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PROCESS PARAMETERS OPTIMIZATION USING KNOWLEDGE BASED CONTROL AND A CLASSIFICATION MODEL FOR SMART INJECTION MOLDING

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Abstract. *The manufacturing industry has been facing several challenges, including sustainability, performance and quality of production. Manufacturers attempt to enhance their competitiveness of companies by implementing CPS (Cyber-Physical Systems) through the convergence of IoT (Internet of Things) and ICT (Information & Communication Technology) in the manufacturing process level. Artificial intelligence technology and machine learning are widely used to optimize process parameters for injection molding. An optimization method for process parameters has been evolving from traditional trial-error approach to the data-based optimization by using IoT and CPS technologies. In this paper, we define a framework of a smart injection molding system (SIMS) and describe detailed functions for efficiently controlling various kinds of equipment and processes by using IoT. We propose a new optimization methodology which integrates the existing rules to control parameters as well as a classification model in applying a machine learning method. This research reveals that traditional rules for parameter settings can also be applied to the classification model in order to achieve optimal parameters.*
Keywords: Machine learning, Parameter optimization, Internet of Things, Injection molding

1. **Introduction.** Injection molding is one of the most important manufacturing techniques for mass production of complex products made by plastic. This technology is difficult to be optimized because of two main problems including 1) a huge loss for setting process parameters before production and 2) difficulty in changing control parameters during operation even when defects occur. In order to derive the optimal parameters, operators need to continuously adjust the process parameters in a trial-error manner before production. To solve aforementioned problems, many researchers have tried to set optimized initial parameters by using statistical methods based on data from mold design. However, previous studies have mainly addressed on the problem of initial parameter optimization, and more efforts are needed to solve the problem of parameter optimization in processing. Therefore, we propose a framework of smart injection molding system (SIMS) for the optimization of parameters during the process. Furthermore, we apply an ensemble classification method consisting of artificial neural network, logistic regression, random forest method, and knowledge based control. The main contribution of this study is to optimize the process parameters during production based on actual product and production data. Chapter 2 reviews literature on optimizing process variables in injection molding through statistical methods, heuristics, or machine learning techniques. A framework for SIMS and knowledge-based parameter optimization methodology, the main bodies of this research, are described in Chapters 3 and 4, respectively. Chapter 5 concludes this research.

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2. **Literature Study.** The traditional parameter optimization method was the trial-error method [1]. However, such a method is known as time consuming and costly because the efficiency depends on the experience of the operator [2]. Over the past decades, experimental design and optimization approaches have been widely applied to determining process parameters [3]. In recent years, many techniques are being developed to solve multiple-input-multiple-output (MIMO) parameter based problems such as artificial neural network (ANN), group method of data handling (GMDH) algorithm, and fuzzy logic. Erzurumlu et al. [4-6] have studied the quality and process problems according to the characteristics of injection products by using neural networks, the Taguchi method, and meta-heuristic methods. In addition, the control parameters of an injection molding machine were derived on the main characteristics such as defects (e.g., surface defects, shrinkage, and warping) of the injection molding, and proposed a method for deriving the optimal parameters. Chen et al. [7-9] conducted a sequential analysis process using the Taguchi method, ANOVA, response surface analysis, and a hybrid heuristic method, which includes genetic algorithm (GA) and particle swam algorithm (PSA), to derive manufacturing time. Several MIMO studies have been conducted to optimize multiple quality levels using ANN. Gao et al. [10-13] integrated optimization techniques such as GA, PSA and simulated annealing (SA) to minimize warpage in initial process parameters. They also proposed a methodology to monitor the quality of products online by using a support vector regression (SVR) method, design of experiments, and simulation based on data of melting temperature and filling pressure of the initial mold. Taghizadeh et al. [14] studied the initial process parameter for optimum quality by learning the mold temperature, melt temperature, settling value and degree of warping of the product using back propagation neural network (BPNN). Nam et al. [15] analyzed the temperature and pressure data inside the mold and controlled the process variables to optimize the quality using a K-fold cross validation method. Recently, Kitayama et al. [16] studied that a cooling performance of conformal cooling channel in plastic injection molding is numerically and experimentally examined. To examine the cooling performance, cycle time and warpage were considered. They applied a radial basis function network to identifying a pareto-frontier in the multi-objective optimization problem. Gao et al. [17] proposed a novel classification model by utilizing the fact that the domain of a feasible parameter is usually sandwiched between two opposite defects when a parameter increases from a low level to a high level. The aforementioned researches focus on the reduction of defects by using historical data and simulation data, and are mainly focused on the optimal setting of process parameters right after the product design step. One of purposes of such studies can be considered as the initial parameter optimization according to product and production characteristics by combining various statistical techniques and soft computing methods. However, control parameters should also be corrected and managed while production not only in the initial stage in order to increase quality of products and system performance. Therefore, we attempt to define a framework of SIMS for optimizing the in-process parameters by analyzing the real-time data from a shop floor. In addition, we suggest a novel concept of classification method consisting of statistical methods, ANN, and knowledge based control rules for the optimization of process parameters.

3. **Smart Injection Molding System (SIMS).** The proposed framework for SIMS is shown in Figure 1. The SIMS includes a set of technologies that conduct self-decision-making, prediction, verification, control to optimize quality, and production based on variable data generated during the process through data analysis, simulation, and control enhancement technology [18]. The system is able to conduct a self-learning of know-how and knowledge on characteristics of product quality and search the optimal process parameter. The framework consists of three layers including a planning layer, an execution layer, and a control layer according to the ISA-95 control hierarchy levels.

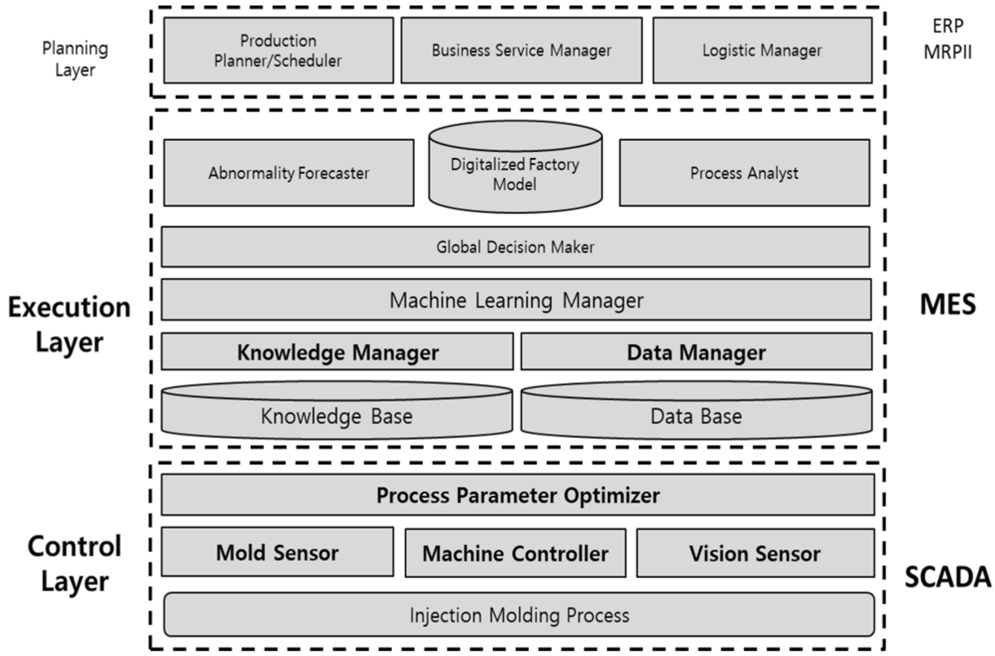

Figure 1. Framework of smart injection molding system

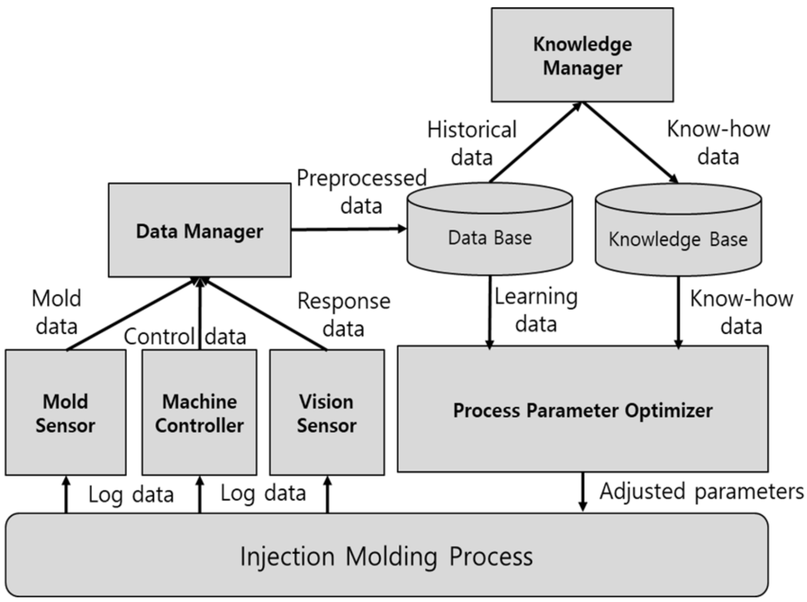

Figure 2. Data flow between functional modules

In this paper, we focus intensively on *knowledge manager*, *data manager* in the execution layer and *process parameter optimizer*, *mold sensors, machine controller* and *vision sensors* in the control layer. The *knowledge manager* stores cases for defects and know-how to respond to defects and suggest historical and experiential solution. This suggested solution is to be a reference opinion for the *process parameter optimizer*. The *data manager* deletes missing data in the acquired data and pre-processes them for effective machine learning. The *mold sensors* collect temperature and pressure data inside the mold. The *machine controller* provides process parameters, temperature and pressure of the internal cylinder. The *vision sensors* collect defects data of the final product. The *process parameter optimizer* derives optimal process parameters to minimize defects using the machine learning methodology. These analysis functions with the data flow are presented in Figure 2. The working scenario of the framework is as follows. First, the *machine controller* acquires control log data (melting temperature, packing time, etc.) generated by the machine, and provides temperature and pressure of the cylinder zone, usually divided by three or four zones inside the machine.

And then the *mold sensors* acquire temperature and pressure data inside the actual mold to determine the difference between the control variables in the mold and injection machine. After the injection operation is completed, the *vision sensors* try to detect defects such as warpage, shrinkage, and gas mark, of the finished product. The data collected from the data acquisition module is pre-processed and stored by the *data manager*. The *process parameter optimizer* learns input parameters from the *mold sensors* and the *machine controller* as well as output parameters from the *vision sensors*. This module constantly keeps learning the continuous and discrete process data from shop floor and predicts defects. The *knowledge manager* supports the *process parameter optimizer* to predict the solution to rearrange process parameters by referring to the existing control rules.

The purpose of using the *mold sensors*, *machine controller*, and *vision sensors* in the control layer is to acquire the exact and real-time process data. The *mold sensors* can acquire uncontrollable variables (temperature and pressure) inside the mold. Uncontrollable variables caused by *machine controller* have a direct impact on quality. As shown in Figure 3, the trends of temperature and pressure in the machine and the mold are different from each other. The *vision sensors* process the image data by using cameras to identify defects of the product (Refer to Figure 4). The data on defects obtained is labelled as an output data in the process parameter optimization model.

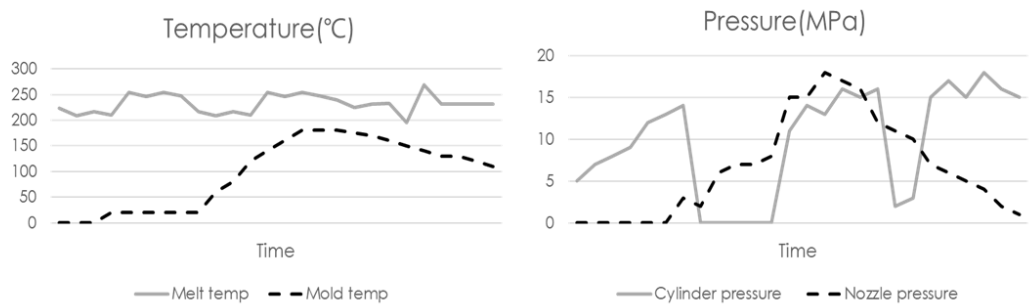

Figure 3. Difference between the control and mold data [18]

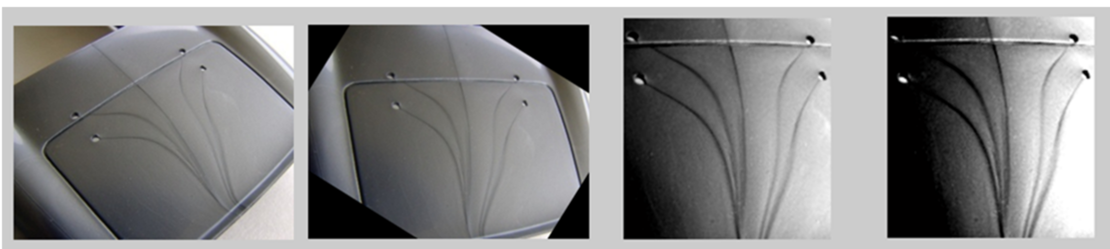

Figure 4. Image processing in the vision sensor

4. **Knowledge Control Based Parameter Optimization.** There is a feasible process zone for the optimization for process parameters. This defect-free zone is always referred to as the process window [19]. The process window is usually a closed area in high dimensional space. The process window shown in Figure 5 is just for demonstration in case of two parameters. It is always established on a convex form between margin borders in classification problems. In order to find the process window, therefore, it is necessary to

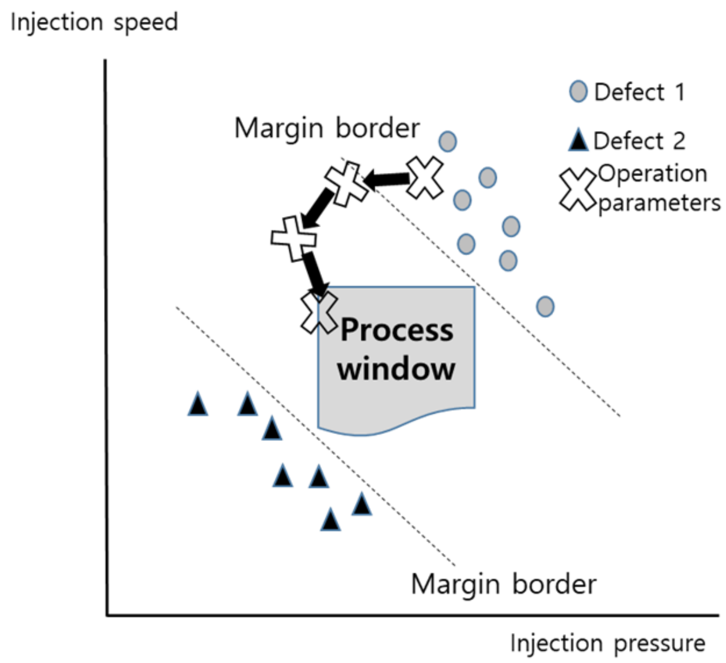

Figure 5. Process window for injection molding

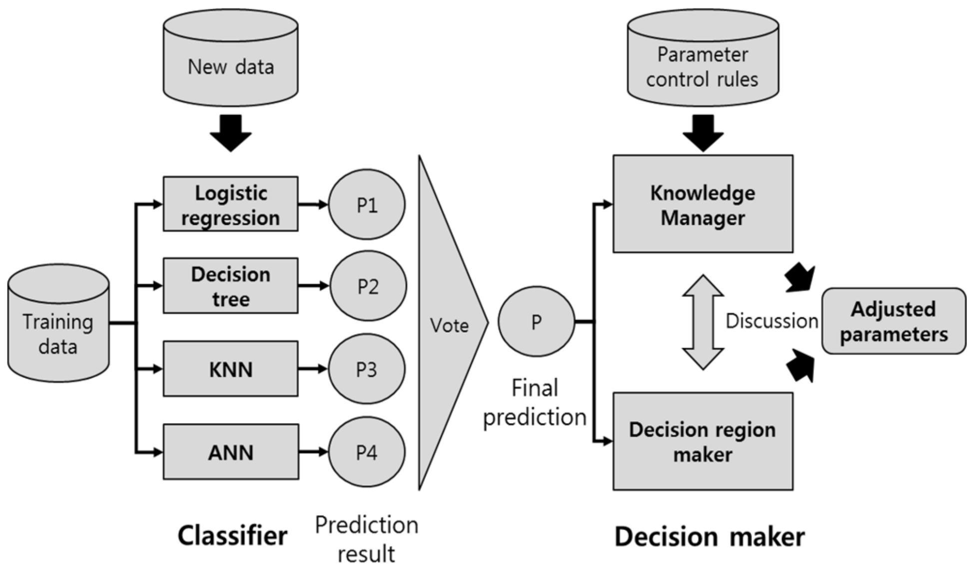

Figure 6. Knowledge based ensemble parameter optimization method

derive the decision regions where failure occurs through the classification algorithm. Once the process window is defined, the parameters should be adjusted within the process window. This approach is similar to such optimization methods as meta-heuristics and grid methods. Figure 6 presents an analysis procedure of knowledge control based parameter optimization methodology which is performed by the parameter optimizer consisting of a classifier and a decision maker. The classifier uses the ensemble classification algorithm based on logistic regression, decision tree, k-nearest neighbors and ANN to determine the final predictive value. The performance of ensemble classification is better than the single classification for the large number of MIMO. If a result of the single classification is better than results of the majority voting, however, the single classification is taken automatically by the system. When the process window is defined, the knowledge manager proposes opinions among existing rules or know-how gained from existing literature and experience. The decision maker constructs the decision region using parameters related to the opinion for axes. The parameter optimizer verifies the opinion by using the decision region. If this opinion allows the approach to the process window, the system accepts the opinion. Otherwise the system will apply the grid method to finding a solution which might be acceptable results in the current state.

We checked receiver operating characteristic (ROC) curve to diagnose the ensemble model. As shown in Figure 7, the ensemble classifier shows good performance with test data. The majority voting method produced the best results, and ANN method tended to show overfitted results with training data so such results were excluded from the voting. After the results of the ensemble classifier are derived, the knowledge manager applies the existing rules for the problem. Table 1 shows an exemplary suggestion to solve the warpage problem by the knowledge manager. Figure 8 depicts the decision region to verify that the suggested parameters are approaching to the process window. Defect zones filled in blue are spreading on right and upper side of the current parameter setting.

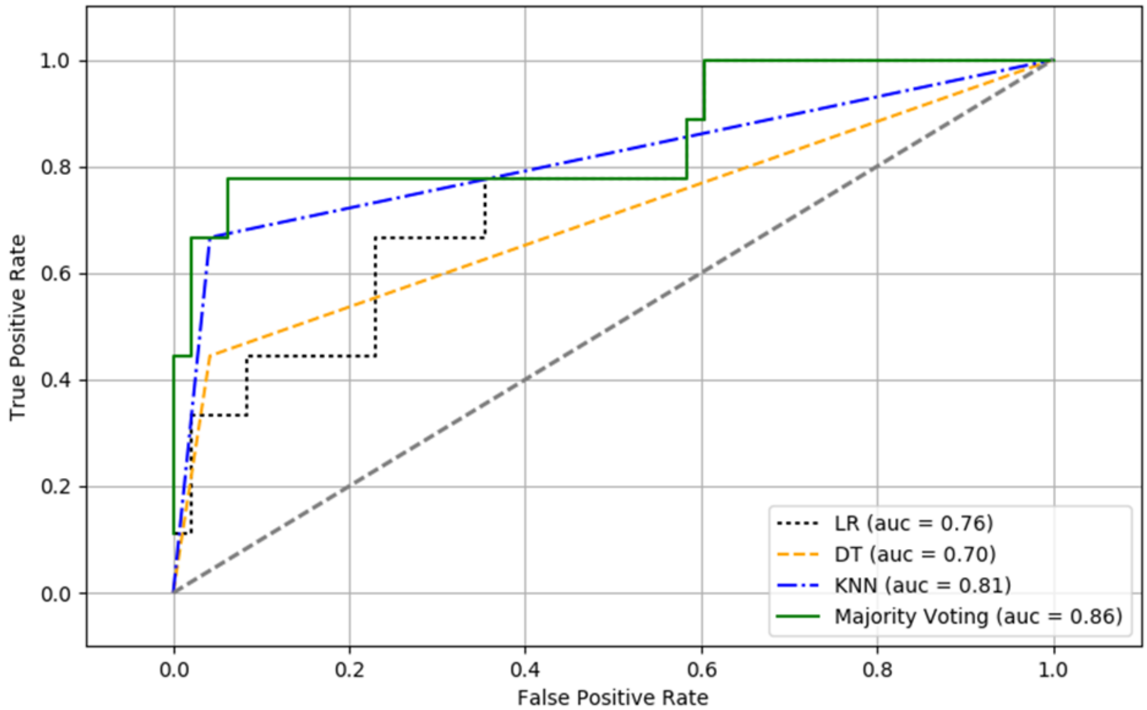

FIGURE 7. Performance of ensemble classification

TABLE 1. Parameter adjustment based on historical knowledge

Parameters	Current value	Suggested value
Packing pressure (MPa)	60	0
Injection time (S)	8.0	2.0

5. **Conclusions.** In this study, we focused on the point of time after the initial parameter setting is completed. We proposed a novel methodology for classifying and predicting process parameters based on data obtained from the shop floor. The proposed methodology is expected to be the main function of the SIMS. The proposed methodology can classify parameters using a selectable ensemble classifier and can propose a modified process parameter control based on existing rules and know-how gained from existing literature and experience. This research has a contribution to supporting an engineering of the smart injection molding research. However, reliability of the framework should be verified based on various types of actual data in further research.

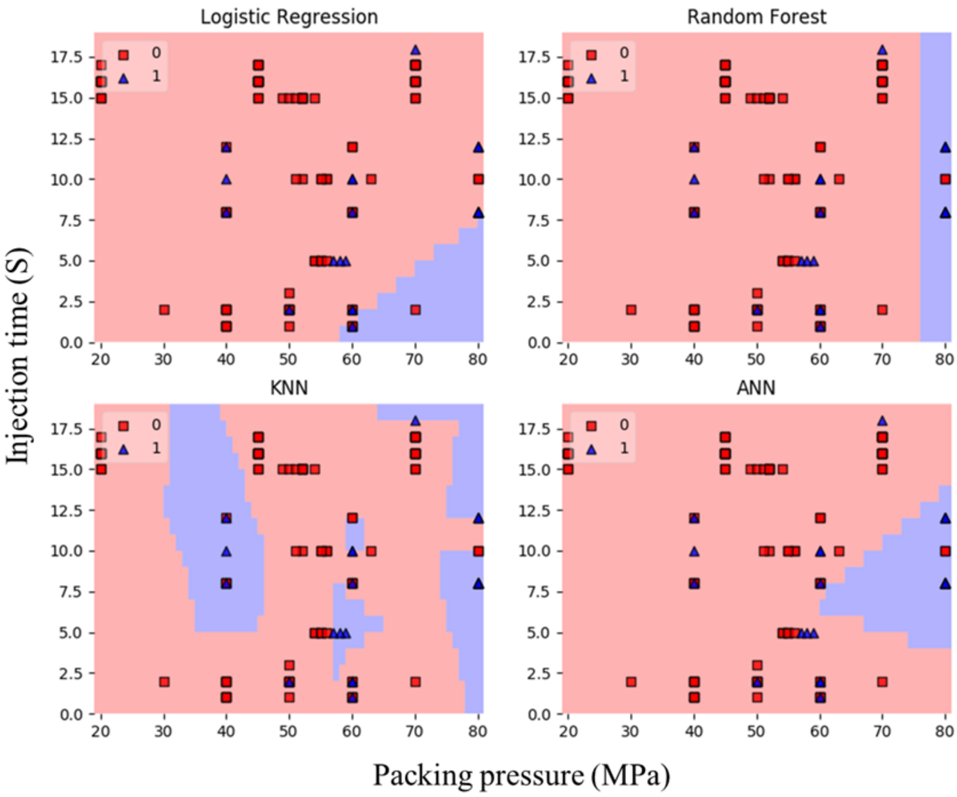

Figure 8. (color online) Performance of ensemble classification

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