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Conceptual Framework for Development of Intelligent Control Systems for Thermoplastics Injection Molding

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Abstract. Injection molding is one of the most widely used processes for production of plastic parts. It allows manufacturing of products of various shapes and sizes with high efficiency and production rates. However, setting up process parameters for manufacturing high-quality items and no in-process variation is often a tricky task, which is usually solved using the trial-and-error method and the experience of injection molding machine operators. Such an approach has several disadvantages, as it requires a significant amount of time, also it might lead to production of scrap. An intelligent monitoring and control system for thermoplastics injection molding can be implemented to avoid this. The article presents a conceptual framework for development of such system using a systems engineering (SE) approach. The system would allow the collection, storage and analysis of injection molding process data in order to predict the quality of produced parts without the need for the application of the trial-and-error method. Machine Learning methods are proposed to be a part of the computational core. The article lists stakeholders' needs relevant for the system, defines the problem at hand, introduces what needs to be done and what has been done to find a relevant solution. Lack of use of the SE during design and development of similar systems might lead to creation of a system that is not workable, lacks required functionality or parts of it fail to work together.

Keywords: Injection Molding, Intelligent Control, Machine Learning, Systems Engineering.

1 Introduction

Injection molding is one of the most wide-spread processes used for production of plastic parts. It is responsible for over 30% of all plastic products being produced [1]. High quality and repeatability of the process are extremely important for mass production. Selection of improper settings of machine and process parameters will lead to various defects and result in production of parts that are waste of material [2, 3].

Thermoplastics injection molding includes four main stages: plasticization, injection, cooling and ejection. The cooling stage is the one taking most of the time during the process: from 50% to 80% of the cycle time [4]. Due to a high number of changes that plastic material undergoes, it is not easy to have a full control over the process. Therefore, monitoring and control of in-process variations and understanding which exactly parameter values are responsible for getting an unsatisfactory output is not a simple task. It is often attempted to be solved through trial-and-error method based on assumptions of experienced machine operators.

Development of an intelligent control system that would facilitate these functions would be beneficial. It is important to precisely design, measure and monitor the process to make the key variables observable and controllable [5]. This will allow to increase controllability and repeatability of the overall process, as well as to decrease need in use of trial-and-error method while starting production with use of a new mold. In addition, this will allow to predict quality of the produced part with a current set of machine parameters.

The control system can use critical injection molding machine parameters, as well as temperature and pressure data from sensors embedded in the mold (if available) in order to predict quality of the part with the current set of parameters. The system will apply Machine Learning (ML) methods for creation of classification and regression models of the process, as these methods are able to give a better performance in comparison to conventional statistical methods and, in addition, are capable of coping with high level of complexity of the mathematical models [6].

To develop a system of this kind it would be beneficial to have a conceptual framework that would facilitate its implementation. The main objective of this paper is to present a corresponding framework through application of a systems engineering methodology.

2 Systems Engineering Methodology

Systems engineering enables the successful development, realization, use and retirement of engineered systems. This is achieved using systems principles and concepts, as well as various relevant technological and scientific methods [7]. SE is known to be applied for development of a large number of different technical systems related to various domains, such as the commercial aircraft [8], future integrated factories [9], maintenance of railway vehicles [10], environmental systems [11], digital twin concept for oil storage tanks [12] and many others.

In this paper SE methodology called SPADE [13] will be used. The acronym stands for: Stakeholders, Problem, Alternatives, Decision-making, and Evaluation [13]. Stakeholder in this case is any group or individual that can affect or be affected by the system at hand [14]. The SPADE methodology is chosen due to its ability to consider needs of various stakeholders and identifying potential system improvements [13].

Application of SPADE to support development of the framework for the control system of interest will be shown throughout sections of the paper divided as follows:

- the main stakeholders and the problems related to the system's development;
- analysis of what has been done and what needs to be done for development of the system of interest;
- discussion of the decisions and evaluation of the system.

3 Stakeholders and Problems

According to Aven and Renn [15] a stakeholder is any individual, group or organization that may affect or be affected by decisions related to the system of interest. To define different types of stakeholders, it is possible to measure their attributes such as power, urgency and legitimacy [16]. Table 1 shows stakeholders of the intelligent control system for thermoplastics injection molding and their needs.

Table 1. System's stakeholders

Stakeholders	Needs
Academia/ researchers	• New knowledge that can be beneficial for ongoing and future research on the topic; • Publication of research articles.
Injection molding companies	Control system that: • is able to predict quality of manufactured parts; • facilitates monitoring and control of process parameters.
Injection molding machine manufacturing companies	• A control system solution that can be commercialized and will have a high demand.
Customers of injection molding companies	• High quality of injection molded parts; • Short delivery times.
Standards/ Regulations	• Systematic research.
Environment, community, society	• Reduction of the negative environmental impact through elimination of plastic waste.

As it is easy to see from Table 1 that there are two main categories of stakeholders: academia/ regulatory bodies and industry. The first category is interested in obtaining more systematic knowledge on the matter at hand and the second one – an increased efficiency and controllability of the injection molding process, as well as reduction of waste.

When it comes to the problems that the intelligent system is to solve, it is important to remember that (a) when starting production of a plastic part, the process parameters are often set through trial-and-error method; (b) parameters' values affect productivity, cycle time, as well as energy consumption and (c) modern injection molding machines are still not able to detect and eliminate unnecessary variations in process parameters [16], neither are they able to define if the used set of parameters is going to result in production of defected parts. Therefore, the main functions of the intelligent control system for thermoplastics injection molding are:

- monitor and log production process data from injection molding machine, as well as temperature and pressure data from sensors in the mold (if available);
- process data and build a classification model to predict whether produced part is with or without defects;

- process the data and build a regression model to predict values of various quality parameters of the manufactured parts, such as width, thickness (dimensional properties) and Young's modulus, Tensile strength (mechanical properties);
- store created models to reuse them, when current combination of mold and material is used next time.

4 Analysis

4.1 What has been done?

In order to develop a system that is able to perform the functions listed in the previous section collection and analysis of the production process data is necessary. Most of the scholars discuss the analysis part without focusing much on the data collection, as various commercial systems are available for these purposes. Ogorodnyk et al. [17], however, propose an open application programming interface that can be used with injection molding machines without necessity of acquiring costly commercial solutions.

Since modern injection molding machines allow collection of large amounts of process data, it is natural to assume that application of Machine Learning methods for their analysis would be rather beneficial. These methods, unlike more classical methods such as finite element method (FEM) or response surface methodology, are able to map complex non-linear relationships and handle multi-dimensional data, as well as data of different types. The models developed using ML can be used for process automation and be a subject for continuous improvement when more relevant data is obtained.

A significant number of scholars provide successful examples of Machine Learning application for prediction of parts quality. Chen et al. [18] compare two models used as dynamic quality predictors for the injection molding process. The first one uses combination of a Self-organizing Map (SOM) and an Artificial Neural Network (ANN), while the second one is a pure ANN model.

Manjunath and Krishna [19] use an ANN model for forward and reverse mapping. In the forward mapping, holding pressure, injection speed, mold temperature and melt temperature parameters were used as input variables for prediction of dimensional shrinkage of the injection molded parts. In the reverse mapping, values of an appropriate set of process parameters were predicted to reach certain quality of the part.

Lotti et al. [20] use design of experiments (DOE) to plan experiments for the data collection and ANNs to create models for prediction of shrinkage of produced parts. Artificial Neural Network has four input parameters: melt and mold temperatures, holding pressure and flow rate. Yin et al. [21] compare performance of an ANN with the FEM. Developed models are used for prediction of warpage of an automobile glove compartment cap and optimization of mold temperature, melt temperature, holding pressure, holding time and cooling time. Simulation time used by the ANN is significantly shorter than the one used by FEM.

Zhu and Chen [22] develop a fuzzy neural network-based in-process prediction system. The system is used for prediction of flash defect occurrence during injection molding. Kozjek and Kralj [23], on the other hand, propose a data mining approach for the identification of complex faults, such as unplanned machine stops. They apply decision trees, random naïve Bayes and k-nearest neighbors ML methods. The results show that the interpretation capacity of the tested methods is high and that they can be effectively used to reveal patterns related to the faulty operation conditions.

4.2 What needs to be done?

To create a system that will be able to perform the functions mentioned in the Section 3, it is necessary to include the following main components: interface, database, application programming interface (API) for communication with the injection molding machines and the calculation core. Schematic representation of the system components and their connections is presented in Fig. 1.

The **interface** is needed to facilitate user experience with the system: accept the user inputs, as well as display and obtain the system's outputs. **API** will be used to establish communication between the system and the injection molding machine(s), obtain the necessary process parameter values and store them in the database. The **database** is needed to store the data recorded during the production process either through the API or from a file uploaded by users, as well as to save the models developed using the system's calculation core. The **calculation core** should have access to the database and be able to analyze this data to create and maintain the quality prediction models, as well as to make predictions. Fig. 1 shows simplified flows of data between the above-mentioned components, where the color of the arrows corresponds to the color of the components the data originates from (orange – system's interface, blue – computation core, yellow – API, gray – database), while green color is a user input, which is entered through the system's interface.

To reach the goal of standardizing and universalizing the system it is also necessary to adjust the monitoring and control system in such a way that it will be possible to use it with machines from different manufacturers.

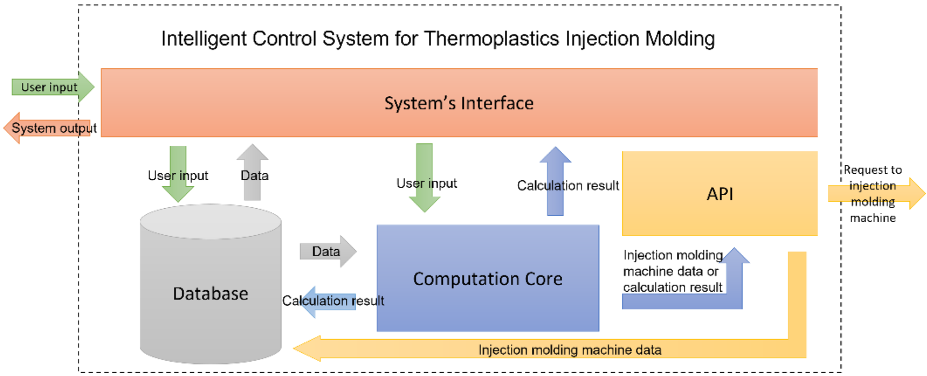

Fig. 1. Intelligent Control System for Thermoplastics Injection Molding [24].

5 Decision-making and Evaluation

When the project is completed, it will be necessary to analyze performance of the system and to understand how well the proposed solution meets previously defined stakeholders' needs and requirements. To be able to do this, it is necessary to define so-called measures of effectiveness (MOEs). One of the definitions of MOEs is standards that allow to understand how well certain solution meets requirements of stakeholders [25]. Table 2 shows possible measures of effectiveness for classification and regression models that will be created with help of the control system discussed in the paper.

Since classification and regression models are completely different, they need different measures of effectiveness. Models of the first type need measures that will show how often the classification model makes mistakes and what is the rate of classifying good parts as bad and vice versa (e.g., confusion matrix, accuracy, precision and receiver operator characteristics (ROC)). The regression models, on the other hand, need to be assessed through the measures that reflect their performance on the data they were developed on and on previously unseen data. In this case, R^2, root mean square error (RMSE) and correlation coefficient suite well as the model quality measures. If quality of the models generated by the control system is high, it would mean that control system works as required. If the models' performance is poor, control system needs to be modified until the quality becomes satisfactory. System's stakeholders might be the ones to decide what is the acceptable level of the proposed MOEs.

If a regression model for prediction of width and thickness of the produced parts is developed, stakeholders might decide that the acceptable level of RMSE is 0,001 mm and Pearson's correlation between the measured and predicted values should not be lower than 0,9. In this case, RMSE and Spearman correlation coefficient values of the developed model will be compared with the defined threshold values and effectiveness of the system decided accordingly.

Table 2. Measures of effectiveness.

Model type	MOE
Classification	Confusion matrix
	Accuracy and/or Precision
	Receiver operator characteristics (ROC)
Regression	Root mean squared error (RMSE)
	Correlation coefficient (Spearman, Pearson)
	R^2

6 Conclusions

Injection molding is used for mass production, it needs to be repeatable and requires manufactured products to be of high quality. However, the process is rather complex and is influenced by a lot of process parameters. The quality of a final part depends on each of them, so, process monitoring and control are of high importance. ML methods can be beneficial for design of a model used for control, as they are able to deal with large data sets and multi-dimensional data, as well as suite well for process automation.

At the same time, the system designed in the proposed way will have certain limitations. The first one is **the necessity to acquire large amounts of production data**. Without the data no meaningful ML models for control of the injection process can be developed. The second issue is **time and computation demand**. The more data will be used to train the models, the more time and resource consuming this process will become. The third limitation is **interpretability of the models**, as some of the ML models might be hard to interpret for a human being and appear as "black boxes". In addition, **data or concept drift** might occur resulting in necessity of re-training the model. Therefore, it is important to establish routines for timely maintenance of the system and the prediction models that are its part.

To successfully design and develop such system, it is necessary to clearly understand what its purpose is, which behavior it needs to follow, which functions to perform, which elements to include and so on. Systems engineering is a meaningful approach to design the system and the SPADE methodology, in particular. Following the suggested methodology steps, stakeholders and their needs were identified, problem has been formulated and described through analyzing what needs to be done, what has been done by others and identifying measures of effectiveness for future evaluation of the system.

It is necessary to mention that lack of the systems engineering approach such as SPADE during design and development of similar systems might lead to creation of a system that is not workable, lacks required functionality or parts of it fail to work together. Intelligent control system for thermoplastics injection molding is no exception, as any other system, it also needs a systemic approach on the design phase.

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