Process Monitoring for Plastics Injection Molding
by
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Process Monitoring for Plastics Injection Molding
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Daniel John Berkery

Submitted to the MIT Sloan School of Management and the Department of Electrical Engineering and Computer Science in Partial Fulfillment of the Requirements for the Degrees of Master of Science in Electrical Engineering and Computer Science and Master of Science in Management

Abstract

This thesis summarizes efforts to develop process monitoring techniques for an injection molding plant. The goal of the thesis was to develop techniques that could monitor process variables on an injection molding machine and use the values of the process variables to perform in-process quality assurance. This thesis summarizes five experiments in monitoring injection molding processes. Two process monitoring strategies were evaluated. The first strategy focused on identifying process outliers—parts that had dimensions that were on the tails of the process output distribution. The second strategy evaluated focused on using the values of the process variables to predict the dimensions of the parts produced.

Multiple analysis techniques were tested for each monitoring strategy. To identify process outliers, both statistical process control (SPC) and neural network techniques were evaluated. For the SPC techniques, the process variables were plotted on control charts; the monitoring system marked as defective those parts for which at least one process variable had an out of control value. For the neural network techniques, a learning vector quantization (LVQ) network was used to classify parts into either an acceptable or an unacceptable category based on the values of the process variables under which the parts were produced. For predicting part dimensions both regression and neural network techniques were evaluated. The neural network used for dimensional prediction was a multilayer backpropagation network (MBPN).

The potential benefits of process monitoring were demonstrated by the results of one the experiments. Using SPC analysis of process variables to eliminate process outliers resulted in more than a 75% decrease in the process standard deviation. This reduction in the standard deviation equated to more than a fourfold increase in the process capability index.

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Chapter One
Introduction

1.1 Introduction

This thesis summarizes efforts to develop process monitoring techniques for an injection molding plant. The goal of the thesis was to develop techniques that could monitor process variables on an injection molding machine and use the values of the process variables to perform in-process quality assurance. The thesis analyzes two process monitoring strategies: one focused strictly on identifying process outliers--parts with dimensions that were on the tails of the process output distribution--and the other focused on using process variables to predict actual part dimensions. Multiple experiments were performed to test each strategy and multiple analysis techniques were performed for each experiment. The conclusion of the thesis analyzes the results and offers suggestions for further experimentation.

1.2 Process Overview

The plants for which this thesis research was done were part of United Technologies Automotive (UTA), the automotive parts division of United Technologies Corporation (UTC). The plants produce injection molded parts for the automobile industry. A typical part from one of the plants is shown in Figure 1-1.
Injection molding is a cyclic process consisting of four stages. The first stage is plastication. In this stage, a shot of molten plastic is built up for injection into the mold. During the second stage of injection the molten plastic is injected into the mold. The third stage is the pack stage. During this stage, pressure is maintained as the plastic solidifies in the mold. The fourth and final stage is the cooling stage. During the cooling stage the part solidifies in the mold. At the end of the cycle, the mold opens, the parts are ejected, and the next cycle begins when the mold closes.

1.3 Process Monitoring

For the remainder of this thesis, process monitoring will be defined as monitoring process variables with the goal of identifying and diverting potentially defective parts. In the experiments described in the thesis, process monitoring was implemented on a personal computer that logged the process variables. Although it was not needed for the experimentation, the personal computer had the ability to actuate a part diverter on each machine.
In practice, these part diverters would be used to direct potentially defective parts to the scrap bin.

Figure 1-2 shows the difference between process monitoring and quality assurance techniques that rely on measuring quality attributes of finished parts.

![Diagram showing Material, Machine, and Mold with Process Variables and Part Quality Attributes](image)

**Figure 1-2: Monitoring Process Variables versus Monitoring Process Output**

As shown in the diagram, monitoring process variables, such as injection pressure or shot size, has the advantage of being mold independent. Although the target values for the measurements may differ for different molds, the methodology of making the measurements is the same. Thus, the cost of measurement is almost entirely the fixed cost involved in installing the appropriate sensors. Part quality attributes, such as part length or the width of a slot, are unique to each part and more difficult to measure. As a result it is more expensive to measure part quality attributes. Part quality attributes are what is important to the customer, however, so monitoring process variables is only useful to the extent that the process variables correlate with the part quality attributes.

Two types of process variables were used in the process monitoring experiments. The first were the variables that were measure by the machine.
They consisted mainly of temperatures, pressures, and velocities measured at different locations and at different times during the molding cycle. The machine variables were all discrete values representing point measurements. The second set of variables used were complete pressure traces from pressure transducers added to the machine and mold. One pressure transducer measured the hydraulic pressure used to force the plastic into the mold and the other transducer measured the pressure of the molten plastic in a cavity of the mold.

1.4 Goals and Motivation

The basic goal of process monitoring was to reduced the variability of the parts shipped to the customer by automatically diverting defective parts to the scrap bin.

The project was motivated by the results of industry benchmarking efforts that were undertaken early in the assignment. The industry benchmarking identified three trends that drove the plant toward process monitoring.

*Customer demand for zero defects* Throughout the industry molders are discovering that their customers were unwilling to tolerate any defects. This demand posed quite a challenge because of the high production volumes in the industry. When thousands of parts are being shipped per day, even extremely capable processes may allow shipment of defective parts to a customer. The price of the parts is also quite low, so inspection of more than a small percentage of parts is prohibitively expensive. Process monitoring provides an attractive alternative because it equates to 100% inspection at zero variable cost.
Customer demand for tighter tolerances At the same time as customers are demanding zero defects they are also narrowing part tolerances. This places further demands on process capability. The narrowing of part tolerances requires a reduction in the variation of the molding process. Process monitoring is a first step in reducing process variation and may serve as a basis for more pro-active techniques.

Limits of statistical quality control Although statistical quality control is an extremely useful tool, it is ill-suited to detect one of the common problems in injection molding, the process outlier. Injection molding is subject to high frequency disturbances that often affect only one or two shots and then disappear without a trace. A typical example is localized contamination of raw materials that may affect one shot without affecting any of the shots before or after it. Random samples and measurements of parts are not well suited to detect this type of variation. Because process monitoring observes every shot, it may be more successful in identifying high frequency disturbances.

The final factor encouraging the adoption of process monitoring is the machines themselves. Injection molding machines are heavily instrumented and the microprocessor controls are typically capable of routing process data directly to external computers for analysis. They are often equipped with part diverters that allow monitoring computers to direct potentially defective parts to the scrap bin. These developments have made process monitoring much simpler and more cost effective to implement.

1.5 Summary of Research

This thesis evaluates two process monitoring strategies. The less ambitious strategy will be referred to as exception catching. The goal of this
strategy is to identify process outliers. Process outliers will be defined as parts with significantly different quality characteristics from the parts that were produced at nearly the same time. This strategy is a relative strategy in that it defines parts as acceptable by comparing them to other parts rather than an absolute standard. The strategy is also limited in the process problems that it can detect. An exception catching strategy will not detect gradual changes in the process mean or standard deviation because it is focused on looking for dramatic shifts. As a result, exception catching is a complement of, rather than a replacement for, statistical process control (SPC).

The more ambitious strategy of predictive modeling is an attempt to replace the current statistical quality control techniques. The goal of predictive modeling is to construct a process model that maps process variables to quality characteristics. The output of this strategy is a prediction of a part's key quality characteristics. For the experiments discussed in this thesis the critical quality attributes were part dimensions. This strategy has the potential to replace the statistical sampling and measuring of parts. If the process model were accurate and robust, control charting could be done on the model output rather than on the actual measurements.

Figure 1-3 summarizes the roles of each of these strategies with respect to identifying the most common process problems.
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**Figure 1-3: Identifying Process Problems through Process Monitoring**

These strategies were pursued by monitoring two sets of variables. The first set of variables is called the machine variables. The machine variables represent all of the process variables that are measured by the machine and made available for transmission to an external computer. For the most part, they are temperatures, pressures, and velocities measured at different
locations on the machine and at various times during the molding cycle. The second set of monitored variables were pressure traces. Pressure transducers were used to record the pressure profiles for the hydraulic injection pressure and the pressure of the molten plastic in the mold. The readings from these transducers transferred to a Personal Computer via data acquisition hardware and software.

Both sets of variables were used to do exception catching, but only the pressure traces were used to do predictive modeling. Although the machine variables indicate the average conditions across all cavities of a multicavity mold, they do not provide information about what is occurring in the individual cavities. Therefore, they could not be used to predict the dimensions for individual parts from a multicavity mold.

Multiple experiments were conducted for each combination of monitoring strategies and process variables. Table 1-1 summarizes the experimentation done.

<table>
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**Table 1-1: Summary of Experimentation**

Finally, different experiments tested different analysis techniques. Table 1-2 summarizes the analysis techniques used in the experiments.
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<td></td>
<td>Chapter 7, Experiment #1</td>
</tr>
</tbody>
</table>

Table 1-2: Summary of Analysis Techniques

1.6 Thesis Overview

This thesis is organized into eight chapters. Since different readers will be interested in different areas of the thesis, the chapters are written to be fairly self-sufficient. The author apologizes to those who will read the thesis in its entirety, as the independence of the chapters necessitates some redundancy.

Chapter 2 provides an overview of injection molding for those who are unfamiliar with the process. Chapter 3 describes the environment of the injection molding plant in which much of this work was completed. The plant description identifies many factors that influenced the development of the process monitoring methodologies. Chapter 4 describes related work drawn from a survey of academic work and industry benchmarking.

Chapter 5 begins the core of the thesis with a discussion of how process monitoring could fit into the complete quality assurance system in a plant. Chapter 6 begins the specific experimental results with descriptions of
two experiments in which machine variables were monitored. Chapter 7 continues the experimental results with descriptions of three experiments in which hydraulic and cavity pressure traces were monitored. Chapter 8 concludes the thesis with a discussion of the most significant results and recommendations for future work.

The research described in this thesis was done in cooperation with the research described in Kristine T. Budill's thesis, "A Systematic Approach to Tool Qualification for Injection Molding."\(^1\) Since that thesis presents complementary work to this one, Chapters 2 and 3 are shared between the two theses.

Chapter Two
Overview of Injection Molding

2.1 Introduction

This chapter provides a background in injection molding of thermoplastics for those who are unfamiliar with this process technology. The injection molding process is primarily a sequential operation that results in the transformation of plastic pellets into a molded part. The technology is being increasingly utilized in the manufacture of lower cost, lighter and safer consumer products. Typical applications range from the automotive to camera industries; with the size and quality of the final product having considerable variability. Factors which contribute to the increased use of injection molded plastics are:

1. Production of complex shapes in a single step

2. Ability to automate the process with tendent increases in production rates and manufacturing productivity

3. Replacement of metal components by plastic parts for lower cost consumer products

Critical to the adoption of this high volume, low cost process technology is the ability to consistently produce quality parts. In describing the injection molding process, factors which influence the repeatability of the molding process will be highlighted.

---

2.2 Process Description

The injection molding machine production cycle is characterized by four successive stages of plastication, injection, packing, and cooling (Figure 2-1). During plastication, the plastic material is pushed forward from the feed hopper through the barrel and toward the nozzle by a rotating screw (also referred to as a reciprocating or plasticizing screw) and, at the same time, is heated by electric heater bands which surround the barrel. Plastication transforms the solid plastic pellets into a melt which is at an elevated and uniform temperature and uniform viscosity.

As pressure builds up at the mold entrance, the rotating screw moves backward to a predetermined distance, thus controlling the volume of material to be injected, and stops rotating. Upon injection, the melt is pushed through the nozzle and into the mold cavity by the application of hydraulic pressure to the screw.

After the mold cavity is filled, continued pressure on the piston connected to the screw forces more melt into the cavity to compensate for part shrinkage due to initial cooling. As the plastic material is trapped due to the mold gate freeze-off, the mold continues to cool the molten part until it solidifies in the cavity shape.

When the hold pressure is removed, plastication within the barrel occurs once more in preparation for the next cycle. After solidification and cooling is complete, the part is ejected from the mold and the process repeats.\(^3\)

\(^3\)Ibid.
2.3 Raw Materials Description

The molder works with commercial plastics which are composed of a base plastic plus additives (Figure 2-2). Base plastics are man-made materials known as polymers. Polymers are very long molecular chains composed of repeating smaller, simpler chemical units. Additives are used to enhance the properties of the base plastics. Individual additives fulfill many requirements, including: reduction in heat sensitivity during molding; stability during exposure to ultraviolet light; color; reduction of flammability; reduction in material cost. The complex composition of commercial plastics limits the processing range of the material. Exact processing specifications, unique for each plastic, are outlined by the material manufacturers.4

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2.3.1 Plastic Properties

The polymer chains that comprise the plastic fold, intertwine with each other, and are held together by covalent and van der Waals bonding forces. Thermoplastics are classified as either amorphous or crystalline depending on their molecular structure at room temperature (Figure 2-3).

Amorphous

Crystalline

Figure 2-3: Plastic Structure

Amorphous plastics have a random structure. Crystalline plastics
have an ordered structure, which takes up much less space than the amorphous state. Actually, no material is perfectly crystalline; amorphous sections will occur throughout a crystalline material. At melt temperature, all plastics are amorphous. The structure of the plastic is important because it affects the plastic's properties (Table 2-1).5

<table>
<thead>
<tr>
<th>Properties</th>
<th>Amorphous</th>
<th>Crystalline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Example</td>
<td>Nylon (Minlon®)</td>
<td>Polycarbonate (Lexan®)</td>
</tr>
<tr>
<td>Structure</td>
<td>Random</td>
<td>Ordered</td>
</tr>
<tr>
<td>Melting point</td>
<td>Gradually softens</td>
<td>Distinct (i.e. ice to water)</td>
</tr>
<tr>
<td>Shrinkage</td>
<td>Less shrinkage</td>
<td>Higher shrinkage</td>
</tr>
<tr>
<td>Density</td>
<td>Lower density</td>
<td>Higher density</td>
</tr>
<tr>
<td>Stiffness</td>
<td>Lower</td>
<td>Higher</td>
</tr>
<tr>
<td>Tensile strength</td>
<td>Lower</td>
<td>Higher</td>
</tr>
<tr>
<td>Impact strength</td>
<td>Higher</td>
<td>Lower</td>
</tr>
<tr>
<td>Permeability</td>
<td>Higher</td>
<td>Lower</td>
</tr>
<tr>
<td>Warp</td>
<td>Lower</td>
<td>Higher</td>
</tr>
</tbody>
</table>

Table 2-1: Plastic Properties Related to Structure

Because the amount of crystallinity varies with the material and molding conditions, it is much more difficult to hold tolerances in crystalline materials than in amorphous ones. Plastics have several additional properties which influence the repeatability of the molding process (Table 2-2). First, plastics are compressible. The pressure in the mold cavity determines how much the melt is compressed. If all other variables are held constant, a higher hydraulic pressure results in a higher cavity pressure and will force more plastic into the mold cavities. Second, plastics shrink significantly when cooled. Together these properties indicate the need for the

---

packing stage during the molding cycle. After the mold cavity is filled, continued pressure on the piston connected to the screw forces more melt into the cavity to compensate for part shrinkage due to initial cooling.

Shrinkage is also influenced by the cooling rate. A faster cooling rate—i.e. colder mold temperature—results in less shrinkage. When a part is cooled very quickly, the dimensions are "frozen-in" and, therefore, the part will shrink less. A slower cooling rate gives more time for the molecules to align and, consequently, the part will exhibit greater shrinkage. This discussion reveals the importance of controlling mold temperature to produce parts of consistent quality.

Finally, shrinkage is affected by polymer orientation—the alignment of the molecule and molecular segments in the direction of flow. Shrinkage is a result of two factors—a normal decrease in volume due to temperature change and relaxation of the stretching caused by carbon-carbon linkages. As there are more carbon-carbon linkages in the direction of the oriented flow, there will be greater shrinkage. Any parameter that affects the mobility of the molecular segments will affect orientation and consequently part shrinkage. This indicates the need for accurate temperature control for a repeatable molding process. Orientation is also affected by melt flow rate. A fast fill rate increases orientation on the part surface and decreases orientation in the center of the part. A slow fill rate results in a less locally intense but more evenly distributed orientation through the whole cross section of the part.\(^6\)

\(^6\)Ibid, p. 158.

The third property of plastic is that its viscosity is dependent on temperature and flow rate of the melt. Viscosity is a measure of a material's resistance to flow and is defined as the ratio of shear stress to shear rate:

$$\eta = \frac{\sigma}{\gamma'}$$  \hspace{2cm} (2.1)

where:  \hspace{0.5cm} \eta = \text{viscosity} \\
\hspace{1cm} \sigma = \text{shear stress} \\
\hspace{1cm} \gamma' = \text{shear rate}

The viscosity of the plastic melt decreases as the shear rate increases. Fluids that behave in this way are said to be shear thinning. Based on high-shear-rate data for a number of polymers, an empirical "power law" expression has been suggested to describe the dependence of viscosity on shear rate:

$$\eta = \frac{\sigma}{\gamma'^n}$$  \hspace{2cm} (2.2)

The shear stress is then given by:

$$\sigma = K\gamma'^n$$  \hspace{2cm} (2.3)

A Newtonian liquid is special case for which \( n=1 \). For molten polymers, \( n \) is usually observed to be in the range of 0.3 to 1.0.\(^8\)

The viscosity of the melt also decreases with an increase in temperature. A simple expression often used to describe this effect is given by the equation:

$$\eta(T) = Ae^{E/RT}$$  \hspace{2cm} (2.4)

where:  \hspace{0.5cm} T = \text{temperature} \\
\hspace{1cm} R = \text{gas constant} \\
\hspace{1cm} E = \text{activation energy for viscosity}

Mold filling software packages must model the dependence of viscosity on both shear rate and temperature. One example of such an expression is:

$$\eta = Ae^{E/RT} |\gamma'|^{n-1}$$  \hspace{2cm} (2.5)

---

\(^8\)Ibid, p. 637.
A qualitative explanation for why an increase in temperature lowers viscosity is related to the concept of free volume. This is the volume of space in the melt that is not actually occupied by molecules and is thus available to permit the mobility of the molecules. The greater the free volume, the easier it is for molecules to adjust to deformations, and this will be reflected in a lower viscosity. An increase in temperature results in thermal expansion and thus an increase in free volume. This explains the decrease in viscosity as the temperature increases.\textsuperscript{9}

To summarize, increases in either flow rate or temperature reduce viscosity. An increase in flow rate results in greater shear thinning and consequently lower viscosity. Higher temperatures are an indication of greater molecular motion and consequently lower viscosity. Constant viscosity is required to produce parts of consistent quality. Viscosity can affect how much the polymer is compressed in the cavity and therefore how much shrink will take place. Lower viscosity results in smaller pressure drops along the flow path (runner and gate) and consequently higher cavity pressure. Higher cavity pressure results in greater compressibility and consequently less shrinkage.

\textsuperscript{9}Ibid, pp. 635-636.
<table>
<thead>
<tr>
<th>Properties</th>
<th>Influences</th>
<th>Critical Process Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1. Plastics are compressible</strong></td>
<td>• Higher hydraulic pressures force more plastic into the mold cavity</td>
<td>• Cavity Pressure</td>
</tr>
<tr>
<td></td>
<td>• Reduced viscosity allows more efficient compression</td>
<td></td>
</tr>
<tr>
<td><strong>2. Plastics shrink when they cool</strong></td>
<td>• Higher compression results in less shrinkage</td>
<td>• Cavity Pressure</td>
</tr>
<tr>
<td></td>
<td>• Faster cooling rates result in less shrinkage</td>
<td>• Mold Temperature</td>
</tr>
<tr>
<td></td>
<td>• Less orientation results in less shrinkage</td>
<td>• Melt Temperature</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Flow Rate</td>
</tr>
<tr>
<td><strong>3. Plastic viscosity is dependent on</strong></td>
<td>• Higher flow rates produce greater shear thinning and consequently lower viscosity</td>
<td></td>
</tr>
<tr>
<td><strong>temperature and flow rate</strong></td>
<td>• Higher temperatures are an indication of greater molecular motion and consequently lower viscosity</td>
<td>• Flow Rate</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Melt Temperature</td>
</tr>
</tbody>
</table>

Table 2-2: Plastic Properties which Influence Molding

2.4 Machine Description

An injection molding machine is composed of an injection unit, a clamping unit, a hydraulic unit and a control unit (Figure 2-4). The injection unit consists of the hopper, the barrel, the barrel heaters, the reciprocating screw and the nozzle (Figure 2-5). The clamping unit consists of the hydraulic clamping mechanism and the mold platens. The hydraulic unit consists of the hydraulic pump and all the associated plumbing and valving required to actuate the injection unit and the clamping unit.
Figure 2-4: Injection Molding Machine

Figure 2-5: The Injection Unit

The purpose of the control unit is to establish the conditions for transferring from one stage to another, to impose process limits and to prevent damage to the equipment and personnel. Inputs are usually restricted to set point values unless the machine is in manual mode. Outputs from the control unit typically result in the opening or closing of hydraulic
valves or in the actuation of the screw. In actual implementation, the control unit may be driven simply by dial indicators and relays or by more sophisticated equipment involving microprocessors.10

2.4.1 Machine Settings vs. Molding Variables

The goal of injection molding is to produce parts of consistent quality. Part dimensions are frequently the measure of quality used. This leads to an argument for controlling shrinkage of the plastic part. The previous discussion on plastics indicated that shrinkage is dependent on the molding variables of cavity pressure, mold temperature, melt temperature, and flow rate. Consequently, these variables should be controlled.

The injection molding machine does not permit direct control over these variables but allows the operator to adjust machine settings that influence the molding variables. The inability to directly set and measure the molding variables that affect part shrinkage complicates the injection molding process. It is molding variables, properly defined and measured, not necessarily machine settings, that can be correlated with part properties. For example, if one increases barrel temperatures, melt temperatures do not necessarily also increase. Melt temperature is also influenced by screw design, rpm, back pressure and residence time. It is much more accurate to measure melt temperature and correlate it with properties than to correlate barrel settings with properties.

The following discussion reviews the four stages of the injection molding cycle (plastication, injection, packing, cooling) and indicates how

machine settings are used to control the molding variables and consequently part shrinkage (Table 2-3).

<table>
<thead>
<tr>
<th>Process Stage</th>
<th>Molding Variable</th>
<th>Machine Setting</th>
</tr>
</thead>
</table>
| 1. Plastication | • Melt Temperature  
                 | • Flow Rate            | • Barrel Temperatures   |
|               |                        |                         | • Screw Speed           |
|               |                        |                         | • Back Pressure         |
| 2. Injection  | • Flow Rate            | • Injection Velocity    |
| 3. Packing    | • Cavity Pressure      | • Hold Pressure         |
| 4. Cooling    | • Mold Temperature     | • Coolant Temperature   |
|               |                        | • Coolant Flow Rate     |
|               |                        | • Cycle Time            |

Table 2-3: Influences on Part Shrinkage

2.4.2 Plastication

Plastication affects the repeatability of the molding process by influencing the viscosity of the melt. As previously discussed, viscosity is dependent on melt temperature and flow rate. During plastication, these molding variables are influenced by barrel temperatures and screw speed. Heat transferred from the barrel to the plastic results in the melting of the plastic pellets. The screw speed controls the shear force applied to the material. Shear force results in further heating—i.e. viscous dissipation—of the plastic. Back pressure also influences repeatability of the molding process because it determines the quantity of plastic in the barrel (compresses the plastic). Ranges for these temperature, speed and pressure settings are usually provided by the material suppliers, and should be repeated accurately set-up to set-up.
2.4.3 Injection

When the barrel is full and the mold halves are clamped and ready, hydraulic pressure is exerted on a piston connected to the screw. The pressure is intensified as a result of the difference in the area between the piston surface and the cross section of the screw. The screw moves forward and plastic is discharged through the nozzle and into the mold.

Traditionally, injection was run under pressure control (Figure 2-6). In pressure control, the machine follows the pre-set injection pressure until switchover to packing. Injection rates that maintain the set hydraulic pressure will result. Today, injection controlled by velocity is preferred (Figure 2-7). In velocity control, the machine follows the set injection velocity. The hydraulic pressure limit is set high enough to allow the machine to maintain the set injection speeds without saturation.

The preference for velocity controlled injection relates to the goal of producing parts of consistent quality. Under hydraulic pressure control, variable injection rates result in response to fluctuations in material viscosity. Variable injection rates produce variations in pressure and flow characteristics in the mold cavities (Figure 2-8). (Section 2.3.1 described how flow rate affects viscosity, orientation, and the ability to compress the plastic.) Variation at the mold cavity usually translates to variation in finished part quality. Injection rate control does result in variable hydraulic pressures; however, cavity flow, pressure, and orientation are more consistent (Figure 2-9). Less variation at the cavity results in less variation in part quality. Therefore, velocity controlled injection is preferred.
Figure 2-6: Hydraulic Pressure Control

Figure 2-7: Injection Velocity Control
Figure 2-8: Effects of Hydraulic Pressure Control

Figure 2-9: Effects of Injection Velocity Control
2.4.4 Switchover from Injection to Packing

Repeatability in the molding process is also dependent on consistent injection to pack switchover. Early switchover may result in short shots and insufficient packing. Late switchover can result in overpacking or flash. Switchover can be controlled by injection time, hydraulic pressure, injection position, or cavity pressure. Injection time is dependent on the operation of hydraulic valves and solenoid timing. The variability that occurs in these systems make injection time a poor candidate for switchover control. When injection is controlled by velocity, hydraulic pressure may vary slightly. Thus, switchover on hydraulic pressure is not recommended when the machine is operating in velocity control.

Switchover controlled by injection screw position corresponds to switching over when a certain volume of plastic has filled the cavity. Consistency in cavity fill helps ensure finished part consistency; therefore, injection position switchover is an acceptable choice. Cavity pressure gives an accurate assessment of conditions in the mold cavity, thereby providing the best indication of when to switchover. Cavity pressure switchover, however, requires additional instrumentation and, consequently, higher cost.

The experiments reviewed in this thesis used switchover controlled by injection screw position. In order to set the switchover position, use of cavity pressure sensors--located in the part close to the gate--or analysis of the hydraulic pressure is required. Switchover must occur before the part is completely full to avoid overpacking and/or flash. Therefore, when pressure begins to increase rapidly, switchover should occur.

Peak pressures in the cavity can be controlled by adjusting the point at which the molding machine switches over from injection to holding pressure. Figure 2-10 shows a late switchover (dotted line) compared to a good
switchover. If the pressure is peaking very high, the switchover position can be moved up—i.e. to a position it reaches earlier. If this is done, hold pressure may have to be raised slightly to allow completion of fill.

![Diagram showing switchover from injection to pack](image)

**Figure 2-10: Switchover from Injection to Pack**

### 2.4.5 Determination of Hold Time

After the mold cavity is filled, continued pressure on the piston connected to the screw forces more melt into the cavity to compensate for part shrinkage due to initial cooling. In order to achieve consistent part quality, hold pressure should be maintained until the gate freezes. Gate freeze-off time may be determined through use of cavity pressure sensors or part weight.

When using cavity pressure sensors, gate freeze-off time will be indicated by a sudden change in the slope of the cavity pressure trace during hold. This results because the cavity sensor no longer "sees" the pressure from the machine screw pushing. The cavity is now isolated from the hold.
pressure so no more plastic can be forced into the cavity to compensate for part shrinkage. The contracting of the part as it cools results in a pressure drop.

If the hold pressure is released too early, a sudden reduction in cavity pressure will result, producing sinks, warp, or other dimensional problems. This results because plastic is now allowed to leave the part before solidification (Figure 2-11). Hold time which is too long, while not detrimental to the part, wastes energy.

![Diagram showing pressure and time relationship]

**Figure 2-11: Determining Hold Time based on Cavity Pressure**

If cavity sensors are not available, hold time may be progressively increased as each successive part is weighed. When increasing hold time no longer results in an increased part weight, the gate has frozen, and hold time may be set (Figure 2-12).
2.4.6 Cooling

Cooling allows the plastic to solidify and become dimensionally stable before ejection. As discussed in section 2.3.1, cooling rate, which is determined by mold temperature, affects plastic orientation and shrinkage. Mold temperature, however, cannot be directly controlled. Heat that has been transferred to the mold by the molten plastic is carried away by a coolant that circulates through cored passages in the mold (Figure 2-13). Coolant temperature and flow rate determine the efficiency of heat removal.
The design of the mold cooling passages also affects the ability to remove heat from the mold. The mold surfaces closest to the cored passages will cool first. Hook-up of the external hoses to the mold inlets and outlets will also influence cooling rate. Differences in mold temperature or mold temperature distribution will affect reproducibility of part moldings. Consequently, repeatability in molding requires optimizing cooling line hook-up and reproducing the same hook-up with every set-up. In general, the inlets and outlets for each cavity should be connected in parallel to their source of supply given that the pump can meet the required flow rates. Too many waterlines in series can cause high pressure drops and uneven mold surface temperature due to high temperature rise of the coolant (Figure 2-14). In addition, inside diameter of the hoses should be at least as large as,
or preferably larger than, the coolant line diameter in the mold to avoid pressure drops and loss of cooling efficiency.\textsuperscript{11}

\begin{center}
\begin{tabular}{cc}
\textbf{Series} & \textbf{Parallel} \\
\end{tabular}
\end{center}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{cooling_line_hook_up}
\caption{Cooling Line Hook-Up}
\end{figure}

2.5 Mold Design

As discussed in chapter one, mold design influences the ability to produce the desired part dimensions. The mold cavities are cut to dimensions larger than the desired part dimensions to compensate for the plastic shrinkage which occurs during cooling. The cavity dimensions are equal to the part dimensions plus some shrink factor which is supplied by the material manufacturer. There are usually two shrink factors given, one for dimensions in the direction of flow and one for dimensions across the direction of flow. Estimating shrinkage, however, is not straightforward. It is often difficult to predict the melt flow path in parts with complex geometries and therefore, not clear which shrink factor to apply. Also, as discussed earlier in the chapter, part shrinkage is influenced by the process conditions selected.

Mold design also affects the variation across cavities in a multicavity mold. First, the cavities must have very tight dimensional tolerances. Second, they must be geometrically balanced—each cavity has equal runner and gate dimensions (Figure 2-15). Finally, mold cooling passages must provide uniform cooling to all the cavities.

![Diagram of geometric balance](image)

Figure 2-15: Geometric Balance

2.6 Material Variation

Material variation results in different melt viscosities and, therefore, different part quality. Sources of material variation include material lot number, dryness, and regrind level. Material suppliers produce plastic in "lots"—referring to batches of blended materials. Not all lots are the same; differences include molecular weights, molecular weight distributions, degrees of polymerization, and impurities. The molder can identify potential problems by sampling incoming material and comparing its characteristics with previous lots.

Material must be dry to allow proper processing. Some materials—i.e. Nylon—are especially sensitive to moisture. Dryness is controlled by residence time in the drying hopper, dryness of the air in the hopper—"dew point", and temperature of the air in the drying hopper.
Repeatable molding also requires consistent levels of regrind in the hopper. Sources of inconsistencies include regrind/virgin supply, proportional loader settings, and proportional loader function (Figure 2-16). Loader settings should be adjusted to maintain consistent regrind levels, not require periodic adjustments. Figure 2-17 demonstrates the impact of varying regrind levels. As previously mentioned, material variation results in different melt viscosities. The viscosity of the melt influences how the cavities fill and, consequently, the weight of the plastic part.

Figure 2-16: Proportional Loader System

---

Figure 2-17 displays the results of an experiment conducted at UTRC. The mold used in the study has four identical cavities which produce wiring harness connectors. The material used was Noryl. Different levels of regrind were produced by mixing different proportions by weight of virgin material and 100% regrind material—provided by the UTA Peru plant from which the mold was borrowed. The average part weight was determined by weighing the four parts produced in a single shot and averaging these weights.
Figure 2-17: Effect of Variation in Material Regrind Levels

This chapter described the injection molding process with special emphasis on the issues which influence repeatable molding. Figure 2-18 summarizes the factors that determine part quality. The only area which the molder completely controls is machine settings. This is, therefore, the first area to target in eliminating variation from the process. Consistent machine settings must be used set-up after set-up. Process problems should be traced to their cause, not corrected for by tweaking machine settings.

Some sources of material variation—dryness and regrind level—are also under the molder's control and can be eliminated by following systematic procedures. Reducing lot to lot material variation will involve working with the material suppliers, and improving mold design will require collaboration with the tool designers and makers.
Figure 2-18: Influences on Part Quality
Chapter Three
UTA Taylor Plant

3.1 Introduction

Research that led to the development of the tool qualification procedure and process monitoring techniques was inspired by UTA's desire to accelerate the manufacturing approval process for new injection molded parts and increase the capability of production processes. Just as the Japanese automotive companies have attacked U.S. automotive companies' market share, so have the Japanese automotive suppliers attacked the U.S. automotive suppliers' market share. The ability to win business in the more competitive automotive market depends on a company's ability to compress product development cycle time and improve quality.

3.2 An Overview of UTA

In order to strengthen its position as an automotive supplier, UTA headquarters is attempting to identify industry best practices and implement them across the company. The ability to disseminate learning, however, is hindered by the autonomous nature of UTA's plants.

The autonomous nature of UTA is perhaps influenced by its parent corporation, United Technologies (UTC) (Figure 3-1). UTC provides a broad range of high-technology products and support services to customers in the aerospace, building and automotive industries worldwide. The corporation's best known products include Pratt & Whitney aircraft engines, Otis elevators and escalators, Carrier heating and air conditioning systems, Sikorsky helicopters, Hamilton Standard aerospace systems, Norden defense systems
and UT Automotive components and systems. United Technologies also supplies equipment and services for the U.S. space program.

![Figure 3-1: UTC Organization](image)

In general, UTC is very decentralized and its unifying corporate culture is quite weak. Most of UTC's divisions were acquisitions. The culture of those organizations is tied strongly to the founder of the business, and the divisions continue to be recognized by the founder's name (e.g. Sikorsky Aircraft for founder Igor Sikorsky). In addition, there seems to be little movement of people between divisions, further insulating the cultures from one another.

United Technologies Automotive is, in some ways, a microcosm of the parent corporation. UTA's culture is weak. Most of UTA's injection molding plants were acquisitions and they have retained their original workforce and culture. Even when the plants are created by the division, the cultures that evolve are unique, strongly linked to the personality of the plant manager.

Development of a company culture is also hindered by UTA's decentralized structure. While both Sikorsky and UTA produce similar revenues, Sikorsky employs one third the people and concentrates production in southern Connecticut; UTA consists of over 100 manufacturing facilities in fourteen countries.
UTA's decentralized structure has also resulted in a wide range in sophistication of production control mechanisms employed across its plants. UTA leadership is currently focusing on how to elevate all the plants to an equally advanced level. One method is to devise systematic procedures, such as the tool qualification process, which can be applied across plants which use the same manufacturing technologies.

United Technologies Automotive produces 10% ($2.1 billion in 1991) of UTC's revenues. 1991 revenues decreased $537 million (20%). Approximately one-half the decrease was due to significantly lower North American automobile production with the remainder primarily attributable to the divestiture of certain related businesses in 1990.\textsuperscript{13} By increasing the company's ability to compete globally, UTA's leadership hopes to reduce the current dependence on North American car volume.

UTA includes 6 business units, organized by five product groups and one geographic region (Figures 3-2 and 3-3). Within the five product groups, over fifty major product lines are produced including: wire harnesses, electromechanical switches and controls, power window controls, wiper motors, door trim panels, instrument panels, and power brake hoses. UTA products are supplied to U.S., Japanese and European automotive companies.

\textsuperscript{13}United Technologies 1991 Annual Report, p. 25.
3.3 An Overview of the Input Controls Division

UTA's Input Controls Division provides dozens of different subassemblies to the automobile manufacturers. Some of their product lines include: electromechanical switches and controls for turn signals, headlights, and windshield wipers; relays; electronic controls for power windows and door locks; and diagnostic modules. The research conducted in tool qualification and process monitoring is applicable to injection molding plants across UTA's business units. The Input Controls Division, however, is leading the company in adoption of new procedures. Several facts influence their receptiveness to new methods. First is the fact that the Input Controls' molding plant, Taylor, is a greenfield site. The opportunity to start over with the latest technology and human resource practices offers great opportunity as well as significant pressure to succeed. With less than two year's history, resistance to change is relatively low, and the employees are eager to
demonstrate improved performance. Second, one of the business unit's manufacturing engineers had the opportunity to spend six months at one of UTA's Japanese competitors. Since his return, he has been able to vividly convey that change is required in order to meet the Japanese standards. Third, Input Controls' business strategy includes aggressive pursuit of tight tolerance and insert molding business, both of which depend on extremely capable processes.

In order to compete effectively in the more competitive market, Input Controls must also transform their sequential product development process. The current product development cycle begins when the automobile manufacturer supplies the design envelope (or design specifications) for the subassembly. Input Controls engineers then design the subassembly and the tools required to produce it. The construction of the molds used to produce the plastic parts is subcontracted to a tool builder; UTA does not own any tool makers. The finished mold is delivered to the injection molding plant. Molded plastic parts are shipped to assembly plants and completed subassemblies are delivered to the automotive producers.

Traditionally, there has been very little opportunity for the molding plant to transfer its experiential knowledge about part and mold design back to the design engineers. UTA's recognition that the ability to establish production capable processes is dependent on the quality of part and mold design led to the selection of Taylor as the site for the new molding plant. Located fifteen minutes from the design facility, Taylor offers the opportunity for molder and designer to work together daily.

One huge disconnect in the product development cycle has been produced by the use of an outside tool maker. The problem results from a difference in what the tool maker wants to sell and what the molder wants to
buy. The tool maker sells steel cut to certain dimensions, while the molder would like to buy the ability to produce a plastic part which meets the customer specifications.

Mold construction for plastic parts is extremely complicated. Differential shrinkage as the plastic part cools requires the mold maker to cut the tool steel larger than the print dimensions. Shrinkage estimates are based on material supplier recommendations and the tool maker's experience. Very few tool builders conduct a systematic try out of the mold before it is delivered to the molder. If the molding plant then identifies the need for tool modifications, it costs the molder's nickel. If Input Controls is unable to find an independent mold maker who is willing to work with them to produce parts, they may consider purchasing a tool shop.

3.4 An Overview of Taylor

The Taylor plant was inspired by a vision of what a world class molding facility might be. Extensive research effort was dedicated to the technology selection, facility layout, and development of human resource policies. The plant site was selected in early 1991 with actual production beginning in June of that year.

Taylor uses traditional injection molding and insert molding technologies. The plant manufacturing equipment includes 24 injection molding machines ranging in size from 55 to 200 tons and 4 insert injection molding machines ranging in size from 30 to 150 tons. Four more insert molding machines will be added in mid 1993 and an additional 4 insert machines in 1994.

The 24 injection molding machines were all purchased from the same vendor. This is important for several reasons. First, the injection molding
process is sensitive to changes in any input variable, including machine settings, material, or machine calibration. By buying all the machines from the same vendor, there is a better chance that the machine calibration variable will be eliminated. Being able to run molds on different machines using the same machine settings is almost a requirement given the large number of part numbers Taylor produces. Taylor has close to 100 different part numbers. Given this variety, it would be almost impossible to dedicate machines to molds. Second, by standardizing the equipment in the plant, training effort is minimized.

The layout of the facility was also given special consideration. The machines are organized into three identical cells of eight machines. While this involves higher initial training costs because each employee must learn to run the variety of machine sizes that comprise the cell, in the long run it allows individuals to be moved to a different cell with no extra training investment. An electronic mold storage unit and overhead electronic cranes facilitate mold changes which can be both time-consuming and dangerous when more manual labor is required.

Job descriptions are purposely vague in order to keep all employees aligned toward the ultimate goal of producing quality parts. In general, however, process engineers are responsible for technology development at the plant and for interfacing with the customer. The process engineers are organized by customer rather than by product line in order to provide better service.

The plant superintendent is responsible for scheduling and overseeing production. Production runs three shifts, with the workers on each shift referred to as Team One, Two and Three. Process technicians on each shift set-up the machines and lead problem solving efforts on the plant floor.
Utility technicians are each assigned three machines. They watch for any process disturbances, ensure that the machine has sufficient material, and empty full part bins. Minor mold repairs are attended to by the first shift mold technician.

In order to facilitate the development of a team environment, all employees are referred to as associates and everyone is salaried. Hiring has been extremely selective, even when it required current employees to assume additional responsibilities in the interim. Production began in June 1991 with 3 employees; the plant manager and two manufacturing engineers. One year later there were close to twenty employees. Today, the number of associates is approaching fifty and all the key positions in the plant have been filled (Figure 3-4). As a result of just recently filling all these positions and the focus on training in the technical areas, the formal training in team skills has not yet happened. The task for 1993 is to build team skills without losing the focus on improving quality, launching a significant number of new programs, and increasing volume to budgeted levels.
Until recently, Taylor has been a captive supplier to the Input Controls assembly plants. This was advantageous during start-up of the plant because it guaranteed Taylor business, while it was trying to improve its operating efficiency. Soon Taylor will begin supplying Chrysler directly. Figures 3-5 and 3-6 show examples of the parts supplied by Input Controls.

As mentioned earlier, Input Controls business strategy involves becoming a significant player in the tight tolerance molding market. The challenges associated with tight tolerance molding are increased by complex part geometries and use of multicavity molds (most of Taylor's molds are four or eight cavity molds). The tool qualification procedure and process
monitoring techniques developed during the LFM internship address Taylor's need for increasingly capable processes.

**Figure 3-5: Heater Blower Assembly**
OPERATOR INSTRUCTION
1. Place (1) base, frame and coil assembly into the fixture as shown above.
2. Press palm buttons to seat the frame into the base and twist the frame legs under the base.
   Note: You must remove the relay immediately after the top air cylinder begins to move up.
3. Place the finished assembly on the belt conveyor, terminals down.

OPERATOR INSPECTION
Visual and check for the following defects:
1. Frame legs (3) not twisted.
2. Foreign material.
   Place defective assembly in red reject container.
   Keep work area clean at all times.
3. Compare the S.O.P. settings to the actual machine settings whenever you start running this operation. Insure that the actual settings agree with the S.O.P.

Figure 3-6: Power Relay Assembly
Chapter Four
Related Work

4.1 Literature Survey

The first step in identifying related work was a traditional literature survey of relevant scientific journals. In addition to the directly related work in process monitoring, this survey identified relevant work in mold filling simulation and process modeling. Mold filling simulation and process modeling were included because they discuss the dynamics of the molding process. The dynamics of the process determine which parameters are worthwhile to monitor.

4.1.1 Mold Filling Simulation

Mold filling simulation is the most common type of process modeling. Commercial Computer Aided Engineering (CAE) Software has been available since 1978. Over the years, the software has been expanded beyond filling analysis to include cooling analysis, part gate location, runner sizing, weld-line prediction, gas-trap prediction, warpage and residual stress analysis, cycle time and cost optimization, shrinkage analysis, and material selection.14

Naitove and De Gaspari presented a comprehensive survey of the usage of CAE software in the molding industry. The results of the survey indicated that the vast majority of simulation is done during mold design and construction. They also indicated that the more basic analysis features of

mold filling, gate location, runner sizing, weld line prediction, and gas trap prediction were the most commonly used. Furthermore, they identified several weaknesses of the CAE packages. First, they highlighted the problems with the software's lack of true three-dimensional modeling. Although the software can represent three-dimensional parts, it represents them as a sequence of two-dimensional layers. As a result, some of the more complex phenomena, such as the effects of reinforcing fibers, cannot be completely modeled. In addition, many users question the accuracy of some or the more advanced features, such as warpage or shrinkage prediction.\textsuperscript{15}

Mavridis, et al offer a theoretical introduction to mold filling simulation. Their article presents the theoretical foundations for the simulation programs and a survey of the mathematical models used in simulation.\textsuperscript{16}

Although the mold filling simulation is very well developed, it is designed for the part and mold design. As a result, it is not helpful with respect to process monitoring.

4.1.2 Process Control

Another branch of process modeling has been used to evaluate process control strategies. After developing their models, some authors have continued and developed new control strategies based on their models. This work is relevant to process monitoring because it helps identify which

\textsuperscript{15}Ibid.
variables are likely to have the largest impact on part quality and which variables are likely to be the most difficult to control.

Agrawal, et al provide a comprehensive system for evaluating process control strategies. They review the current injection molding control strategies and categorize the controlled variables into three groups. On the basis of their categorization, they evaluate the control strategies for the controlled variables and propose potential improvements. Their work represents an excellent introduction to the general issues of process control in injection molding.  

17

Other authors have proposed models through which injection molding control strategies can be evaluated. Shankar and Paul present "a deterministic nonlinear lumped parameter model useful for the study and design of polymer injection molding machines and their associated controllers."  

18 Baranano offers a fundamental architecture required for injection molding control models.  

19 Chiu, et al present the "development of a nonlinear mathematical model for the study of the mold filling process in an injection molding machine."  


Some authors have proposed process models and control strategies concurrently. Control strategies involving cavity pressure are fairly common. Chiu, et al compared an adaptive model following control technique (AMFC) to PI control of cavity pressure during mold filling. The AMFC control technique was based on a modified Popov-Landau method. The control techniques were compared based on their ability to maintain a constant cavity pressure gradient when acrylonitrile-butadiene-styrene (ABS) was injected into a test mold. Their results showed that AMFC control was superior to PI control in tracking the desired cavity pressure profile.\textsuperscript{21}

Srinivasan, et al describe another novel control methodology applied to cavity pressure control during injection. They implemented a learning control technique as shown in Figure 4-1.

where

\[ P_{cd} = \text{Desired Cavity Pressure} \]
\[ e = \text{Cavity Pressure Error} \]
\[ m = \text{Hydraulic Pressure Servovalve Opening} \]
\[ P_c = \text{Cavity Pressure} \]

Figure 4-1: Block Diagram for Learning Control Application to Cavity Pressure Control\textsuperscript{22}

They compared the results of the learning control algorithm with more traditional controller. Their results showed that the accuracy of the learning controller is higher than the traditional controllers and its performance is robust with respect to model parameter variation.\textsuperscript{23}

Smud, et al also concentrated on cavity pressure regulation, but during the cooling phase. They demonstrated the effectiveness of a control system using a PI algorithm. They conducted a 24 hour experiment that demonstrated almost a 66% reduction in the variation of part flatness when the closed loop system was compared to the normal open loop system.\textsuperscript{24}

\textsuperscript{23}Ibid.
Another cavity pressure control strategy focuses on regulating the packing stage. Michaeli and Lauterbach's pmT control attempts to create an optimum pressure profile in the mold using the material's pvT curve. Their strategy controls the initiation of the cooling stage by actuating a valve in the nozzle that interrupts the material supply. The initiation time of the cooling stage is varied in response to variation in the melt temperature and the cavity pressure. As a result pmT control strategy is able to compensate for melt temperature and cavity pressure variation. Their results show a dramatic increase in the robustness of process output to variation of melt temperature and cavity pressure.

4.1.3 Process Monitoring

As with most manufacturing processes, statistical process control (SPC) is commonly used to analyze the output of injection molding processes. Werner and Berenter describe a fairly complete implementation of a statistical quality control system in an injection molding plant. The part studied was a thermoplastic bumper for the Ford Escort and Mercury Lynx. Their system started with the measurement of melt flow index (MFI), an indication of material viscosity, for random samples of incoming material. The data from this sampling allowed the plant to demand more consistent material from its raw material supplier. The next step was SPC charting on material moisture content for dried material. The SPC charting proved that material moisture content was consistent enough that it did not cause problems with part quality. The final step implemented was SPC charting of part weight. This X-bar and R charting was used to signal process problems. Operators were instructed not to adjust the press unless the control chart indicated an out of control condition. As a result of the new operating
procedures, the injection molding machine was able to run for 14 shifts without producing a defect.25

Hurkar applied SPC techniques to the process variables rather than the process output. The study emphasized monitoring approximately 30 process variables in order to diagnosis improper adjustments to the machine settings and failure of machine systems. Although the study also mentioned the use of process monitoring to identify of defective parts, the methodology was not fully explained.26

Wang and Wang, the latter of particular distinction for his work in mold filling simulation, attempted a more ambitious use of process variables for quality control. They implemented a predictive model to be used to control part thickness. The model was used to make shot to shot adjustments in the hydraulic packing pressure. This semi-mechanistic model combines numerical simulation with on-line data acquisition. It was tested on a center gated disk mold that was instrumented with two in-cavity pressure sensors and a in-cavity thermocouple. After a four cycle learning period in which the coefficients of the model were tuned, the model's predictions demonstrated good accuracy, even in the event of changes in the process settings.27

4.2 Competitive Benchmarking

Since much of the less theoretical injection molding research is proprietary, it was important to perform competitive benchmarking in addition to the technical literature search. The competitive benchmarking identified two firms that had made significant progress in implementing process monitoring.

4.2.1 Intesys

Intesys, formerly Pixley-Richards, is an injection molder specializing in thin-walled, cosmetic parts. They are particularly well known for their manufacture of the plastic casings of Motorola's MicroTAC® line of cellular phones. Intesys has incorporated the monitoring of peak cavity pressure into their quality control system. For one part, they have been successful enough to totally eliminate statistical sampling of part measurements and rely totally on process monitoring.\textsuperscript{28}

4.2.2 RJG, Inc.

RJG, Inc. is an injection molding consulting company that also markets process monitoring systems. RJG has worked with a molder of large parts, such as lawn chairs or garbage cans, to develop process monitoring techniques. They established the integral under the hydraulic pressure curve during mold filling as an indicator of effective material viscosity. Effective material viscosity is a product of the material viscosity and the mold temperature.

\textsuperscript{28}Information provided by Blair V. Souder, of the United Technologies Research Center, after a visit to the Intesys plant.
They also established cavity pressure integral as an indicator of part weight.29

4.3 Conclusions from Related Work

Although mold filling simulation is one of the most-developed areas of process simulation, it is focused on part and mold design, so it is not particularly helpful with respect to process monitoring. The process modeling that has focused on development and evaluation of machine control strategies is helpful, however. It shows the limitations of the commercially available machine controllers and identifies the process variables that would be the most important to monitor. In particular, the literature identifies cavity pressure and cavity temperature as particularly important process variables.

The competitive benchmarking was also helpful in identifying fruitful areas for process monitoring. The benchmarking confirmed the importance of cavity pressure monitoring and added insight into the importance of monitoring hydraulic pressure.

29Information provided by Brad Wadkins, of RJG, Inc., during a phone interview.
Chapter Five
Quality Assurance For Injection Molding

5.1 Introduction

As injection molding machines have incorporated microprocessor controls, they have added instrumentation necessary to maintain their control loops. This instrumentation measures the pressures, temperatures, and flows at various locations on the machine and at various times during the machine cycle. The variables measured by the machine are commonly referred to as machine variables. The newest machines make the machine variables available, in real time, for transfer to personal computers (PCs). They also provide a part diverter that can direct parts to the scrap bin.

These two developments make it feasible to use a PC to perform process monitoring. The machine variables can be used to detect defective parts and a PC can trigger the part diverter to direct the defects to the scrap bin.

The prevalence of PCs on the shop floor has also made it feasible to perform more advanced process monitoring. A common area of interest is in monitoring cavity and hydraulic pressure traces. The pressure traces are attractive for two reasons. First, they contain substantially more information than is available from the machine—the measurements provided by the machine are point measurements rather than the complete curves. Second, cavity pressure provides information about the conditions in the individual cavities. By comparison, the machine variables provide aggregate information about all of the cavities.

Figure 5-1 shows the difference between process monitoring and quality assurance techniques that rely on measuring quality attributes of finished parts.
Figure 5-1: Monitoring Process Variables versus Monitoring Process Output

As shown in the diagram, monitoring process variables, such as injection pressure or shot size, has the advantage of being mold independent. Although the target values for the measurements may differ for different molds, the methodology of making the measurements is the same. Thus, the cost of measurement is almost entirely the fixed cost involved in installing the appropriate sensors. Part quality attributes, such as part length or the width of a slot, are unique to each part and more difficult to measure. As a result it is more expensive to measure part quality attributes. Part quality attributes are what is important to the customer, however, so monitoring process variables is only useful to the extent that the process variables correlate with the part quality attributes.

5.2 Process Monitoring Strategies

There are two strategies that can be pursued with process monitoring: exception catching and predictive modeling. Exception catching is the less ambitious strategy; the goal is to use monitoring to identify process outliers. Simply stated, exception catching focuses on identifying parts that are significantly different from the other parts produced at approximately the
same time. Predictive modeling is more ambitious. Its goal is to predict part dimensions based on the values of process variables. In contrast to exception catching, predictive modeling does not evaluate parts with respect to the immediately around them but compares them to an absolute standard—the acceptable dimensions.

The differences between the two strategies become clear when one thinks about how they would integrate into the complete quality assurance methodology in an injection molding plant. There are five typical process control problems in injection molding: a gradual drift in the process mean, an abrupt shift in the process mean, a gradual increase in the standard deviation, an abrupt increase in the standard deviation, and an outlier. These problems are shown graphically in Figure 5-2. Depending on how process monitoring is implemented, it may identify some or all of these problems.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Process</td>
<td><img src="image" alt="Graph" /></td>
<td>not applicable</td>
<td>not applicable</td>
</tr>
<tr>
<td>Gradual Shift in Process Mean</td>
<td><img src="image" alt="Graph" /></td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Dramatic Shift in Process Mean</td>
<td><img src="image" alt="Graph" /></td>
<td>maybe</td>
<td>yes</td>
</tr>
<tr>
<td>Gradual Increase in Process Variation</td>
<td><img src="image" alt="Graph" /></td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Dramatic Increase in Process Variation</td>
<td><img src="image" alt="Graph" /></td>
<td>maybe</td>
<td>yes</td>
</tr>
<tr>
<td>Process Outlier</td>
<td><img src="image" alt="Graph" /></td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

**Figure 5-2: Identifying Process Problems through Process Monitoring**

The only process problem that exception catching would definitely identify is the outlier. Therefore, it would be a complement rather than a substitute for the current quality assurance technique of periodically measuring parts. The exception catching methodology would focus on identifying the higher frequency process variation that causes process
outliers. Periodic part measurements would still be needed to catch the lower frequency problems of drifts and shifts in the process mean and increases in the process standard deviation.

Predictive modeling, on the other hand, would identify all of the process problems. The monitoring system would be predicting part dimensions, so measurements would no longer be necessary. Control charting could be done on the predictions in order to detect changes in the process. To be successful, the process model that predicted dimensions would have to be very robust, however, since the predictions would be expected to be accurate even in the face of process variation.

5.3 Experimentation

The next two chapters will present five experiments that test the two process monitoring strategies. Chapter Six will present two experiments testing the effectiveness of monitoring machine variables to pursue the exception catching strategy. Chapter Seven will present three experiments testing the effectiveness of monitoring cavity and hydraulic pressure traces. Since the cavity and hydraulic pressure traces contain more information than the machine variables, the traces will be used to perform predictive modeling as well as exception catching. Table 5-1 summarizes the experimentation done in each area.
<table>
<thead>
<tr>
<th>Process Variables</th>
<th>Monitoring Strategy</th>
</tr>
</thead>
</table>
| Machine Variables | Exception Catching: Chapter 6, Experiment #1, Chapter 6, Experiment #2  
Predictive Modelling: Not Applicable |
| Pressure Traces   | Exception Catching: Chapter 7, Experiment #2, Chapter 7, Experiment #3  
Predictive Modelling: Chapter 7, Experiment #1, Chapter 7, Experiment #3 |

**Table 5-1: Summary of Experimentation**

Three analysis techniques were also tested in order to determine which analysis techniques were most effective for each monitoring strategy. Where applicable, the data from an experiment was analyzed in more than one way. Table 5-2 summarizes the analysis techniques that were tested.

<table>
<thead>
<tr>
<th>Analysis Technique</th>
<th>Monitoring Strategy</th>
</tr>
</thead>
</table>
| SPC Analysis       | Exception Catching: Chapter 6, Experiment #1, Chapter 6, Experiment #2, Chapter 7, Experiment #2, Chapter 7, Experiment #3  
Predictive Modelling: Not Applicable |
| Neural Network Analysis | Exception Catching: Chapter 6, Experiment #1, Chapter 7, Experiment #3  
Predictive Modelling: Chapter 7, Experiment #3 |
| Regression Analysis | Exception Catching: Not Applicable  
Predictive Modelling: Chapter 7, Experiment #1 |

**Table 5-2: Summary of Analysis Techniques**

The remainder of the thesis is organized as follows. Chapters Six and Seven are structured in the same way. They begin with an introduction and
summary of experimentation and results. Next is a discussion of each experiment. The chapters end with a conclusion section that combines the results from each experiment. Each experiment is presented in the same way; the information is organized into three sections: methodology of experimentation, methodology of analysis, results of analysis, and conclusions. In cases where the experimental data was analyzed in more than one way, there are methodology of analysis and results of analysis sections for each analysis technique. Chapter Eight is the conclusion of this thesis and combines the results from Chapters Six and Seven.
Chapter Six
Monitoring Machine Variables

6.1 Introduction

The potential benefits of monitoring the machine variables were tested through two experiments run at an injection molding plant. Both experiments were run under normal production conditions. The first experiment was run with a two cavity mold that produced parts for an automobile heater switch. The second experiment was run with a four cavity mold that produced a terminal block for an automobile fuse assembly.

For each experiment an IBM-compatible personal computer was connected to the injection molding machine via an RS-232C serial port. The computer was used to monitor the process variables that the machine measures. These variables, which are commonly referred to as machine variables, were logged directly to disk, as ASCII files. The logging was performed by Procomm, a typical PC communication package. The log files were then loaded into Microsoft Excel for Windows 4.0 where the data was analyzed. The neural network analysis was performed using the HNC Explorenet 3.0 neural network environment. The details of the available machine variables are discussed fully in Appendix A. The mold and machine used in the first experiment were equipped with cavity pressure and hydraulic pressure sensors that recorded pressure traces during the experiment; the pressure trace data will be analyzed in Chapter 7.

In both experiments, the machine variables were monitored with the goal of identifying parts with out of control dimensions. In practice, such a
process monitoring system would be used to trigger a part diverter that would direct defective parts into the scrap bin. All machines in the plant were equipped with part diverters.

The goal of process monitoring would normally be to identify parts that were outside specification limits, since the specification represents the customer's concerns. For the experiments in this thesis, however, it was more interesting to evaluate the process monitoring in terms of its ability to identify parts that had quality attributes more than three standard deviations away from the mean. For the first experiment, the tolerances were so wide that only one of over 1400 samples had out of tolerance dimensions. By comparison, there were more than ten samples with weights more than three standard deviations from the mean. It would not have been very interesting to discuss whether or not process monitoring identified the one defective part. Furthermore, for most parts in the plant, the tolerances are tighter than they are for the part used in this experiment. Thus, by evaluating process monitoring with respect to a tighter standard than the tolerance for the part used in Experiment #1, one gets a more accurate picture of the likely effectiveness of process monitoring for other parts in the plant.

Evaluating process monitoring with respect to the part specification was also problematic for the second experiment. For the second experiment, the process mean for the critical dimension was outside the specification limit. As a result, the vast majority of parts produced were outside specification. It would not be a useful test to see if process monitoring could identify the out of specification parts in this situation.
For the remainder of the thesis, defective and out of control will be used synonymously, except when specifically noted otherwise.

6.1.1 Limitations of Monitoring Machine Variables

Because the machine variables, with the exception of the mold temperature, are measured on the machine as opposed to the mold, there are limitations to the data that they can provide. The schematic in Figure 6-1 shows the machine and mold configuration.

![Diagram of Machine and Mold Configuration]

**Figure 6-1: Schematic of Machine and Mold**

As shown in the diagram, the machine variable sensors are located on the machine. This means that their values indicate the aggregate conditions in both cavities but not necessarily the conditions in either cavity individually.

An example makes this concept more clear. The shot size is measured as the displacement of the barrel during injection. If the shot size were small for a particular shot, one might be tempted to assume that both parts would
have below average weights. Unfortunately, while that is one explanation, there are also others.

Often what has really happened in these situations is that one cavity has experienced some sort of flow blockage--either at the gate or within the cavity. As a result, the amount of material in that cavity will be less than average. Because of its control methods, the machine still attempts to inject the same amount of material, however. As a result, the cavity without the blockage gets overpacked and ends up with an above average weight. Despite the efforts of the control loop, the shot size often ends up being smaller than average because after the blockage the machine cannot pack all of the remaining shot into a single cavity.

It is also important to recognize that even if one could establish the cause of the problem, such as blockage in one cavity. One could never establish whether it was occurring in cavity one or cavity two. To the sensors on the machine, the conditions look exactly the same whether cavity one is blocked or cavity two is blocked.

As a result, the machine sensors cannot be used to predict individual part dimensions. The conditions in the individual cavities are not observable through the machine variables. This is not to say, however, that monitoring the machine variables is not useful. As will be shown below, machine variables can be used very effectively to give indications of process problems.

6.1.2 Expected Results

By focusing on identifying the process outliers, the exception catching strategy focuses on identifying the high frequency variation in the process. Due to the physics of injection molding, variables associated with the
injection stage is the most likely variables to produce this type of high frequency variation.

Part quality is largely a function of material characteristics, mold temperature distribution, and the process of mold filling. Material characteristics and temperature distributions are subject to significant inertias that make it unlikely that they would cause a process outlier. If their values vary, they are likely to stay at the new values for a significant period of time. Thus, their variation could cause a process shift or drift, but it is unlikely that it would cause an outlier.

One notable exception is point contamination of the process raw material—localized raw material contamination such as the presence of several grains of high melt temperature material in a low melt temperature raw material. The high melt temperature contaminants would remain in the solid state through plastication and block the gate or a portion of the mold during injection. Once the parts were ejected, however, the contamination would be out of the system and the process would immediately return to normal. Although it is caused by material variation, the resulting problem is really a flow disturbance.

Flow disturbances during injection are the type of rapid variation that is capable of producing process outliers. The time constants for the fill rate are fast enough that the injection rate must be regulated by a control loop during injection. This rate of variation is more than fast enough to produce process outliers.
6.1.3 Summary of Experimentation and Results

The expectation was to analyze the data from the experiments in two ways. The first analysis method was based on the principles of statistical process control (SPC). It involved analyzing each machine variable individually. The second analysis method was a neural network. The neural network analysis, in contrast to the SPC technique, incorporated interactions among the process variables. In analyzing the terminal block data, however, the results from the SPC analysis indicated that there were fundamental problems with the experiment. As a result, no neural network analysis was done for the second experiment.

The results of the analyses are shown in Table 6-1. As shown in the table, the results from the first experiment were more impressive than those from the second. The potential reasons for this are discussed in the conclusion section for the second experiment. The table also shows that although the neural network identified a higher percentage of defects, it did so at the cost of dramatically increasing the number of false rejections. Although missed defects are more costly than false rejections, the neural network's detection of 3 more defects does not seem to justify its false rejection of more than 10% of the shots.

<table>
<thead>
<tr>
<th>Experiment Number</th>
<th>SPC Analysis</th>
<th>Neural Network Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Defects Identified</td>
<td>False Rejections</td>
</tr>
<tr>
<td>1</td>
<td>5 of 11 defects were identified</td>
<td>0 false rejections in 288 shots</td>
</tr>
<tr>
<td>2</td>
<td>3 of 65 defects were identified</td>
<td>6 false rejections in 515 shots</td>
</tr>
</tbody>
</table>

Table 6-1: Summary of Experimentation and Results
6.2 Experiment #1: The Heater Switch Part

The first experiment was performed on a 55 ton Toyo Plastar injection molding machine. The mold used was a two-cavity mold that produced the containment structure for a heater switch in an automobile. A sketch of the part is shown in Figure 6-2. The control dimensions were the overall length and width. These dimensions indicated how well the part would mate with the other pieces of the switch. As this containment structure was hidden from view, minor cosmetic details were not significant.

Figure 6-2: Containment Structure for Automobile Heater Switch

6.2.1 Methodology of Experimentation

At the time of the experiment, the part was not in high demand, so the parts could be fully measured and analyzed before they had to be shipped to the customer. This allowed a more complete experimental methodology than would be possible for the other experiment run at the plant. The methodology of experimentation was as follows:

- The mold and machine were prepared exactly as they would be for a production run.
- The machine settings were set to the standard production process. The process limit for First Pressure was set high enough that the injection would not reach the limit under normal conditions. As
will be discussed in the next section, for most of the molds in the plant, the standard process settings were set such that the injection pressure limit would be encountered under normal conditions.

- The mold was preheated in the standard manner.
- Production was started.
- Starting at shot number 212 and continuing until shot number 944, the parts from each shot were bagged and numbered.

6.2.2 SPC Analysis

6.2.1 Methodology of Analysis

After the samples were taken, they were allowed to cool overnight so that their dimensions and weight would stabilize before measurement. Once the dimensions had stabilized, the parts were analyzed in the following manner:

- Twenty-two random samples were taken in order to characterize the process. The overall length and width and weight were measured for these samples.
- Shots for which the value of at least one machine variable was greater than three standard deviations from the mean were identified as exceptional shots. The use of three standard deviation limits as the criterion for an exceptional shot is entirely arbitrary. The limits were chosen as such because three standard deviations is a common level for separating random noise from variation associated with assignable causes. The tradeoffs involved in choosing tighter limits are discussed in the results of analysis.
section. The overall length and width and weight were measured for these exceptional samples.

- For the parts with exceptional dimensions, the correlation between weight and dimensions was checked.

- In order to determine how many defects were not detected by the machine variables, shots 212 through 499 were weighed. Weight was chosen as a quality metric because it was a quick and repeatable measurement.

- The proportions of false positives and false negatives, using weight as an indicator of quality, were calculated for each machine variable. As discussed previously, parts with weights more than three standard deviations away from the mean were classified as defective.

6.2.2.2 Results of the Analysis

6.2.2.2.1 Correlation of Part Weight and Part Dimensions

Since the experiment required a large number of parts to be measured, the measurement procedure had to be quick and repeatable. Part weight was such a measurement. It was important, however, to determine how well weight correlated to part dimensions. In order to test this a sample of parts were weighed and measured. Scatter graphs of part weight versus part dimensions are shown in Figures 6-3 through 6-6.
Figure 6-3: Scatter Graph of Part Width versus Part Weight for Cavity One

Figure 6-4: Scatter Graph of Part Width versus Part Weight for Cavity Two
Figure 6-5: Scatter Graph of Part Weight Versus Part Length for Cavity One

Figure 6-6: Scatter Graph of Part Width Versus Part Weight for Cavity Two
The graphs show that the correlation between weight and dimensions is quite good for cavity one—with the exception of one significant outlier. Unfortunately, the correlation is not nearly as good for cavity two. As a result, conclusions made about cavity two may be subject to question.

6.2.2.2.2 Relevant Machine Variables

As discussed in Appendix A, the process settings determine which process variables are relevant to analysis. For this experiment the process was set for a single stage injection under velocity control. Switchover was set to be based on position. For such process settings, the following process variables were defined: Barrel Temperatures, Hopper Temperature, Mold Temperatures, Melt Temperature, Shot Size, First Pressure, Back Pressure 1, First Speed, First Speed Pressure, and First Injection Time.

Back Pressure was immediately eliminated from the analysis because during the experiment it varied by only 4 pounds per square inch (PSI).

Since the goal of monitoring the machine variables was to catch exceptional shots, the set of relevant process variables could be further reduced. An exceptional shot is a high frequency disturbance. Thus, as discussed earlier, when one looks for its cause, one must look for high frequency variation. The temperatures in the system—Barrel Temperatures, Hopper Temperature, and Mold Temperature—are subject to substantial inceptions and, therefore, vary fairly slowly. As a result, these variables can be eliminated from the analysis without hindering its effectiveness. Melt Temperature is a borderline candidate, so it was kept in the analysis.
6.2.2.2.3 The Fraction of Defects Identified

One of the key measures of the success of a process monitoring methodology is the fraction of defective parts that the monitor detects. This measure is the complement of the proportion of false negatives in the familiar probability terminology. For the discussion in this thesis, it is defined in the following manner:

\[
\text{Fraction of Defects Identified} = \frac{\text{Number of Defects Identified}}{\text{Total Number of Defects}}
\]

In order to determine the fraction of defects identified, the parts from shots 212 through 499 were weighed. The results are shown in Figures 6-7 and 6-8.

Of the approximately 600 parts weighed, only a small number had weights more than three standard deviations from the process mean. Table 6-2 shows the machine variables, in terms of standard deviations from the mean, for the eleven shots with out of control weights. Only four of the relevant machine variables—Melt Temperature, First Pressure, First Speed Pressure, and First Injection Time—had an out of control value for at least one of the eleven exceptional shots.
Note: Weights are normalized to be expressed in terms of standard deviations from the mean.

**Figure 6-7: Part Weights for Cavity One**

Note: Weights are normalized to be expressed in terms of standard deviations from the mean.

**Figure 6-8: Part Weights for Cavity Two**
<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Melt Temp.</th>
<th>First Pressure</th>
<th>First Speed Pressure</th>
<th>First Injection Time</th>
<th>Cavity 1 Weight</th>
<th>Cavity 2 Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>212</td>
<td>3.56</td>
<td>5.20</td>
<td>4.01</td>
<td>0.75</td>
<td>0.07</td>
<td>-12.53</td>
</tr>
<tr>
<td>230</td>
<td>2.82</td>
<td>0.50</td>
<td>0.42</td>
<td>-0.25</td>
<td>-3.24</td>
<td>-2.65</td>
</tr>
<tr>
<td>284</td>
<td>0.99</td>
<td>0.37</td>
<td>0.34</td>
<td>0.25</td>
<td>-5.87</td>
<td>-5.87</td>
</tr>
<tr>
<td>285</td>
<td>0.99</td>
<td>4.35</td>
<td>7.76</td>
<td>2.25</td>
<td>-1.28</td>
<td>16.39</td>
</tr>
<tr>
<td>297</td>
<td>0.62</td>
<td>0.29</td>
<td>0.34</td>
<td>-0.25</td>
<td>-5.06</td>
<td>-4.22</td>
</tr>
<tr>
<td>321</td>
<td>1.35</td>
<td>0.17</td>
<td>0.50</td>
<td>-0.25</td>
<td>-7.22</td>
<td>-0.18</td>
</tr>
<tr>
<td>344</td>
<td>-0.85</td>
<td>4.31</td>
<td>0.34</td>
<td>0.25</td>
<td>-42.55</td>
<td>1.93</td>
</tr>
<tr>
<td>358</td>
<td>-0.85</td>
<td>0.29</td>
<td>0.50</td>
<td>-0.25</td>
<td>-3.98</td>
<td>-3.60</td>
</tr>
<tr>
<td>417</td>
<td>0.62</td>
<td>11.36</td>
<td>0.02</td>
<td>1.25</td>
<td>-13.19</td>
<td>10.47</td>
</tr>
<tr>
<td>418</td>
<td>-1.59</td>
<td>14.36</td>
<td>15.33</td>
<td>25.74</td>
<td>-76.07</td>
<td>54.32</td>
</tr>
<tr>
<td>440</td>
<td>1.35</td>
<td>0.05</td>
<td>0.10</td>
<td>-0.25</td>
<td>0.39</td>
<td>-7.24</td>
</tr>
</tbody>
</table>

Note: Weights are normalized to be expressed in terms of standard deviations from the mean.

The shaded entries indicate the shots identified through process monitoring.

**Table 6-2: Process Variables for Parts with Out of Control Weights**

**6.2.2.2.3.1 Overall Fraction of Defects Identified**

From Table 6-2, one can estimate the overall effectiveness of monitoring machine variables. Of the eleven shots in which at least one part had an out of control weight, five were identified through process monitoring. Thus, if all of the relevant machine variables were monitored, the overall effectiveness would be 45%. Ordering the parts by degree of deviation from the mean is revealing. As shown in Table 6-3, the effectiveness of the monitoring methodology is higher for the most extreme parts. All parts with weights beyond ten standard deviations from the mean were identified by monitoring the process variables.
<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Cavity 1 Weight</th>
<th>Cavity 2 Weight</th>
<th>Identified by Process Monitoring?</th>
</tr>
</thead>
<tbody>
<tr>
<td>418</td>
<td>-76.07</td>
<td>54.32</td>
<td>yes</td>
</tr>
<tr>
<td>344</td>
<td>-42.55</td>
<td>1.93</td>
<td>yes</td>
</tr>
<tr>
<td>285</td>
<td>-1.28</td>
<td>16.39</td>
<td>yes</td>
</tr>
<tr>
<td>417</td>
<td>-13.19</td>
<td>10.47</td>
<td>yes</td>
</tr>
<tr>
<td>212</td>
<td>0.07</td>
<td>-12.53</td>
<td>yes</td>
</tr>
<tr>
<td>440</td>
<td>0.39</td>
<td>-7.24</td>
<td>no</td>
</tr>
<tr>
<td>321</td>
<td>-7.22</td>
<td>-0.18</td>
<td>no</td>
</tr>
<tr>
<td>284</td>
<td>-5.87</td>
<td>-5.87</td>
<td>no</td>
</tr>
<tr>
<td>297</td>
<td>-5.06</td>
<td>-4.22</td>
<td>no</td>
</tr>
<tr>
<td>358</td>
<td>-3.98</td>
<td>-3.60</td>
<td>no</td>
</tr>
<tr>
<td>230</td>
<td>-3.24</td>
<td>-2.65</td>
<td>no</td>
</tr>
</tbody>
</table>

Note: Weights are normalized to be expressed in terms of standard deviations from the mean.

**Table 6-3: Sorted List of Shots with Out of Control Weights**

Although a weight ten standard deviations from the mean may seem extreme, the capability of the process is such that all but the most extreme parts will be within specification. According to the tolerance for the part used in this experiment, the only unacceptable part was shot 418 in which cavity two flashed severely.

**6.2.2.2.3.2 Fraction of Defects Identified by Individual Process Variables**

From Table 6-2, the fraction of defects identified by individual process variables can also be evaluated. Only four of the relevant machine variables--Melt Temperature, First Pressure, First Speed Pressure, and First Injection Time--had an out of control value for at least one of the eleven exceptional
shots. Thus, these four machine variables were the only machine variables that had to be looked at individually.

It is not surprising that First Pressure and First Speed Pressure were effective in identifying defective parts. Since the machine was set in velocity control with switch over based on position, the machine's control system varied injection pressure in order to overcome the flow resistance and inject the specified amount of material at the specified rate of injection. Therefore, variations in the flow resistance of the material into the mold would show up as variations in injection pressure. The factors that would change resistance to the flow of the material into the mold are things such as a change in material viscosity, a change in material temperature, a change in mold temperature, and a blockage of a gate. Some of these disturbances, such as the blockage of a gate, are the type of high frequency disturbances that would effect only one shot and therefore produce process outliers.

Because of the machine setup, it is not surprising that the First Injection Time was not very successful in identifying defective parts. Although injection time is a significant quality determinant, its effectiveness for process monitoring is limited by the fact that it is a controlled variable. Since the machine was setup in velocity control, the machine was performing closed loop control on the injection time. For shot 418, however, there was such a disturbance in the process that the machine was unable to control the injection time. Although such instances are rare, they are significant.

It seems to be coincidence that Melt Temperature was successful in identifying defective parts. There seem to be two potential reasons that melt temperature was not very successful. First, as discussed previously, the variation in Melt Temperature may be of a lower frequency than the variation
required to produce process outliers. Second, although melt temperature is a significant process variable, it is difficult to measure. On the machine used in the experiment, melt temperature is measured by a thermocouple in the nozzle. The thermocouple protrudes into the molten plastic and measures its temperature. Many injection molding experts question the accuracy and response time of such measurements of melt temperature. 30, 31, 32

6.2.2.2.4 False Rejection Rate

The second key measure of the value of process monitoring is the false rejection rate. Since a rejection is a positive in the SPC analysis, this measure is analogous to the false positives in the familiar probability terminology. For the discussion is this thesis, it is defined in the following manner:

\[
\text{False Rejection Rate} = \frac{\text{Number of Good Parts Rejected}}{\text{Number of Parts Rejected}}
\]

Table 6-4 provides the data to assess the false rejection rates associated with monitoring the machine variables. It identifies the shots for which at least one of the features was out of control. The table includes the outlying process variables and part weights for these shots.

<table>
<thead>
<tr>
<th>Shot Num</th>
<th>Melt Temp</th>
<th>Shot Size</th>
<th>First Pressure</th>
<th>First Speed</th>
<th>First Speed Pressure</th>
<th>First Injection Time</th>
<th>Cavity 1 Part Weight</th>
<th>Cavity 2 Part Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>212</td>
<td>3.56</td>
<td>-1.10</td>
<td>5.20</td>
<td>0.31</td>
<td>4.01</td>
<td>0.75</td>
<td>0.07</td>
<td>-12.53</td>
</tr>
<tr>
<td>215</td>
<td>3.19</td>
<td>-2.02</td>
<td>0.37</td>
<td>-1.33</td>
<td>0.34</td>
<td>0.75</td>
<td>-0.13</td>
<td>0.83</td>
</tr>
<tr>
<td>218</td>
<td>3.56</td>
<td>-1.23</td>
<td>0.29</td>
<td>0.31</td>
<td>0.34</td>
<td>0.25</td>
<td>-0.28</td>
<td>0.16</td>
</tr>
<tr>
<td>226</td>
<td>3.19</td>
<td>-1.76</td>
<td>0.50</td>
<td>2.16</td>
<td>0.50</td>
<td>-0.25</td>
<td>-0.82</td>
<td>-0.11</td>
</tr>
<tr>
<td>238</td>
<td>3.19</td>
<td>-0.97</td>
<td>0.21</td>
<td>0.31</td>
<td>0.34</td>
<td>0.25</td>
<td>-0.27</td>
<td>0.91</td>
</tr>
<tr>
<td>250</td>
<td>3.55</td>
<td>-0.97</td>
<td>0.25</td>
<td>0.31</td>
<td>0.34</td>
<td>0.25</td>
<td>-0.48</td>
<td>0.16</td>
</tr>
<tr>
<td>255</td>
<td>3.19</td>
<td>-1.50</td>
<td>0.50</td>
<td>-1.33</td>
<td>0.50</td>
<td>-0.25</td>
<td>-0.08</td>
<td>0.44</td>
</tr>
<tr>
<td>285</td>
<td>0.99</td>
<td>-0.44</td>
<td>4.35</td>
<td>-1.63</td>
<td>7.76</td>
<td>2.25</td>
<td>-1.28</td>
<td>16.39</td>
</tr>
<tr>
<td>344</td>
<td>-0.85</td>
<td>-0.83</td>
<td>4.31</td>
<td>-1.33</td>
<td>0.34</td>
<td>0.25</td>
<td>-42.55</td>
<td>1.93</td>
</tr>
<tr>
<td>360</td>
<td>-1.22</td>
<td>-0.70</td>
<td>0.13</td>
<td>3.18</td>
<td>0.42</td>
<td>-0.25</td>
<td>-0.27</td>
<td>0.75</td>
</tr>
<tr>
<td>417</td>
<td>0.62</td>
<td>-0.57</td>
<td>11.36</td>
<td>-0.41</td>
<td>0.02</td>
<td>1.25</td>
<td>-13.19</td>
<td>10.47</td>
</tr>
<tr>
<td>418</td>
<td>-1.59</td>
<td>-0.44</td>
<td>14.36</td>
<td>0.17</td>
<td>15.33</td>
<td>25.74</td>
<td>-76.17</td>
<td>54.32</td>
</tr>
<tr>
<td>455</td>
<td>3.19</td>
<td>-0.70</td>
<td>0.09</td>
<td>0.31</td>
<td>0.10</td>
<td>0.25</td>
<td>0.27</td>
<td>0.11</td>
</tr>
<tr>
<td>459</td>
<td>3.19</td>
<td>-0.09</td>
<td>-0.11</td>
<td>0.51</td>
<td>0.18</td>
<td>0.25</td>
<td>0.46</td>
<td>-0.18</td>
</tr>
<tr>
<td>622</td>
<td>0.25</td>
<td>-0.30</td>
<td>6.62</td>
<td>0.51</td>
<td>5.68</td>
<td>0.75</td>
<td>13.80</td>
<td>2.01</td>
</tr>
<tr>
<td>631</td>
<td>-0.48</td>
<td>0.23</td>
<td>3.46</td>
<td>-0.41</td>
<td>12.78</td>
<td>3.75</td>
<td>7.88</td>
<td>-6.36</td>
</tr>
<tr>
<td>640</td>
<td>-1.59</td>
<td>-3.08</td>
<td>0.17</td>
<td>-0.41</td>
<td>0.10</td>
<td>0.25</td>
<td>65.03</td>
<td>73.13</td>
</tr>
<tr>
<td>641</td>
<td>-0.85</td>
<td>3.27</td>
<td>-0.80</td>
<td>-0.27</td>
<td>-0.54</td>
<td>-0.25</td>
<td>40.26</td>
<td>44.44</td>
</tr>
<tr>
<td>649</td>
<td>1.35</td>
<td>0.89</td>
<td>6.46</td>
<td>-1.33</td>
<td>-0.46</td>
<td>0.25</td>
<td>0.54</td>
<td>2.25</td>
</tr>
<tr>
<td>656</td>
<td>0.25</td>
<td>0.09</td>
<td>8.48</td>
<td>-0.41</td>
<td>-0.06</td>
<td>0.75</td>
<td>-24.98</td>
<td>3.04</td>
</tr>
<tr>
<td>686</td>
<td>0.25</td>
<td>0.23</td>
<td>-0.27</td>
<td>3.18</td>
<td>-0.30</td>
<td>-0.25</td>
<td>0.34</td>
<td>-0.12</td>
</tr>
<tr>
<td>752</td>
<td>0.62</td>
<td>0.09</td>
<td>-0.27</td>
<td>3.03</td>
<td>-0.38</td>
<td>-0.25</td>
<td>-0.20</td>
<td>-0.20</td>
</tr>
<tr>
<td>904</td>
<td>-0.48</td>
<td>1.28</td>
<td>3.33</td>
<td>-1.48</td>
<td>1.37</td>
<td>0.25</td>
<td>-11.38</td>
<td>0.98</td>
</tr>
<tr>
<td>944</td>
<td>0.25</td>
<td>2.61</td>
<td>6.98</td>
<td>-0.56</td>
<td>2.97</td>
<td>0.25</td>
<td>8.15</td>
<td>-20.98</td>
</tr>
</tbody>
</table>

Note: Weights and process variables are normalized to be expressed in terms of standard deviations from the mean.

The shaded entries indicate the shots identified through process monitoring.

Table 6-4: Process Variables and Part Weights for Exceptional Shots
The four machine variables with low percentages of false rejections—
Shot Size, First Pressure, First Speed Pressure, and First Injection Time—are excellent choices for process monitoring. In terms of efficiency, the three machine variables with no false rejections obviously performed well in this experiment. Although First Pressure had a slightly higher number of false rejections than the most efficient process variables, it identified twelve exceptional shots, as many as all of the other process variables combined. Thus, it had the best balance of efficiency and effectiveness.

The other two machine variables, First Speed and Melt Temperature, seem like poor choices. First speed, which produced only false rejections, was not useful for monitoring. Melt temperature, for which 89% of the parts diverted were false rejections, would only be useful if it were the only process variable to catch the one exceptional shot that it successfully identified. Since shot 212, the one exceptional shot that melt temperature successfully identified, is also identified by other machine variables, melt temperature added no value to the process monitoring.

If the number of variables that could be monitored were limited, as it is in many Computer Integrated Manufacturing (CIM) systems, it would be important to consider overlap among the process variables. For instance, of the most effective process variables, First Pressure and First Speed Pressure both correspond to the injection pressure during the first stage of injection. Therefore, as can be seen in Table 6-4, their values are highly correlated. In the experiment above, First Speed Pressure could have been ignored without reducing the number of exceptional shots identified. On the other hand, Shot Size was clearly independent of the other variables; it was the only machine variable to identify the problems with shots 640 and 641.
6.2.2.2.4 Balancing Defect Detection Rate and False Rejection Rate

There is a tradeoff between identifying a higher fraction of the defective parts and having a low false rejection rate. In practice, the control limits for each variable should be tuned so that the tradeoff between detection rate and false rejection rate reflects of the costs associated with each. Figure 6-9 shows the tradeoff curve for First Pressure. Table 6-5 presents the same data in tabular form. The choice of control limits should reflect the fact that the cost of delivering a defective part to a customer is higher than the cost of a false rejection. From the data in the table, it is clear that the First Pressure control limits should be tighter than three standard deviations.

![Graph showing the tradeoff curve between defects identified and false rejections.](image)

Figure 6-9: Tradeoff Curve Between the Number of Defects Identified and the Number of False Rejections
### Table 6-5: The Number of Defects Identified and False Rejections Associated with Different Control Limits for *First Pressure*

<table>
<thead>
<tr>
<th>Control Limits</th>
<th>Number of Defects Identified</th>
<th>Number of False Rejections</th>
<th>Percentage of Defects Identified</th>
<th>False Rejection Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.00</td>
<td>2</td>
<td>0</td>
<td>18%</td>
<td>0%</td>
</tr>
<tr>
<td>5.00</td>
<td>3</td>
<td>0</td>
<td>27%</td>
<td>0%</td>
</tr>
<tr>
<td>4.00</td>
<td>5</td>
<td>0</td>
<td>45%</td>
<td>0%</td>
</tr>
<tr>
<td>3.00</td>
<td>5</td>
<td>0</td>
<td>45%</td>
<td>0%</td>
</tr>
<tr>
<td>2.00</td>
<td>5</td>
<td>0</td>
<td>45%</td>
<td>0%</td>
</tr>
<tr>
<td>1.00</td>
<td>5</td>
<td>0</td>
<td>45%</td>
<td>0%</td>
</tr>
<tr>
<td>0.75</td>
<td>5</td>
<td>0</td>
<td>45%</td>
<td>0%</td>
</tr>
<tr>
<td>0.50</td>
<td>6</td>
<td>9</td>
<td>55%</td>
<td>3%</td>
</tr>
<tr>
<td>0.45</td>
<td>6</td>
<td>14</td>
<td>55%</td>
<td>5%</td>
</tr>
<tr>
<td>0.40</td>
<td>6</td>
<td>21</td>
<td>55%</td>
<td>8%</td>
</tr>
<tr>
<td>0.35</td>
<td>7</td>
<td>37</td>
<td>64%</td>
<td>13%</td>
</tr>
<tr>
<td>0.30</td>
<td>7</td>
<td>45</td>
<td>64%</td>
<td>16%</td>
</tr>
<tr>
<td>0.25</td>
<td>9</td>
<td>87</td>
<td>82%</td>
<td>31%</td>
</tr>
<tr>
<td>0.20</td>
<td>9</td>
<td>106</td>
<td>82%</td>
<td>38%</td>
</tr>
<tr>
<td>0.15</td>
<td>10</td>
<td>159</td>
<td>91%</td>
<td>57%</td>
</tr>
<tr>
<td>0.10</td>
<td>10</td>
<td>188</td>
<td>91%</td>
<td>68%</td>
</tr>
<tr>
<td>0.05</td>
<td>11</td>
<td>244</td>
<td>100%</td>
<td>88%</td>
</tr>
</tbody>
</table>

Note: Control limits are expressed in terms of the number of standard deviations from the mean.

#### 6.2.3 Neural Network Analysis

The goal of the machine variable analysis was to identify a function that mapped combinations of machine variable values to two categories, acceptable and unacceptable. Problems such as this are often referred to as classification problems. The results of the SPC analysis proved the feasibility at least a limited mapping that identified the most extreme parts; the goal of the neural network analysis was to try to establish a more complete mapping. In other words, the neural network was evaluated to see if it could identify some of the defective parts that were missed in the SPC analysis.
The SPC approach represented a very straightforward set of classification functions. A shot was classified as acceptable if the value of the machine variable was within a certain limits and the shot was classified as unacceptable if the machine variable was outside the limits. The SPC approach had one crucial limitation, however: it analyzed the process variables independently. This limitation was not inherent to SPC, since the SPC techniques could be applied to any function of the machine variables. Applying SPC techniques, however, does require a priori knowledge of the process interaction.

Neural networks, on the other hand, require no a priori knowledge of the process interactions, since the network learning algorithms attempt to identify any interactions in the data. Neural networks were also attractive for two other reasons:

- neural networks have been successfully applied to many classification problems
- neural networks have been successfully applied to process monitoring and process control problems\(^{33}\)

A Learning Vector Quantization (LVQ) network was chosen for the analysis because such networks were often successful on difficult classification problems.

6.2.3.1 Introduction to the LVQ Network

The neural network software used for analysis was *HNC ExploreNet* 3.0. This explanation of the LVQ network is paraphrased from the *ExploreNet* manual.\(^{34}\) The LVQ network is organized into slabs, or layers, as shown in Figure 6-10. Each slab consists of one or more processing elements (PEs), indicated by circles in the figure.

![Diagram of LVQ Network](image)

**Figure 6-10: Structure of an LVQ Network\(^ {35}\)**

The network is trained through presentation with a set of training examples. The training examples consist of an input vector representing the pattern to be classified and a training output representing the correct classification for the pattern. The input vectors are presented to the network input slab, which includes one PE for each member of the input vector. The input slab feeds the input vector to the Kohonen slab. The Kohonen Slab is organized into equal sized groups of PEs for each category. Each PE in the Kohonen slab has a connection to each PE in the input slab. Associated with each connection is a weight. Thus, each Kohonen PE has a weight vector.


\(^{35}\) Ibid, p. 8-2.
whose elements have a one-to-one correspondence to the network input vector.

The classification algorithm works as follows. The Euclidean distance is calculated between each Kohonen PE's weight vector and the input vector. The Kohonen PE with the least distance between its weight vector and the input vector is classified as the network-wide winner. The network output is the classification group that corresponds to the winning Kohonen PE.

When the network is in learning mode, the network classification is compared to the correct classification, which is presented to the training slab. If the classification is correct, the winning PE's weight vector moved a small distance toward the input vector along the line connecting the input vector and the weight vector for the winning PE. If the classification is not correct, the winning PE's weight vector is moved a small distance away from the input vector along the line connecting the input vector and the weight vector for the winning PE. There are minor optimizations of the learning algorithm to improve performance in the early and late stages of training.

An example is helpful for clarification. In order to facilitate visualization of the learning process, a two input function will be used. Assume an LVQ network is being trained to emulate the logical function exclusive-or, a mapping of two 0 or 1 inputs to one 0 or 1 output. Figure 6-11 is a graphical representation of the training set that would be used to train the network.
The network format required to emulate this function would be one with two inputs and one output. The output would classify each combination of inputs into one of two categories. From the graph of the training set and an understanding of the LVQ classification algorithm, it is clear that at least two Kohonen PE's would be required for each category. In this example three Kohonen PE's will be used for each category. For the initial weight vectors, which are generated randomly, the range of weights will be limited to 0 to 1 inclusive. Representing the weight vectors as points in two-dimensional space, the distribution of the initial weight vectors could be as shown in Figure 6-12.
During training the network would adjust the weight vectors with the goal of reaching the state where, for each input vector, the nearest weight vector represented the correct classification. Figure 6-13 shows a configuration of weight vectors, again represented as two-dimensional points, that would provide the correct classifications.

![Weight Vectors for Trained LVQ Network](image)

**Figure 6-13: Weight Vectors for Trained LVQ Network**

### 6.2.3.1 Methodology of Analysis

The process outlined in the example above is the exact process that was used by the LVQ network to try to establish a mapping of machine variables to a classification of shots into an acceptable category and an unacceptable category. For the experiments, the input vector contained 11 elements: *Melt Temperature, Hydraulic Oil Temperature, Mold Temperature 1, Mold Temperature 2, Shot Size, First Pressure, First Speed, First Speed Pressure, Cycle Time, Injection Time, and Charge Time*. The values for the machine variables were normalized; they were expressed in terms of the
number of standard deviations from the mean. The inputs were classified into two categories: one representing acceptable shots in which both parts had in control weights and the other representing unacceptable shots in which at least one part had an out of control weight.

The neural network analysis was performed on the same data as the SPC analysis, but the methodology of analysis was slightly different. There were three steps to the neural network analysis:

- Training sets were constructed.
- The network was configured and trained.
- The network performance was evaluated.

Unfortunately, each of these steps represented more of an art than a science. As a result many different combinations had to be tested, and, as necessary, iterations were performed.

6.2.3.1.1 Training Sets

Training sets provide representative mappings of inputs to outputs and the network learning algorithms try to identify the patterns that underlie the mappings. The goal of training is to construct a network that can be used to classify future events as they occur. In the case of injection molding, once a network was trained its output would be used to control the part diverter on the injection molding machine.

The training of the network determines a large part of a network's success in practice. If the network training has been incomplete, the network will encounter combinations unlike those that it has seen in training and is likely to make many incorrect classifications. On the other hand, if the network has been well trained, it can interpolate between the examples in its
training set to deal with slightly different combinations. Since the mapping between inputs and outputs is unknown at the start of the training process, it is impossible to know exactly which examples should be included in the training set. As a result, training sets are usually constructed by intuition.

For this experiment, there seemed to be two intuitive ways to develop training sets, so two training sets were developed. The choice of membership for the first training set was based the parts themselves. The shots could be classified into six groups:

1. Both parts had in control weights.
2. One part too heavy and the other part was in control.
3. One part was too light and the other part was in control.
4. One part was too heavy and the other part was too light.
5. Both parts were too heavy.
6. Both parts were too light.

The first training set was constructed by starting with a representative from each of groups one through five and a random sample of 33 parts from group six. Table 6-6 shows the classification of the extreme shots.

Table 6-7 shows the shots that were chosen for the first training set. Since a network should be evaluated on its classification of patterns that are not part of its training set, only one part was chosen from groups one through five. Thirty-three parts were chosen from group six because this group, the group of in-control parts, represented the vast majority of the samples. The training set's ratio of five exceptional shots to thirty-three normal shots was four times greater than the ratio among all the samples. Since missing the diagnosis of a defective part is more costly than rejecting an acceptable part, it seemed appropriate to bias the training set in this way.
Table 6-6: A Classification of Shots into Groups

<table>
<thead>
<tr>
<th>Output Group</th>
<th>Weights</th>
<th>Group Members</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>+</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td>All shots except those listed under other groups</td>
</tr>
<tr>
<td></td>
<td></td>
<td>285</td>
</tr>
<tr>
<td></td>
<td></td>
<td>212, 344, 622, 904, 926</td>
</tr>
<tr>
<td></td>
<td></td>
<td>417, 418, 631, 656, 944</td>
</tr>
<tr>
<td></td>
<td></td>
<td>640, 641</td>
</tr>
<tr>
<td></td>
<td></td>
<td>230, 284, 297, 321, 358, 440</td>
</tr>
</tbody>
</table>

Table 6-7: Members of Training Set One

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>285</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>+</td>
</tr>
<tr>
<td>321</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
</tr>
<tr>
<td>641</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>+</td>
</tr>
<tr>
<td>904</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>-</td>
</tr>
<tr>
<td>944</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>+</td>
</tr>
<tr>
<td>33 Random Samples</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>0</td>
</tr>
</tbody>
</table>

The second training set was slightly different. The choice of membership for the second training set was based on the values of the machine variables. The logic behind this training set was as follows: if the network is going to achieve a full mapping of machine variable values to shot classifications, then the network must be trained with shots that represent the full range of machine variable values. The make up of training set two is shown in Table 6-8. For comparison sake training set two included the same number of exceptional shots as training set one, utilized the same 33 random samples as its in-control shots, and, therefore, maintained the same ratio of exceptional to in-control shots.
### Table 6-8: Members of Training Set Two

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Reason for Inclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>284</td>
<td>Low Shot Size</td>
</tr>
<tr>
<td>344</td>
<td>High First Pressure</td>
</tr>
<tr>
<td>631</td>
<td>High Cycle Time</td>
</tr>
<tr>
<td>641</td>
<td>High Shot Size</td>
</tr>
<tr>
<td>904</td>
<td>High First Pressure</td>
</tr>
<tr>
<td>33 Random Samples</td>
<td>Normal Shots</td>
</tr>
</tbody>
</table>

Once networks were trained, they were analyzed to identify the limits of their effectiveness. Steps were then taken to try to overcome the networks' limitations: different network configurations were constructed, different training parameters were set, and more training cycles were tried. The section below presents the results from the most significant of these experiments.

#### 6.2.3.2 Results of Analysis

The first experiments established a baseline of performance. Identical experiments were run with each training set:

- The network was configured with 32 units per category.
- The network was trained for 15,000 cycles.

Once the network was trained its performance was evaluated on the 287 shots for which complete data was available, shots 212 through 499. The results are shown in Table 6-9. The results were mixed. For correct rejections, the most important performance criteria for process monitoring, both networks outperformed the SPC analysis. Both networks had a high number of false rejections. In comparison, for the SPC analysis, monitoring the two most effective process variables—First Pressure and Shot Size—
produced five correct rejections and no false rejections for shots 212 through 499.

<table>
<thead>
<tr>
<th>Training Set</th>
<th>Correct Rejections</th>
<th>Correct Acceptances</th>
<th>False Rejections</th>
<th>False Acceptances</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td>245</td>
<td>32</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>7</td>
<td>250</td>
<td>27</td>
<td>4</td>
</tr>
</tbody>
</table>

Note: Each network included 32 PEs per category.

Each network was trained for 15,000 cycles.

Table 6-9: Results of Neural Networks Trained by Training Sets One and Two

Although the networks used above were large and were trained for many training cycles, it is impossible to know whether bigger networks or more training cycles would produce better results. Since the network trained with training set one identified more defective parts, it was chosen for further work. Unfortunately, experiments with larger networks and more training cycles did not improve the results.

Another potential way to improve network performance is changing the training set. If the training set is not representative of all the types of variation the network is likely to see, the network is likely to make incorrect diagnoses when it encounters unfamiliar combinations of inputs. Unfortunately, there was very limited data available, so adding to the number of defects included in the training set would leave few defects left for testing. What was attempted instead was to establish an upper limit of performance. The upper limit of performance was established by training the network with all of the available data and evaluating its performance.
A network with 32 units per category was used and it was trained for 40,000 cycles. Table 6-10 shows results. The results are very impressive, but they must be taken for what they are. Since the network was tested on the same data with which it was trained, the results only prove that for that data a very good mapping can be achieved between the machine variables and the output classification. What is still unknown is whether the mapping is a robust. It is unknown how the mapping would perform if the machine were set up in an identical manner and the network were used to classify the parts as they were made.

<table>
<thead>
<tr>
<th>Correct Rejections</th>
<th>Correct Acceptances</th>
<th>False Rejections</th>
<th>False Acceptances</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>276</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: Each network included 32 PEs per category.

Each network was trained for 15,000 cycles.

**Table 6-10: Results from Network Trained with all Available Data**

### 6.2.4 Conclusions from the Heater Switch Experiment

The SPC analysis of the process variables was clearly successful; by removing the most extreme parts from the distribution, it reduced the standard deviation by 82% in cavity one and 74% in cavity two. This reduction in the standard deviation resulted in a fivefold increase in the process capability index for cavity one and fourfold increase for cavity two.

It is revealing to take a closer look at the best machine variables for detecting defects—*First Pressure, Shot Size, First Speed Pressure*, and *Injection Time*. All were associated with mold filling. This seems to support the hypothesis that the high frequency disturbances in process output,
outliers, are caused by the quality determinant that is subject to the highest frequency variation, mold filling.

The second interesting fact is that the three most sensitive machine variables for process monitoring—First Pressure, Shot Size, and First Speed Pressure—were all uncontrolled variables that were "free" to vary in response to process disturbances. Although the amount of plastic injected during the injection stage of the cycle was a controlled variable, the amount of material injected during the constant pressure of the pack stage was not. The variation in the amount of plastic injected during the pack stage was almost entirely responsible for the variation in the Shot Size. As a result, Shot Size was subject to the variation of an uncontrolled variable. Injection Time, on the other hand, was a controlled variable and therefore only varied in response to a very extreme process disturbance. In the next experiment a contrasting process setup is presented.

Analyzing the defect identification and false rejection rates for different First Pressure Control limits revealed that the control limits for First Pressure should have been set to be much tighter than three standard deviations. If process monitoring were put into practice, the control limits for each process variable should be set so that the balance between the defect identification and false rejection rates reflects the costs associated with each.

As successful as the SPC analysis was, however, it was still only able to detect extreme part variations that were beyond ten standard deviations from the mean. While that was acceptable for the mold used in the experiment, it would not be acceptable for most of the molds in the plant. The goal of the neural network analysis was to identify whether a more advanced analysis technique could provide better performance.
Unfortunately, it is hard to draw conclusions from the neural network results. Networks trained with small training sets were plagued by a high number of false rejections. Networks trained with all the data available were very successful, but there was not any data left to test the breadth of the mappings identified. Further experiment is required to determine the true potential of neural networks.

6.3 Experiment #2: The Terminal Block

The second experiment was performed on a 90 ton Toyo Plastar injection molding machine. The mold used was a four-cavity mold that produced a terminal block. A sketch of the part is shown in Figure 6-14. The critical dimension was the width of slot P-1, which is shown in the figure. The specification called for the slot width to be between .9 millimeters and 1.0 millimeter. Widths less than .9 millimeters were the particular concern, as they caused jams in the customer's automated assembly equipment.

Note: The problematic dimension is the width of P-1 slot which is circled in the drawing.

Figure 6-14: Top View of Terminal Block Part
The terminal block was chosen for several reasons. First, it was a problem mold. Second, the process for this mold was a typical production process for the plant. Third, it was a four cavity mold. It was important to test whether molds with more cavities were more difficult to monitor.

6.3.1 Methodology of Experimentation

For the second experiment the methodology was slightly different from that used in the first. Since the terminal block was in high demand, the mold had been running round-the-clock production. Thus the mold was already at equilibrium at the start of the experiment. The experiment started at shot number 10195 and continued until shot number 10709. For each shot, the parts were bagged and numbered.

6.3.2 Methodology of Analysis

At the time of the experiment, the terminal block parts were being shipped daily. Therefore, there was only time to measure and analyze the exceptional shots and random samples. The methodology of analysis was as follows:

- Twenty-four random samples were taken in order to characterize the process.
- Shots for which the value of at least one relevant machine variable was greater than three standard deviations from the mean were identified as exceptional shots.
- The width of slot P-1 was measure for each part
- The false rejection rate was calculated for each of the machine variables was calculated.
• The fraction of defects identified was estimated for each machine variable was calculated.

6.3.3 Results of Analysis

6.3.3.1 Relevant Machine Variables

As discussed previously, the process settings determine which process variables are relevant to the analyses. For this experiment the process was setup in velocity control with switch-over based on position. The injection was profiled into two stages. For such a set up, the following process variables were relevant: Barrel Temperatures, Hopper Temperature, Mold Temperatures, Shot Size, First Pressure, Second Pressure, Back Pressure 1, First Speed, Second Speed, First Speed Pressure, Second Speed Pressure, and First Injection Time.

Unfortunately, the process settings for First Pressure and Second Pressure were low enough that the process was pressure limited. This meant that the machine, in trying to maintain the prescribed injection speed encountered the injection pressure limit on each shot. The result was a reduction in the variation in the variables that were related to the injection pressure--First Pressure, Second Pressure, First Speed Pressure, and Second Speed Pressure. Although the reduced variation these four variables undoubtedly interfered with the process monitoring techniques, it was important to run the experiment to test the degree of the interference.
6.3.3.2 The False Rejection Rate

As described previously, one metric of the efficiency of process monitoring is the fraction of false rejections. In order to identify the false rejections, the shots for which at least one of the relevant process variables was an outlier were identified. Table 6-11 shows the outlying process variables and slot dimensions for these shots. All machine variable values are in terms of deviations from the mean. For out of control slot widths, the number of standard deviations from the mean is given in parentheses. The performance is not very impressive. The only variable that had a high efficiency, Second Speed, only detected one exceptional part. The other variables all had low efficiencies.
<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Shot Size</th>
<th>First Pressure</th>
<th>Second Pressure</th>
<th>Second Speed</th>
<th>Second Speed Pressure</th>
<th>Cavity 1 Slot Width</th>
<th>Cavity 2 Slot Width</th>
<th>Cavity 3 Slot Width</th>
<th>Cavity 4 Slot Width</th>
</tr>
</thead>
<tbody>
<tr>
<td>10208</td>
<td>0.03</td>
<td>1.92</td>
<td>3.61</td>
<td>-0.78</td>
<td>1.92</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10242</td>
<td>-0.15</td>
<td>1.35</td>
<td>0.49</td>
<td>4.42</td>
<td>1.35</td>
<td>0.91 (5.1)</td>
<td>0.89</td>
<td>0.89 (3.5)</td>
<td>0.91 (5.1)</td>
</tr>
<tr>
<td>10363</td>
<td>3.27</td>
<td>-0.36</td>
<td>-1.08</td>
<td>1.06</td>
<td>-0.36</td>
<td>0.89</td>
<td>0.89 (5.1)</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>10369</td>
<td>3.45</td>
<td>-0.93</td>
<td>-1.08</td>
<td>1.06</td>
<td>-0.93</td>
<td>0.89</td>
<td>0.89</td>
<td>0.89</td>
<td>0.91 (5.1)</td>
</tr>
<tr>
<td>10442</td>
<td>-0.51</td>
<td>-3.20</td>
<td>-1.08</td>
<td>1.06</td>
<td>-3.20</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10490</td>
<td>3.81</td>
<td>-2.63</td>
<td>0.49</td>
<td>1.06</td>
<td>-2.63</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10494</td>
<td>5.25</td>
<td>-0.93</td>
<td>0.49</td>
<td>0.60</td>
<td>-0.93</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10522</td>
<td>3.45</td>
<td>-1.50</td>
<td>0.49</td>
<td>-0.78</td>
<td>-1.50</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10659</td>
<td>3.81</td>
<td>-0.07</td>
<td>-1.08</td>
<td>0.60</td>
<td>-0.07</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
</tbody>
</table>

False Rejection Rate: 67% 100% 100% 0% 100%

Note: Process variables are normalized to be expressed in terms of standard deviations from the mean.

For out of control parts, normalized dimensions are given in parentheses.

The shaded entries indicate the shots identified through process monitoring.

**Table 6-11: Process Variables and Part Weights for Exceptional Shots**

### 6.3.3.3 The Fraction of Defects Identified

Due to the extreme consequences of delivering a defective part to the customer, the most important metric of process monitoring is the fraction of defects that are detected. Although production demands precluded the measurement of a large number of parts and direct calculation of the ratio of false acceptances, measurement a statistical sample of parts made an estimation possible. The chart of the dimensions from the random samples, shown in Table 6-12, is the basis for this analysis.
<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Cavity 1 Slot Width</th>
<th>Cavity 2 Slot Width</th>
<th>Cavity 3 Slot Width</th>
<th>Cavity 4 Slot Width</th>
</tr>
</thead>
<tbody>
<tr>
<td>10216</td>
<td>0.89</td>
<td>0.89</td>
<td>0.89 (3.5)</td>
<td>0.89</td>
</tr>
<tr>
<td>10226</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10236</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10253</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10314</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.91 (5.1)</td>
</tr>
<tr>
<td>10348</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10367</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10387</td>
<td>0.89</td>
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<td>0.89</td>
</tr>
<tr>
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<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10418</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10434</td>
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<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10473</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10503</td>
<td>0.89</td>
<td>0.86 (5.1)</td>
<td>0.89 (3.5)</td>
<td>0.89</td>
</tr>
<tr>
<td>10504</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10510</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10518</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10521</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10531</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>10580</td>
<td>0.89</td>
<td>0.89</td>
<td>0.86</td>
<td>0.89</td>
</tr>
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Note: For out of control shots, the normalized values are given in parentheses. Normalized values are expressed in terms of standard deviations from the mean.

**Table 6-12: Dimensions for Statistical Samples of the Process**
Of the twenty-four shots taken to characterize the process, three had at least one part in which the slot dimension was beyond three standard deviations from the mean. If this were a representative sample of the process, then it would be reasonable to expect that in the 514 samples taken there would be about 65 parts with out of control dimensions. This would make the fraction of defects identified $\frac{3}{65} = 4.5\%$. Even if the statistical sample substantially over-estimated the number of out of control parts, the performance would still be evaluated as poor.

6.3.4 Conclusions from the Terminal Block Experiment

Process monitoring was not very successful for this mold. The efficiencies were low for all except one of the process variables. More importantly, the estimated effectiveness of monitoring all of the process variables was only 4.5%.

There are several possible explanations. A look at the part measurements from Experiment #2 reveals that the parts with the most extreme dimensions were less than 6 standard deviations from the mean. In Experiment #1, by comparison, the parts with the most extreme measurements were over 50 standard deviations from the mean. The results from Experiment #1 suggest that monitoring machine variables is only effective for catching significant outliers. The results from Experiment #2 could also be interpreted as supporting this conclusion.

As mentioned earlier in the chapter, the effectiveness of the process monitoring was potentially reduced by the fact that the process was pressure-limited. The injection pressure limit was low enough that it was reached on
every shot and, therefore, injection pressure was subject to little variation. This reduction in variation impaired the sensitivities of four of the relevant process variables—First Pressure, Second Pressure, First Speed Pressure, Second Speed Pressure.

Figure 6-15 shows a comparison of the variation of First Pressure in the two experiments. In the previous experiment, the injection pressure related variables were the most effective variables for monitoring, so it seems likely that reduction in the variation of injection pressure forced by the pressure-limited process setup had a strong negative impact on the effectiveness of process monitoring.
Figure 6-15: A Comparison of *First Pressure* Variation in Experiments #1 and #2

A third explanation is based on the fact that the mold used in Experiment #2 was a four cavity mold. In the two cavity mold in Experiment #1, problems in one cavity can only be masked by one other cavity. For instance, if the machine were in velocity control with switchover based on position and there were a blockage in the gate of cavity one halfway through
injection, then the machine would try to inject 50% more material cavity two. As a result the injection pressure would be dramatically higher than usual. If the same thing happened in the four cavity mold used in Experiment #2, the machine would try to inject 17% more material into each of the remaining cavities. The injection pressure would not jump as dramatically as it did in the two cavity mold. Thus, it may be reasonable to expect that the more cavities in a mold, the less successful monitoring the machine variables will be.

While seems likely that all of the factors discussed above influenced the experimental results, further experimentation is necessary to determine their relative importance. In any case, a close look at the data from the experiment suggests that process monitoring did not deal with the root cause of the problems with the mold.

Although standard deviations were quite small for each cavity, the process means were not near the tolerance means. Thus, the easiest way to improve process capability was to center the process means on the tolerance means. This is precisely the goal of the research on tool qualification conducted by Kristine Budill, a student who also completed her thesis research at UTC.36 If the process mean were centered on the tolerance mean, the process would be extremely capable. Cavity three had the highest standard deviation at .007 millimeters. The tolerance for the part is .9 millimeters to 1.0 millimeter. Thus, if the process mean were .95

millimeters, the process capability ratio would be \[ \frac{0.05 \text{ mm}}{3 \times 0.007 \text{ mm}} = 2.38 \] and the expected defects per million would be less than one. This most likely overstates the case, but the point remains that the leverage here is in tool qualification, not process monitoring.

6.4 Conclusions
Given the limited experimentation it is dangerous to draw broad conclusions. It is, however, useful to generate hypotheses that merit further testing. Below are discussions of several key areas that seem to merit further experimentation.

6.4.1 Key Process Variables
For Experiment #1, the two the machine variables that gave the best indications of process disturbances were the First Pressure and Shot Size. Both of the variables were uncontrolled variables:

- First Pressure was the free variable that allowed the machine to perform closed loop control on injection speed. The controller varied injection pressure in response variations in flow resistance. These variations were both within and between shots. When there was a substantial flow disturbance, the First Pressure was a good indicator. Since flow disturbances are the type of high frequency process disturbances that are likely to produce process outliers, it is not surprising that First Pressure is a good indicator for process monitoring.
• *Shot Size* should probably be called a partially controlled variable. The amount of material during the injection stage is under closed loop control when the machine is setup in velocity control with position switchover, as it was for the first experiment. During the pack stage, however, the process maintains a constant hydraulic pressure, so the flow varies in response to flow resistance in the mold. During Experiment #1, the molding machines were extremely repeatable in the amount of material that is injected during the fill stage, so almost all of the variation in shot size came from variation in the amount of material that flows into the mold during the pack stage. *Shot Size* has the additional distinction of being a physically important machine variable; that is to say that the shot size has a direct physical impact on the size of the part. If the shot size is larger than normal, the part is likely to be larger than normal and if the shot size is smaller than normal, the part is likely to be smaller than normal.

The second experiment, by comparison, had no disturbance sensitive process variables. Further experimentation is merited to determine whether the first or the second experiment is the more typical case.

**6.4.2 Comparison of Analysis Techniques**

The SPC demonstrated the ability to detect the most extreme part variations. It could be implemented easily by attaching a machine or machines to a personal computer and having the computer perform the control charting and actuate the machine's part diverter when necessary.
Since some of the important machine variables drift slightly over time, the SPC methodology should be based on a moving average. Figure 6-16 shows the gradual decrease in *First Pressure* as the mold warmed up. The data in the graph represents about 6 hours of machine operation. A moving average SPC method could automatically adjust for the process drift. It would have the added advantage of being self-adjusting with respect to mold changes. The operator would only have to inform the monitoring computer that the mold had been changed and the system could start a new moving average of the process variables.

Note: Outliers have been removed since they disturb the presentation of the trend.

**Figure 6-16: Time Series Showing Gradual Decrease in *First Pressure***

The results of the experimentation also showed that the control limits for each process variable should be tuned to strike the correct balance.
between the defect identification rate and the false rejection rate. In determining the balance it is important to consider the very high cost associated with a missed diagnosis of a defect versus the relatively low cost associated with a false rejection.

Because it could handle interactions between the process variables, the neural network analysis seemed promising on theoretical grounds. Unfortunately, there was insufficient experimental data to prove or refute this hypothesis. When small training sets were used, the neural network analysis was plagued with false negatives. Large training sets solved this problem, but since most or all of the available data was used in training the network, there was not enough data left accurately gauge network performance. More experiments are necessary to test the value of neural network analysis.

6.4.3 Potential Benefits of Process Monitoring

The results from the first experiment show the potential benefits of process monitoring. By eliminating the five most extreme outliers, process monitoring reduced the standard deviation by 80% in cavity one and 75% in cavity two. This equates to a fivefold increase in the process capability index for cavity one and a fourfold increase for cavity two.

Unfortunately, the results of the second experiment tell a conflicting story. Process monitoring had no significant effect on process variation for the second experiment. Further experimentation is necessary to identify whether the first experiment or the second experiment is more typical.
Chapter Seven
Monitoring Pressure Traces

7.1 Introduction

The machine variables discussed in the previous chapter were limited in one key way; all of the sensors were on the machine rather than in the mold. As a result, the values of the machine variables reflected the combination of the conditions in all the cavities. A cavity pressure sensor, on the other hand, can be located in mold cavity and, therefore, it can give information about the conditions in that cavity. Knowledge of the conditions in the individual cavities is necessary if there is to be any hope of predicting part dimensions from process variables.

The cavity pressure traces were recorded by a pressure transducers located behind ejector pins in each mold. The data was transferred to a personal computer via data acquisition software and hardware. The software used was Workbench by Strawberry Tree, Incorporated. The software interface with the pressure transducers through a Strawberry Tree data acquisition board that performed the analog to digital conversions.

7.2 Summary of Experimentation and Results

This chapter focuses on using cavity pressure traces to monitor processes. Hydraulic pressure data is also analyzed because it was readily available and the competitive benchmarking results suggested that it was valuable to monitor. A progression of three experiments is described. The first experiment was the outgrowth of tool qualification experimentation
being done by Kristine Budill for inclusion in her thesis.\textsuperscript{37} The goal was to try to use a process model constructed through designed experiments to predict dimensions in a process monitoring exercise. Unfortunately, the predictions were inaccurate.

The second experiment was a test of some conclusions from the first experiment. On the basis of the designed experiments, the cavity pressure and hydraulic pressure traces were quantified into seven features. These features represented integrals, slopes, and peaks drawn from the curves. Although these features varied in the designed experiments, it was not established that they would vary in response to typical process disturbances. The second experiment presents the results introducing two typical process disturbances while monitoring the seven identified features of the pressure traces. The experiment demonstrated that the features of the pressure traces did vary in response to the two process disturbances.

The third experiment built on the second experiment to try to apply the monitoring of the pressure traces in a shop-floor situation. This experiment was performed on the same data as the first experiment in the previous chapter, but in this chapter it will be analyzed through the pressure traces rather than the machine variables. The results from the third experiment were mixed. Although monitoring pressure traces was a fairly successful way of detecting outliers, it was certainly no more effective than monitoring machine variables. The results from the predictive modeling experiments were poor, monitoring the pressure traces was not sufficient to accurately predict part dimensions.

\footnote{Ibid.}
7.3 Experiment #1: Using Data from Designed Experiments to Construct a Process Model

The process monitoring research described in this thesis was being done in conjunction with research on tool qualification, the process by which a mold is proven to be capable of producing acceptable parts and an optimal process is identified. The methodology for tool qualification involved conducting a set of designed experiments in order to construct a process model that mapped process settings to part dimensions. The process model was then used to identify the optimal process settings. Since process monitoring involves a similar mapping of process variables to part dimensions, it was natural to try to use the data from the designed experiments to establish a model that could be used for process monitoring.

7.3.1 Methodology of Experimentation and Analysis

The methodology of experimentation and analysis was as follows:

- During the designed experiments\textsuperscript{38}, the cavity pressure and hydraulic pressure traces were recorded. Cavity pressure was recorded through a pressure transducer located behind an ejector pin in cavity one. Hydraulic pressure was recorded through a pressure transducer installed on the molding machine's injection manifold.

\textsuperscript{38}The designed experiment was a twenty-seven run Bo\textsuperscript{2}-Benkin design in which for settings were tested at three values each. The process settings that were varied were mold cooling water temperature, barrel temperature profile, injection speed, and hold pressure. A complete description of the designed experiment is available in Kristine T. Budill, "A Systematic Approach to Tool Qualification for Injection Molding", MIT Master's Thesis, Department of Electrical Engineering and Computer Science, 1993.
The graphs were analyzed qualitatively to determine what features of the traces varied under the different processing conditions. The values of these features were calculated for each run. A regression was done. The regression mapped the process settings and features of the pressure traces to the part dimensions. The regression was used to predict the dimensions of samples from the optimal process settings.

7.3.2 Results

7.3.2.1 Features of the Pressure Traces

Figure 7-1 shows several cavity pressure traces from different runs of the designed experiments. From the figure, several features that differentiate traces can easily be seen: maximum cavity pressure, integral under the curve, maximum slope, and minimum slope. These features were the features that were used for analysis.
Figure 7-1: Sample Cavity Pressure Traces from the Designed Experiments

A similar graphical analysis was done on the hydraulic pressure traces. Figure 7-2 shows several of the hydraulic pressure traces from the designed experiments. Again, there are several features that differentiate the traces: initial peak pressure, integral under the curve, the more or less steady pressure applied during the middle three or four seconds of the curve. As one could guess from the patterns in the graph, the steady pressure applied during the middle of the curve is a controlled variable, the hold pressure. Two uncontrolled features of the hydraulic pressure trace, the initial peak and the integral under the curve during injection, were used in the analysis.

Figure 7-2: Sample Hydraulic Pressure Traces from the Designed Experiments
The hold pressure and other controlled variables such as the injection speed, the barrel temperatures, and the mold cooling water temperatures were incorporated in the analysis by including the process setting for designed experiment.

7.3.2.2 Regression Results

As outlined above, the regression included four features of the cavity pressure traces, two features of the hydraulic pressure traces, and four process variables. Regressions were done to predict part length based on these values. The data was taken from the 27 runs of the designed experiments. The response variable was the average length of the parts from each run. As shown by the statistics in Table 7-1, the regressions achieved good fits to the data from the designed experiments.

Unfortunately, the regressions were not nearly as accurate in predicting the part dimensions for the samples from the optimized process identified by the designed experiments. When the model developed from the designed experiments' data was used to predict the dimensions for individual samples from the optimized run, the results were poor. From Figure 7-3 it can be seen that the dimensional predictions were continuously in error and from Figure 7-4 can be seen that the variation in the predictions was not correlated with the variation in the actual dimensions.
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**Table 7-1:** Statistics for Regression of Process Variables to Average Length for each DOE Run
Figure 7-3: Comparison of Regression Predictions and Actual Values

Figure 7-4: Comparison of the Correlation between Regression Predictions and Actual Values
7.3.3 Conclusions

There are at least two potential explanations for the inability of the model based on the designed experiments to predict dimensions accurately. The first explanation is that the DOE model was not fine-grain enough. Although the designed experiments produced a process model that was accurate enough to establish the optimal process settings and predict the process mean associated with those settings, the process model may not have been accurate enough to predict the shot to shot variation in dimensions.

A second potential explanation is that the arbitrary features that were extracted from the cavity pressure and hydraulic pressure traces were not the relevant features for detecting process variation. The next experiment was an attempt to discover whether the features chosen for the regression analysis were the features that were likely to indicate process variation.

7.4 Experiment #2: Monitoring Pressure Traces During Process Disturbances

Although the features of pressure traces varied from run to run in the designed experiments, the previous experiment did not prove that these features would indicate process disturbances. Monitoring the pressure traces during two typical process disturbances, however, did show that the features identified in the previous experiment varied in response to process disturbances.

7.4.1 Methodology of Experimentation

This experiment was performed on the same mold and machine as the previous experiment. Cavity pressure traces were recorded through a pressure transducer located behind an ejector pin in cavity one. Hydraulic
pressure traces were recorded through a pressure transducer installed on the molding machine's injection manifold. The process used was the optimized process identified by the designed experiments. The baseline was 100% virgin material. Thirty samples were taken from the baseline run and used to establish control limits for each feature of the pressure traces. The first disturbance was 60% regrind material. The second disturbance was material with more than twice the normal moisture content. For each disturbance run, thirty samples were taken and the pressure trace data were plotted on the control charts established in the baseline run.

7.4.2 Results of Experimentation

Shown in Figures 7-5 through 7-11 are the control charts for each feature of the pressure traces. The solid lines represent the upper control limit, center line, and lower control limit for the baseline process. The figures show that some features were more sensitive to the disturbances than others. Cavity Pressure Maximum and Cavity Pressure Integral identified both disturbances clearly. Cavity Pressure Maximum Slope and Cavity Pressure Minimum Slope identified only the wet material disturbance. Hydraulic Pressure Maximum, Hydraulic Pressure Integral, and Cavity Pressure Integral/Hydraulic Pressure Integral also identified both disturbances clearly.
Figure 7-5: Control Chart for Cavity Pressure Maximum

Figure 7-6: Control Chart for Cavity Pressure Integral
Figure 7-7: Control Chart for Cavity Pressure Maximum Slope

Figure 7-8: Control Chart for Cavity Pressure Minimum Slope
Figure 7-9: Control Chart for Hydraulic Pressure Maximum

Figure 7-10: Control Chart for Hydraulic Pressure Integral
Figure 7-11: Control Chart for Ratio of Cavity Pressure Integral to Hydraulic Pressure Integral

7.4.3 Conclusions

Plotting the features of the pressure traces during the disturbances showed that the identified features varied in response to two typical process disturbances—an increase in the regrind percentage and an increase in the material moisture content. *Cavity Pressure Maximum*, *Cavity Pressure Integral*, *Hydraulic Pressure Maximum*, *Hydraulic Pressure Integral*, and *Cavity Pressure Integral/Hydraulic Pressure Integral* identified both disturbances. *Cavity Pressure Maximum Slope* and *Cavity Pressure Minimum Slope* only identified the wet material disturbance.

7.5 Experiment #3: The Automobile Heater Switch

The third cavity pressure monitoring experiment was conducted at the same time as the first machine variable monitoring experiment. While the machine variables were recorded, cavity pressure and hydraulic pressure
traces were also recorded. Cavity pressure was recorded through a pressure transducer located behind an ejector pin in cavity one. Hydraulic pressure was recorded through a pressure transducer installed on the molding machine's injection manifold.

Although the same parts were used in both experiments, because the cavity pressure sensor was located in cavity one, only cavity one is analyzed in this chapter. Thus, the shots treated as defects in this chapter are only those for which cavity one is outside the control limits.

As discussed in the previous chapter, the part used in the experiment was a containment structure for an automobile heater switch. The critical dimensions were the length and width.

The data from this experiment was analyzed from two perspectives. The first analysis, which was similar to the analysis of the machine variable data, focused on catching exceptional parts. The exception catching analysis compared the results from two techniques--SPC and neural networks. The second analysis focused on predicting part dimensions. The predictive modeling analysis compared two approaches. The first approach was a feature based approach; this approach analyzed features of the pressure traces such as integrals, slopes, or the maximums. The second approach was a pattern recognition approach that analyzed the pressure curves themselves. Table 7-2 summarizes the results for the different analysis techniques used in this experiment. The complete methodologies, results, and conclusions are presented in the sections below.
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<th>Analysis Technique</th>
<th>Exception Catching</th>
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<td>4 of 8 defects caught 6% false rejection rate</td>
<td>3 most extreme parts identified</td>
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Note: The results only consider cavity one since the cavity pressure sensor was located in cavity pressure one.

Table 7-2: Summary of Analysis and Results

7.6.1 Exception Catching

The exception catching section of this experiment is identical to the same section in the first experiment in the previous chapter. The only major differences in the analyses are the inputs: the previous chapter used machine variables as the inputs to the analyses and this chapter used the cavity pressure traces as the inputs to the analyses. Minor differences are discussed in the introduction to each analysis section. Readers familiar with the first experiment from the previous chapter should read the introduction to each analysis section and can then skip directly to the results and conclusions.

7.5.1.1 Methodology of Experimentation

At the time of the experiment the part was not in high demand, so the parts could be fully measured and analyzed before they had to be shipped to
the customer. This allowed a more complete experimental methodology than
would be possible for the experiments that were run at the plant. The
methodology of experimentation was as follows:

- The mold and machine were prepared exactly as they would be for
  a production run.
- The machine settings were set to the standard production process.
- The mold was preheated in the standard manner.
- The production was started.
- Starting at shot number 212 and continuing until shot number 944,
  the parts from each shot were bagged and numbered.

7.5.1.2 SPC Analysis

The SPC analysis was not suited to be performed directly on the
pressure traces themselves, instead it was applied to features extracted from
the traces. The features used were those discussed in the first two
experiments in this chapter. These features were handled in the same way
that machine variables were handled in the previous chapter.

7.5.1.2.1 Methodology of Analysis

After the samples were taken, they were allowed to cool overnight so
that their dimensions and weight would be stabilized before measurement.
Once the dimensions had stabilized, the parts were analyzed in the following
manner:

- Twenty-two random samples were taken in order to characterize
  the process. The overall length and width and weight were
  measured for these samples.
• Shots for which the value of at least one feature of a pressure trace was greater than three standard deviations from the mean were identified as exceptional shots. The use of three standard deviation limits as the criterion for an exceptional shot is entirely arbitrary. The limits were chosen as such because three standard deviations is a common standard for separating random noise from variation associated with assignable causes. The tradeoffs involved with using tighter limits are discussed in the results of analysis. The length, width, and weight were measured for these exceptional samples.

• For the parts with exceptional dimensions, the correlation between weight and dimensions was checked.

• In order determine how many defects were not detected by the monitoring the features of the pressure traces, shots 212 through 499 were weighed. Weight was used as a quality metric, because, it was quick and repeatable. As shown in the previous chapter, the correlation between weight and part dimensions was good for cavity one and poor for cavity two.

• The fraction of defects identified and false rejection rates were calculated for each feature of the pressure traces.

7.5.1.2.2 Results of the Analysis

7.5.1.2.2.1 Relevant Features of the Cavity Pressure and Hydraulic Pressure Traces

On the basis of the results of the previous experiment, seven key features of the cavity pressure traces were identified. They were the Cavity
Pressure Integral, Cavity Pressure Peak, Maximum Slope of the Cavity Pressure Curve, Minimum Slope of the Cavity Pressure Curve, Hydraulic Pressure Integral, Hydraulic Pressure Integral, and Cavity Pressure Integral/Hydraulic Pressure Integral. These seven features were the features monitored during this experiment.

7.5.1.2.2.2 The Fraction of Defects Identified

In order to determine the effectiveness of monitoring the features of the pressure traces, for shots 212 through 499, the parts from each shot were weighed. The results are shown in Figures 7-12 and 7-13. Of the approximately 600 parts weighed, only a small number had weights more than three standard deviations from the process mean. Table 7-3 shows the values of the pressure trace features, in terms of standard deviations from the mean, for the eight shots with out of control weights for cavity one. Only cavity one was considered in the analysis because the cavity pressure sensor was located in cavity one.
Note: Weights are normalized to be expressed in terms of standard deviations from the mean.

**Figure 7-12: Part Weights for Cavity One**

Note: Weights are normalized to be expressed in terms of standard deviations from the mean.

**Figure 7-13: Part Weights for Cavity Two**
Chapter 7

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Cavity Pressure Integral</th>
<th>Cavity Pressure Peak</th>
<th>Maximum Slope of Cavity Pressure Curve</th>
<th>Minimum Slope of Cavity Pressure Curve</th>
<th>Hydraulic Pressure Integral</th>
<th>Hydraulic Pressure Peak</th>
<th>Cavity Pressure Integral / Hydraulic Pressure Integral</th>
<th>Cavity 1 Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>230</td>
<td>1.15</td>
<td>1.15</td>
<td>0.68</td>
<td>-1.23</td>
<td>0.64</td>
<td>0.00</td>
<td>0.82</td>
<td>-3.24</td>
</tr>
<tr>
<td>284</td>
<td>1.14</td>
<td>0.83</td>
<td>0.66</td>
<td>-0.95</td>
<td>0.32</td>
<td>0.61</td>
<td>1.03</td>
<td>-5.87</td>
</tr>
<tr>
<td>297</td>
<td>0.82</td>
<td>0.70</td>
<td>1.01</td>
<td>-0.93</td>
<td>0.61</td>
<td>0.21</td>
<td>0.48</td>
<td>-5.06</td>
</tr>
<tr>
<td>321</td>
<td>0.72</td>
<td>0.22</td>
<td>0.68</td>
<td>0.40</td>
<td>0.78</td>
<td>0.19</td>
<td>0.26</td>
<td>-7.22</td>
</tr>
<tr>
<td>344</td>
<td>-5.78</td>
<td>-5.45</td>
<td>-4.37</td>
<td>5.18</td>
<td>1.58</td>
<td>3.42</td>
<td>-7.10</td>
<td>-42.55</td>
</tr>
<tr>
<td>358</td>
<td>0.67</td>
<td>0.54</td>
<td>0.51</td>
<td>-0.55</td>
<td>0.64</td>
<td>0.23</td>
<td>0.31</td>
<td>-3.98</td>
</tr>
<tr>
<td>417</td>
<td>-2.70</td>
<td>-5.15</td>
<td>-4.28</td>
<td>4.94</td>
<td>3.86</td>
<td>9.93</td>
<td>-5.00</td>
<td>-13.19</td>
</tr>
<tr>
<td>418</td>
<td>-11.73</td>
<td>-10.20</td>
<td>-8.89</td>
<td>6.89</td>
<td>12.88</td>
<td>13.66</td>
<td>-16.12</td>
<td>-76.07</td>
</tr>
<tr>
<td>Defects Identified</td>
<td>29%</td>
<td>43%</td>
<td>43%</td>
<td>43%</td>
<td>29%</td>
<td>43%</td>
<td>43%</td>
<td></td>
</tr>
</tbody>
</table>

Note: Pressure trace features and weights are normalized to be expressed in terms of standard deviations from the mean.

Only cavity one is included because the cavity pressure sensor is located in cavity one.

The shaded entries indicate the shots identified through process monitoring.

**Table 7-3: Pressure Trace Features for Parts with Out of Control Weights for Cavity One**

7.5.1.2.2.2.1 Overall Fraction of Defects Identified

From Table 7-3, one can estimate the overall effectiveness of monitoring features of the cavity pressure traces and hydraulic pressure traces. Of the seven shots in which cavity one had an out of control weight, three were identified through process monitoring. Thus, if all of the features of the cavity pressure and hydraulic pressure traces were monitored, the overall fraction of defects identified would be 43%.

Ordering the parts by degree of deviation from the mean is revealing. As shown in Table 7-4, the effectiveness of the monitoring methodology is
higher for the most extreme parts; for example, all shots for which cavity one was beyond eight standard deviations from the mean are identified.

Although a weight eight standard deviations from the mean may seem extreme, the capability of the process is such that all but the most extreme parts will be within specification. According to the tolerance for the part used in this experiment, the only unacceptable part was shot 418, cavity two which flashed severely.

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Cavity 1 Weight</th>
<th>Identified by Process Monitoring?</th>
</tr>
</thead>
<tbody>
<tr>
<td>418</td>
<td>-76.07</td>
<td>yes</td>
</tr>
<tr>
<td>344</td>
<td>-42.55</td>
<td>yes</td>
</tr>
<tr>
<td>417</td>
<td>-13.19</td>
<td>yes</td>
</tr>
<tr>
<td>321</td>
<td>-7.22</td>
<td>no</td>
</tr>
<tr>
<td>284</td>
<td>-5.87</td>
<td>no</td>
</tr>
<tr>
<td>297</td>
<td>-5.06</td>
<td>no</td>
</tr>
<tr>
<td>358</td>
<td>-3.98</td>
<td>no</td>
</tr>
<tr>
<td>230</td>
<td>-3.24</td>
<td>no</td>
</tr>
</tbody>
</table>

Note: Weights are normalized to be expressed in terms of standard deviations from the mean.

Only cavity one is included because the cavity pressure sensor is located in cavity one.

Table 7-4: Sorted List of Shots with Out of Control Weights for Cavity One

7.5.1.2.2.2 Fraction of Defects Identified by Individual Features

From Table 7-3, one can estimate the effectiveness of monitoring each of the features of the pressure traces. All seven of the features had an out of control value for at least one of the eleven exceptional shots. The range of
effectiveness was not large: all seven variables had effectiveness between
29% and 43%.

7.5.1.2.2.3 The False Rejection Rate

Table 7-5 identifies the shots for which at least one feature of the
pressure traces had a value more than three standard deviations from the
mean; these are the parts that would have been rejected if process
monitoring had been in effect. The table includes values of the features of
the pressure traces and part weights for these shots. From the table, it can
be seen that none of the features produced any false rejections.
### Chapter 7

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Cavity Pressure Integral</th>
<th>Cavity Pressure Maximum</th>
<th>Maximum Slope of Cavity Pressure Trace</th>
<th>Minimum Slope of Cavity Pressure Trace</th>
<th>Hydraulic Pressure Integral</th>
<th>Hydraulic Pressure Peak</th>
<th>Cavity Pressure Integral / Hydraulic Pressure Integral</th>
<th>Cavity 1 Part Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>344</td>
<td>-5.78</td>
<td>-5.45</td>
<td>-4.37</td>
<td>5.18</td>
<td>1.58</td>
<td>3.42</td>
<td>-7.10</td>
<td>-42.55</td>
</tr>
<tr>
<td>417</td>
<td>-2.70</td>
<td>-5.15</td>
<td>-4.28</td>
<td>4.94</td>
<td>3.86</td>
<td>9.93</td>
<td>-5.00</td>
<td>-13.19</td>
</tr>
<tr>
<td>418</td>
<td>-11.73</td>
<td>-10.20</td>
<td>-8.89</td>
<td>6.89</td>
<td>12.88</td>
<td>13.66</td>
<td>-16.12</td>
<td>-76.07</td>
</tr>
<tr>
<td>622</td>
<td>-2.40</td>
<td>-2.86</td>
<td>-2.33</td>
<td>3.35</td>
<td>3.16</td>
<td>2.68</td>
<td>-4.36</td>
<td>-13.80</td>
</tr>
<tr>
<td>631</td>
<td>6.59</td>
<td>8.02</td>
<td>12.23</td>
<td>-12.67</td>
<td>7.82</td>
<td>11.24</td>
<td>1.78</td>
<td>7.88</td>
</tr>
<tr>
<td>652</td>
<td>-2.37</td>
<td>-2.32</td>
<td>1.30</td>
<td>3.35</td>
<td>0.56</td>
<td>0.02</td>
<td>-2.93</td>
<td>-11.17</td>
</tr>
<tr>
<td>803</td>
<td>-2.33</td>
<td>-2.17</td>
<td>1.96</td>
<td>2.84</td>
<td>1.39</td>
<td>2.02</td>
<td>-3.36</td>
<td>-7.40</td>
</tr>
<tr>
<td>904</td>
<td>-3.60</td>
<td>-4.18</td>
<td>-1.56</td>
<td>3.96</td>
<td>0.20</td>
<td>1.28</td>
<td>-4.06</td>
<td>-11.38</td>
</tr>
<tr>
<td>944</td>
<td>0.00</td>
<td>0.89</td>
<td>-0.30</td>
<td>-2.15</td>
<td>0.75</td>
<td>3.10</td>
<td>-0.48</td>
<td>8.15</td>
</tr>
</tbody>
</table>

| False Rejection Rate | 0% | 0% | 0% | 0% | 0% | 0% | 0% | 0% |

Note: Pressure trace features and weights are normalized to be expressed in terms of standard deviations from the mean.

Only cavity one is included because the cavity pressure sensor is located in cavity one.

The shaded entries indicate the shots with an out of control weight for cavity one.

**Table 7-5: Pressure Trace Features and Part Weights for Exceptional Shots**

It is interesting to compare the shots identified in Table 7-5 to those identified in Table 6-4, which was based on the machine variables. Four shots that were identified by the machine variables were not identified by the features of the pressure traces. Two of those shots are shot numbers 640 and 641 which were only detected by monitoring the shot size. The other two were shots 212 and 926. Both of these shots had the distinction of having in
control values for cavity one and out of control values for cavity two. The only other shots that had an in control value for cavity one and an out of control value for cavity two were shot numbers 285 and 440. The pressure traces identified only one of these four parts. By comparison, the features of the pressure traces identified 10 of the sixteen shots in which cavity one was out of control.

7.5.1.2.2.4 Balancing Defect Detection Rate and False Rejection Rate

There is a tradeoff between identifying a higher fraction of the defective parts and having a low false rejection rate. In practice, the control limits for each variable should be tuned so that the tradeoff between detection rate and false rejection rate reflects of the costs associated with each. Figure 7-14 shows the tradeoff curve for Cavity Pressure Integral. Table 7-6 presents the same data in tabular form. The choice of control limits should reflect the fact that the cost of delivering a defective part to a customer is higher than the cost of a false rejection. From the data in the table, it is clear that the Cavity Pressure Integral control limits should be tighter than three standard deviations.
Figure 7-14: Tradeoff Curve Between the Number of Defects Identified and the Number of False Rejections

<table>
<thead>
<tr>
<th>Control Limits</th>
<th>Number of Defects Identified</th>
<th>Number of False Rejections</th>
<th>Percentage of Defects Identified</th>
<th>False Rejection Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.00</td>
<td>1</td>
<td>0</td>
<td>13%</td>
<td>0%</td>
</tr>
<tr>
<td>5.00</td>
<td>2</td>
<td>0</td>
<td>25%</td>
<td>0%</td>
</tr>
<tr>
<td>4.00</td>
<td>2</td>
<td>0</td>
<td>25%</td>
<td>0%</td>
</tr>
<tr>
<td>3.00</td>
<td>2</td>
<td>0</td>
<td>25%</td>
<td>0%</td>
</tr>
<tr>
<td>2.00</td>
<td>3</td>
<td>0</td>
<td>38%</td>
<td>0%</td>
</tr>
<tr>
<td>1.75</td>
<td>3</td>
<td>0</td>
<td>38%</td>
<td>0%</td>
</tr>
<tr>
<td>1.50</td>
<td>3</td>
<td>10</td>
<td>38%</td>
<td>4%</td>
</tr>
<tr>
<td>1.25</td>
<td>3</td>
<td>38</td>
<td>38%</td>
<td>14%</td>
</tr>
<tr>
<td>1.00</td>
<td>5</td>
<td>83</td>
<td>63%</td>
<td>30%</td>
</tr>
<tr>
<td>0.75</td>
<td>6</td>
<td>141</td>
<td>7.5%</td>
<td>51%</td>
</tr>
<tr>
<td>0.50</td>
<td>8</td>
<td>217</td>
<td>100%</td>
<td>78%</td>
</tr>
<tr>
<td>0.25</td>
<td>8</td>
<td>273</td>
<td>100%</td>
<td>98%</td>
</tr>
</tbody>
</table>

Note: Control limits are expressed in terms of the number of standard deviations from the mean.

Table 7-6: The Number of Defects Identified and False Rejections Associated with Different Control Limits for Cavity Pressure Integral
7.5.1.3 Neural Network Approach

The neural network analysis presented below was essentially the same as the neural network analysis of the machine variables in the first experiment discussed in the previous chapter. There were only two major differences between the analysis in the previous chapter and the analysis in this chapter. The first is the obvious fact that the analysis in the previous chapter used the machine variables as its input and the analysis in this chapter used features of the pressure traces as inputs. The second is that two different forms of inputs were tested for the pressure traces. The first experiments were done using the same features of the pressure traces used in the SPC analysis. The second experiments were done using the raw samples of the cavity pressure curves themselves. This was not done for the SPC analysis because SPC techniques are not easily applicable to patterns. In addition to pressure trace data, each training set also included melt, mold, and hydraulic oil temperature data. The temperature data were included because they were believed to interact with the pressure data to affect process output.

For comparison purposes, the training sets used in both analyses were constructed in the same way and included exactly the same shots as the training sets used in the analysis of the first experiment in the previous chapter. The presentation of results is also structured the same way in both analyses to simplify comparisons. A full explanation of the methodology of analysis is included below, but readers familiar with the first experiment in the previous chapter can skip directly to the results.

The goal of the SPC analysis was to identify a function that mapped combinations of features of pressure traces to two categories, acceptable and unacceptable. Problems such as this are often referred to as classification
problems. The SPC results proved the feasibility of at least a limited
mapping that identified the most extreme parts; the goal of the neural
network analysis was to try to establish a more complete mapping. In other
words, the neural network was evaluated to see if it could identify some of
the defective parts that were missed in the SPC analysis.

The SPC approach represented a very straightforward set of
classification functions. A shot was classified as acceptable if the value of the
machine variable was within a certain limits and the shot was classified as
unacceptable if the machine variable was outside the limits. The SPC
approach had one crucial limitation, however: it analyzed the process
variables independently. This limitation was not inherent to SPC, since the
SPC techniques could be applied to any function of the machine variables.
Applying SPC techniques, however, does require \textit{a priori} knowledge of the
process interaction.

Neural networks, on the other hand, require no \textit{a priori} knowledge of
the process interactions, since the network learning algorithms inherently
attempt to identify any interactions in the data. Neural networks were also
attractive for two other reasons:

- neural networks have been successfully applied to many
classification problems

- neural networks have been successfully applied to process
monitoring and process control problems\textsuperscript{39}

A Learning Vector Quantization (LVQ) network was chosen for the analysis
because such networks have often been successful in solving difficult

\textsuperscript{39}Deborah F. Cook and Robert E. Shannon, "A Predictive Neural Network
Modelling System for Manufacturing Process Parameters", \textit{International
classification problems. The theory behind the LVQ network is described fully in the explanation of Experiment #3 in Chapter 6.

7.5.1.3.1 Methodology of Analysis

The neural network analysis was performed on the same data as the SPC analysis, but the methodology of analysis was slightly different. There were three steps to the neural network analysis:

- Training sets were constructed.
- The network was configured and trained.
- The network performance was evaluated.

Unfortunately, each of these steps represented more of an art than a science. As a result, many different combinations had to be tested, and, as necessary, iterations were performed.

7.5.1.3.1.1 Training Sets

Training sets provide representative mappings of inputs to outputs and the network learning algorithms try to identify the patterns that underlie the mappings. The goal of training is to construct a network that can be used to classify future events as they occur. In the case of injection molding, once a network was trained its output would be used to control the part diverter on the injection molding machine.

The training of the network determines a large part of a network's success in practice. If the network training has been incomplete, the network will encounter combinations unlike those that it has seen in training and is likely to make many incorrect classifications. On the other hand, if the network has been well trained, it can interpolate between the examples in its training set to deal with slightly different combinations. Since the mapping
between inputs and outputs is unknown at the start of the training process, it is impossible to know exactly which examples should be included in the training set. As a result, training sets are usually constructed by intuition.

For this experiment, there seemed to be two intuitive ways to develop training sets, so two training sets were developed for each input format. Each training set included the same shot numbers but different input formats.

The training sets for the feature analysis include eleven inputs per shot: the seven features extracted from the pressure traces and the mold, melt, and hydraulic oil temperatures.

The training sets for the raw trace analysis included substantially more data for each shot: 125 samples representing the cavity pressure trace for the first 2.5 seconds after the start of injection and the values for the mold, melt, and hydraulic oil temperatures. In order to balance the large number of inputs from samples of the cavity pressure trace, each of the temperature values was included 25 times. Thus the training set consisted of 225 entries per shot with 125 representing the cavity pressure traces and 100 representing the four temperatures.

The choice of membership for the first training set was based on the parts themselves. The shots could be classified into six groups:

1. Both parts had in control weights.
2. One part too heavy and the other part was in control.
3. One part was too light and the other part was in control.
4. One part was too heavy and the other part was too light.
5. Both parts were too heavy.
6. Both parts were too light.
The first training set was constructed by starting with a representative from each of groups one through five and a random sample of 33 parts from group six. Table 7-7 shows the classification of the extreme shots. Table 7-8 shows the shots that were chosen for the first training set.

Since a network should be evaluated on its classification of patterns that are not part of its training set, only one part was chosen from each of groups one through five. Thirty-three parts were chosen from group six because this group, the group of in-control parts, represented the vast majority of the samples. The training set's ratio of five exceptional shots to thirty-three normal shots was four times greater than the ratio among all the samples. Since missing the diagnosis of a defective part is more costly than rejecting an acceptable part, it seemed appropriate to bias the training set.

<table>
<thead>
<tr>
<th>Output Group</th>
<th>Weights</th>
<th>Group Members</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>+</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>212, 344, 622, 904, 926</td>
</tr>
<tr>
<td>4</td>
<td>+</td>
<td>- 417, 418, 631, 656, 944</td>
</tr>
<tr>
<td>5</td>
<td>+</td>
<td>+ 640, 641</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
<td>- 230, 284, 297, 321, 358, 440</td>
</tr>
</tbody>
</table>

**Table 7-7: Output Group Classification of Shots**

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>285</td>
<td>-</td>
</tr>
<tr>
<td>321</td>
<td>-</td>
</tr>
<tr>
<td>641</td>
<td>+</td>
</tr>
<tr>
<td>904</td>
<td>0</td>
</tr>
<tr>
<td>944</td>
<td>-</td>
</tr>
<tr>
<td>33 Random Samples</td>
<td>0 0</td>
</tr>
</tbody>
</table>

**Table 7-8: Members of Training Set One**
The second training set was slightly different. The choice of membership for the second training set was based on the values of the pressure trace features. The logic behind this training set was as follows: if the network is going to achieve a full mapping of machine variable values to shot classifications, then the network must be trained with shots that represent the full range of machine variable values. The make up of training set two is shown in Table 7-9. For comparison sake training set two included the same number of exceptional shots as training set one, utilized the same 33 random samples as its in-control shots, and, therefore, maintained the same ratio of exceptional to in-control shots.

<table>
<thead>
<tr>
<th>Shot Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>284</td>
</tr>
<tr>
<td>344</td>
</tr>
<tr>
<td>631</td>
</tr>
<tr>
<td>641</td>
</tr>
<tr>
<td>904</td>
</tr>
<tr>
<td>33 Random Samples</td>
</tr>
</tbody>
</table>

Table 7-9: Members of Training Set Two

Once networks were trained, they were analyzed to identify the limits of their effectiveness. Steps were then taken to try to overcome the networks' limitations: different network configurations were constructed, different training parameters were set, and more training cycles were tried. The section below presents the results from the most significant of these experiments.
7.5.1.3.2 Results of Analysis

As mentioned above, the analyses were performed with two different input formats. The results from the networks trained with the features of the pressure traces will be presented first. The results from the networks trained with the raw pressure traces are presented next. The results from both analyses are presented in the same format.

7.5.1.3.2.1 Feature Analysis

The first experiments established a baseline of performance. Identical experiments were run with each training set:

- The network was configured with 32 units per category.
- The network was trained for 15,000 cycles.

Once the network was trained its performance was evaluated on the 287 shots for which complete data was available, shots 212 through 499. The results are shown in Table 7-10.

<table>
<thead>
<tr>
<th>Training Set</th>
<th>Correct Rejections</th>
<th>Correct Acceptances</th>
<th>False Rejections</th>
<th>False Acceptances</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4</td>
<td>276</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>242</td>
<td>38</td>
<td>4</td>
</tr>
</tbody>
</table>

Note: Each network included 32 PEs per category.

Each network was trained for 15,000 cycles.

Table 7-10: Results of Neural Networks Trained by Training Sets

One and Two

The results were fairly impressive. For correct rejections, the most important performance criteria for process monitoring, both networks performed on par with the SPC analysis identifying exactly the same number of defects. Both
networks had a higher number of false rejections than the SPC analysis, but one only marginally higher at 4. In comparison the SPC analysis produced no false rejections.

Although the networks used above were large and were trained for many training cycles, it is impossible to know whether bigger networks or more training cycles would produce better results. Since the network trained with training set one produced far fewer false rejections, it was chosen for further work. Unfortunately, experiments with larger networks and more training cycles failed to improve results.

Another potential way to improve network performance is changing the training set. If the training set is not representative of all the types of variation the network is likely to see, the network is likely to make incorrect diagnoses when it encounters unfamiliar combinations of inputs. Unfortunately, there was very limited data available, so adding to the number of defects included in the training set would leave few defects left for testing. What was attempted instead was to establish an upper limit of performance. The upper limit of performance was established by training the network with all of the available data and evaluating its performance. A network with 64 units per category was used and it was trained for 100,000 cycles. Table 7-11 shows results.

<table>
<thead>
<tr>
<th>Correct Rejections</th>
<th>Correct Acceptances</th>
<th>False Rejections</th>
<th>False Acceptances</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>278</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: The network included 64 PEs per category.

The network was trained for 15,000 cycles.

Table 7-11: Results from Network Trained with all Available Data
The results are very impressive, but they must be taken for what they are. Since the network was tested on the same data with which it was trained, the results only prove that for that data a very good mapping can be achieved between the machine variables and the output classification. What is still unknown is whether the mapping is robust. It is unknown how well the mapping would perform if the machine were set up in an identical manner and the network were used to classify the parts as they were made.

7.5.1.3.2.2 Pattern Analysis

The first experiments established a baseline of performance. Identical experiments were run with each training set:

- The network was configured with 32 units per category.
- The network was trained for 15,000 cycles.

Once the network was trained its performance was evaluated on the shots for which complete data was available, shots 212 through 499. The results are shown in Table 7-12. The results were not impressive. For correct rejections, the most important performance criteria for process monitoring, both networks performed on par with the SPC analysis identifying exactly the same number of defects. Both networks had a higher number of false rejections than the SPC analysis--one substantially higher at 38. In comparison the SPC analysis produced no false rejections.
<table>
<thead>
<tr>
<th>Training Set</th>
<th>Correct Rejections</th>
<th>Correct Acceptances</th>
<th>False Rejections</th>
<th>False Acceptances</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4</td>
<td>264</td>
<td>16</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>242</td>
<td>38</td>
<td>4</td>
</tr>
</tbody>
</table>

Note: Each network included 32 PEs per category.

Each network was trained for 15,000 cycles.

**Table 7-12: Results of Neural Networks Trained with Training Sets One and Two**

Although the networks used above were large and were trained for many training cycles, it is impossible to know whether bigger networks or more training cycles would produce better results. Since the network trained with training set one produced far fewer false rejections, it was chosen for further work. Unfortunately, experiments with larger networks and more training cycles failed to improve results.

Another potential way to improve network performance is changing the training set. If the training set is not representative of all the types of variation the network is likely to see, the network is likely to make incorrect diagnoses when it encounters unfamiliar combinations of inputs. Unfortunately, there was very limited data available, so adding to the number of defects included in the training set would leave few defects left for testing. What was attempted instead was to establish an upper limit of performance. The upper limit of performance was established by training the network with all of the available data and evaluating its performance. A network with 64 units per category was used and it was trained for 100,000 cycles. Table 7-13 shows results. The results are slightly better than the previous results, but not very impressive when compared with the results from the feature analysis.
Note: The network included 64 PEs per category.

The network was trained for 100,000 cycles.

Table 7-13: Results from Network Trained with all Available Data

<table>
<thead>
<tr>
<th>Correct Rejections</th>
<th>Correct Acceptances</th>
<th>False Rejections</th>
<th>False Acceptances</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>275</td>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

7.5.1.3.2.3 Conclusions from Neural Network Analysis

The best network trained with a small training set detected three defects and had four false rejections. The networks trained with the complete dataset achieved much better results, but it was impossible to evaluate the robustness of the mappings that they achieved because all the available data had been incorporated into the training sets.

In all cases, the networks trained with the features of the traces outperformed the networks trained with the raw traces. This may be partly explained by the fact that the networks used to analyze the traces had to process far more data than the networks that analyzed the features. Unfortunately, these networks took more than five times as long as the feature analysis networks to complete the same number of cycles. Training them for even longer periods is hard to justify since they have given no indication of the potential for superior performance.

7.5.1.4 Conclusions from Exception Catching Analysis

The SPC analysis performed fairly well on shots 212 through 499; it identified three of the eight shots for which cavity one was out of control and produced no false rejections. The best neural network was able to identify
four of the eight defects in the same data, but also produced four false rejections. Given the expensive consequences of delivering a defective part to a customer, it would certainly make sense to tradeoff four additional rejections to detect one more defective part. The results from the networks trained with the complete dataset are even more promising, but since all available data was used in the training set there is no way to know whether the mapping achieved is robust.

7.5.2 Predictive Modeling

Exception catching is limited in that it is a purely relative measure. As such, it can only be a complement to part sampling and part measurements. Predictive Modeling, however, would allow the control charting to be done automatically based on the output of a process model. This would effectively reduce the variable cost of quality control to zero.

The predictive modeling was attempted through a neural network. The LVQ network used in the previous experimentation was not appropriate for predictive model because its output was a classification rather than a continuous dimension. A multilayer backpropagation network (MBPN) was used instead. The MBPN is one of the basic neural networks that has proven itself in many applications. Cook and Shannon present a representative application of a MBPN in a process control application.40

7.5.2.1 Introduction to the MBPN Network

The MBPN network is organized into slabs, or layers, of processing elements (PEs) as shown in Figure 7-15.

![Figure 7-15: Organization of MBPN Network](image)

The network is trained with a set of training examples. The training examples consist of an input vector representing the pattern to be evaluated and a training vector representing the correct outputs for the pattern. The input vector is fed into the input slab. Each PE in the first hidden layer is connected to each PE in the input slab. Associated with each connection is a weight.

The output of each PE is calculated as follows. The inputs from each connection are multiplied by the weight associated with that connection and, then summed. The mathematical formulation is given below:
\[ I_{li} = \sum_{j=1}^{M_{l-1}} w_{lj} z_{(l-1)j} \]  

where

- \( I_{li} \) = weighted sum for \( i^{th} \) PE in \( l^{th} \) layer
- \( M_{l-1} \) = number of PEs in \( (l-1)^{th} \) layer
- \( w_{lj} \) = weight for the connection between the \( j^{th} \) PE in the \( (l-1)^{th} \) layer and the \( i^{th} \) PE in the \( l^{th} \) layer
- \( z_{(l-1)j} \) = output from the \( j^{th} \) PE in the \( (l-1)^{th} \) layer

An activation function for the network is applied to the weighted sum of the inputs. The output of this activation function is the output for the PE. The most common activation function is the logistic function. A graph of the logistic function is shown in Figure 7-16.

![Logistic Function Graph](image)

**Figure 7-16: The Logistic Function**

The logistic function is usually scaled so that its inputs range from -1 to 1. If output variables outside this range are necessary, the network's output is usually scaled linearly.

Information propagates forward through the network. The input slab feeds the input vector to the first hidden layer. Then using the inputs from the input slab, each PE in the first hidden layer calculates its output. These...
outputs serve as the inputs for the next hidden layer. The outputs from each slab are fed forward to the next slab until the output slab is reached. The outputs from the PEs in the output slab of the network are the outputs of the network.

When the network is in training mode, its outputs are compared with the training outputs. If they differ the weights are adjusted based on the difference between the desired and actual outputs. The learning rule for the PEs in the output slab is shown below:

\[
\begin{align*}
\delta_h &= f'(I_h) (t_i - z_h) \\
\Delta w_{ij} &= \alpha \delta_h z_{(l-1)j} \\
w_{ij}^{\text{new}} &= w_{ij}^{\text{old}} + \Delta w_{ij}
\end{align*}
\]  
(7.2-7.4)

where

- The \(l\)th slab is the output slab, the \((l-1)\)th slab is the last hidden slab and
- \(f'(x)\) = first derivative of the logistic function
- \(t_i\) = training output for the \(i\)th PE in the output slab
- \(z_j\) = output from the \(i\)th PE in the output slab
- \(\alpha\) = learning rate for output slab
- \(z_{(l-1)j}\) = output from the \(i\)th PE in the last hidden slab
- \(w_{ij}\) = weight for the connection between the \(j\)th PE in the last hidden slab and the \(i\)th PE in the output slab

Once the \(\delta\)'s have been calculated for the output slab, they can be calculated for the last hidden slab. For the hidden slabs the calculation of \(\delta_{l+1}\) is slightly different:

\[
\delta_{l+1} = f'(I_{l+1}) \sum_{k=1}^{M_{l+1}} \delta_{(l+1)k} w_{(l+1)kj}
\]  
(7.5)

where

- \(f'(x)\) = first derivative of the logistic function
- \(M_{l+1}\) = the number of PEs in the \((l+1)\)th slab
- \(w_{(l+1)kj}\) = weight for the connection between the \(i\)th PE in the current slab and the \(k\)th PE in the next slab
The adjustments are propagated back through the network until the input slab is reached. This backpropagation of learning rule is what gives the network its name.

7.5.2.2 Methodology of Analysis

Two types of data were used for the predictive modeling. One set of analyses used the features of the pressure traces as inputs and the other set used the raw cavity pressure traces. Both analyses also included temperature data since the temperatures are believed to interact with the pressure traces to affect part dimensions.

Although a different type of neural network was used, the predictive modeling was performed in the same manner and on the same data as the exception catching analysis. As before there were three steps to the neural network analysis:

- A training set was constructed.
- The network was configured and trained.
- The network performance was evaluated.

Unfortunately, each of these steps represented more of an art than a science. As a result many different combinations had to be tested, and, as necessary, iterations were performed.

7.5.2.2.1 The Training Set

Both the feature analysis and pattern analysis training sets included the same shot numbers. Both training sets were constructed by choosing six of the shots that included the twelve most extreme parts and a random sample of 44 other shots. The reasoning was that these shots would fully represent the variation in the data. Because the network training was time
consuming and there was relatively little data available, experimentation was limited to one data set for feature analysis and one data set for pattern analysis.

For the feature analysis, the input vector in the training set included the seven features extracted from the pressure traces: Cavity Pressure Integral, Cavity Pressure Peak, Maximum Slope of the Cavity Pressure Curve, Minimum Slope of the Cavity Pressure Curve, Hydraulic Pressure Integral, Hydraulic Pressure Peak, and Cavity Pressure Integral / Hydraulic Pressure Integral. Also included were the amount of time after injection that the Cavity Pressure Peak, Maximum Slope of the Cavity Pressure Curve, Minimum Slope of the Cavity Pressure Curve, and Hydraulic Pressure Peak occurred. Finally the training set also included the following temperature data: Melt Temperature, Hydraulic Oil Temperature, Mold Temperature 1, and Mold Temperature 2. All of the values included in the training set were normalized to be expressed in terms of the number of standard deviations from the process mean.

For the pattern analysis training set, the most important components of the input vector were 125 samples from the cavity pressure trace. The samples were taken at a rate of 50 per second starting at the beginning of injection, so the 125 samples represent the cavity pressure trace for the first 2.5 seconds after injection. Analysis of the complete cavity pressure trace showed that the first 2.5 seconds after injection included almost all of the variation in the data.

Each sample was presented to the network as a normalized value; for each sample, the value presented to the network was the number of standard deviations by which the sample differed from the process mean. For instance, if the fifth sample of a cavity pressure trace had a value of 36 psi
and the average and standard deviation for the fifth sample from all of the traces were 42 psi and 2 psi, respectively, then the value presented to the network was -3.

Four temperature variables were also included in the training set: Melt Temperature, Hydraulic Oil Temperature, Mold Temperature 1, and Mold Temperature 2. The temperature data was normalized for its presentation to the network; the data was presented in terms of the number of standard deviations by which the value was away from the many. In order to assure that the temperature data was not overshadowed by the 125 samples from the cavity pressure trace, each temperature value was repeated 25 times in the input vector. Thus, the complete input vector was composed of 225 elements, 125 elements representing the cavity pressure samples and 100 elements representing the temperature values.

7.5.2.3 Results of Analysis

7.5.2.3.1 Feature Analysis

Figure 7-17 shows the predicted versus actual weights for a network trained for 25,000 cycles. Figures 7-18 and 7-19 show the same data presented in a scatter graph format and Table 7-14 gives some statistics on the accuracy of the network's predictions.
Note: The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

Figure 7-17: Comparison of Network Predictions to Actual Weights
Note: The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The network was trained for 25,000 cycles with $\alpha = 0.1$.

**Figure 7-18**: Scatter Graph of Network Predictions versus Actual Weights
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Figure 7-19: Scatter Graph of Network Predictions versus Actual Weights for In Control Parts**

<table>
<thead>
<tr>
<th>Mea., Absolute Error</th>
<th>Mean Squared Error</th>
<th>Standard Deviation of Error</th>
<th>Coefficient for Correlation of Predictions and Actual Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.08</td>
<td>4.31</td>
<td>1.36</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Note: Weights were normalized to be expressed in terms of standard deviations from the mean.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Table 7-14: Statistics for Neural Network Prediction of Part Weight**
In order to compare the accuracy of the predictions to previous analyses, it is useful to look at which parts would be rejected based on the neural network's output. Table 7-15 shows a sorted list of the 10 shots for which the neural network predicted the most extreme dimensions. Of these 10 shots, only the first three have out of control weights.

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Predicted Weight</th>
<th>Actual Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>418</td>
<td>-65.46</td>
<td>-76.07</td>
</tr>
<tr>
<td>344</td>
<td>-26.72</td>
<td>-42.55</td>
</tr>
<tr>
<td>417</td>
<td>-13.86</td>
<td>-13.20</td>
</tr>
<tr>
<td>212</td>
<td>-7.24</td>
<td>0.07</td>
</tr>
<tr>
<td>401</td>
<td>-3.93</td>
<td>0.26</td>
</tr>
<tr>
<td>220</td>
<td>-3.87</td>
<td>0.26</td>
</tr>
<tr>
<td>478</td>
<td>-3.62</td>
<td>0.26</td>
</tr>
<tr>
<td>467</td>
<td>-3.03</td>
<td>0.46</td>
</tr>
<tr>
<td>468</td>
<td>-3.00</td>
<td>0.80</td>
</tr>
<tr>
<td>469</td>
<td>-2.88</td>
<td>1.67</td>
</tr>
</tbody>
</table>

Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

Only cavity one weights are included because cavity pressure sensor is in cavity one.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The network was trained for 25,000 cycles with $\alpha = 0.1$.

Table 7-15: Sorted List of Shots for which the Neural Network Predicted the Most Extreme Dimensions

In order to determine the limits of the potential of predictive modeling, a network was trained with a training set consisting of all available data. The Network was trained for 100,000 training cycles. Figures 7-20, 7-21, and 7-22 and Tables 7-16 and 7-17 show the results from this network.
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The network was trained for 25,000 cycles with $\alpha = 0.1$.

Figure 7-20: Comparison of Network Predictions to Actual Weights
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

Figure 7-21: Scatter Graph of Network Predictions versus Actual Weights
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Figure 7-22: Scatter Graph of Network Predictions versus Actual Weights for In Control Parts**

<table>
<thead>
<tr>
<th>Mean Absolute Error</th>
<th>Mean Squared Error</th>
<th>Standard Deviation of Error</th>
<th>Coefficient for Correlation of Predictions and Actual Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.95</td>
<td>1.87</td>
<td>4.11</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Note: Weights were normalized to be expressed in terms of standard deviations from the mean.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Table 7-16: Statistics for Neural Network Prediction of Part Weight**
<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Predicted Weight</th>
<th>Actual Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>418</td>
<td>-65.29</td>
<td>-76.07</td>
</tr>
<tr>
<td>344</td>
<td>-40.84</td>
<td>-42.55</td>
</tr>
<tr>
<td>417</td>
<td>-15.34</td>
<td>-13.20</td>
</tr>
<tr>
<td>212</td>
<td>-3.41</td>
<td>0.07</td>
</tr>
<tr>
<td>401</td>
<td>-2.56</td>
<td>0.26</td>
</tr>
<tr>
<td>321</td>
<td>-2.55</td>
<td>-7.22</td>
</tr>
<tr>
<td>279</td>
<td>-2.45</td>
<td>-0.68</td>
</tr>
<tr>
<td>297</td>
<td>-2.38</td>
<td>-5.06</td>
</tr>
<tr>
<td>299</td>
<td>-2.16</td>
<td>-0.95</td>
</tr>
<tr>
<td>296</td>
<td>-2.12</td>
<td>-1.56</td>
</tr>
</tbody>
</table>

Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

Only cavity one is included because the cavity pressure sensor was in cavity one.

The network consisted of five slabs of 15, 12, 8, 4, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Table 7-17: Sorted List of Shots for which the Neural Network Predicted the Most Extreme Dimensions**

7.5.2.3.2 Pattern Analysis

Figure 7-23 shows the predicted versus actual weights for a network trained for 25,000 cycles. Figures 7-24 and 7-25 show the same data presented in a scatter graph format and Table 7-17 gives some statistics on the accuracy of the network's predictions. Table 7-18 shows a sorted list of the 10 shots for which the neural network predicted the most extreme dimensions.
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

Figure 7-23: Comparison of Network Predictions to Actual Weights
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

Figure 7-24: Scatter Graph of Network Predictions versus Actual Weights
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Figure 7-25**: Scatter Graph of Network Predictions versus Actual Weights for In Control Parts
<table>
<thead>
<tr>
<th>Mean Absolute Error</th>
<th>Mean Squared Error</th>
<th>Standard Deviation of Error</th>
<th>Coefficient for Correlation of Predictions and Actual Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.93</td>
<td>6.37</td>
<td>2.46</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Note: Weights were normalized to be expressed in terms of standard deviations from the mean.

Only cavity one is included because cavity pressure sensor was located in cavity one.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Table 7-18: Statistics for Neural Network Prediction of Part Weight**

<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Predicted Weight</th>
<th>Actual Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>418</td>
<td>-70.50</td>
<td>-76.07</td>
</tr>
<tr>
<td>344</td>
<td>-44.03</td>
<td>-42.55</td>
</tr>
<tr>
<td>417</td>
<td>-12.75</td>
<td>-13.20</td>
</tr>
<tr>
<td>339</td>
<td>-7.93</td>
<td>-0.42</td>
</tr>
<tr>
<td>262</td>
<td>-7.61</td>
<td>-0.75</td>
</tr>
<tr>
<td>472</td>
<td>-7.00</td>
<td>0.52</td>
</tr>
<tr>
<td>431</td>
<td>-6.96</td>
<td>0.66</td>
</tr>
<tr>
<td>462</td>
<td>-6.53</td>
<td>-1.56</td>
</tr>
<tr>
<td>466</td>
<td>-6.50</td>
<td>0.19</td>
</tr>
<tr>
<td>421</td>
<td>-6.33</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

Only cavity one is included because cavity pressure sensor was located in cavity one.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Table 7-19: Sorted List of Shots for which the Neural Network Predicted the most Extreme Dimensions**
In order to determine the limits of the potential of predictive modeling, a network was trained with a training set consisting of all available data. The Network was trained for 100,000 training cycles. Figures 7-26, 7-27, and 7-28 and Tables 7-20 and 7-21 show the results from this network.

![Graph showing predicted and actual weights](image)

**Note:** Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Figure 7-26:** Comparison of Network Predictions to Actual Weights
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

Figure 7-27: Scatter Graph of Network Predictions versus Actual Weights
Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Figure 7-28: Scatter Graph of Network Predictions versus Actual Weights for In Control Parts**

<table>
<thead>
<tr>
<th>Mean Absolute Error</th>
<th>Mean Squared Error</th>
<th>Standard Deviation of Error</th>
<th>Coefficient for Correlation of Predictions and Actual Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.20</td>
<td>2.93</td>
<td>1.72</td>
<td>0.95</td>
</tr>
</tbody>
</table>

Note: Weights were normalized to be expressed in terms of standard deviations from the mean.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Table 7-20: Statistics for Neural Network Prediction of Part Weight**

184
<table>
<thead>
<tr>
<th>Shot Number</th>
<th>Predicted Weight</th>
<th>Actual Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>418</td>
<td>-65.83</td>
<td>-76.07</td>
</tr>
<tr>
<td>344</td>
<td>-38.17</td>
<td>-42.55</td>
</tr>
<tr>
<td>417</td>
<td>-15.23</td>
<td>-13.20</td>
</tr>
<tr>
<td>212</td>
<td>-6.84</td>
<td>0.07</td>
</tr>
<tr>
<td>213</td>
<td>5.95</td>
<td>-0.14</td>
</tr>
<tr>
<td>337</td>
<td>4.03</td>
<td>-0.88</td>
</tr>
<tr>
<td>285</td>
<td>-3.81</td>
<td>-1.28</td>
</tr>
<tr>
<td>280</td>
<td>3.69</td>
<td>-0.14</td>
</tr>
<tr>
<td>214</td>
<td>3.55</td>
<td>-0.01</td>
</tr>
<tr>
<td>475</td>
<td>3.44</td>
<td>0.59</td>
</tr>
</tbody>
</table>

Note: Weights have been normalized to be expressed in terms of standard deviations from the mean.

Only cavity one was included because the cavity pressure sensor was located in cavity one.

The network consisted of four slabs of 225, 50, 25, and 1 unit each.

The Network was trained for 25,000 cycles with $\alpha = 0.1$.

**Table 7-21: Sorted List of Shots for which the Neural Network Predicted the most Extreme Dimensions**

7.5.2.4 Conclusions from the Predictive Modeling Experiments

Unfortunately, the predictive modeling experiments did not produce good results. The predictions were only accurate enough to identify the most extreme parts--parts that all of the exception catching techniques identified with ease. Even tests in which the all available data were incorporated into training sets did not produce good results. This seems to suggest that the data was not sufficient to identify a mapping from inputs to outputs. Perhaps one or more significant process variables are not reflected in the data presented to the network.
There is also the possibility the cavity pressure sensor was not located in a good location for prediction of part dimensions. The sensor was located at one of the last areas of the mold to fill. Other mold locations could potentially provide better predictions. Further experimentation would be necessary to determine whether different placement of the pressure sensor would yield better results.

7.6 Conclusions

7.6.1 Exception Catching

The exception catching techniques showed promise. The SPC analysis performed about on par with the SPC analysis of the machine variables. The neural networks' results were more impressive. Even the networks trained with small data sets performed well, and the network trained with the complete data set performed extremely well. Although there is no way to guarantee that any of the mappings achieved are generalizable, the results justify further experimentation.

7.6.2 Predictive Modeling

The predictive modeling results were not impressive. The dimensional predictions were only accurate enough to identify the most extreme parts--parts that less complicated techniques identified with ease. The most likely explanation is that one or more critical process variables were not reflected in the data presented to the network. As new techniques are developed to measure process variables, the predictive modeling strategy deserves reconsideration.
Chapter Eight
Conclusion

8.1 Summary of Experimentation

This thesis summarized five experiments: two experiments involving the monitoring of machine variables and three involving the monitoring of pressure traces. Through these experiments two monitoring strategies were evaluated. Table 8-1 shows a summary of experimentation.

<table>
<thead>
<tr>
<th>Process Variables</th>
<th>Monitoring Strategy</th>
</tr>
</thead>
</table>
| Machine Variables | Exception Catching: Chapter 6, Experiment #1  
                       Chapter 6, Experiment #2  
Predictive Modelling: Not Applicable |
| Pressure Traces   | Exception Catching: Chapter 7, Experiment #2  
                       Chapter 7, Experiment #3  
Predictive Modelling: Chapter 7, Experiment #1  
                       Chapter 7, Experiment #3 |

Table 8-1: Summary of Experimentation

Three analysis techniques were also evaluated through the experiments. A summary of the analysis techniques is shown in Table 8-2.
### Monitoring Strategy

<table>
<thead>
<tr>
<th>Analysis Technique</th>
<th>Exception Catching</th>
<th>Predictive Modelling</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPC Analysis</td>
<td>Chapter 6, Experiment #1, Chapter 6, Experiment #2, Chapter 7, Experiment #2, Chapter 7, Experiment #3</td>
<td>Not Applicable</td>
</tr>
<tr>
<td>Neural Network Analysis</td>
<td>Chapter 6, Experiment #1, Chapter 7, Experiment #3</td>
<td>Chapter 7, Experiment #3</td>
</tr>
<tr>
<td>Regression Analysis</td>
<td>Not Applicable</td>
<td>Chapter 7, Experiment #1</td>
</tr>
</tbody>
</table>

**Table 8-2: Summary of Analysis Techniques**

#### 8.2 Summary of Results

The SPC analysis of machine variables was very successful for Experiment #1 in Chapter 6. The SPC analysis identified the 5 parts with the most extreme dimensions in the experiment. Monitoring two machine variables, *First Pressure* and *Shot Size*, was sufficient to catch all of the defects that were identified by any machine variable. By eliminating the 5 most extreme parts from the output distribution, process monitoring reduced the process standard deviation by more than 75%. This reduction in the standard deviation equated to a fourfold increase in the process capability index.

The results of the neural network analysis are more difficult to interpret. Most networks were plagued with high false rejection rates, except when trained with the complete dataset. Unfortunately, it is impossible to know whether the excellent performance of networks trained with the complete dataset is generalizable.
The SPC analysis of the machine variables was not successful for the for Experiment #2 in Chapter 6. There are at least three potential reasons that process monitoring was not successful in this experiment:

- The process set up for the experiment was pressure limited. As a result the variation in the machine variables related to injection pressure variables. Since these variables are usually among the most effective for process monitoring, limiting their variation could interfere with effective process monitoring.

- The variation in the second experiment was less dramatic than in the first experiment. The variation may not have been significant enough to be detected by process monitoring.

- The mold used in the second experiment was a four cavity mold, while the mold used in the first experiment was a two cavity mold. Monitoring machine variables for a four cavity mold may be less effective, since, if there is a disturbance in one cavity, there are three cavities to mask its effects from the machine variable sensors. Monitoring the cavity pressure was only effective for diagnosing problems in the cavity in which the pressure sensor was installed.

Furthermore, a comparison of the SPC analysis results from Experiment #1 in Chapter 6 and Experiment #3 in Chapter 7, which were run on the same data, showed that monitoring machine variables was more effective than monitoring the features of the pressure traces. The machine variables identified 45% of the shots with at least one out of control part, while the pressure traces identified only 38% of the shots in which cavity one had an out of control weight.
For detecting out of control parts, the neural network analysis of the pressure traces was not as effective neural network analysis of the machine variables. On the other hand, the neural network analysis of the pressure traces did not produce as many false rejections as the neural network analysis of the machine variables. The pattern analysis did not perform as well as the feature analysis.

The attempts at predictive modeling were not very successful. In Experiment #1 in Chapter 7, when the cavity pressure traces and machine variables from a set of designed experiments were used to construct process monitoring, the results were poor. In Experiment #3 in Chapter 7, when the pressure traces and temperature values were used to train a neural network, the network was only able to identify the 3 most extreme shots. By comparison, the SPC analysis of the machine variables was able to identify the same shots with substantially less effort.

8.3 Summary of Recommendations

The results of the SPC analysis of the machine variables are sufficient to justify pilot implementation. The results of the first experiment in Chapter 6 suggest that two classes of variables are worthwhile to monitor. The first are the uncontrolled variables—the variables are not directly controlled by the machine's control loops. As a result, they can vary in response to process disturbances. The uncontrolled variables depend on the machine control strategy. Table 8-3 summarizes the uncontrolled variables for different control and switchover combinations.
Table 8-3: Uncontrolled Process Variables for Different Control Combinations

There is no entry in the table for hydraulic pressure switchover under hydraulic pressure injection control, because this is not a consistent combination. In addition to the variables listed above, shot size is an uncontrolled variable if the process setup includes a constant pressure pack stage.

As pointed out by Hunkar, process monitoring strategy should also monitor the controlled variables.⁴¹ These variables should be monitored to make sure that the control loops are maintaining proper control. For instance, monitoring the barrel temperatures would allow the monitoring system to detect a heater band failure, before it impacted part quality.

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8.4 Integrating Process Monitoring into a CIM System

Since even the newest injection molding machines incorporate only limited process monitoring capabilities, the most efficient way to implement process monitoring would be as part of a computer integrated manufacturing (CIM) system. A modern CIM system has the processing power and data handling capabilities to perform process monitoring.

8.4.1 Current Needs

The current needs and technology suggest integration of machine variable monitoring into a plant's CIM system. The results from Experiment #1 in Chapter 6 suggest that the minimum requirements would be a system that could handle moving average SPC charting and perform mathematical manipulation of the machine variables. The moving average capability is necessary because, as shown in Figure 8-1, the values for process variables can drift over time. The mathematical manipulation capabilities are necessary because one might want to monitor some function of machine variables rather than a machine variable itself. For example, in Experiments #1 and #2 in Chapter 6, the monitored variable shot size represented the difference between two machine variables, charge finish position and cushion position.
Note: Outliers have been removed because they disturb the presentation of the trend.

**Figure 8-1: Time Series Showing Gradual Decline in First Pressure**

### 8.4.2 Future Goals

There are two sets of future goals. The first is to develop monitoring techniques that can predict actual part dimensions. The second is to develop better control systems that make the process more robust.

Although an exception catching system is valuable, as shown in Figure 8-2, a predictive modeling system would have a much larger impact. As discussed previously, implementing a predictive monitoring strategy requires sensors to observe the conditions in the individual cavities. The results from Experiment #3 in Chapter 7 suggest that neural network analysis of cavity pressure data may not be sufficient. More powerful analysis techniques and/or more sensors could be required. Wang and Wang provided an
example of a fairly successful predictive modeling system. Their system incorporated two cavity pressure sensors, an in-cavity temperature sensor, and a very complicated process model.

The high data and processing requirements make it unlikely that a predictive modeling system could be part a centralized CIM system. In the initial phases, such a system would probably be best implemented on a personal computers that were dedicated to each molding machine. In the long term, the most efficient solution would be for predictive modeling systems to be integrated into the machine controllers.

The second long term need is to develop more advanced control techniques. This is superior to process monitoring because it has the potential to stop defects from being produced rather than simply identify them. It is also complementary to process monitoring, however, since process monitoring can help identify the type of variation that causes the most defects. Thus, process monitoring helps to focus the efforts to develop advanced control techniques.

---

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Normal Process</td>
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<td>not applicable</td>
</tr>
<tr>
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<tr>
<td>Dramatic Shift in Process Mean</td>
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<td>yes</td>
</tr>
<tr>
<td>Gradual Increase in Process Variation</td>
<td><img src="image" alt="Graph" /></td>
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<td>yes</td>
</tr>
<tr>
<td>Dramatic Increase in Process Variation</td>
<td><img src="image" alt="Graph" /></td>
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<td>yes</td>
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<tr>
<td>Process Outlier</td>
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Figure 8-2: Identifying Process Problems Through Process Monitoring
Bibliography


Appendix A
Available Machine Variables

The controller on the Toyo Plastar injection molding machines tracks 57 machine variables for each shot. The values for these variables are available for export via an RS-232C communications port. The available variables and a description of their meaning are shown in Tables A-1 through A-3.

Not all of the temperature variables are defined for all machines. Smaller machines do not include a rear-most heater zone, so Heater 5 Temperature is not defined for smaller machines. Many machines are not equipped with thermocouples to measure melt temperature, so Heater 6 Temperature is not defined for these machines. Many molds do not include thermocouples to measure mold temperature, so Mold 1 Temperature and Mold 2 Temperature would not be defined for these molds.

Not all process variables are defined for all machine settings. The number of screw revolution and back pressure variables defined depends on the number of charging stages that are defined in the machine settings. If one screw speed and back pressure was defined, only Screw Revolution 1 and Back Pressure 1 would be defined. The number of pressures and speeds defined depends on the number of injection stages defined. For instance, if the machine were set in velocity control and a first injection speed and a second injection speed were set, then the following pressures and speeds would be defined: First Pressure, Second Pressure, First Speed, Second Speed, First Speed Pressure, and Second Speed Pressure.
Pressure 1, Speed 1, Pressure 2, Speed 2, Pressure 3, Speed 3, Pressure 4, and Speed 4 are only defined if the corresponding points are designated. For example, if points 2 and 4 were designated, then the Pressure 2, Speed 2, Pressure 4, and Speed 4 would be defined. Rise-Up Time is defined only when a target injection pressure is designated for the measurement.
<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heater 1 Temperature</td>
<td>Barrel temperature at the nozzle</td>
<td>Degrees Fahrenheit</td>
</tr>
<tr>
<td>Heater 2 Temperature</td>
<td>Barrel temperature in the front zone</td>
<td>Degrees Fahrenheit</td>
</tr>
<tr>
<td>Heater 3 Temperature</td>
<td>Barrel temperature in center zone</td>
<td>Degrees Fahrenheit</td>
</tr>
<tr>
<td>Heater 4 Temperature</td>
<td>Barrel temperature in rear zone</td>
<td>Degrees Fahrenheit</td>
</tr>
<tr>
<td>Heater 5 Temperature</td>
<td>Barrel temperature in rear-most zone</td>
<td>Degrees Fahrenheit</td>
</tr>
<tr>
<td>Heater 6 Temperature</td>
<td>Temperature from melt thermocouple</td>
<td>Degrees Fahrenheit</td>
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<tr>
<td>Hopper Temperature</td>
<td>Hopper throat temperature</td>
<td>Degrees Fahrenheit</td>
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<td>Oil Temperature</td>
<td>Hydraulic oil temperature</td>
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<td>Mold 1 Temperature</td>
<td>Temperature from thermocouple in mold half 1</td>
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</tr>
<tr>
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<td>Degrees Fahrenheit</td>
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<tr>
<td>Hold Pressure Position</td>
<td>Screw position at hold pressure start</td>
<td>Inches</td>
</tr>
<tr>
<td>Cushion Position</td>
<td>Screw position at injection completion</td>
<td>Inches</td>
</tr>
<tr>
<td>Charge-Finish Position</td>
<td>Screw position at charging completion</td>
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</tr>
<tr>
<td>Open-Finish Position</td>
<td>Die plate position at start of mold closing</td>
<td>Inches</td>
</tr>
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<td>Screw Revolution 1</td>
<td>Screw RPM at completion of screw speed 1</td>
<td>RPM</td>
</tr>
<tr>
<td>Screw Revolution 2</td>
<td>Screw RPM at completion of screw speed 2</td>
<td>RPM</td>
</tr>
<tr>
<td>Screw Revolution 3</td>
<td>Screw RPM at completion of screw speed 3</td>
<td>RPM</td>
</tr>
<tr>
<td>Screw Revolution 4</td>
<td>Screw RPM at completion of screw speed 4</td>
<td>RPM</td>
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Note:  All Temperatures are measured at the start of injection.

Source:  Operating Manual for Toyo Plastar Injection Molding Machines

**Table A-1: Available Machine Variables**
<table>
<thead>
<tr>
<th>Name</th>
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</thead>
<tbody>
<tr>
<td>First Pressure</td>
<td>Pressure at completion of first injection stage</td>
<td>PSI</td>
</tr>
<tr>
<td>Second Pressure</td>
<td>Pressure at completion of second injection stage</td>
<td>PSI</td>
</tr>
<tr>
<td>Third Pressure</td>
<td>Pressure at completion of third injection stage</td>
<td>PSI</td>
</tr>
<tr>
<td>Fourth Pressure</td>
<td>Pressure at completion of fourth injection stage</td>
<td>PSI</td>
</tr>
<tr>
<td>Fifth Pressure</td>
<td>Pressure at completion of fifth injection stage</td>
<td>PSI</td>
</tr>
<tr>
<td>Sixth Pressure</td>
<td>Pressure at completion of sixth injection stage</td>
<td>PSI</td>
</tr>
<tr>
<td>Back Pressure 1</td>
<td>Pressure at completion of screw speed 1</td>
<td>PSI</td>
</tr>
<tr>
<td>Back Pressure 2</td>
<td>Pressure at completion of screw speed 2</td>
<td>PSI</td>
</tr>
<tr>
<td>Back Pressure 3</td>
<td>Pressure at completion of screw speed 3</td>
<td>PSI</td>
</tr>
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<td>Back Pressure 4</td>
<td>Pressure at completion of screw speed 4</td>
<td>PSI</td>
</tr>
<tr>
<td>First Speed</td>
<td>Speed at completion of first injection stage</td>
<td>Inches/Second</td>
</tr>
<tr>
<td>Second Speed</td>
<td>Speed at completion of second injection stage</td>
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</tr>
<tr>
<td>Third Speed</td>
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Source: Operating Manual for Toyo Plastar Injection Molding Machines

Table A-2: Available Machine Variables, Continued
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<td>Pressure 1</td>
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<tr>
<td>Speed 3</td>
<td>Ram speed at designated point 3</td>
<td>Inches/Second</td>
</tr>
<tr>
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<td>Injection pressure at designated point 4</td>
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<td>Speed 4</td>
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<tr>
<td>Charging Time</td>
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<td>Seconds</td>
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</table>

Source: Operating Manual for Toyo Plastar Injection Molding Machines

Table A-3: Available Machine Variables, Continued