Prediction of Width and Thickness of Injection Molded Parts Using Machine Learning Methods

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Abstract

Injection molding is one of the major processes applied for production of thermoplastic products. Thermoplastic materials are used in manufacturing of dozens of products seen in everyday life, such as: car bumpers, children toys, bodies of electronic devices, etc. At the same time, plastic pollution is a well-known problem. One of the sources of this pollution is plastic scrap, which might appear because of using faulty process parameters during production process. To decrease amount of scrap, injection molding needs to include better process and quality control routines. Quality of a product can be defined in different ways and product dimensions can be one of criteria for accepting or declining a product. The following paper applies machine learning (ML) methods to predict width and thickness of the injection molded HDPE dogbone specimens with 4 mm thickness based on process parameter values used to produce the parts. Data used for creation of regression models with help of ML methods was acquired during an experiment, which included 160 machine runs during which 47 machine and process parameters were logged. Application of ML methods for training of product dimensions prediction models will increase overall intellectual level of injection molding machines and their compliance with Industry 4.0 standards. Beforehand prediction of product's dimensions will allow to decrease amount of scrap and energy consumption. This will contribute to more environmentally conscious use of thermoplastic materials and more sustainable design of manufacturing systems.

Keywords:

Machine Learning, Artificial Neural Networks, k-Nearest Neighbors, Decision Trees, Injection molding, Quality prediction

1 INTRODUCTION

In the last thirty years, the popularity of the injection molding (IM) process had an increasing growth due to new applications in the fields of appliances, packaging and automotive industry [1]. As a result, today injection molding is one of the most frequently used processes for the production of thermoplastic parts in high volume and low cost.

Injection molding includes only four main phases: plasticization, injection, cooling and ejection, however, it is a rather complicated process due to the presence of non-linearities [2]. At the same time, due to its use for mass production, high process repeatability is extremely important [3] and keeping quality of the products as high and as similar as possible is a "must".

Depending on the application of the manufactured product, its quality can be defined in different ways. Usually, the good quality of the part means desired mechanical performance, dimensional consistency and proper appearance [1]. *"Dimensional consistency is a critical attribute for injection molded part quality and is highly dependent on various processing parameters"* [4]. Product dimensions can be one of the criteria for accepting or declining a thermoplastic product.

The part quality, including dimensional accuracy, can be influenced by a significant number of factors such as general condition of the injection molding machine (IMM), mold that is in use, input material condition, drifting of the process parameter settings or the machine operator's fatigue [5]. Some of the process parameters that may cause product quality variations are melt temperature, mold temperature, holding pressure, cooling time, etc. [6]. Because of the faulty setting of some of those parameters, such defects as warpage, sink mark, air traps, and weld lines might occur. As a result, prediction of final parts quality using certain process parameter values and *"optimal setting of injection molding process variables plays a very important role in controlling the quality of the injection molded products"* [7, 8].

The optimal process parameter settings were used to be determined by engineers and IMM operators based on their experience, intuition and trial-and-error [9, 10]. However, due to the increasing quality requirements new approaches for optimization of the plastics injection molding are being continuously developed. *"Researchers introduced the design of experiment (DOE), Taguchi orthogonal array and flow analysis software such as Moldflow Plastic Insight"* [11].

Apart from statistical process control, design of experiments and Taguchi approach, machine learning methods show all of the necessary capabilities for the development of predictive models for the quality of the injection molded products [11]. Moreover, they have been proven to be better at dealing with non-linearities in comparison to conventional statistical methods such as linear regression [3].

Quality requirements are not the only challenge that the thermoplastics injection molding industry faces today. Another important issue is plastic pollution, which became a problem for the whole world. Keeping process parameters under control and beforehand prediction of quality of the plastic products can decrease amounts of produced plastic scrap and energy consumption, contributing to the more environmentally conscious use of the plastic materials.

This paper uses data from 160 machine runs during which 47 machine and process parameters were logged while producing dogbone specimens type A defined by ISO 527-2 [12]. REPTree (decision tree), random forest, k-nearest neighbors (kNN) and multilayered perceptron (MLP) machine learning algorithms were applied to create models for prediction of width and thickness of the focus parts. The results are discussed in terms of the ability to accurately predict the part's quality and interpretability of the chosen methods.

2 LITERATURE REVIEW

In recent years new methods for quality prediction and optimization of the injection molding process have been proposed and applied. Some of the approaches include the application of machine learning methods [2, 13-15], the use of simulation approaches [16, 17] and the development of particular hardware solutions [4, 18].

Machine learning methods

Machine learning methods (ANN, genetic algorithm, self-organizing maps, etc.) have been used for the development of prediction models of parts shrinkage, general parts quality, to find solutions for multi-objective optimization problem of the injection molding process parameters, etc. Different researchers have used numbers of samples ranging from 27 to 1000, some of them were collected through the simulation software, others during laboratory experiments.

For example, in [2] the authors used a combination of a self-organizing map and a back-propagation neural network to create a dynamic quality predictor for the injection molding process. Nine process parameters were included in the model to predict the weight of the final part. To enhance the performance of the neural network, Taguchi's parameter design was also utilized. The dataset included 160 samples of experimental data. Manjunath and Krishna [13] applied forward and reverse mapping ANN to predict dimensional shrinkage of the produced part and appropriate set of process parameters to reach the required dimensional shrinkage correspondingly. The networks were trained using 1000 samples generated in the simulation software using equations reported by other researchers. In [19] the multi-layered perceptron artificial neural network model and J48 decision trees algorithm is used to create models for prediction of injection molded parts quality. Data from 160 machine runs is utilized to train the models.

At the same time, Kuo, Su [14] applied Taguchi quality method to establish the design of experiment for nine process parameters and analysis of variance to define the most important factors influencing the production process, while back-propagation neural network model was trained to tune the optimum conditions received from the Taguchi's quality method. The model was created using 180 data samples. In [11] a methodology that includes variable complexity methods, constrained non-dominated sorted genetic algorithm, back-propagation neural network and MoldFlow analysis are applied to solve the multi-objective optimization problem of injection molding parameters. The data is generated using the MoldFlow analysis software.

In [20] the orthogonal experiment with Taguchi method was performed, and ANOVA analysis was carried out to define which parameters are the most influential for the injection molding process. In total 81 samples were obtained and used to train models with the help of the back-propagation neural network and multi-class support vector machine methods. Finally, the multi-objective optimization was performed on the obtained models using the nondominated sorting genetic algorithm.

Lotti, Ueki [15] used DOE and ANNs to create models for prediction of shrinkage of iPP plaques based on 30 data samples collected. The neural network model has shown better results in comparison to those calculated with the help of the MoldFlow^{TM} software package. In [21] injection process parameters optimization procedure is proposed. A combination of the response surface methodology, artificial neural networks, radial basis function, and Kriging surrogate is used.

Nagorny, Pillet [22] collected thermal images of 204 rectangular specimens, as well as signals of pressure and temperature sensors situated in the mold and used the data to train models using support vector regression, random forest, k-nearest neighbors, stochastic gradient descent, bagging decision tree, Ada boosting decision tree, as well as convolutional neural network and long-short term memory network. Neural networks models show better results in comparison to other regression methods for prediction of parts quality. While in [23] Taguchi method, design of experiments, analysis of variance were used to design the experiment and choose the most influential process parameters. In total 27 samples of data were collected and used in this study. ANN model was trained to predict the part's shrinkage in injection molding.

Simulation approaches

Another approach to optimization of the injection molding process is the use of numerical simulations and different sorts of simulation software, such as in [16], for example. Here an approach based on a combination of numerical simulations, response surface methodology, and stochastic simulations is proposed to create a virtual prototyping environment to enable robust optimization of the IM process. At the same time, in [17] authors propose a method to simulate the influence of the early part ejection on its final quality using the integration of MoldFlow™ and Ansys™ on the contrary to the stand-alone molding simulation.

Liau, Lee [24], on the other hand, explain that simulation should not be based only on the historical data, but needs to include current process data to make a meaningful decision. Their solution is a framework for the development of a digital twin for injection molding that models the entire process and allows bidirectional control of the physical process. In [9] fractional factorial design of experiments was used to screen some of the injection molding process parameters obtained from the process simulation in the MoldFlow™ software. Later the parameters were used to create a mathematical model with the help of central composite design and finite element simulation to predict warpage during the plastic injection molding.

Hardware solutions

Some other researchers use hardware development to enhance control and prediction of the outcomes of the IM process. For example, in [4] the authors propose a button cell type in-mold shrinkage sensor. The sensor's performance was validated and compared to traditional shrinkage prediction methods. *"The sensor signals acquired during each molding cycle were analyzed to validate the sensor performance in a design of experiments as a function of packing pressure, melt temperature, cooling time, and coolant temperature"* [4]. In [18] an auxiliary process controller for online multivariate optimization of the injection molding process is proposed. The objective function includes terms related to process variation and energy control.

3 EXPERIMENTAL SETUP

The research described in this paper includes the following steps:

Step 1: Process data collection. To collect the data design of experiment has been used, namely Latin Hypercube sampling technique [25]. 32 combinations of *holding pressure, holding pressure time, backpressure, cooling time, injection speed, screw speed, barrel temperature, and mold temperature* process parameters were included in the DOE. Each of these combinations has been launched five times, resulting in 160 machine runs in total and 320 HDPE dogbone specimens, since during each run two of them are produced. This should be sufficient for the application of machine learning algorithms, as the minimum recommended number of samples according to [26] is 50.

The use of DOE resulted in the following ranges for width and thickness [mm] for the dogbone specimens 1 and 2: thickness1 $\in$ [3.3, 3.84]; thickness2 $\in$ [3.32, 3.84]; width1 $\in$ [9.02, 9.95]; width2 $\in$ [8.84, 9.96]. According to the CAD model of the target parts, the width is 10 and the thickness is 4 mm. However, 3-3.5% shrinkage rate is considered a regular shrinkage rate for the HDPE, thus resulting in a width of 9.65-9.7 mm and thickness of 3.86-3.88. It is possible to say that the use of the design of experiments allowed to vary the width and thickness of the parts quite significantly covering values close to the best possible ones, as well as those significantly lower.

During the experiment "ENGEL insert 130" vertical injection molding machine with CC300 control unit has been used and 47 machine and process parameters from the built-in by the machine manufacturer sensors were logged. The logging system has been developed using the Python programming language to be able to establish a connection with the machine and access all the necessary process parameter values.

Step 2: Data pre-processing. The logged experimental data included values of different machine and process parameters for every 0.5 seconds during every production cycle. However, some of the signals vary less than the others during one production cycle but change a lot from one cycle to another. As a result, the logged data needed certain "pre-processing" before any further use. Pre-processing resulted in one value of a process parameter per production cycle, some of the parameter values were averaged, some were taken the maximum or minimum value of, etc. An example of the structure of the data after the "pre-processing" is shown in Table 1. The top row includes names of the logged parameters and each following row corresponds to one data sample. The "pre-processing" has been done using scripts developed in the Python programming language.

Table 1: Experimental data

ID	Max screw speed	Pressure at switchover	Cushion size after holding pressure
1.	239.18	1058.69	4.90
2.	239.40	1059.35	4.92
3.	239.52	1059.62	4.98

Step 3: Quality data collection. After the production of the focus parts, the quality data needed to be obtained. Since dimensional consistency is one of the important criteria for the part's acceptance, the produced dogbone specimens were measured using ZEISS DuraMax coordinate measuring machine [27].

The measurements have been done according to the *"ISO 16012: Plastics - Determination of linear dimensions of the test specimens"* [28], the accuracy of the machine in the temperature 18 – 22 ^{0}C is ± 2.4 μm. The precision error doesn't exceed ± 0.02 mm for dimensions <10 (thickness) and ± 0.1 (width) for ≥10. Fig.1 depicts one of the specimens being measured by the coordinate measuring machine.

Step 4: Important parameters selection. After obtaining both process and quality data, it was necessary to understand which parameters should be included in the quality prediction model. First, all parameters that had constant values during all 160 runs were excluded.

Secondly, six parameters (*machine time, shot counter, good parts counter, bad parts counter, parts counter and machine date*) were eliminated, because they do not contain any necessary information about the process.

Thirdly, feature selection algorithms were applied to define which parameters out of 25 that were left are the most influential. According to the Correlation-based feature selection algorithm with the Best First search algorithm only seven parameters should be included in the model: *cushion after holding pressure, plasticizing time, holding pressure time, cushion smallest value, injection work, holding pressure and tool temperature*. If Greedy Stepwise search algorithm is used instead of the Best First one, then the same seven parameters were chosen, as well as *the last ejector position* parameter.

ReliefF algorithm, on the other hand, doesn't exclude unnecessary in its opinion parameters but ranks all the parameters. The higher the ReliefF score gets a parameter, the more important it is. If the ReliefF score is negative, it means that the parameter is unimportant. Parameters that scored lower than 0.02 were considered unimportant, thus resulting in 18 parameters that were to be included into the width and thickness prediction models (*cushion after holding pressure, tool temperature, holding pressure, backpressure, injection speed, cushion smallest value, cushion average value, cooling time, holding pressure time, barrel temperature, average temperature in the zone 2 of the nozzle, pressure at the switchover, maximum screw speed, screw speed, plasticizing time, last cooling time, flow number and injection work*).

Step 5: Training of the width and thickness prediction models. The last step includes training the predictive models for the width and thickness of the focus parts. Separate models for prediction of width and thickness are built for the first and the second dogbones produced during a single cycle. This results in four models per method (model for prediction of the thickness of dogbone 1, the width of dogbone 1, the thickness of dogbone 2 and width of dogbone 2) and the number of parameters included. Decision trees, random forest, k-nearest neighbors and artificial neural network algorithms are used to create the models.

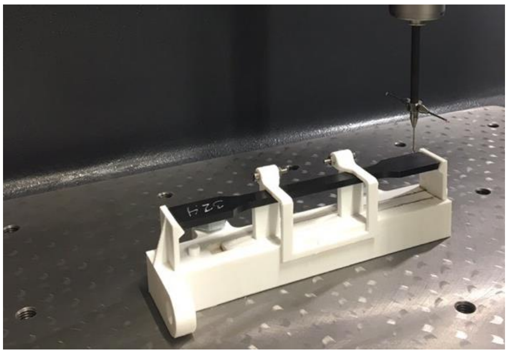

Fig.1: Coordinate measurement of the specimens

4 BRIEF DESCRIPTION OF THE USED MACHINE LEARNING METHODS

The ML algorithms used in this study (REPTree decision tree, random forest, k-nearest neighbors and multilayer perceptron) were induced and evaluated using WEKA – WAIKATO Environment for Knowledge Analysis [29]. 10-folds cross-validation was used to estimate the skill of the model on the new data. The correlation coefficient, mean absolute error and root mean squared error was used to estimate the difference between the measured and predicted values of width and thickness of the dogbone parts.

4.1 REPTree (decision tree)

REPTree stands for Reduced Error Pruning Tree. It is a decision tree algorithm that follows the regression tree logics through the creation of multiple trees in different iterations [30], information gain is used as a splitting criterion in this case. The best tree from all the generated ones is then chosen and considered as representative. Pruning of the tree is done using the mean square error on the predictions of the tree. The result of the algorithm application is a predictive model in the form of a decision tree or a set of if-then rules. In this study minimum number of instances in a leaf has been tested to see how it would influence the prediction quality of the obtained model.

4.2 Random forest

Random forest is an ensemble learning algorithm that includes many separate learners [31]. Each tree is created using a random sample of cases from the dataset. The collection of several tree predictors, in this case, is called a forest. In the case of regression, the model's output *"is the average of the responses over all the trees in the forest"* [30]. In the experiment, different numbers of trees in the forest are tested.

4.3 k-Nearest Neighbors

The k-nearest neighbors algorithm uses parameter similarity to predict values of the new data points [32]. The new point is assigned value depending on the values of instances closest to it. The number of closest instances is the *k* input parameter of the algorithm. In the case of regression, the average value of the closest data points is taken as the model's output. Euclidean distance is used in the experiment to calculate distances between the data points, a different number of nearest neighbors is also used to build the models.

4.4 Multilayer Perceptron

The last algorithm used in this experiment is the Multilayer Perceptron (MLP) ANN. It is one of the classic ANN models and is based on the sequence of layers of neurons interconnected between each other with weights. Every time a new sample of data is given to the network, those weights are adjusted accordingly. In addition to that, *"layer-to-layer mapping is activated with a non-linear function"* [19]. In this study, the sigmoid function is used as an activation function and the number of neurons in the hidden layer of the network is calculated as *(number_of_parameters + number_of_output_neurons)/2*. In this experiment, the MP was built using a different number of parameters as suggested by different feature selection algorithms (7, 8, 18 and 25).

5 RESULTS

Predictive models for the thickness and width of the injection molded dogbone specimens have been built using different machine learning algorithms presented in the previous section. Depending on the algorithm, parameter configurations were varied to see how they affect the quality of the resulting model. Fig.2 shows the dependence of the correlation coefficient of the measured and predicted values of the part's dimensions and different algorithm parameters that were tested. The quality of the models was estimated using the 10-folds cross-validation procedure.

Table 2 shows the performance of tested algorithms using the correlation coefficient, mean absolute error (MAR) and root square mean error (RSME). The numbers are shown for the best algorithm parameter configurations. For the REPTree the best minimum number of instances in a leaf for thickness1, thickness2, and width2 is equal to 2, while for width1 it is 5. In the case of the random forest algorithm, the number of trees that gives better results for thickness1 and width1 is 100, for thickness2 and width2 it is 200. At the same time for the kNN method the best numbers of neighbors are 5 and 1, the first number shows better results for the thickness1 and width1, while the second number for thickness2 and width2. For the MLP, on the other hand, 8 features have shown the best result for the width2 model, 25 for thickness2 and 18 for thickness1 and width1 models.

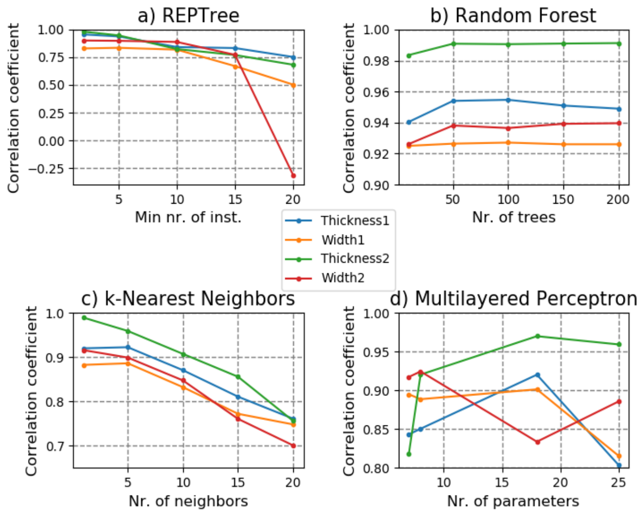

Fig.2: Prediction quality of tested algorithms

Table 2: Performance of the tested algorithms

Perf. meas.	REPTree	Random Forest	kNN	MLP
Thickness 1				
Corr. coef.	0.9566	0.9547	0.9226	0.9203
MAR	0.0172	0.0171	0.0227	0.0243
RMSE	0.0355	0.037	0.047	0.0528
Width 1				
Corr. coef.	0.8357	0.9271	0.8863	0.9014
MAR	0.0722	0.0499	0.0788	0.0644
RMSE	0.1172	0.0788	0.0976	0.1002
Thickness 2				
Corr. coef.	0.9811	0.9913	0.9893	0.977
MAR	0.0144	0.0118	0.0108	0.0198
RMSE	0.0261	0.0189	0.0194	0.0388
Width 2				
Corr. coef.	0.9017	0.9396	0.9159	0.9245
MAR	0.0697	0.0516	0.0621	0.0785
RMSE	0.1288	0.1012	0.1213	0.118

5.1 Interpretation

The only algorithm out of those used in this study that is easy to interpret for a human being is REPTree decision tree algorithm. Fig.3 shows the structure of a decision tree with the minimum number of instances in a leaf equal to 2 that has shown the best results for prediction of the width of dogbone 1.

Since pruning was enabled during the algorithm's work, not all the 25 parameters were included in the tree. The decision tree uses *holding pressure*, *plasticizing time*, *pressure at switchover*, *injection time*, *average cushion value*, *injection work*, *backpressure*, *cushion after holding pressure and injection speed* as parameters to take the decision about the value of the thickness of the dogbone specimen.

For example, if looking at the tree from the very top, we can easily get the following: if the value of the holding pressure is less than 27.5, and value of plasticizing time is less than 1.53, then, on average, the value of the width of the first dogbone will be 3.39. Numbers in the brackets indicate the number of samples belonging to that leave and number of instances from the pruning.

multilayer perceptron requires choosing the proper number of layers, neurons, selecting the learning rate, etc. In the case of decision trees, the minimum number of instances in a leaf is an important parameter, while for the random forest choosing the correct number of trees is crucial. However, out of the methods tested in this study MLP is probably the hardest to tune.

When it comes to the interpretability of the chosen methods, it is only the decision trees algorithm that is easily interpretable for a human. Models obtained through the use of the other algorithms are not as easy to interpret, especially the multilayered perceptron and the random forest.

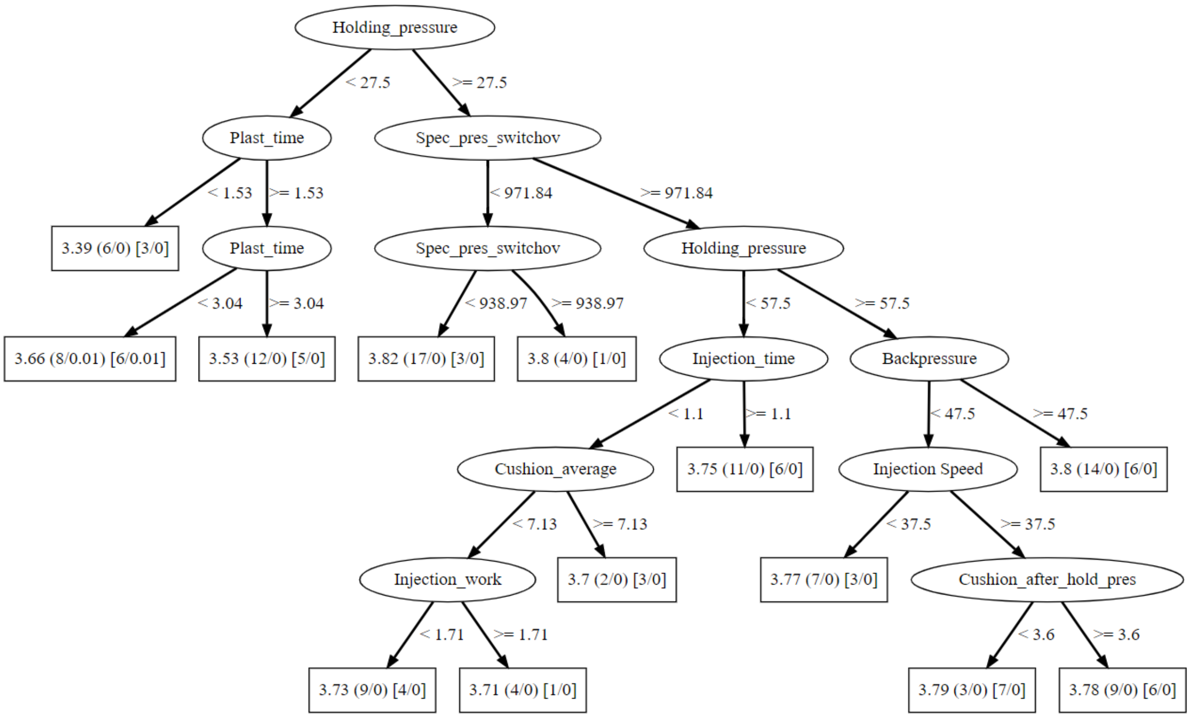

Fig.3: Obtained structure of a decision tree for prediction of thickness1

5.2 Discussion

The results show that all the machine learning methods used in this study show the high capability of predicting the width and thickness of the focus parts. The best results in terms of the correlation coefficient are achieved using the random forest algorithm, while the second-best result is received through the application of the MLP. At the same time, REPTree decision tree performs a little bit better, than kNN. However, overall all four methods show quite high prediction capabilities on this data. Overfitting should not be present since the 10-folds cross-validation technique has been used in order to estimate skill of the models on the new data.

All these algorithms require certain tuning to receive a model of the highest quality. For kNN it is important to find the best matching number of nearest neighbors,

The reliability of the proposed methodology can depend on the quality of data, computational tools used to induce the methods, as well as the correct interpretation of the results. The data used in this study was obtained through the above-mentioned laboratory experiment. The experiment was designed and planned in a way that would exclude the possibility of getting missing or erroneous data. Unfortunately, that might not always be the case, especially when the data is obtained from manufacturing companies. As mentioned before, the use of DOE helped to vary dimensions of the produced parts quite significantly. This allowed obtaining a dataset that includes dimension values close to the ideal ones, as well as those remarkably lower.

Use of different knowledge discovery platform or application of variation of any machine learning algorithm presented might lead to receiving results that are slightly different from the ones presented in this study. The ability to correctly interpret obtained results is also crucial, as a misunderstanding of certain model quality measures might lead to missing important aspects related to the model's performance capabilities.

The models presented in this study are capable of predicting dimensions of only the dogbone part since the dataset they are trained on doesn't include samples related to any other products. To create models for the prediction of dimensions of other products, the corresponding dataset needs to be obtained at first. At the same time, it is hard to say how accurate will the models' predictions be if the mold for production of the dogbones is changed. However, it is possible to assume that if mold has properties similar to the one used in the experiment, the models' predictions should be of similar quality. Such an approach could be a good starting point for manufacturing industries, including thermoplastics injection molding, to start analyzing and interpreting their data.

Amounts of data logged through manufacturing execution systems, enterprise resource planning systems, etc. continue to grow. There might be interesting and unrecognized at the moment patterns, that could potentially improve the quality of manufactured products, the overall flow of the production process, decrease amounts of produced scrap and energy consumption.

Future work includes obtaining more data, possibly for products of different geometry and material and testing machine learning methods on larger amounts of data. In addition to the real production or experimental data, simulated data can be used to pre-train the prediction models for further use of transfer -learning, as shown in [33]. This might help to increase the generalization abilities of the models so that they are able to predict dimensions and final quality not only for the dogbone specimens from HDPE but for a bigger variety of products and materials. It is also planned to do extended optimization of the model's parameters to possibly increase the prediction quality.

6 CONCLUSION

Injection molding is one of the major processes for the manufacturing of products from thermoplastic polymers. It is easily suited for the production of large amounts of plastic parts of different shapes and sizes [7]. However, the final quality of the plastic product depends on many factors, such as injection molding machine, mold in use and parameter settings [20]. Choosing the correct production parameters might be a complicated task leading to production of large quantities of scrap. That is why it is important to predict the final part quality based on the chosen process parameters.

This study presents an approach that involves the application of the machine learning methods, such as REPTree decision tree, random forest, k-nearest neighbors and multilayer perceptron ANN to create prediction models for the thickness and width of the HDPE dogbone specimens.

The model assessment is based on the application of 10-folds cross-validation, as well as correlation coefficient, mean absolute error and root square mean error. For all the algorithms some of their parameters were varied to see how it would influence the quality of the obtained prediction model. The results of the study indicate that such an approach has the potential to facilitate the process of finding optimal production conditions and decrease amounts of produced plastic scrap in the field of thermoplastics injection molding.

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