quality control and assurance techniques currently used in the medical device community do not adequately prevent defective parts from getting through the manufacturing operations [2]. This need for automatic quality assurance has led to the investigation of various analysis and monitoring approaches in the plastics industry and other manufacturing environments. Univariate analysis (UVA) and monitoring methods, looking at one variable at a time, have been and are still very commonly used in the injection molding industry to attempt to achieve these high levels of quality assurance and process automation. One of the most common and most well understood methods of UVA is statistical process control (SPC).

SPC is used at a variety of levels at and around the molding process, from looking at critical process variables to looking at the final resultant part dimensions. This approach is utilized by creating and observing control charts of multiple variables, both from the process data and from the final quality data. These charts are then viewed on an individual basis to provide more detailed process understanding, which can lead to improved process changes or in some cases to perform in-line detection of out-of-spec parts. These methods however, have proven to be inadequate for most injection molding applications. The goal of this paper is to address why these UVA methods have been inadequate and what improved alternatives exist, specifically the alternative method of multivariate analysis (MVA).

Multivariate analysis is a statistical design tool used to deal with large datasets. One of the most important aspects of multivariate data analysis and monitoring is that it doesn’t perform prediction decisions solely based on upper and lower variable limits, but that it takes into consideration the correlation structure and the relationships that exist between all of the variables that are being monitored and modeled. This approach of using both the perturbations of single variables and the changes that are created in correlation structure provide a greater sensitivity and accuracy when compared to UVA.

MVA is a relatively new idea to the injection molding world, but recent research [1-4] suggests that the results of MVA provide significant improvements to existing methods that we use today regarding online fault detection of the injection molding process. Apart from the molding industry, many other industries rely on MVA for much improved fault detection and process understanding [5].

Various types of multivariate methods exist, but the method most commonly used for injection molding fault detection is known as Principal Component Analysis (PCA). PCA measures the correlations structure between the different observations in the data matrix and then uses a projections method to provide a set of new latent variables, also called principal components, which are linear combinations of the various measured process variables. The principal components are created so that they explain as much variation in the data set as possible and they also allow for improved visualization of an entire system. [6]
Theory and Discussion

SPC is a common tool used for measuring the consistency of a process by comparing individual variables to their associated upper and lower control limits. These upper and lower limits are typically calculated by using a certain percentage, often three-sigma, above or below the variable of interests’ calculated average or range. One of the problems with this technique is that many different process variables will need to be charted and monitored to ensure process stability. Also it becomes very difficult to observe trends and patterns in the data when viewing one variable at a time.

Real-time SPC for the use of process fault detection provides two significant issues as well. First of all, an SPC system will typically only monitor, in real-time, a few to possibly a handful of variables to perform accept and reject decisions. This is an ongoing problem for molders because even though there are variables that are known to be the most critical, many types of defects often occur than cannot be observed in this short list of so-called critical variables. Because of this, it becomes necessary to look at many variables in the molding process to accurately characterize and model the process behavior and then to determine when a part is in or out-of-spec or defective visually. In order to observe more variable in the process, the user must then create univariate control limits for these additional variables, and this leads to the second major issue with using univariate SPC on the molding process in real-time which is false alarm rates.

How many times, as molders, do we see an alarm and start to investigate the alarm only to find out that there wasn’t really an issue at all. This is an ongoing problem that processors deal with when they apply inline SPC tools to their manufacturing processes. The fact is that by using univariate upper and lower control limits, we cannot confidently and consistently determine when our process is “in control” or “out of control”. The reason is because univariate monitoring and real-time fault detection do not take into consideration the interaction and relationship between variables in the process. For further explanation, let’s look at two variables from the molding process such as temperature and viscosity, see Figure 1. Upper and lower control limits are created for temperature and then for viscosity. These two plots when overlaid over one another create a box that represents the process when it is “in control”. Using this acceptable control space for fault detection purposes would mean that when the process is within this box, the part would be accepted and when the process varies outside this box, the product would be rejected because the process is shown to be “out of control” which leads to out-of-spec parts. This type of approach is completely acceptable when looking at variables that are unrelated or independent of each other, but if the two variables are somehow correlated (viscosity and temperature are highly correlated for example), this “in control” space changes and must be accounted for if accurate fault detection is to be achieved. This can only be done by taking into consideration the relationship between these two variables, and is why multivariate fault detection has recently emerged as a new and improved method for real-time fault detection of the molding process.

Multivariate analysis, when used for fault detection purposes, uses a different approach to setting variable accept and reject limits. In Figure 1 a univariate control chart was presented; Figure 2 is used to illustrate how a multivariate system would handle two variables, such as temperature and viscosity that are correlated. The “in control” space has now changed from a box to an oval shape which now accounts for the relationship between pressure and temperature. The higher temperatures result in an easier flowing material or lower viscosity, and the lower temperatures result in a higher viscosity. This relationship is very important and if for some reason an observation results in a high temperature and a high viscosity, the process could still be within the univariate space (box) but would be statistically “out of control”, and the multivariate control space would recognize this and reject the associated part.

Based on these two examples, if a molder is to rely on SPC for fault detection they have to decide where they will set their univariate limits and on how many individual variables. They have two choices, either to set the limits very tight and within the multivariate control space or they can set the limits more broad and will actually accept product from a process that is statistically “out of control”, see Figure 3. The choice of setpoints will most likely vary per application, but hopefully the limits are set tighter as opposed to wider, as this is the preferred option. This option however, still has many false alarms, rejecting parts that are actually “good”! The number of false alarms will be highly correlated to both the tightness of the control limits and also the number of variables that are monitored. Table 1 displays the calculation, using basic statistics, of false alarms per 1000 observations at different numbers of variables and between UVA and MVA. The disparity between the two methods is quite substantial. For every ten variables that are added to a monitoring or fault detection system, the false alarm rate increases by 29, over a period of 1000 observations. The false alarm rate for the multivariate system, however, will not increase as more variables are added to the system.

The ability to observe and closely monitor many more variables in a system provides a tremendous amount of power and knowledge, and is one of the key benefits of MVA. This increased knowledge about the system allows the user to find the root cause of the problems much more quickly.
Application of Methodology

The use of multivariate technology for injection molding can be applied in many ways. The most commonly used approach for online multivariate fault detection uses the Principle Component Analysis technique described above. The typical application of this type of technology consists of [4]:

- Acquiring the key and available signals from the process
- Calculating the most important features of each signal or variable, such as cushion, fill pressure, injection velocity, viscosity, barrel temperatures, screw displacement, etc.
- Creating a multivariate model of a known acceptable process window, design of experiments are often utilized to provide effective and robust multivariate models
- Performing a multivariate comparison and analysis on each cycle against the known model
- Accepting or rejecting the part based on the comparison
- Saving and sending data to storage for later use

Figure 4 shows a graphical representation of this setup for an injection molding application.

Conclusions

The use of multivariate technology has been used in a variety of molding applications over the past few years and has proven to provide excellent fault detection results. The benefits of MVA over SPC are well known and well documented in not just injection molding or plastics manufacturing, but in many other application areas as well. The use of MVA for fault detection in injection molding will continue to be heavily utilized over the next few years as the demand for improved process technologies and continued innovation keep our manufacturing competitive.

References

Figure 2 - Multivariate Control Space

Figure 3 - Comparison of Control Windows

Table 1 - False Alarm Calculations

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<th>Parameters monitored</th>
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