Real-Time Quality Control of Injection Molding

Patrick Bangert
algorithmica technologies GmbH; Gustav-Heinemann-Str. 101; 28215 Bremen; Germany

Pablo Cajaraville
Reiner Microtek; Poligono Industrial Itziar,Parcela H-3; 20820 Itziar-Deba; Spain

Björn Dormann and Maik Köhler
Klöckner Desma Schuhmaschinen GmbH; Desmastr. 3/5; 28832 Achim; Germany

Philipp Imgrund, Janne Haack, and Jörg Volkert
Fraunhofer Institute IFAM; Wiener Strasse 12; 28359 Bremen; Germany

Oscar Lopez, Pedro Rodriguez, and Leo Martinez
MIM TECH ALFA, S.L.; Avenida Otaola 4; 20600 Eibar; Spain

Natalie Salk
PolyMIM GmbH; Am Gefach; 55566 Bad Sobernheim; Germany
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Injection molding produces parts whose quality must generally be determined by some separate quality control process after molding itself. In the case of metal injection molding, typically the sintering step must be performed before final quality control as well. Quality control mechanisms inside molding machines are known to be insufficient to correctly identify all scrap parts. A method is presented to analyze the production data from the molding machine and to reliably interpret the part’s final quality on its basis. For this, a pilot production series must be quality controlled and presented to a machine learning algorithm so that it can learn, for this particular part and machine, what criteria make it scrap or not. We demonstrate on various machines that the recognition efficiency is high enough for significant practical use on average 0.92. This method will reduce production cost and increase the quality in the final shipment from a normal production scrap rate of about 10% down to about 0.8%.

I. STATEMENT OF THE PROBLEM

The injection molding technology is a widely used technology for the mass production of components with complex geometries. Almost all material classes can be processed with this technology. For polymers the pelletized material is injection molded under elevated temperatures in a mold cavity showing the negative structure of the resulting part. The part is cooled down and ejected to the finished component.

In the case of metals and ceramics the so called metal injection molding (MIM) or ceramic injection molding (CIM) process is applied. Both processes fall under the umbrella term powder injection molding (PIM). In all cases, the material powder is mixed with a binder system composed of polymers and/or waxes. This so-called feedstock is injection molded and the ejected parts, called green parts, still contain the binder material that acted as a flowing agent during the injection molding process. To remove the binder, the components have to be debound in a solvent or water solution for a certain amount of time. Subsequently, a thermal debinding step is needed to decompose the residual binder acting as the backbone in what is now called the brown part. During the final sintering step, the parts are heated up to approximately 3/4 of the melting point of the integrated material powder. During the sintering process the material densifies to a full metallic or ceramic part, showing the same material properties as the respective material.

Often, the damages to a part that occur during injection can only been seen on the final part. The unnecessarily performed steps of debinding and sintering have expended significant amounts of electrical energy and have also made the material useless. If we could identify a damaged part during its green stage, we could recycle the material and also save the energy for debinding and sintering. For all parts, there is an effort involved in determining whether the part is good or not. Today, this effort is usually made manually, which is expensive. If we could make the identification automatic, then we would save this effort as well.

An injection molding machine is controlled by manually inputting a series of values known as set-points. These are the values for various physical quantities that we desire to have during the injection process. It is the responsibility of the machine to attempt to realize these set-points in actual operation. This attempt is generally achieved but there are deviations in the details. Indeed it turns out in our investigation that the instability of the machine to realize the set-points is the principle cause for scrap. In order to monitor what the actual value of these various measurements is, an injection machine will also
I. Statement of the Problem

I have sensors that output these measurements over time, i.e. a time-series.

For each part produced, we thus have the set-points $\alpha_i$ and also a variety of time-series $\beta_i(t)$ over the duration of its injection. This information is available in order to characterize a part. We will describe here a system by which such an automated diagnosis can be effected and how it was tested under real conditions.

II. METHOD

All partners have determined that a tensile test bar (dogbone) is an ideal test part. Using this test bar it is possible to do any time reproducible tensile and bending tests without any influence of geometric differences.

![Image](image_url)

**FIG. 1.** In order, we see here: (a) The drawing of the test bar “dogbone” (in mm), position of the ejector (left circle) and position of the pressure / temperature sensor (right circle). (b) Dimensions to be measured on the micro tensile test specimens. (c) A selection of sintered parts.

In terms of Micro MIM, two stainless steel feedstock types were processed on two different types of injection molding machines to produce the parts for evaluation of the system performance.

In the first case, at IFAM a 316L stainless steel feedstock was prepared with a binder made of a mixture of paraffin waxes and polymers. Spherical stainless steel powder with a mean particle size of 5µm was received for this purpose from Sandvik Osprey Ltd., UK. The binder was specially designed for the micro metal injection molding process by using 50 wt% low density polyethylene, 49% waxes and 1% detergent. This mixture was blended in a Brabender plastograph kneader for 2h at 120°C to assure complete homogenization of the material. Following preparation, injection molding trials with this feedstock were performed on a Desma FormicaPlast injection molding machine at DesmaTec. In the second case, a commercially available stainless steel feedstock, type Catamold®316L from BASF, was received at MIMTec Alfa to perform injection molding trials using an Arburg Allrounder 320C injection molding machine.

The system was installed on both machines and, for training of the system, a set of selected process parameters was varied to specifically obtain molded parts of different quality. For each parameter set, 60 samples were produced. In total 18 different parameter sets were evaluated, thereby varying feedstock temperature, injection speed and after-pressure. Sintering of all samples was performed in one sintering run at 1200°C for two hours under hydrogen atmosphere. The part quality was determined for each specimen by optical analysis, measuring the weight and dimensions of the parts after injection molding and sintering, respectively. The dimensions that were selected for measuring and examples of sintered parts are presented in Fig. 1.

Weights of green and sintered parts were measured using a micro balance. The dimensions were determined using and FRT white light profilometer equipment for semi-automatic detection and analysis of the part dimen-
II Method

sions. Fig. 2 shows the setup of the equipment and exemplary sample profile. According to the data obtained, the parts were classified in “good” and “bad” parts in terms of optical quality, weight and dimensional tolerance.

This data was used to train the system’s recognition capability. In order to test it under real production conditions, the parameter set offering the highest quality of results in the sintered parts was then selected. The optimum parameter set in this study was found to be a feedstock temperature of 120°C, injection speed of 240 mm/s and active after-pressure. Using these parameters, a series of 1080 parts was molded, sintered and inspected with the same methodology as described for the training run. The results of the visual, weight and dimensional inspection were again evaluated to classify the parts in the “good” and “bad” categories. In principle the same methodology was applied at MIM Tech Alfa for evaluation of the parts processed using the Catamold® material, whereas here the dimensional inspection was performed manually.

The same procedure was used at Reiner Microtek using a Battenfeld Microsystem 50 machine and the polymer POM Hostaform C9021 by Ticona. As polymer materials do not require debinding and sintering, the injected part is the final part. Otherwise the production sequence and mathematical treatment was the same.

III. PRODUCTION

In order to measure the mold temperature and pressure, it was necessary to integrate a relevant sensor into the mold. The Kistler 6198A was chosen, which yields a signal that was amplified by the Kistler 5155 multi channel amplifier. The integration of the sensor required the machine’s programming to be altered. All measurement quantities and set-points were saved to one XML file per produced part.

Fig. 4 shows the interaction of recorded dynamic parameters consisting of injection pressure, internal temperature, internal mold pressure, piston position and piston / injection velocity. With the help of the recorded values it was possible to compare the process parameters for each injection. Based on the injection curves, the moment of material arrival into the cavity (mold temperature increase) and the moment of complete filling (maximum cavity pressure) can be computed. The fluctuation of injection pressure during the injection process is based on the fact that the injection piston is moving with constant speed and moves the material through different geometries starting at the nozzle, passing the runner until reaching the mold cavity and filling it completely. The holding pressure avoids not completely solidified material flowing back through the runner. The machine exerts a predefined pressure onto the injection piston for a set time in order to hold the injected material inside the cavity for it to solidify.

With assistance of simulation software, the mold filling process can be simulated, see fig. 5, in advance of the injections. Comparing the simulation with the real article shows that there is a marked difference but this difference is acceptable.

IV. THEORY

The set-points $\alpha$ and the measured time-series $\beta(t)$ in totality somehow correlate with the binary result of scrap (value zero) versus good (value unity), $\gamma$, by means of some decision function,

$$\gamma = [f(\alpha_1, \alpha_2, \ldots, \alpha_N, \beta_1(t), \beta_2(t), \ldots, \beta_M(t)) + \Delta]$$

where we have inserted two assumptions.
First, we have added a term $\Delta$ that is meant to encapsulate noise to the function $f(\cdots)$. This noise arises from the fact that our measured variables are only a partial observation of the events inside the machine and thus it may happen that an identical observation will lead to diverse results. In the absence of further information, we may assume white Gaussian noise but this is most likely false in favor of some form of structured noise.

Second, we have assigned the binary result $\gamma$ to the floor of the function plus the noise. This reflects our desire that, in the case of doubt, we would like to default the answer to scrap. If we identify a good part as scrap, this is a mistake, but it is a cheap one. If we identify a scrap part as good, then this is an expensive mistake as we must follow through with debinding and sintering. Additionally, the six-sigma quality requirement for many molding processes does not like to see a scrap part get into production and is thus unrealistic. We must live with this information to the learning method. We have determined that a good number of observations is 500 or more. Furthermore, it is good to use several settings of the set-points within these 500 parts.

When a new part is now injected, its data $x$ is provided to the decision function and it computes whether this part is good or bad $\gamma$ and outputs this value. As a result a robot can be triggered to remove the scrap parts from further production.

We may define four different recognition rates:

1. **good rate**, $\rho_g$ – The number of correctly identified good parts
2. **scrap rate**, $\rho_s$ – The number of correctly identified scrap parts
3. **false-negative rate**, $\rho_n$ – The number of good parts identified as scrap
4. **false-positive rate**, $\rho_p$ – The number of scrap parts identified as good

where each count is divided by the total number of produced parts in order to make each item into a genuine rate. Please note that these rates are thus normalized by definition, i.e. $\rho_g + \rho_s + \rho_n + \rho_p = 1$. It is generally not possible to design a system that will have perfect recognition efficiency ($\rho_n = \rho_p = 0$). We would rather throw away a good part than let a scrap part through. Thus, the overall objective is to minimize the false-positive rate $\rho_p$ by designing a decision function that is as accurate as possible.

This enumeration is, of course, theoretical as it would require the user to know which parts are actually good or bad. This identification would require the manual characterization that we want to avoid using the present methods (except for the training data set for which it is necessary). Thus, we will never actually know what these rates are except in two cases: the pilot series where the data is used for training the function and, possibly, in any quality control spot checks that are usually too infrequent to really allow the computation of a rate. Thus, these rates must be interpreted as a useful guideline for thinking but not practical numerical quantities except at training time when we actually know the quality state of all parts.

**V. METRIC**

Obtaining the scalar quantities $\zeta_i$ from the time-series $\beta_i(t)$ is done via a metric procedure. The following are the time-series, typically measured using BNC analog output cables from the machine and recorded once every few milliseconds:
V Metric

1. Mold temperature
2. Cavity pressure
3. Cavity temperature
4. Injection pressure
5. Injection speed
6. Feedstock temperature
7. After pressure

We have had success with three metrics.
First, a general metric based on turning points (see figure 6 for an example):

1. Take all observations of good parts over the pilot series. For each time series, create an averaged time series over all these good parts.
2. Disregarding local noise in the time-series, compute the turning points of this time series.
3. For every part encountered, perform the same turning point analysis.
4. For every part, we now compute the difference between the turning points in the present part relative to the turning points of the averaged series. If we find differences, then these will be taken as salient features.
5. These differences form the salient features and these will constitute the vector $x$. For practicality, we limit ourselves to a specific maximum number of turning points allowed.

FIG. 6. The bottom curve is the average pressure observed at the nozzle averaged over all parts known to be good. The top curve is a single observation of a part known to be bad. The black arrows pointing up indicate the position of the turning points of the bottom curve and the black arrows pointing down indicate the position of the turning points of the top curve. We observe that the top curve has two extra turning points. We also observe that the vertical position of several turning points is higher than that of the average good curve.

Second, a metric based on physical measurements. Compute as many of the following quantities from the time-series as possible depending on what time-series are available.

1. Maximum injection pressure
2. Injection work
3. Injection volume
4. Injection volume during afterpressure
5. Injection duration
6. After pressure duration
7. Compression duration
8. Screw position at end of afterpressure
9. Cushion
10. Tool temperature maximum
11. Tool temperature at end of afterpressure
12. Tool temperature maximal change during cycle
13. Tool pressure maximum
14. Tool pressure slope from start to maximum
15. Tool pressure integral over injection
16. Plastification volume
17. Plastification duration
18. Dosification volume

Third, the most general metric is the corridor metric. For each time-series and each value of time from the start of injection, compute the maximum and minimum value of that time-series over all good parts. This obtains a corridor over time. For every part encountered, determine how many instantaneous measurements lie outside of this corridor. If this is above a certain cut-off number, then the part is interpreted to be scrap.

VI. RESULTS

Experiments were made using three different production facilities involving different machines from different manufacturers. All experiments manufactured the same part, simple small dumbbell in metal. Each producer made and manually characterized over 1000 parts for training the model. Then each producer made a similar number of parts for testing. A manual characterization of this test batch was also carried out but only after the computational identification was done. A comparison between the manual and computational identification of these parts is the final test to see if this methodology works. See table I for the results.

We find during training that we identify, on average, 0.89 of all parts produced correctly and produce only 0.02 false positives. During the testing run, these rates even improved to an accuracy rate of 0.92 and a false positive rate of 0.009.

Out of any 1000 parts made, we find that on average 16% are scrap. We identify 92% of both good and scrap
TABLE I. Results in training and testing for all three producers.

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<thead>
<tr>
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<th>Desma Reiner Alfa</th>
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<tbody>
<tr>
<td><strong>Training</strong></td>
<td></td>
</tr>
<tr>
<td>Correct Goods</td>
<td>665 1182 1247</td>
</tr>
<tr>
<td>Incorrect Goods</td>
<td>75 110 187</td>
</tr>
<tr>
<td>Correct Bads</td>
<td>270 201 161</td>
</tr>
<tr>
<td>Incorrect Bads</td>
<td>42 18 27</td>
</tr>
<tr>
<td>Total Parts Made</td>
<td>1052 1511 1622</td>
</tr>
<tr>
<td>Recognition Rate</td>
<td>0.89 0.92 0.87</td>
</tr>
<tr>
<td>False-Positive Rate</td>
<td>0.04 0.01 0.02</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Test</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct Goods</td>
<td>910 1287 279</td>
</tr>
<tr>
<td>Incorrect Goods</td>
<td>45 54 6</td>
</tr>
<tr>
<td>Correct Bads</td>
<td>15 167 251</td>
</tr>
<tr>
<td>Incorrect Bads</td>
<td>7 4 18</td>
</tr>
<tr>
<td>Total Parts Made</td>
<td>977 1512 554</td>
</tr>
<tr>
<td>Recognition Rate</td>
<td>0.95 0.96 0.96</td>
</tr>
<tr>
<td>False-Positive Rate</td>
<td>0.007 0.002 0.03</td>
</tr>
</tbody>
</table>

parts correctly and 0.9% false positives. Thus we deliver 786 to the client, of which 773 are good and 13 are bad. We throw away the other 214 parts, of which 147 are scrap and 67 are good. The production scrap rate of 16% is thus lowered to a delivery scrap rate of 1.7% without any other quality control steps. Recall that the objective of training the network was to minimize the false positive rate. It is clear that this cannot be reliably zero and so getting a rate lowered by a factor of 10 can be interpreted as a success. The system is certainly more reliable than manual quality control, which is common in the industry.

VII. CONCLUSION

We have verified that it is possible to reliably identify scrap from good parts based only on process data. This has two major ramifications for quality improvement.

First, the quality of the delivered product. If 1000 parts are produced, so are 160 scrap parts. Using this method, we are able to lower the relative number of bad parts delivered after quality control from 16% to 1.7%, i.e. by a factor of 10. We note in passing that a production scrap rate of 16% is quite high and unrealistically so in a real production. For the purposes of testing a quality control device, it was considered good to intentionally produce more scrap than normal.

Second, we also save the energy costs that would have flown into the steps of debinding and sintering of parts that later are recognized as scrap. It is hard to quantify this in any general manner but we assume that this lowers the total production cost per delivered part by another 4%.

We finally conclude by observing that the method is practically capable of automatically separating good from bad parts with an accuracy of over 90%, which makes the method relevant for industrial practice in order to lower production cost and increase the quality of part shipments.

VIII. ACKNOWLEDGMENTS

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