Data Driven Injection Moulding

Curdin Wick[✉], Frank Ehrig, and Guido Schuster

University of applied science Rapperswil, Rapperswil SG, Switzerland
{curdin.wick,frank.ehrig,guido.schuster}@hsr.ch

Abstract. The injection moulding process for the production of plastic parts is a very complex process. Therefore, a lot of experience and expert knowledge is necessary to produce parts with high quality. Changes in granule-batches, environmental influences and wear of the machine and the mould can strongly affect the quality of the produced parts. For this reason an injection moulding machine needs an experienced operator, who reacts properly to changing input variables and sets appropriate countermeasures. Modern injection moulding machines are able to record all countermeasures and have access to a wealth of internal machine data. Consequently, an adequate machine learning (ML) method should be able to observe, to learn the proper countermeasures and to evaluate their effectiveness. With deep learning (DL), a state of the art technology in ML, it will be possible to predictively detect process anomalies for the first time, based only on the knowledge about the internal machine data. If an operator changes the setting parameters of the injection moulding machine, the correlation between the adjustment and the anomaly is being learnt. The aim is to get process adjustment recommendations from the machine learning system.

This is a fundamentally new approach for process management in injection moulding, as the machine learning system detects problems long before they can be seen by an operator. Furthermore, the system provides process adjustment recommendations, based on the supervised and automatically generalized actions from different operators using different injection moulding machines, moulds and materials.

Keywords: Injection moulding · Machine learning · Process anomalies

1 State of the Art

1.1 Use of Machine Learning in the Field of Injection Moulding

To our knowledge today there is no machine learning or deep learning (ML/DL) based process management system for injection moulding on the market. An adaption of ML/DL by industry hasn't taken place yet, because DL is still a relatively new approach for ML, which requires a lot of data and computing power. To get more attraction from the industry for this technology, it needs to be more robust, which means the available samples for the analysis need to be increased.

C. Hopmann and R. Dahlmann (Eds.): *Advances in Polymer Processing 2020*,
pp. 128–136, 2020. https://doi.org/10.1007/978-3-662-60809-8_11

For a long time injection moulding machines have been able to record process data and to export them manually after the end of manufacturing. However only averaged values or maxima and just a small amount of curve data (often only injection pressure) can usually be exported. Modern injection moulding machines are able to record all internal machine data with a very high frequency, which increase the chances of success for a machine learning based system. But only recently it is possible to export such data from the machine, e.g. with the DataXplorer from Krauss Maffei. A further reason, why there is currently no ML based process management system for injection moulding on the market. Therefore now is the right time to invest in this technology, because theory, software, hardware and data quality are finally good enough for the development of an auspicious system.

"Added value in practice: Intelligent use of process and machine data from injection moulding production" [1] describes the state of the art. In this presentation process anomalies were detected by manually fitted features, meaning without any use of a DL approach. With such an approach detectors are learnt automatically and don't need to be programmed manually by an operator. The idea of deriving process adjustment recommendations for the operator is mentioned in the outlook.

At the University of Applied Science in Rapperswil a feasibility study [7] was performed, where with internal machine data from the DataXplorer (40 signals, 45s cycle time with a frequency of 200 Hz = 360 k data points for each part and cycle) the weight and the dimensions of an injection moulded part were predicted. The relative accuracy (standard deviation/average) of these predictions for a test set that wasn't included in the training set is better than 1%. For example, the tool temperature is intentionally increased (but no information about the tool is made available to the ML algorithm) to see if the method can still predict the resulting changes – it can, within the above relative accuracy. Although, as mentioned above, no information about the tool is available to the process, so no cavity pressure curve and/or any tool temperatures. Since these quality data could be estimated with a high relative accuracy, it is possible to perform physical quality checks less often, or at least if the quality prediction will fall outside a defined tolerance band. Whenever a physical quality check is performed, this data is fed back into the ML algorithm to further learn and improve future predictions.

1.2 Goals and Risks

Because of the good results of the feasibility study and the well-known state of the art in the detection of anomalies [2–5], it can be assumed that an automatic detection of anomalies in the field of injection moulding can be achieved. The highest risk is that not enough data samples could be generated, due to the high effort for the injection moulding trials. If a process variation occurs, the whole project slows down. This is a big difference to the ML, which Internet companies perform, because digital data is constantly generated without a physical process having to run. In other words, with real physical processes it may be difficult to exploit the power of DL because data collection is expensive and time consuming.

The next step is to learn the ML system the operator's countermeasures as a result of the detected anomaly, an "imitation learning" (IL). The paper "Bridging the gap between imitation learning and inverse reinforcement learning" together with the references in this publication define the state of the art [6]. This is a very active field of research and only a few of these ideas have been incorporated into a real product. Based on the preliminary project, however, this represents a real opportunity, since it is a clearly defined environment and the IL is therefore highly focused.

The aim is to take a step towards complete automation of the injection moulding process ("lights-out manufacturing"). Anomalies have to be detected independently by the ML system, without the help of an experienced operator, but only based on internal machine data. Injection moulding data is well suited for this purpose, as the process is inherently cyclic and a lot of very similar data is quickly available. In the last few years, current ML systems have clearly shown that they can detect such anomalies independently. During the learning phase the anomalies are detected and the following adjustment actions of the experienced operator are observed. This creates a "Supervised Learning" situation in which an appropriate action can be learned for each detected anomaly. Modern ML systems can then generalise on the basis of such data, which means that with sufficient training data and a suitable ML system, even reasonable adjustment actions for anomalies never seen before can be suggested. This is a fundamental step forward in the automation of such a complex process and represents a significant innovation in process management. By generalising the process adjustment actions to new anomalies never seen before, the ML system can retrieve more than just known actions. Thus it can propose actions that may have never been used as such before, but are still useful for this never-before-observed anomaly.

2 Investigations

2.1 Feasibility Study for the Usage of ML: Quality Data Prediction

In an already mentioned feasibility study [7] by the University of Applied Science in Rapperswil first investigations for the usage of ML in the field of injection moulding were performed. Therefore a Krauss Maffei PX120-380 injection moulding machine with an integrated DataXplorer was used. The DataXplorer records almost all machine data during one cycle, like temperatures, pressure, power, triggers and positions. More than 300 k data points per cycle could be used for interpretation and generation of the ML models. The investigations were performed on a simple ice scraper, displayed in Fig. 1. Starting from an optimised operating point, specific disturbances, which can also occur in a real production, were introduced:

- Trial series 1 (72 parts) - reference trial series → ice scrapers lie within the tolerances
- Trial series 2 (56 parts) - calcified cooling channels → temperature of the mould temperature medium increased
- Trial series 3 (57 parts) - batch fluctuation → cylinder temperature increased
- Trial series 4 (52 parts) - wrong material → 10% foreign material added

The material for all trials was polypropylene HF955MO. For each series the corresponding quality data were measured. As quality data the length, width, weight and lip distance (for the follow-up assembly of a sealing lip) were used, shown in Fig. 1.

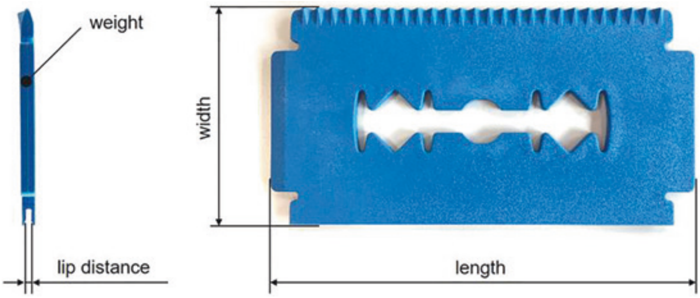

Fig. 1. Evaluated quality data of the ice scraper

The models were derived and trained by measuring the quality data of the manufactured parts and comparing them with the recorded machine data. The first step was to analyse which and how many features need to be used to classify the individual trial series. To find out which features have the biggest influence on the classification a forward stepwise selection was executed. As a result this procedure provides a ranked list of suitable features. The data from the trial series V1-V4 can be completely classified with just two of these important features. An example of features that allow this separation is shown in Fig. 2. A linear discriminant analysis (LDA) was used for the actual classification of the trial series.

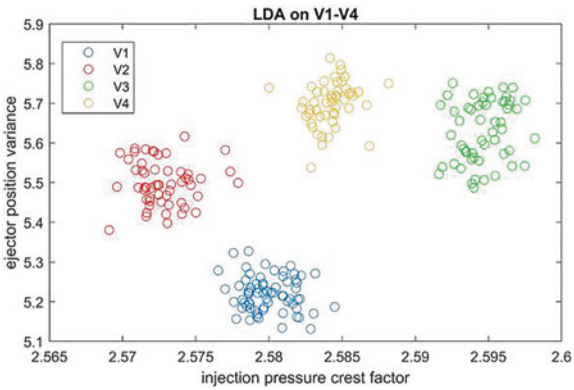

Fig. 2. Results after classification with LDA V1-V4

Test set (random data from the trial series that were not used for the development of the models) were used to test the models by predicting the quality data of the already moulded parts. The results are shown in Fig. 3.

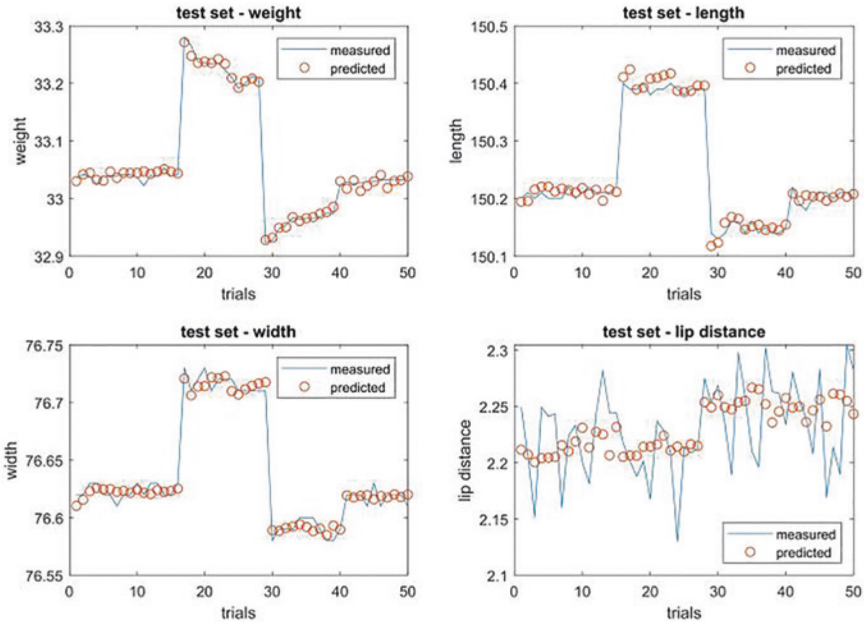

Fig. 3. Quality data prediction by the ML system

The relative accuracy (standard deviation/average) of these predictions is better than 1% for components that were not in the training set. For example, in this preliminary project 10% foreign material is intentionally added to simulate a batch variation. No batch information was made available to the algorithm and yet this method can still achieve the above relative accuracy.

Basically, the models become better for new unknown test sets if they are trained with more data. The easiest way to further improve quality is to add more data and there is still potential to further improve the models too. The results show that there could be some high-dimensional dependencies between the features used and the quality characteristics. An analysis with higher-dimensional regression models could also lead to an improvement. Another approach would be to switch to other methods of linear regression like local regression.

Objective for the next steps in prediction of quality data is to transfer the findings on other parts, because the ice scraper is a relatively simple part. Through the analysis of other parts (with different wall thicknesses, hot runner, multiple cavities) and the use of other materials more effects can be detected and the feature selection can be optimized.

2.2 Anomaly Detection: Capabilities for Predictive Maintenance

In a second investigation the focus was on the detection of process anomalies with an ML based process management system. One well-known anomaly in the injection moulding process is the wear of non-return valve. The process drifts slowly and continuously, thus after a certain time the setting parameters of the machine need to be adjusted, to guarantee proper parts. In order to simulate this behaviour, several non-return valves were machined, meaning a quantifiable damage was artificially introduced.

Starting from an optimised operating point the dosage volume was artificially increased, that even with a worn non-return valve still a sufficient melt cushion is available and the same process can be run through all trials. The material for all trials was ASA Luran S KR2858G3.

For a first set of trials non-return valves with notches with a depth of 0.33, 0.67 and 1.00 mm were machined. Afterwards the injection moulding trials with the different valves and same setting parameters were performed on the Krauss Maffei machine with DataXplorer and all internal machine data were recorded. The difference between the damaged series and the intact non-return valve can clearly be identified when considering the screw position as a function of time, shown in Fig. 4.

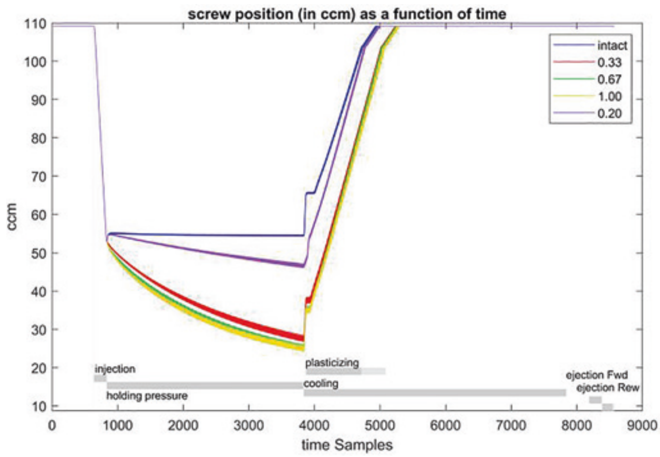

Fig. 4. Screw position as a function of time

These observations correlate with existing knowledge in the injection moulding industry which expects a decrease of the melt cushion the higher the wear of the non-return valve. A classification of single process curves to the various damages to the valve is more difficult. More process curves of the recorded internal machine data are needed for this, even then a manually assignment is very difficult or almost impossible.

By using all the recorded internal machine data and the developed ML algorithms with several features the possibilities are getting extended. Again a forward stepwise selection was executed to get a ranked list of suitable features to classify the various trials. A worn non-return valve can be clearly detected by selecting the appropriate features. Two of the best features were the first and second principal component score resulting from a principal component analysis (PCA) performed with all the calculated features. With this the various trials can be clearly classified, shown in the left diagram of Fig. 5.

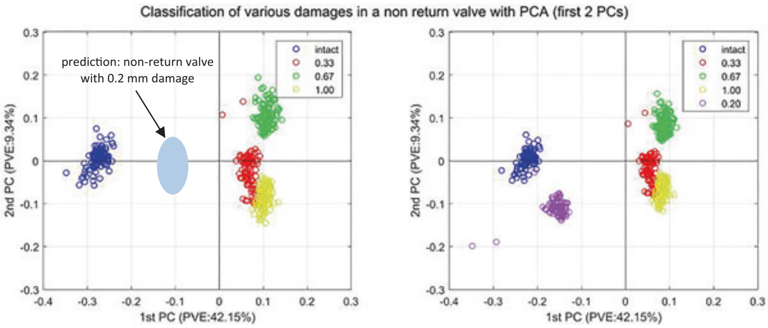

Fig. 5. Classification of the various damages with PCA

Furthermore the first principle component score seems to be a good indicator for the height or the progress of the damage on the non-return valve, probably the damage can even be reliably estimated. As the machined damage seems quite high, a valve with a smaller damage of about 0.2 mm should be located somewhere in the marked region in Fig. 5 on the left. To check this expectation another ring of a non-return valve with a notch with a depth of 0.2 mm was machined and the same injection moulding trials were done. The first principle component score is still a quite good indicator for the height or the progress of the damage on the non-return valve. Next trials with an unhardened non-return valve in combination with a highly reinforced material should simulate a continuous wear to check the correlation to existing results.

Coming back to an ML based process management system, these investigations clearly show the potential for such a system. Process anomalies should be detected probably long before they can be seen by an operator if the appropriate features are selected. A predictive maintenance system could be established too.

In a next step longer trial series will be done to detect different kind of process anomalies. If the produced parts no longer correspond to the required quality and the operator changes the setting parameters of the injection moulding machine, the correlation between the adjustment and the anomaly should be learnt in the future. The aim is to get process adjustment recommendations from the ML system, based on the supervised and automatically generalized actions from different operators using different injection moulding machines, moulds and materials.

3 Conclusion and Outlook

The biggest success factor of a ML based process management system is to record and export enough and especially the right data from the injection moulding machine. On the one hand internal machine data (process data) are needed, but on the other hand also setting parameters and quality data of the moulded parts are required to build up a multifunctional system. As the quality data of the produced parts are often not available, at least the reason for the process adjustment should be put on record. The recorded data should also be handled and interpreted with care, because of the new possibilities even software updates can be detected in internal machine data.

But one big issue is that only a few injection moulding machines, like a Krauss Maffei equipped with a DataXplorer, currently allow to collect all internal machine data and most important to easily export them. Therefore there is a lot of ongoing development on the market to export process data from the injection moulding machines and peripheral devices through uniform interfaces, like the several Euromap interfaces. Euromap 77 is one solution for a faster, easier and standardized exchange of data, but the sample frequency is limited to 10 Hz (to our knowledge), which is probably too poor for the use in a ML based process management system for injection moulding. Furthermore just the most modern machines are equipped with this interface. Euromap 63 is an alternative, but is less standardized and the sample frequency is still limited.

Other solutions needs to be found and therefore an attempt was made to collect internal machine data from a Engel e-victory injection moulding machine, with the same sample frequency as the DataXplorer provides its data. In cooperation with Siemens and Engel a first possible workflow was established, where an Industrial Computer (IPC) is connected to the injection moulding machine and gathers process data packages directly from the machine controller and uploads them into Siemens Mindsphere. Another advantage of having all the data samples in the cloud is the ability to use it live for the ML based process management system, even from several different machines.

References

1. Brexeler, I., Kruppa, S. et al.: Mehrwert in der Praxis: Intelligente Nutzung von Prozess- und Maschinendaten aus der Spritzgiessproduktion. In: VDI-Jahrestagung Spritzgiessen, Baden-Baden, 20./21.02.2018
2. Baomarand, H., Bentley, P.J.: An intelligent autopilot system that learns piloting skills from human pilots by imitation. In: 2016 International Conference on Unmanned Aircraft Systems (ICUAS), Arlington, VA, USA, pp. 1023–1031 (2013)
3. Baomarand, H., Bentley, P.J.: An intelligent autopilot system that learns flight emergency procedures by imitating human pilots. In: 2016 IEEE Symposium Series on Computational Intelligence (SSCI), Athens, pp. 1–9 (2016)
4. Baomarand, H., Bentley, P.J.: Autonomous navigation and landing of airliners using artificial neural networks and learning by imitation. In: 2017 IEEE Symposium Series on Computational Intelligence (SSCI), Hawaii, USA, (2017) (accepted)

5. Baomarm H., Bentley, P.J.: Autonomous landing and go-around of airliners under severe weather conditions using artificial neural networks. In: The 2017 International Workshop on Research, Education and Development on Unmanned Aerial Systems (RED-AUS), Linköping, Sweden (2017) (accepted)
6. Piot, B., Geist, M., Pietquin, O.: Bridging the gap between imitation learning and inverse reinforcement learning. IEEE Trans. Neural Networks Learn. Systems. **28**(8), 1814–1826 (2017)
7. Ehrig, F., Schuster, G.: Machine Learning zur Erkennung von Veränderungen beim Spritzgiessprozess. In: VDI-Jahrestagung Spritzgiessen, Baden-Baden, 19./20.02.2019