Application of machine learning methods for prediction of parts quality in thermoplastics injection molding

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Abstract. Nowadays significant part of plastic and, in particular, thermoplastic products of different sizes is manufactured using injection molding process. Due to the complex nature of changes that thermoplastic materials undergo during different stages of the injection molding process, it is critically important to control parameters that influence final part quality. In addition, injection molding process requires high repeatability due to its wide application for mass-production. As a result, it is necessary to be able to predict the final product quality based on critical process parameters values. The following paper investigates possibility of using Artificial Neural Networks (ANN) and, in particular, Multilayered Perceptron (MLP), as well as Decision Trees, such as J48, to create models for prediction of quality of dog bone specimens manufactured from high density polyethylene. Short theory overview for these two machine learning methods is provided, as well as comparison of obtained models' quality.

Keywords: Artificial Neural Network, Decision Trees, Injection Molding, Machine Learning

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1 Introduction

In 2016 there were 335 million metric tons of plastics produced worldwide and 60 million metric tons in Europe [1]. At the same time, more than one third of all plastic products is produced using injection molding process [2], this makes injection molding one of the most frequently used processes for mass production of plastic parts for variety of applications.

Injection molding process includes such stages as: plasticization, filling, injection, cooling and ejection [3]. At first, material is fed into a heated barrel, where it is mixed and turned into molten plastic. The melt is then inserted into a cavity with help of injection pressure and reciprocating screw and afterwards packed with packing pressure to obtain part with a desired shape. The molten plastic cools down and solidifies inside of the mold, later the final part is ejected.

The process includes three main control loops: control loop of machine parameters (speed, pressure, temperature), control loop of process parameters (in-mold temperature and pressure) and quality control loop [4]. In order to obtain a final part of high quality, it is necessary to use optimal machine and process parameters [5], which are not always easy to define and are often obtained through trial and error method by injection molding machine operators based on their experience [3]. A problem with such approach is fact that injection molding is a highly competitive industry and it is not enough anymore to utilize only experience to determine the optimal parameters.

It would be of high convenience if, in case of insertion of machine/process parameters that may lead to production of defected parts, control system of injection molding machine would notify the operator that parameters need to be adjusted. This is why ability to predict part quality based on values of inputted process and machine parameters is of high importance.

Some of the most frequently occurring defects during injection molding are flash, short shot, sink mark, warpage and flow line [6]. *"Low injection pressure, short injection time, and low mold temperature will easily lead to short shot, and low packing pressure and short cooling time will cause warpage"* [7]. In this paper 41 machine and process parameters were logged during 160 machine runs. Models for prediction of the final part quality were then built using Artificial Neural Networks (ANN) and Decision Trees machine learning (ML) algorithms. Proposed prediction models are able to distinguish only good or bad parts, without possibility to categorize which type of defect occurs. There are multiple studies, where prediction models for injection molding are built with help of different ML methods. For example, Yen, Lin [8] use ANN in order to design runner dimensions to minimize warpage, Altan [9] use Taguchi, ANOVA and ANN methods to minimize shrinkage, Zhu and Chen [10] apply fuzzy neural network approach to predict flash. In [11, 12] genetic algorithm is used to obtain optimized process parameters and avoid warpage, while Che [13] uses particle swarm optimization combined with ANN to optimize costs for product and mold for injection molding. To authors' knowledge there are rare or no examples of use of Decision Trees method for training models in similar studies, that is why it will be interesting to compare it's performance with that of ANN. The following sections will give a broader description of the study setting, data collection, data processing, methods used to build prediction models and comparison of models' quality.

2 Methodology

Described study was conducted with use of "ENGEL insert 130" vertical injection molding machine. Produced part is a standard dog bone specimen with 19 mm width and 165 mm length, as shown on Figure 1. The material used is high density polyethylene.

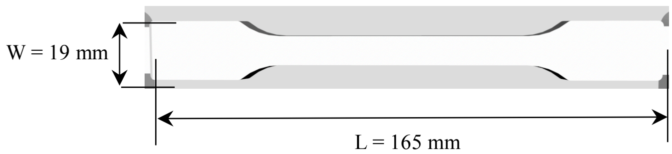

Fig. 1 Dog bone specimen

Latin hypercube method in ModeFRONTIER [14] was used to create design of experiment (DOE) to gather data for a dataset with both high and low quality of the target part. The DOE included 32 different combinations of parameters such as: holding pressure, holding pressure time, backpressure, cooling time, injection speed, screw speed, barrel temperature and temperature of the tool/mold. Each combination has been launched 5 times on the injection molding machine, giving 160 data samples in the end of the experiment. The dataset is slightly unbalanced with 101 data samples representing defected parts and 59 samples for good parts. During each run values of 41 machine and process parameters were logged.

After the data has been gathered, Artificial Neural Network (Multilayered Perceptron) and Decision Trees (J48) methods were applied to the dataset in WEKA (Waikato Environment for Knowledge Analysis) [15]. ANN has been chosen as one of the methods for prediction model building as it is often applied in similar studies [8-10], while Decision Trees was used to compare ANN model with a model that is easier to interpret. In addition, it was of interest to see which parameters will become tree nodes and which values will be chosen as thresholds to make decision about the final part quality. The methods were first applied to the full dataset with 41 parameters included. As a next step Information Gain (InfoGain) feature selection method was used to identify parameters containing the biggest amount of information about the process. Afterwards ML methods were applied to reduced parameters sets of 35 and 18. The following section will give a short theory overview of the applied ML and feature selection methods, as well as explain how reduced number of parameters for prediction models was chosen.

3 Machine Learning Methods

Machine learning methods use statistical techniques to improve algorithm's performance on a particular task. These 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"* [16]. In addition, they are not as resource consuming as regular optimization techniques [17]. However, before applying ML methods, it is important to pre-process the data. Data and features that have missing, incomplete or redundant values are recommended to be avoided, when possible. Feature selection can be one of the ways to select the most "meaningful" parameters/features in the obtained data.

3.1 Feature selection

Feature selection is a process of selecting a subset of features that are most relevant/useful for a model construction. It is also commonly used for dimensionality reduction to decrease amount of time and resources necessary to build a model. Feature selection methods allow to choose the most relevant features for the task and use them to train the model, removing redundant and correlated attributes/parameters.

As mentioned before, Information Gain was used in this study to evaluate quality of parameters logged during the experiment. Information gain *"is defined as the amount of information, obtained from the attribute"* [18]. InfoGain takes values between 0 and 1, the bigger is the value the more relevant is the attribute/parameter. The list of all parameters and their information gain scores is shown in Table 1. The prediction models were at first trained with use of all 41 parameters, afterwards 6 attributes (Machine time, Shot counter, Good parts counter, Bad parts counter, Parts counter and Machine date) were removed as irrelevant by meaning and the models were built one more time with 35 parameters. Later all the attributes that have information gain score equal to 0 were removed and the models were trained again using 18 attributes.

3.2 Artificial Neural Networks

Artificial Neural Networks (ANN) is one of ML methods used for modeling and forecasting in variety of areas of science, business and engineering. The main idea of the method is based on biological neural networks found in animal brains. It includes use of interconnected processing elements called neurons. These elements are organized in separate layers connected with weights. Such models are able to "learn" to perform tasks by considering samples related to the problem they are supposed to solve. Every time a new sample is "fed" to the network, the weights are adjusted accordingly in order to obtain a model that is able to perform a necessary task in the best possible way. In case of this study, ANN is "learning" through processing samples of good and bad parts characterized by number of relevant parameters.

Multilayer Perceptron (MLP) is one of classic ANN models. It is based on sequence of layers of neurons interconnected between each other, where layer-to-layer mapping is activated with a non-linear function. In this study sigmoid function is used as an activation function.

3.3 Decision trees

Decision trees is a class of supervised learning algorithms. The main idea behind the method is to use training data to build a predictive model shown in a form of a tree structure. Final goal is then to find a correct answer to a problem with minimal possible number of decisions using the obtained model. However, this is not always possible due to noise and missing values in data.

The basic algorithm for learning a decision tree consists of the following steps: select parameter or value that gives the "best" data split, create "child" nodes based on the split, run the algorithm recursively on the "child" nodes until certain stopping criteria is reached (the tree is too large, or number of examples left is too small). J48 algorithm used in this study includes additional features such as handling missing values and continuous attributes/parameters values, as well as decision trees pruning. The following section will show results of application of described methods to the obtained data set.

Table 1 Information Gain scores for parameters used in the study

#	InfoGain score	Parameter name
1	0.9497	Machine time
2	0.6694	Shot counter
3	0.6694	Good parts counter
4	0.5685	Cushion after holding pressure
5	0.556	Cushion smallest
6	0.3904	Screw speed max
7	0.3812	Temperature cylinder zone2 average
8	0.3571	Plasticizing number
9	0.2933	Switchover time
10	0.2735	Heating group cylinder1 zone1 set temperature
11	0.2628	Waiting delay
12	0.2312	Injection time
13	0.229	Bad parts counter
14	0.1995	Plasticizing time set max
15	0.1731	Specific pressure at switchover
16	0.1473	Parts counter
17	0.1263	Plasticizing time
18	0.121	Speed max
19	0.0806	Cushion average
20	0.0663	Injection work
21	0.016	Machine date
22	0	Ejector position last
23	0	Decomposition after plasticization
24	0	Switchover volume
25	0	Current station
26	0	Injection pressure limit
27	0	Injection time set max
28	0	Ejector position set max
29	0	Last cycle time
30	0	Closing force
31	0	Plasticizing delay time set
32	0	Shot volume
33	0	Holding pressure time
34	0	Clamping force at switchover
35	0	Cushion smallest set max
36	0	Cooling time last
37	0	Flow number
38	0	Cushion ideal
39	0	Plasticizing time set min
40	0	Ejector position set min
41	0	Injection time set min

4 Results

The main goal of this study was to create prediction models capable of distinguishing between high- and low-quality parts based on machine and process parameters, in particular, dog bone specimens with 19 mm width and 165 mm length manufactured from high density polyethylene. After training the model, it is capable of notifying a machine operator that the parameters need to be adjusted not to produce defected parts. Simplified study procedure used to reach the goal is shown on Figure 2.

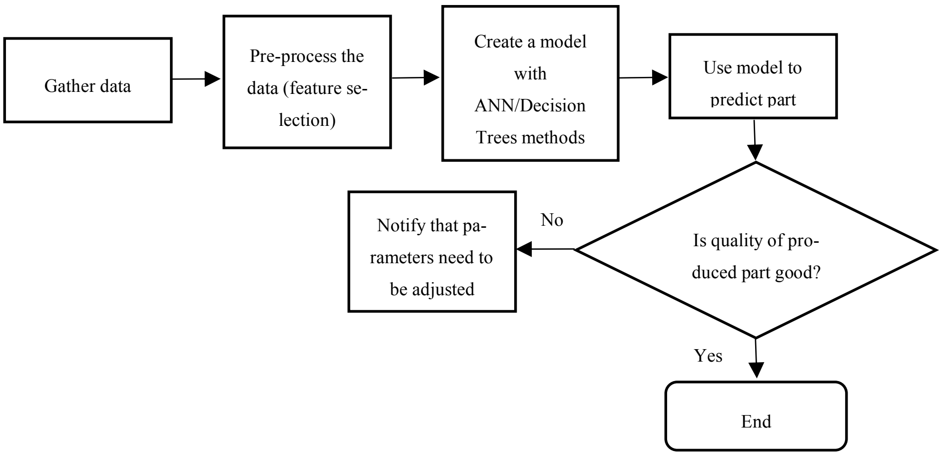

Fig. 2 Simplified study procedure

The first method used to train the model is MLP, to verify quality of the model 10-folds cross validation was used. The algorithm has been launched three times including 41, 35 and 18 parameters based on the feature selection and common sense related to meaning of the logged parameters. The final architecture of the neural network includes 3 layers (input layer, hidden layer and output layer) and 22 neurons in the hidden layer ((number of parameters + number of classes)/2) for the first model, 3 layers and 19 neurons in the hidden layer for the second model, as well as 3 layers and 10 neurons in the hidden layer for the third. Quality of the final models was assessed with help of Accuracy and ROC area metrics, which can be seen in Table 2. The second method applied is Decision Trees (J48). There were three models trained, with the same number of features as in case with ANN, 10 folds cross validation was also applied. Due to ability of J48 algorithm to prune obtained decision trees, no matter how many features were used, the resulting tree always included 6 nodes. Each tree included the following features: Cushion after holding pressure, Screw speed max, Injection time and Holding pressure. In addition to those four, the first model also included Bad parts and Holding pressure time features, the second model – Plasticizing time set max and Holding pressure time, while the third had Plasticizing time set max and Injection work.

Table 2 Comparison of obtained models' quality

	ANN (MLP)	Decision Tree (J48)
Accuracy (41 features)	88.75 %	95.625%
ROC area (41 features)	0.942	0.957
Accuracy (35 features)	96.875%	96.25%
ROC area (35 features)	0.996	0.958
Accuracy (18 features)	99.375%	97.5%
ROC area (18 features)	0.994	0.968
Accuracy average	95%	96.45%

As it is possible to see from Table 2, both algorithms show high quality results with average accuracy of 95% of correctly classified instances of good and bad parts for ANN and 96.45% for Decision Trees. Both algorithms show increase in accuracy after removing features that do not contain much information about the process.

5 Conclusions

In this study, experimental data has been collected from "ENGEL insert 130" vertical injection molding machine. The data includes 41 machine and process parameters from 160 machine runs based on variation of holding pressure, holding pressure time, back-pressure, cooling time, injection speed, screw speed, barrel temperature and temperature of the tool/mold parameters. Parameters are varied according to the DOE consisting of 32 combinations of above mentioned attributes. The obtained data set includes 101 instances of bad and 59 instances of good parts. Due to unbalanced data set 10-folds cross validation is used to increase quality of the final models.

Collected data is then pre-processed with help of Information Gain feature selection algorithm. Later six different quality prediction models are built with help of ANN (MLP) and Decision Trees (J48) methods (three models per method). The models are assessed with help of accuracy and ROC area measures. Models with the highest accuracy rate are obtained with use of 18 parameters/features for both ANN and Decision Trees. The highest accuracy rates are 99.375% and 97.5% for MLP and J48 correspondingly. In addition, Decision Trees algorithm has shown that the main features used to make the final decision about quality of the part are: Cushion after holding pressure, Screw speed max, Injection time, Holding pressure, Holding pressure time, Plasticizing time set max and Injection work.

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References

1. *Statista – The Statistics Portal. Global production of plastics since 1950*. 2018 [cited 2018 20.07]; Available from: https://www.statista.com/statistics/282732/global-production-of-plastics-since-1950/.

2. Hernandez-Ortiz, J.P., *Polymer Processing: Modeling and Simulation*. 2006, Hanser Gardner Publications.

3. Tsai, K.-M. and H.-J. Luo, *An inverse model for injection molding of optical lens using artificial neural network coupled with genetic algorithm.* Journal of Intelligent Manufacturing, 2017. **28**(2): p. 473-487.

4. Karbasi, H. and H. Reiser. *Smart Mold: Real-Time in-Cavity Data Acquisition*. in *First Annual Technical Showcase & Third Annual Workshop, Canada*. 2006. Citeseer.

5. Zhao, P., et al., *A nondestructive online method for monitoring the injection molding process by collecting and analyzing machine running data.* The International Journal of Advanced Manufacturing Technology, 2014. **72**(5-8): p. 765-777.

6. Rosato, D.V. and M.G. Rosato, *Injection molding handbook*. 2012: Springer Science & Business Media.

7. Kitayama, S., et al., *Multi-objective optimization of variable packing pressure profile and process parameters in plastic injection molding for minimizing warpage and cycle time.* The International Journal of Advanced Manufacturing Technology, 2017. **92**(9-12): p. 3991-3999.

8. Yen, C., et al., *An abductive neural network approach to the design of runner dimensions for the minimization of warpage in injection mouldings.* Journal of Materials Processing Technology, 2006. **174**(1-3): p. 22-28.

9. Altan, M., *Reducing shrinkage in injection moldings via the Taguchi, ANOVA and neural network methods.* Materials & Design, 2010. **31**(1): p. 599-604.

10. Zhu, J. and J.C. Chen, *Fuzzy neural network-based in-process mixed material-caused flash prediction (FNN-IPMFP) in injection molding operations.* The International Journal of Advanced Manufacturing Technology, 2006. **29**(3-4): p. 308-316.

11. Ozcelik, B. and T. Erzurumlu, *Determination of effecting dimensional parameters on warpage of thin shell plastic parts using integrated response surface method and genetic algorithm.* International communications in heat and mass transfer, 2005. **32**(8): p. 1085-1094.

12. Yin, F., H. Mao, and L. Hua, *A hybrid of back propagation neural network and genetic algorithm for optimization of injection molding process parameters.* Materials & Design, 2011. **32**(6): p. 3457-3464.

13. Che, Z., *PSO-based back-propagation artificial neural network for product and mold cost estimation of plastic injection molding.* Computers & Industrial Engineering, 2010. **58**(4): p. 625-637.

14. *ModeFRONTIER - Design optimization platform*. [cited 2018 20.07]; Available from: https://www.esteco.com/modefrontier.

15. *WEKA - Waikato Environment for Knowledge Analysis*. [cited 2018 20.07]; Available from: https://www.cs.waikato.ac.nz/ml/weka/.

16. Ogorodnyk, O. and K. Martinsen, *Monitoring and Control for Thermoplastics Injection Molding A Review.* Procedia CIRP, 2018. **67**: p. 380-385.

17. Dang, X.-P., *General frameworks for optimization of plastic injection molding process parameters.* Simulation Modelling Practice and Theory, 2014. **41**: p. 15-27.

18. Kononenko, I. and M. Kukar, *Machine learning and data mining: introduction to principles and algorithms*. 2007: Horwood Publishing.