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Monitoring and control for thermoplastics injection molding A review

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Abstract

Thermoplastics injection molding has found increasing use in several industry sectors. To achieve high effectivity of the process and desirable quality of the manufactured product, correct and precise parameters' setting is critically important. As injection molding is a sophisticated process it is often hard to take care of all the changes occurring during its application. However, implementation of artificial intelligence (AI) methods in control and monitoring systems of injection molding machines can increase controllability and additivity of the process. This paper gives an overview of different studies related to research on the topic of monitoring and control systems for injection molding and explains why application of AI methods would be beneficial.

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Keywords: Injection molding; Artificial intelligence methods; Intelligent process monitoring and control; Intelligent heat management.

1. Introduction

Today more than one third of polymeric products is produced with use of injection molding [1]. It is a complicated process, as the molten polymers undergo complex thermo-mechanical changes. As injection molding is mostly used for mass production, repeatability and quality of the final product is very important. *"Improper settings of process variables will produce various defects in the final product"* [2, 3] and result in increased amounts of waste and scrap. As need for control of the injection molding process is high, the first step in this case is to precisely design, measure and monitor the process to make the key process variables observable and controllable [4]. This will allow to increase controllability and repeatability of the overall process, leading to possibility of lowering probability of unnecessary in-process variations.

The process of injection molding includes four main stages: plasticization, injection, cooling and ejection. Among these four, the cooling stage takes from 50% to 80% of the cycle time [5]. It has always been of a high interest to shorten overall cycle time, as *"the cost-efficiency of the process is dependent on the time spent in the molding cycle"* [6]. One of the ways to shorten the cycle time and, in particular, the cooling stage, without compromising quality of manufactured parts is use of rapid heating and cooling systems, which can include application of variotherm technology and conformal cooling/heating channels.

Process monitoring and control, as well as use of variotherm technology or conformal cooling/warming channels would benefit from application of artificial intelligence methods in order to function in the most optimal way. The following sections will explain importance of monitoring and control systems, give examples of research on these systems and explain why AI methods are of a high importance for the injection molding.

2. Injection molding process variables and artificial intelligence methods

According to Karbasi and Reiser [4], the injection molding process includes three nested process loops shown in Fig. 1. The first loop called machine control includes control of **machine parameters**, such as speed, pressure and temperature.

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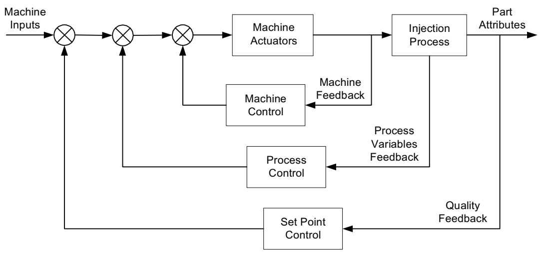

Fig. 1. Injection molding control loops [4].

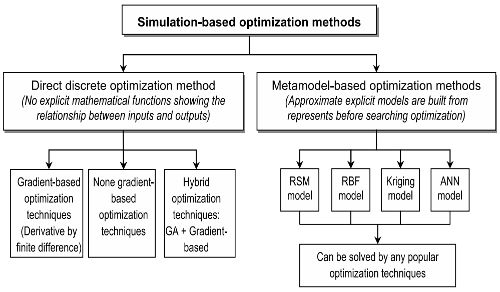

Fig. 2. Classification of optimization methods [12]

The middle one (process control) includes such **variables as in-mold temperature and pressure**. The last loop, which is called set point control, takes care of **part quality feedback**.

Machine control loop is the most developed one, as process variables are handled by the machine manufacturers. The middle loop, on the other hand, is less developed, however, there is significant amount of research going on, while the third one is the least developed, as related development has started only in previous decade [4]. In order to increase controllability of injection molding further work on the three loops is necessary [7]. Among possibilities for process monitoring and control development is application of so-called methods of machine learning or artificial intelligence, for example, neural networks. This would allow to adjust values of necessary variables without involvement of machine operators if conditions change during the manufacturing process. These methods can also be used in rapid heating and cooling systems in micro injection molding [8, 9], as well as in injection molding of bigger components, such as LCD TV frame [10] and automotive interior part [11], for example.

Fast adaptation of important variables to the changed process environment would allow to avoid quality failures in micro injection molding, as well as in molding of large components. This can be done by building a model of the injection molding process or its parts and using the model to adjust current process parameters in order to receive an optimal output during the manufacturing. In other words, through building a self-optimizing injection molding process.

2.1. Artificial Intelligence methods

According to Dang [12], there are two main groups of simulation-based optimization methods, which are direct discrete optimization and metamodel-based optimization methods. The methods and their short description is shown in Fig. 2, where GA stands for genetic algorithm, RSM for response surface methodology, RBF for radial basis function and ANN for artificial neural network. Of course, these are not all the simulation-based optimization methods used.

Among others, in the metamodel-based methods group ANN is mentioned. This is one of the artificial intelligence methods that can be applied to build mathematical models of injection molding process with consideration of the most important parameters.

When the data is analyzed and model is build, the model can be used in order to adjust the current parameters' values to receive a high-quality product as model and process output, as well as to shorten the cycle time.

AI methods give better results when it comes to process modelling and forecasting, as they have higher precision and lower error values compared to conventional modelling methods. In addition, they are not as resource consuming as direct discrete optimization methods [12]. In order to build the model different artificial intelligence methods can be used to process big amounts of data received during the process run.

Artificial neural networks (ANN) is a method that was used for modelling and forecasting in many areas of science and engineering [13]. ANN is a method used for information processing, which includes use of nonlinear and interconnected processing elements called neurons. These elements are organized in separate levels connected with layers' weights. ANNs often consist of three layers: the input layer, the hidden layer and the output layer [14]. At first, the data is "fed" to the network's first layer, in the second layer, it is processed and the model is built, in the third layer the forecast based on the model is handed out as a result of the algorithm's work.

ANFIS or adaptive neural-based inference system is one more method used to create the models and forecasts for certain processes. This method is a composition of artificial neural networks and fuzzy logic approaches. It identifies a set of parameters that the model will be based on using a hybrid learning rule. *"It can be used as a basis for constructing a set of fuzzy If-Then rules with appropriate membership functions in order to generate the previously stipulated input–output pairs"* [14, 15].

Genetic programming can be applied to achieve the same goals. It is a methodology which gives possibility to generate algorithms and expressions to find solution of existing problem. These expressions are represented by a tree structure consisting of leaves/terminals and functions/nodes. When a population of the genetic programming tree is defined procedures similar to the ones used in genetic algorithm are applied. These procedures include defining the fitness function, genetic operators (crossover, mutation and reproduction) and the termination criterion.

These are only three examples of AI methods possible to be applied for injection molding, however, they need to be chosen carefully to fit a purpose of research, as well as parameters or factors used in the model.

2.2. Parameters/factors influencing the quality of injection molded part

Quality of injection molded part depends on a lot of factors and they are related both to plastic material properties and the process parameters [12]. As mentioned before, it is possible to distinguish three groups of injection molding process parameters, while different scholars might use variables from different groups for monitoring and building a model for process control and a framework for injection molding process monitoring. As an example, Shoemaker [16] states that molding conditions comprise melt temperature, mold temperature, filling time, packing time and packing pressure. Karbasi and Reiser [4], on the other hand, use mold and barrel temperatures, velocity profile, screw travel, filling, packing and holding pressure and time as main parameters, while Hopmann, Ressmann [7] and Hopmann, Abel [17] concentrate on consideration of pressure, specific volume and temperature (pvT-behavior) and state that description of these variables behavior gives possibility to describe the link between cavity pressure, melt temperature and resulting part properties.

Parameters considered in the model depend on the part of the process that needs to be controlled and monitored, if the control system is aimed at the overall process, then one group of parameters is important, if the model built will be used to control only cooling and warming of the mold, then other group of parameters should be in focus. Another advantage of AI methods is that they can define which parameters among proposed will be kept in the model and which will be put aside, as they are not influencing the process that much according to the algorithm's calculations. The following section will give an overview of a current status of monitoring, control and heating and cooling systems for injection molding and give examples of use of AI methods for thermoplastics injection molding.

3. Application of AI methods for thermoplastics injection molding

3.1. Heating and cooling systems

There are several techniques that can be applied to reduce time of the cooling stage of injection molding process and increase quality of a produced part. Conformal cooling/heating channels are one of them. They are "conforming" to the shape of the cavity in the mold making it possible to reduce part's temperature faster and more evenly. They allow coolant to access all part locations uniformly, making the process more efficient and consistent [18]. However, they can also be used to increase temperature in the cavity, for example, during injection stage not to allow injected earlier plastics to cool down and solidify too early. This is important for increase of quality of injection molding of parts with very thick and very thin walls. Molds with such channels can be produced using direct metal sintering (additive manufacturing technique), as well as through vacuum diffusion bonding and liquid interface diffusion [19].

Rate of heat exchange is one of the things that need to be payed attention to during design of conformal channels, as it is directly related to the time taken by the cooling phase. *"It is important to understand and optimize the cooling channel design to optimize the rate of heat transfer in an injection molding process"* [20]. In addition, the balance between optimum cooling and insert strength needs to be addressed [21], this is especially important when the mold with conformal cooling channels is manufactured with additive manufacturing technology, as materials used there are often not as strong as conventional ones. As a result, in order to create correct design of conformal heating/cooling channels for a particular mold FEA, thermal heat transfer analysis and different modelling techniques are often used [6, 12].

Application of conformal cooling/heating channels is reported to bring cooling phase reduction in a range from 15% [2] to 50% [22].

Kitayama et al. [23] propose a framework for numerical and experimental examination of conformal cooling channels. To asses cooling performance cycle time and warpage are considered. Melt temperature, injection time, packing pressure, packing time, cooling time, and cooling temperature are taken as the design variables. At first, a multi-objective optimization of the process parameters is performed, then the process parameters of the cooling channel are optimized. A sequential approximate optimization using a radial basis function network is used to identify a pareto-frontier. According to the model with optimized parameters, the conformal cooling channel is produced using additive manufacturing and the experiment is carried out to validate performance of the channel. Wang et al. [24] developed approach for production of spiral and conformal cooling channels with higher flow rate, which increases heat transfer efficiency. Moreover, the channels generated by this new approach are easier to fabricate by using copper duct bending instead of expensive selective laser sintering. He et al. [25], on the other hand, propose a new longitudinal conformal cooling channels design in a B-pillar tool. *"The longitudinal conformal cooling channel design can realize the distance between the channel center and the tool work surface is equidistant which provides a more uniform cooling performance"* [25]. Rahim et al. [26] present the Milled Grooved Square Shape (MGSS) conformal cooling channels which provide more uniform in cooling and have a bigger effective cooling surface area cross sectional area and comparing to circular and others type of cooling channels with similar cross section.

Conventional injection molding usually implies keeping the mold temperature constant during the whole injection cycle. However, variotherm injection molding technique means completely the opposite, because of this it is also called rapid heat cycle molding (RHCM) or rapid thermal response (RTR). *"According to the mold temperature, the whole variotherm injection molding process can be obviously divided into heating stage, high temperature keeping stage, cooling stage, low temperature keeping stage"* [27]. According to variotherm technology, the mold is heated up to resin glass transition temperature before the cavity is filled, during injection and packing stages the temperature should be kept higher than the resin glass transition one to avoid early solidification of polymer. After the packing stage, the mold needs to be rapidly cooled to freeze the polymer melt and prepare the part for ejection, afterwards, the cycle is repeated [27].

Because of complexity of injection molding process, a lot of factors need to be taken into account while applying the variotherm technology. *"For variotherm injection molding, heating and cooling rates are two crucial factors which greatly affect the molding cycle time or injection molding efficiency. So a high effective mold temperature control system is very* *important"* [27]. If the mold has a high temperature during injection stage, but afterwards is quickly cooled down, a lot of problems may occur to the manufactured part: weld mark, sink mark, short shot, flow mark, low gloss, jetting etc. [28-30]. In addition, injection speed, injection pressure and residual stresses need to be under thorough control. As a result, it is hard to find a solution to the problem of dynamical control of the mold temperature.

Investigation in the field of rapid heating and cooling began in the 1960s, when the mold apparatus with additional electric heating source for the mold cavity was invented [31, 32]. Later different variations of variotherm moulds started to appear. Yao et al. [33] developed a rapid heating and cooling system which consisted of a metallic heating layer, an oxide insulation layer, and a mold base. The system was capable of rising the mold temperature from 25^0C to 250^0C in 2 seconds. Fu et al. [8] fabricated a variotherm mold for production of stainless steel microstructures. The mold consisted of a rapid heating/cooling system, vacuum unit, hot sprue and cavity pressure transducer. Chen et al. [30], in their turn, proposed a dynamic mold surface temperature control method, which combines electromagnetic induction heating with coolant cooling. According to the study, with use of the method the mold could be heated from 110^0C to 200^0C in 4 seconds and cooled back to 110^0C in 21 s. Saito et al. [34], on the other hand, used a CO_2 laser to directly heat the resin melt. Wang et al. [27] suggested to use high temperature steam to heat the mold surface and cooling water was used to cool down the mold surface. According to the simulation results, the mold surface can be heated from 30^0C to 140^0C at the central range of the cavity surface in 20 s heating time with saturated steam of 180^0C [27].

The above-mentioned examples show good results, however, they never became widely implemented because of their complexity and necessity to be adjusted for each mold individually. On the other hand, universal monitoring and control system that would be automatically adjusting to different mold forms and process conditions would make implementation of variotherm technology a bit easier. This can be done through application of an intelligent monitoring and control system.

3.2. Monitoring and control systems

Online process monitoring can be destructive and non-destructive. Most of research related to process monitoring in injection molding uses destructive methods. In the last few decades, researchers applied various destructive methods to injection molding process, such as temperature and pressure sensors [35-37], visible mold detectors [38, 39], capacitive transducers [40, 41], fluorescent sensing [42] and near infrared spectroscopy [43].

However, it is also possible to use non-destructive methods, which are not damaging the molds with installation of sensors or other additional equipment, as injection molding machines contain a lot of information about the actual process conditions [44] and the rest might be calculated through use of theoretical models, which describe relation between different injection molding process parameters. Dontula, Sukanek [45], for example, proposed a model, which describes the effect of the machine variables on the melt temperature. Wang, Ying [46], from their side, established an integral mathematical model for the relationship between the packing pressure and the oil pressure in the injection hydro-cylinder in a servo motor-driven injection molding machine. Dubay, Pramujati [47] described the relationship between the fill velocity and the screw velocity and presented two predictive controllers for the screw velocity.

These examples show that data from injection molding machines can be much more useful, than it is considered and that efficient use of this data might help to avoid application of destructive monitoring methods. Zhao, Zhou [3], for example, propose a non-destructive online monitoring method for injection molding process with use of pressure, temperature, and displacement sensors installed in the injection molding machine, not in the mold, for collecting data while the machine runs. A multimedia timer method and a multithread technology are used for maintaining real-time large-capacity data collection. Zhao, Wang [48] developed a non-destructive cavity pressure measurement method based on ultrasonic technology and a Gaussian process. While Zhang, Mao [49] created a statistical quality monitoring method for injection molding. *"In the method, statistical variables are automatically extracted from built-in hydraulic pressure and screw position trajectories, to reduce dimension of the process variables"* [49].

Final quality of a produced plastic part is directly related to the accuracy of a mold, material shrinkage, internal stresses and amount of molten material in the mold [50]. In order to have a high accuracy of the manufactured items in addition to the process monitoring, process control application is needed. It excludes need of trial and error method use and doesn't require immediate actions to the changed process parameters and conditions, as the action is taken by the control unit, when it is necessary.

After the process data is received with help of a chosen monitoring method, it can be handled in different ways to optimize the process parameters and increase controllability of the plastic injection molding process.

Gao, Tang [51] propose an example of *"a quality control system that can predict product quality to an accuracy of 3 errors per million opportunities as specified by six sigma methodologies to ultimately enable fully automatic, high quality production"*. Piezoelectric pressure sensors, an in-mold thermocouple, infrared melt pyrometer, a custom-designed multivariate sensor are some of the devices used to get necessary data to use it for construction of a model based on support vector regression algorithm. Schreiber [52] proposed and proved efficiency of use of an injection molding process model based on artificial neural network. Verification of the model required identification tests, network training and prediction simulations. The model needs to be adjusted every time the mold, machine and plastic material is changed. Hopmann, Ressmann [7] went further and propose to use a model predictive controller combined with artificial neural network to improve repeatability and product quality in plastic injection molding. *"Unlike controllers such as proportional-integral-derivative controllers, the control output is not determined using a well-tuned, but mathematically relatively simple algorithm. Instead, it performs an online optimization based on a process model in order to obtain the control outputs"* [7]. Kim, Gang [53] investigated the cavity filling process to increase process controllability and built a one-dimensional analytical model that describes relationship of four process parameters (injection flow rate, peak cavity pressure, mold temperature and melt temperature) with the filling length. In addition, Hopmann, Abel [17] applied *“a norm optimal iterative learning control combined with a simple follow-up controller”* for cavity pressure control in injection molding.

However, in these cases, the same trend as in intelligent heat management technology application is seen, the results are good, but not widely used, as solutions lack element of standardization. As a result, it is possible to conclude that need for development of a common framework for monitoring and control systems for injection molding systems is high.

4. Conclusion

Quality issues are a common problem for injection molding process due to non-uniform temperature variation in the mold. During design of the molds for injection molding process, it is very difficult to achieve efficient cooling with uniform thermal distribution. It is attempted to be achieved through application of variotherm technology, as well as conformal cooling/heating channels. However, most of rapid heating and cooling systems are still difficult to apply in the mass production of plastic parts in injection molding industry due to extra complex heating setups, weak mechanical strength of the mold and lack of a standardized control option.

Injection molding is used for mass production, it needs to be repeatable and requires manufactured products to be of a high quality. However, it is very sophisticated and includes a lot of process parameters which can be divided into three different groups (machine, process and quality). The quality of a final part depends on each of them, so, process monitoring and control are of a high importance. Process monitoring can be conducted through application of sensors, visible mold detectors, capacitive transducers, fluorescent sensing and near infrared spectroscopy, however, non-destructive methods can also be used. Then relation between parameters that can and cannot be measured should be described through application of models and related formulas. After collecting the necessary data, process control should be used in order to adjust process parameters to the changing environment without additional human involvement.

Here different methods can be used, however, artificial intelligence methods will bring more benefits than the usual ones, as they can adjust and change the model and output parameters depending on changes of conditions and environment, as well as put aside parameters of the process that are not influencing the model to the high extent. Among AI methods that can be applied for development of an intelligent monitoring and control system are artificial neural networks, adaptive neural-based inference system, genetic programming, etc.

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