World Academy of Science, Engineering and Technology
International Journal of Industrial and Manufacturing Engineering
Vol:7, No:7, 2013

Open Science Index, Industrial and Manufacturing Engineering Vol:7, No:7, 2013 publications.waset.org/16381.pdf

Rapid Data Acquisition System for Complex Algorithm Testing in Plastic Molding Industry

A. Tellaeche and R. Arana

***Abstract*—**Injection molding is a very complicated process to monitor and control. With its high complexity and many process parameters, the optimization of these systems is a very challenging problem. To meet the requirements and costs demanded by the market, there has been an intense development and research with the aim to maintain the process under control. This paper outlines the latest advances in necessary algorithms for plastic injection process and monitoring, and also a flexible data acquisition system that allows rapid implementation of complex algorithms to assess their correct performance and can be integrated in the quality control process. This is the main topic of this paper. Finally, to demonstrate the performance achieved by this combination, a real case of use is presented.

***Keywords*—**Plastic injection, machine learning, rapid complex algorithm prototyping.

I. Introduction

INJECTION molding has been a challenging process for many manufacturers and researchers to produce products meeting requirements at the lowest cost. Its complexity and great quantity of process parameter manipulation during real time production demands a lot of dedication to maintain the process under control, usually originating problems and high manufacturing costs.

Generally, quality characteristics in injection molding are classified as mechanical properties, measurable characteristics, and other attributes. In general, some of the main causes of quality problems are material related defects.

Factors that affect the quality of a molded part can be classified into four categories: part design, mold design, machine performance and processing conditions. The part and mold design are assumed established and fixed.

In production, quality characteristics may deviate due to drifting or shifting of processing conditions caused by machine wear, environmental change or operator fatigue.

Optimizing process parameter problems is routinely performed in the manufacturing industry, particularly in setting final optimal process parameters. Final optimal process parameter setting is recognized as one of the most important steps in injection molding for improving the quality of molded products. However, no matter how well is the process adjusted, it is still possible to obtain bad quality parts originated by changes in the raw material properties, errors in the components of the machine due to intensive use, etc.

Taking into account the global market competition it is fundamental to detect part fabrication errors as soon as possible. These errors can be inferred and detected using machine learning algorithms to monitor the process parameters.

The use of machine learning algorithms is justified because of the inherent complexity of the process and its variables, as explained in previous paragraphs.

Although the convenience of use of these algorithms has been explained, the state of the art in quality control in this type of industry presents an important problem. All the systems specifically used in plastic injection molding machines present a closed architecture; they do not present an open interface for developing new algorithms. From this point of view the testing of new advanced algorithms is impossible, and users have to stick to the possibilities these equipments give to them. Under these premises, the development of an open architecture that makes the data acquisition and algorithm development possible is a great advance beyond the state of the art.

After the introduction, a state of the art presents studies of use of advanced algorithms in plastic injection related problems. The solution proposed for data acquisition and algorithm testing is explained in Section III. Finally, a case of use using machine learning algorithms is presented in Section IV, and results and conclusions in Section VI.

II. State of the Art

In the last years, several approaches have been used to determine the process parameters and mold design.

These research based approaches include the Model based classical control, Taguchi techniques, Artificial Neural Networks (ANN), Fuzzy logic, Genetic Algorithms, Support Vector Machines, Finite Element Method, Response Surface Methodology, Case Based Reasoning (CBR), Grey Rational Analysis and Principal Component Analysis.

In [1]-[3], several studies using the Taguchi method can be found. In these articles, this method is used for optimization of machine parameters and quality characteristics.

In [4]-[8] are explained some developments that have the artificial neural networks. These networks are principally used for process modeling, parameter optimization and quality production.

Fuzzy Logic is applied in [9] mainly to predict the flash caused by mixed materials.

A. Tellaeche is with IK4 – Tekniker Research Center, Eibar, 20600 Gipuzkoa, Spain, in the Smart and Autonomous Systems Unit (phone: 303-555-5555; fax: 303-555-5555; e-mail: alberto.tellaeche@tekniker.es).

R. Arana is also with IK4 – Tekniker Research Center, Eibar, 20600, Gipuzkoa, Spain, in the Smart and Autonomous Systems Unit (e-mail: ramon.arana@tekniker.es).

An application of Genetic Algorithms in the plastic injection molding industry can be found in [10], to optimize the parameters of the process.

The method known as Response Surface Methodology is applied in [11] and [12]. This method relates known process variables with output variables to create a non-linear model of the process, used afterwards to control the process.

In [13] and [14] rule based expert systems and case based reasoning techniques are used to design plastic injection processes.

Finally, Linear Regression Models are used in [15] to predict production, and finally, in [16] Support Vector Machines are used for quality monitoring of the process.

The majority of the cases presented in the paragraphs above are research studies that justify the correct performance of advanced techniques for quality control, among which machine learning plays an important role. However, many of them have not been implemented in a real industrial environment. This research covers this step, implementing machine learning algorithms in a real industrial environment.

III. Proposed System Description

Industrial monitoring equipment offer simple algorithms to control process that may be efficient for general purpose but that lack for high demanding requirements. In these last cases ad-hoc designed algorithms by academia or by specialized agents are many times analyzed and developed but hardly tested on real production environments.

The proposed system offers a solution that is able to integrate new algorithms developed in different ways and in different platforms into real industrial environments for its testing and validation.

Commercial equipments use discrimination levels based in rigid threshold levels configured by the operator. Example of this type of detection algorithms are shown, like the bandwidth where a signal is controlled in a narrow area superimposed to a learned curve in a good part, or the boxes, where again the signal is controlled by defining passing through areas with a dispersion.

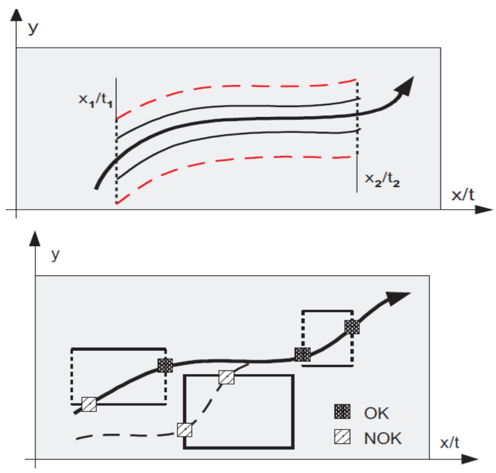

Fig. 1 Quality Control using threshold levels

Another approach followed by industrial monitoring equipment is based on statistics. The quality bands for pressure and temperature values are defined taking into account the correct values of these parameters in the good parts and performing mean and standard deviation calculations. Taking this approach further, multivariate statistics can be used establishing relations among monitored variables. In this last case the available equipment found is typically bi-variable, taking in to account only two variables for correlation analysis.

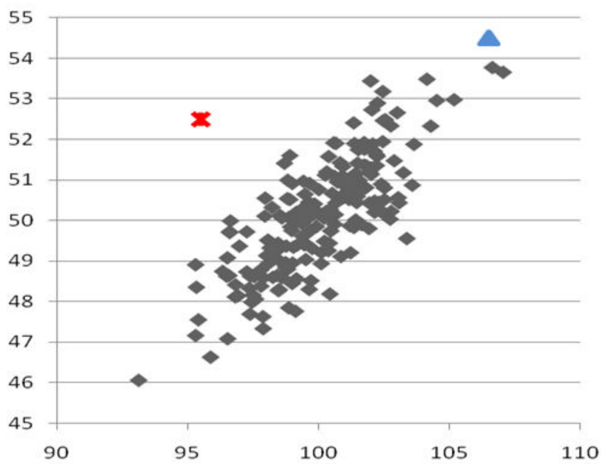

Fig. 2 Bi variable statistics for quality control and two conflictive parts in the limit (X, and triangle)

These equipments are not usually prepared to give response to the variability of production variables like stops, changes in raw material, etc. giving false alarms. In academic research interesting approaches can be found to solve this variability using novel techniques like the previously explained algorithms. Unfortunately these solutions are rarely implemented in real industrial environments since there is no possibility to test them feasibly.

The system presented is designed with this objective. The goal is to be able to test online in the factory new developments and to validate them. This approach is being used for plastic injection process monitoring but it is not exclusive for it. It could also be used as a generic purpose process monitoring testing platform for different processes.

In Fig. 2 the schema to solve the integration of the presented system with plastic injection machines is shown. The main parts are the interface with the machine, the data acquisition and the data processing.

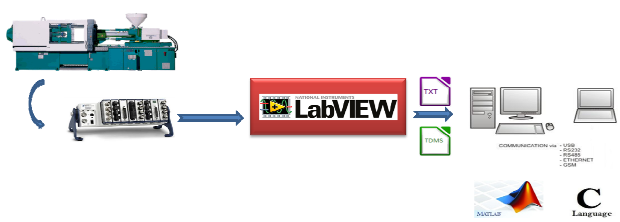

Fig. 3 Integration scheme of the proposed system with plastic injection machines

Open Science Index, Industrial and Manufacturing Engineering Vol:7, No:7, 2013 publications.waset.org/16381.pdf

Open Science Index, Industrial and Manufacturing Engineering Vol:7, No:7, 2013 publications.waset.org/16381.pdf

For data acquisition and processing in the proposed platform, a National Instrument (NI) cDAQ-9188 8 slot chassis has been used. The system is equipped with a four generic analogue 24-bit resolution inputs used for pressure sensors, a thermocouple card for temperature registration and a digital I/O card to interface the machine.

These module boards used in the slot are specifically designed for specific types of sensor, and contain inside the signal converter, connectivity and signal conditioning electronics (amplification, filters, isolation, etc) in a robust module. Finally, this slot is connected by an Ethernet connection to a PC or laptop.

This hardware, with the NI LabView graphical programming language running in the laptop delivers data ready to be processed by the tested algorithms. The data, before being processed, are again conditioned: filtered for noise removal using a Butterworth filter (1), down sampled, etc.

$$|H(\Omega)|^2 = 1 / (1+(\Omega / \Omega_c)^{2N}) \quad (1)$$

H is the frequency response of the filter, and Ωc is the cutoff frequency. N is the order of the filter.

In terms of research in quality control algorithms, they are commonly developed using different techniques and tools. Tools like Matlab, programming languages like C++, C#, Java or Python, are used and tested via desktop applications.

Programming in LabvView offers many possibilities to interact with all these approaches, such as the use of DLL´s, wrappers for Matlab or Python within LabView, launch of executable files, etc. Another general approach is the use of TCP/IP mechanisms between different processes for data processing.

Taking in to account the characteristics of this architecture, this platform is a rapid system for data acquisition and validation of complex algorithms.

IV. Industrial Case of Use

The main objective of the system developed is to detect injection machine deviations, taking into account the pressure curves obtained by indirect measurement in the mold. Monitoring the pressure curves, there are two main objectives, to assess the quality of the plastic piece being injected and to monitor machine tendencies that could derive in erroneous injection process and bad quality parts.

The full automatic process of data acquisition and analysis can be summarized in the following steps:

1. Sensor selection and placement within the mold.
2. Setup of the data acquisition system.
3. Recording of in-process signals and signal conditioning for system training.
4. System training and performance evaluation.

In the following subsections the different steps will be explained in detail.

A. Sensor Selection and Placement within the Mold

To monitor pressure in the mold, two Kistler 9204B force sensors have been selected for mold monitoring. Their characteristics are the following:

TABLE I
Force Sensors Characteristics

Specifications	Type 9204B
Model	Miniature Sensor
Calibration	calibrated
Measuring Range (kN)	0...10
Sensitivity (pC/N)	≈-1.6
Natural Frequency (kHz)	≈80
Cabling	single-wire/coaxial
Cable is exchangeable	Yes
Operating temperature range (ºC)	-50...200
Diameter (mm)	12.6
Height (mm)	9.5
Mass (g)	6

These two indirect sensors located just behind the ejectors of the mold offer the possibility to be adequate substitutes for the direct sensors. Among all the ejectors present in the mold, two are chosen, one on each cavity. The ejector selected is the closest to the entrance on the melted plastic material so that it is possible to obtain pressure information in the whole cycle.

This placement of the sensors is decided by user experience or using simulation software such as Moldflow.

Fig. 4 Detail of the mold used and the sensor placement

B. Setup of the Data Acquisition System

In this case of use, the following signals have been used:

1. Machine signals: synchronism digital signals, trigger of the injection cycle, start of the first injection, start of the second injection. Acquired with the I/O module NI 9403.
2. Pressure (Force) signals: Acquired with the analogic module NI 9239.
3. Temperature signals: J type thermopairs, acquired with the module NI 9211.

A detail of the signals obtained for various cycles can be observed in Fig. 3 (X axis are samples, Y axis is voltage output).

Open Science Index, Industrial and Manufacturing Engineering Vol:7, No:7, 2013 publications.waset.org/16381.pdf

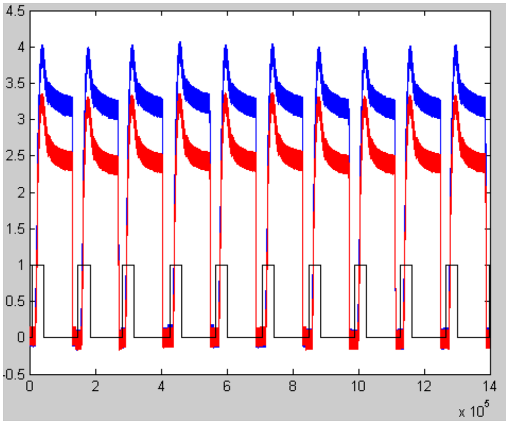

Fig. 5 Two pressure signals (2 sensors) and digital signal recorded in plastic injection process

Once the pressure signals have been acquired, post processing operations are carried out to extract usable information of individual part cycles to be used in the machine learning algorithms.

Taking into account the machine signal correspondent to the trigger of the injection cycle and the sampling rate used of 5kHz, it is possible to isolate the pressure signals of each cycle. The acquired signals also have a 50Hz noise with 0.3V amplitude. This noise is inferred by the mounting of the mold, based on an electromagnetic field.

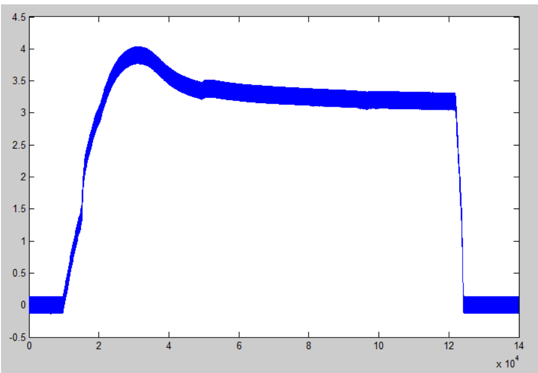

Fig. 6 Single cycle pressure signal with added noise

Using a $N = 5$ order Butterworth filter and $\Omega_c = 2.5$ kHz (by the Nyquist Theorem), the resulting signal is a pure pressure signal, as shown in Fig. 5.

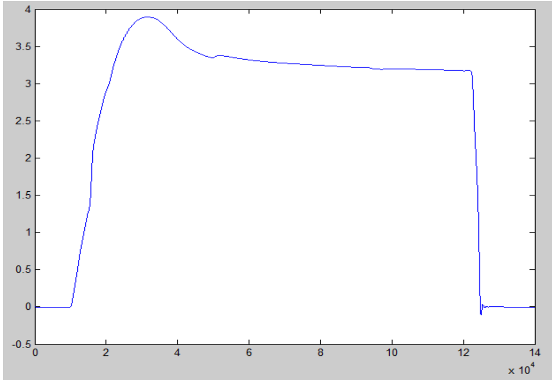

Fig. 7 Pure pressure signal without noise

The final signal down sampled has 14000 points for 25s.

C. Machine Learning Techniques for process Monitoring

Process samples have been acquired in three days, during three months, always using the same plastic injection machine and the same mold. The sample acquisition has been spread in time with the aim of recording process variability due to changes in raw materials, changes in machine, etc.

A total amount of 237 pressure cycles have been recorded and processed as stated in the previous section. Of the total amount of signals, 152 correspond to correct fabricated parts and 85 to faulty pieces, obtained with machine parameter variations. The changes in raw material, makes the process non repetitive, thus, two correct signals of different days present different gains in pressure values, for example.

With the 237 signals, a signal database has been generated, with the signals classified as good parts or bad parts. Each signal in the database is a vector of 14000 values, and a binary value, assigned the value true if the signal corresponds to a good part or false if corresponds to a bad part.

With the database created, a typical machine learning, bi-class classification problem appears.

In this work, various different approaches of classification algorithms have been used and implemented in the system, to assess their performance y real time part production:

1. Supervised Learning:

a. Statistical classifier: Naïve Bayes.
b. Decision trees: C.4.5.
c. Kernel based classifiers: Support Vector Machines (polynomial kernel, radial basis function kernel).

2. Non Supervised Learning:

a. Clustering (1NN, 3NN, 5NN)

V. Results and Conclusions

To assess the performance of the machine learning algorithms used in this research, the 10 fold cross validation method has been used, with the full database of 237 samples.

The objective is to detect a faulty part analyzing its pressure fingerprint.

The results obtained are shown in Table II, showing the percentage of correct classifications performed by a classifier.

TABLE II
PERFORMANCE OF MACHINE LEARNING ALGORITHMS

Classifier	**Correct classification percentage**
Naïve Bayes	40.4 %
C4.5 decision tree	92.24 %
SVM polinomial	**93.46 %**
SVM RBF	87.34 %
1NN Clustering	**93.46 %**
3NN Clustering	91.83 %
5NN Clustering	91.02 %

Analyzing the result, Naïve Bayes classifier gives a very poor performance; this is due to the fact that the samples in the database do not comply with a Gaussian distribution. On the other hand, using SVMs and Clustering techniques perform above 93%. This correct classification percentage is acceptable for in line quality control. Taking in to account that SVM is a supervised approach trained previously, it does not increase decision time when feeding the data base with more signals, provided an offline training is done to learn the new data set. Clustering techniques increase decision time with bigger databases, so SVM are the best option for real time quality control in the case of use presented in this paper.

REFERENCES

[1] Chung-Feng J. K., Te-Li S, “Optimization of multiple quality characteristics for polyether ether ketone injection molding process”, Fibers and Polymers, Dec 2006, Volume 7, Issue 4, pp 404-413.
[2] Chung-Feng J. K., Te-Li S., “Optimization of Injection Molding Processing Parameters for LCD Light-Guide Plates”, Journal of Materials Engineering and Performance, Oct 2007, Volume 16, Issue 5, pp 539-548.
[3] Oktem, Tuncay Erzurumlu, Ibrahim Uzman, “Application of Taguchi optimization technique in determining plastic injection molding process parameters for a thin-shell part”, Materials & Design, Volume 28, Issue 4, 2007, Pages 1271–1278.
[4] Jie-Ren S., “Optimization of injection molding process for contour distortions of polypropylene composite components by a radial basis neural network”, The International Journal of Advanced Manufacturing Technology, April 2008, Volume 36, Issue 11-12, pp 1091-1103.
[5] Sadeghi B.H.M., “A BP-neural network predictor model for plastic injection molding process” Journal of Materials Processing Technology, Volume 103, Issue 3, 17 July 2000, Pages 411–416.
[6] Ozcelik B., Erzurumlu T.,” Comparison of the warpage optimization in the plastic injection molding using ANOVA, neural network model and genetic algorithm”, Journal of Materials Processing Technology, Volume 171, Issue 3, 1 February 2006, Pages 437–445.
[7] Shi F., Lou Z.L., Zhang Y.Q., F. Shi, Lu J.G., “Optimisation of Plastic Injection Moulding Process with Soft Computing”, The International Journal of Advanced Manufacturing Technology, June 2003, Volume 21, Issue 9, pp 656-661.
[8] Chen W.C, Tai P.H., Wang M.W, Deng W.J., Chen C.T. “A neural network-based approach for dynamic quality prediction in a plastic injection molding process”. Expert Systems with Applications, Volume 35, Issue 3, October 2008, Pages 843–849.
[9] Zhu J., Chen J.C., “Fuzzy neural network-based in-process mixed material-caused flash prediction (FNN-IPMFP) in injection molding operations” The International Journal of Advanced Manufacturing Technology, June 2006, Volume 29, Issue 3-4, pp 308-316.
[10] Shi F., Lou Z.L., Zhang Y.Q, Lu J.G, “Optimisation of Plastic Injection Moulding Process with Soft Computing” The International Journal of Advanced Manufacturing Technology. June 2003, Volume 21, Issue 9, pp 656-661.
[11] Mathivanan D., Parthasarathy N.S. “Prediction of sink depths using nonlinear modeling of injection molding variables“, The International Journal of Advanced Manufacturing Technology, August 2009, Volume 43, Issue 7-8, pp 654-663.
[12] Mathivanan D., Parthasarathy N.S., “Sink-mark minimization in injection molding through response surface regression modeling and genetic algorithm” The International Journal of Advanced Manufacturing Technology, December 2009, Volume 45, Issue 9-10, pp 867-874.
[13] Kwong C.K., Smith G.F., “A computational system for process design of injection moulding: Combining a blackboard-based expert system and a case-based reasoning approach” The International Journal of Advanced Manufacturing Technology, 1998, Volume 14, Issue 5, pp 350-357.
[14] Shelesh-Nezhad K., Siores E. “An intelligent system for plastic injection molding process design” Journal of Materials Processing Technology, Volume 63, Issues 1–3, January 1997, Pages 458–462.
[15] DasNeogi P., Cudney E., Adekpedjou A., “Comparing the Predictive Ability of T-Method and Cobb-Douglas Production Function for Warranty Data”, ASME 2009 International Mechanical Engineering Congress and Exposition (IMECE2009) , November 13–19, 2009 , Lake Buena Vista, Florida, USA.
[16] Ribeiro B., “Support vector machines for quality monitoring in a plastic injection molding process”, IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Aug 2005, Volume 35, Issue 3, Pages 401 – 410.

Alberto Tellaeche holds a M.Sc in Automation and Electronics Engineering, obtained in the University of Deusto (2001), and a Ph.D. in Systems Engineering and Automation from the Computer Science faculty in the UNED (2008), obtained with a research based in machine vision and pattern recognition techniques.

In april 2007 he joined IK4 Tekniker as a researcher, in the Smart and Autonomous Systems unit, working in machine vision and pattern recognition systems.

He has numerous papers in peer reviewed international journals and contributions to several congresses related to his field of expertise.

Open Science Index, Industrial and Manufacturing Engineering Vol:7, No:7, 2013 publications.waset.org/16381.pdf