P. Koomsap et al. (Eds.)

doi:10.3233/ATDE230636

Applying Hybrid Machine Learning Models to Assist Small and Medium Enterprises in Achieving Quality Prediction and Adaptive Digital Transformation: A Case Study of Injection Molding Industry

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Abstract. With the rapid development of smart manufacturing in Industry 4.0, many companies, especially small and medium enterprises (SMEs), face the challenge of transformation. Compared to large corporations, SMEs often face more constraints in terms of resources and technology. Therefore, this study provides effective digital transformation strategies for SMEs. While previous research has utilized machine learning methods for product quality prediction, there is still a need for further exploration of digital transformation strategies that combine adaptability and quality prediction, specifically for SMEs. In this study, the injection molding industry is taken as a case study. A method framework is proposed, which combines feature selection using Xgboost, machine parameter prediction using GRU time series models, and quality classification models using SVM. This framework integrates these three methods to achieve quality prediction and adaptability as part of the digital transformation strategy. In the case study, this method framework demonstrates good accuracy in predicting machine parameters and yield. Furthermore, after the small and medium-sized enterprise adjusted their processes based on the optimization recommendations from this study, the process capability index improved significantly by 41%. In addition to the practical contributions mentioned above, this study fills the research gap in the field of quality prediction and adaptability. It provides an digital transformation strategy for SMEs manufacturing companies.

Keywords. Digital Transformation, Adaptability, Deep Learning , Quality Prediction, Small and Medium Enterprises(SMEs)

Introduction

Over the past few decades, traditional manufacturing industry has brought technological innovation and economy to a higher level. However, with low fertility and an aging population, it is difficult to recruit manpower for traditional operations, and the production quality and living space are also affected. Therefore, manufacturing SMEs

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has been looking for digital transformation in recent years to enhance its competitiveness in the market. Digital transformation is an information technology process that integrates digital information with operating processes. In the past 20 years, Digital transformation research has accumulated a large number of different findings [1]. Digital transformation's introduction to the workplace can promote the development of progressively efficient manufacturing processes, accelerating competition in terms of speed and production capacity [2].

The purpose of this study is to utilize modern scientific methods to achieve the goal of digital transformation. At present, how to predict product quality through intelligent methods has attracted the attention of the industry and academia. The biggest reason is that it is currently impossible to achieve full inspection in the case of mass production. In the past, SMEs rarely focused on finding key factors and predicting machine data and product quality. Furthermore, Industry 4.0 adaptability has not yet been achieved. Therefore, this study hopes to use the machine learning hybrid model to make up for the shortcomings in practical and academics, achieve the last stage of Industry 4.0 maturity, and respond favorably according to possible future situations, indicating that this study has adaptability.

1. Literature Review

1.1. Predictability and Adaptability

The concept of Industry 4.0 was proposed at the German Industrial Expo, and it had been widely used in recent years to describe the development direction of the manufacturing industry. Since then, the idea has been widely accepted in business and academia to characterize the effects of the integration of emergent technologies into manufacturing and supply chain processes [3]. In the context of Industry 4.0, the manufacturing system also hoped to achieve the direction of smart manufacturing. As the phenomenon of the intelligent digital transformation of manufacturing is in its emerging phase, there is no generally accepted, and established methodology for assessing Industry 4.0 readiness of enterprises [4].

In order to help company understand the degree of their industrialization and hope to help companies develop Industry 4.0 in a planned way, the acatech (German National Academy of Science and Engineering) defined the Industry 4.0 Maturity Index and divided Industry 4.0 into the six stages, which can be classified as computerization, connectivity, visibility, transparency, predictability, and adaptability. The stages that this research focuses on are predictability and adaptability. The fifth stage was predictability, and its standard was that enterprises could collect past historical data and apply accurate data forecasting models to predict and judge events that might occur in the future; so that decision-makers could predict the results in advance and make corresponding decisions. The standard for the sixth stage was that the enterprise could automatically respond with the most favorable strategy based on predicted events, and provide optimized solutions to on-site executives [5]. The goal of the method framework proposed in this study was to achieve predictability and adaptability. Predictability was achieved by predicting product quality. And the system would have adaptability by analyzing key factors to provide recommended parameters optimization to improve yield.

1.2. Development of Digital Transformation in SMEs

In recent years, with the advancement of technology and the rise of Industry 4.0, many businesses have begun undergoing digital transformation to adapt to the ever-changing market environment. Digital transformation has become an essential part of modern business and societal development. Companies need to keep pace with technological advancements, enhance their digital transformation efforts, and maintain a competitive edge for greater success. SMEs make up 99.83% of total businesses and employ 72.7% of the workforce, playing a crucial role in the economy. They should initiate the transformation of organizational structures and business cultures starting from manufacturing technologies to achieve digital transformation of productivity [6]. Therefore, digital transformation is indispensable for SMEs as it helps improve productivity, efficiency, and innovation capabilities to cope with competition and expand their markets. Digital transformation enables SMEs to remain competitive in an era of continuous technological advancement and digitalization [7].Hence, many SMEs have started recognizing the importance of digital transformation and are actively adopting these technologies to enhance production efficiency and competitiveness. However, SMEs need to consider digital transformation comprehensively, particularly because they have limited resources in planning and implementing digitization projects[8]. In addition to financial and time resources, they often lack the necessary expertise and skills [9]. In recent years, many scholars have identified a range of potential factors that influence the overall success of digital transformation, including management support, technical capabilities, human resources and knowledge, digital platforms, and more [10]. Despite the emergence of numerous studies related to digital transformation, a method framework that combines feature selection, prediction, and classification has not yet been developed to provide a digital transformation solution that integrates quality prediction and adaptability for SMEs. This study combines quality prediction and Industry 4.0 adaptability, analyzes SMEs as a case study, and focuses on key factors for successful digital transformation. By doing so, it aims to successfully complete the digital transformation for SMEs.

1.3. Summary

From past literature, it can be observed that the application of Industry 4.0 and digital transformation in SMEs has been documented. However, previous research has indicated that due to resource and manpower limitations, few SMEs have successfully implemented digital transformation solutions that encompass both quality prediction and Industry 4.0 adaptability. Additionally, the field of quality prediction has not provided corresponding measures when defective products occur.Therefore, this study proposes the utilization of the Xgboost feature selection method followed by the GRU time series model to predict machine parameters. GRU has been proven to be an improved variant of recurrent neural networks (RNN) for predictive modeling. By employing the method framework presented in this study, it aims to assist SMEs in achieving digital transformation while incorporating the concepts of Industry 4.0 adaptability and quality prediction.

2. Research methods

The method framework of this research is to use machine learning techniques to identify the correlation of each machine data, and to find out the key factors of machine parameters and product quality. After selecting the key factors of the machine parameters, the time series forecasting model is applied to predict the machine parameters, and the SVM classifier is also utilized to learn to distinguish good and defective products. Finally, the learned SVM classifier is adapted to judge whether there will be defective products in the combination of predicted machine parameters, and at the same time know the yield rate of the batch of products in the future. If the predicted yield rate does not meet the standard, the on-site personnel can adjust and optimize parameters in real-time according to relevant key factors related to product quality identified by the machine learning model, so as to improve the product yield rate and reduce production costs. Also our method can reach the stage of industry 4.0 predictability and adaptability. The overall method framework diagram is shown in Figure 1.

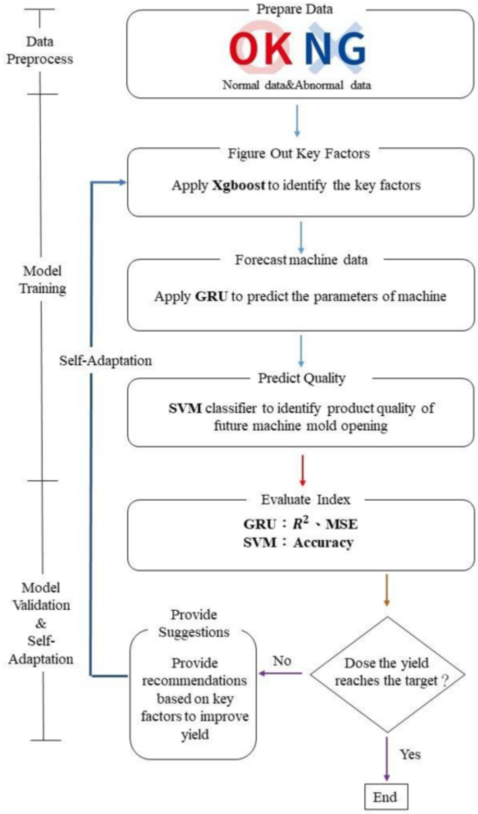

Figure 1. Method framework diagram.

2.1. Data Preprocess

In the pre-processing part of the data, although the data provided by the enterprise has a certain integrity, there are still some missing values. Therefore, in the pre-processing of data in this study, the processing method for missing values is using the mean imputation technique to estimate missing value. And normalize the data so that the data is between 0 and 1. This method can eliminate the comparison restrictions caused by different data units, and then provide the same benchmark for comparative analysis. The formula is as in equation (1), Where X is the original data, $X_{\min}$ is the minimum value in the time series data, $X_{\max}$ is the maximum value in the time series data, and $Xscaled$ is the new converted value.

$$Xscaled = \frac{X - X_{\min}}{X\max - X_{\min}} \tag{1}$$

2.2. Model Training

In the part of model training, this research will use Xgboost for feature screening, and the detailed description will be presented in Section 3.2.1. Next, GRU will be used to predict machine parameters. The detailed description and method introduction will be presented in Section 3.2.1. Finally, SVM is used to predict the quality of future products. The detailed description and method introduction will be presented in Section 3.2.3.

2.2.1. XGBoost for Feature Selection

The full name of XGBoost is eXtreme Gradient Boosting, which is one of the boosting algorithms and a common supervised learning technique. The concept of this algorithm is to combine a large number of classifiers to form a classifier; that is to say, by continuously performing feature selection to generate a tree, and learn a new function to make up for the residual error of the last prediction [14], where each tree is related to each other, the purpose is to hope that the newly generated tree can correct the miscalculated of the previous tree. XGBoost also has the function of feature selection [15]. Feature selection can find the most useful subset of features in the raw data to improve the accuracy of classification or models, and to quantify the effect between features. It is used to remove redundant or irrelevant features in machine learning to create a forecasting model and find a combination of features related to the category to be predicted. For Xgboost, good features will be selected as nodes in the tree. Number of features has little effect on model performance, and we can extract appropriate features to improve training accuracy [16].

2.2.2. GRU for Future Machine Data Prediction

GRU has even been shown to perform better on certain smaller, less complex datasets. The difference with the structure of the LSTM is that GRU only uses two gates. Compared with the LSTM, there is one less gate and fewer parameters are used, so the calculation is much faster than LSTM. The internal structure of the GRU is similar to that of the LSTM, except that the GRU combines the input gate and the forget gate in LSTM into an update gate. This model has two gates: one is the update gate, which controls the scope, and retains previous information in the current state; the other is the reset gate, which confirms whether to associate previous information with the current state. The values of the update gate and the reset gate are determined by the previous hidden layerh_{t-1} and the input layer x_t.

2.2.3. SVM Classifier for Good and Defective Products Judging

Support vector machine (SVM) algorithm was first proposed by Vapnik in 1963 to construct a linear classifier [17]. SVM is a supervised algorithm in machine learning based on statistics. Its concept is to find a hyperplane after model training, which is the so-called decision boundary to maximize the boundary between two categories. The wider the boundary, the better the classification performance of the model for new data, and it will be able to distinguish between the two categories [18].

2.3. Model Validation

The model performance metrics for this study are divided into two parts; prediction and classification. The first is the difference between the predicted machine data and the real machine data, which is the mean square error (MSE) we often hear. It is a metric of precision and is used to represent the standard deviation of the difference between the predicted value of the data and the observed value. The definition is as formula (1), assuming that there are n pieces of verification data (i=1,2,…,n), $\hat{y}_i$ is the predicted machine parameters, and $\hat{y}_i$ is the actual machine parameters.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

Another metric to measure whether the forecasting model has explanatory power is the coefficient of determination R^2, which measures the proportion of the independent variable that can explain the change of the dependent variable. If R^2 is closer to 1.0, it means that the model has more explanatory power. R^2 up to 70% means that it has the ability to represent the model [19]. The calculation formula of R^2 is shown in formula (2). Where SS_{res} means residual sum of squares, SS_{tot} means total sum of squares.

$$R^2 \equiv 1 - \frac{SS_{res}}{SS_{tot}} \tag{2}$$

The second part, which is the measurement metric of the classification, is the binary confusion matrix, as shown in Table 1 below. TP, TN, FP, and FN respectively represent True Positive, True Negative, False Positive, and False Negative in confusion matrix.

Table 1. Confusion matrix.

		Actual	
		Yes	No
Predict	Yes	TP	FP
	No	FN	TN

And calculate the accuracy, as in formula (3).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

3. Case Study

3.1. Case study

This research focuses on a manufacturing company that produces IC packing tray, Memory card lids, USB pen driver housing and Carrier tape solutions. The company faces production yield issues due to incorrect parameter settings, resulting in production waste and reliance on experienced workers for parameter adjustments. To address this, the company provides sensor-related data of an injection molding machine to predict quality and provide adjustment suggestions if the predicted yield rate falls short. The proposed method will be verified in this study.

3.2. Identify key factor results

The company provided 17 types of sensor data for this study, and XGBoost was used to determine the impact of these sensors on product weight. Table 2 presents the importance of each key factor on product quality, allowing on-site personnel to identify potential causes of defective products. The data shows that there is a large gap in the importance between the 1st stage holding average pressure and the 1st stage injection lowest position, so the factors after the 1st stage holding average. Pressure are regarded as unimportant factors. The top six key factors are prioritized for machine setting adjustments based on their importance.

Table 2. Evaluation of the importance of product quality.

	Variable name	Importance
1	**Plasticizing position**	**0.139**
2	**1st stage injection maximum pressure**	**0.133**
3	**2nd stage injection maximum pressure**	**0.128**
4	**2nd stage injection time**	**0.114**
5	**2nd stage injection screw distance**	**0.111**
6	**1st stage holding average pressure**	**0.095**
7	1st stage injection lowest position	0.061
8	1st stage injection screw distance	0.049
9	1st stage injection time	0.037
10	1st stage holding screw distance	0.031
11	Temperature 2	0.03
12	Temperature 4	0.029
13	Temperature N	0.018
14	Temperature 3	0.01
15	Temperature 1	0.003
16	1st stage holding pressure position	0.002
17	1st stage holding pressure time	0

At the same time, the yield can be known in advance by predicting the parameters on the sensors of each machine. However, due to the complex and unexplainable interaction between the parameters, this study uses the importance score from XGBoost to identify the key factor to each parameter.

3.2.1. Model Training Results

The case of this study adopts the GRU model for training. This study measures the effect of different hyperparameters on the model through the design of experimental, using the Taguchi method to establish an experiment with 3 factors and 4 levels. This study uses the L_{16} orthogonal table, and selects better results as the basis for setting hyperparameters. In addition, the Keras package in python is used to establish GRU. It has 64 neurons in the hidden layer, 7 key variables in the input layer, and 1 neuron in the output layer for predicting machine parameters. The batch size is 128, the epoch is 500, the dropout rate is 0.4, the learning rate is 0.001, and the adaptive moment estimation (Adam) algorithm is combined with the MSE loss function to evaluate the model which calculate the difference between the predicted value and the true value. The comparison of three recurrent neural networks such as RNN, LSTM, and GRU are shown in Table 3. The above three models are all predicted by the same feature selection method. From the results, we can know that the performance of LSTM and GRU on evaluation indicators is better than that of traditional RNN.

Table 3. Xgboost+ RNN, LSTM, and GRU performance comparison.

	RNN	LSTM	GRU
MSE	0.0036	0.0027	0.0025
R^2	0.831	0.901	0.903

The third part is for the SVM classifier to judge whether the product is good or defective. In this study, there are a total of 3027 data, and the data is divided into 8:2 according to the training set and test set and the SVM model is trained. The confusion matrix of the SVM classifier for identifying good and defective products is shown in Figure 2, where 0 means good and 1 means defective. From the confusion matrix, it can be obtained that the accuracy of this classification model is 93%. TP, FP, FN, and TN are respectively 0.78, 0.03, 0.04, and 0.15. It means the method proposed in this study also has a certain degree of accuracy in prediction yield.

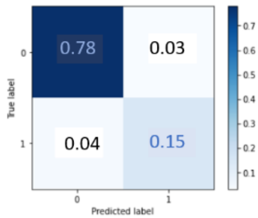

Figure 2. Confusion Matrix For Predictive Quality.

3.2.2. On-site validation

After the enterprise follows the adjustment suggestion direction provided by this research, under the condition of the same machine and the same product, as shown in Table 4, the process capability has been significantly improved, which shows that this research not only makes up for the past shortcomings in the field of injection molding, but also actually reduces the cost and waste of defective products for the enterprise in practice, and improves the process capability, bringing greater benefits to the enterprise.

Table 4. Adjustment results.

	Before adjustment	After adjustment	Improvement rate
Sample size	1009	463	
Standard deviation	0.12	0.1	
Ck	0.42	0.28	
Cp	1.41	1.63	15%
Cpk	0.82	1.16	41%

3.3. Discussion

In order to illustrate the importance and influence of this study in both academic and practical aspects, In this chapter we will illustrate the comparison between this study and other past researches on the injection molding industry. The comparison between this study and related research is shown in Table 5. In the past, Farahani et al. utilized time series forecasting models to predict product weight [20]. Párizs et al. used various machine learning methods and compared their effectiveness in predicting the quality of multi-cavity injection molding [21]. Jung et al. used a variety of machine learning methods to predict product quality and also find out factors related to quality [22]. In our research, We consider that if the predicted situation does not meet the standard, we will provide relevant adjustment suggestions to solve the problem.

Kumar et al. proposed a cyber engineering analysis model to establish upper and lower control limits while proposed algorithm to detect the failures and adjustments to the process parameters [23]. Guo et al. proposed a system combined reinforcement learning framework and artificial neural network model to optimize process parameters [24]. Dong et al. proposed a self-learning parameter optimization method, the method will update the parameters in each iteration until the best parameters are found [25]. However, the quality cannot be known in advance, and the parameters can only be adjusted after defective products appear. Therefore, our study proposes a method to predict the quality and provide relevant parameter adjustment suggestions.

Dănuţ‐Sorin et al. presented a concept within an intelligent and adaptive molding cell fabrication of polymeric products industry [26]. However, the method framework in this paper realizes the adaptability of Industry 4.0, and the field verification proves that the process capability has been significantly improved.

Table 5. Comparison with Previous Researches.

Research	Predictive Quality	Adjustment Suggestion	Ind. 4.0 Adaptability
Farahani et al.(2021) [20]	V		
Guo et al. (2019) [24]		V	
Kumar et al. (2020) [23]		V	
Párizs et al.(2022) [21]	V		
Dănuţ-Sorin et al.(2020) [26]			V
Dong et al.(2021) [25]		V	
Jung et al.(2022) [22]	V		
Our Research	**V**	**V**	**V**

4. Conclusion and Future Development

Overall, this research has both academic and practical contributions in the field of quality prediction and parameter optimization for small and medium manufacturing companies. The proposed machine learning hybrid model has shown good accuracy in both prediction and classification models, and the key factors identified can help on-site personnel to adjust machine settings to improve process capacity. The concept of adaptability of Industry 4.0 can also be applied to automatically respond to predicted events and provide optimization plans to on-site executives.

In future research, more data can be used to further improve the accuracy of the model, and the parameter optimization recommendation system can be made more perfect to achieve automatic parameter adjustment through the concept of cyber-physical systems. The framework proposed in this study can also be applied to other fields to find the most suitable machine learning or deep learning models for data in different manufacturing situations. Overall, this research provides a valuable contribution to the field of quality prediction and parameter optimization in small and medium manufacturing companies, and has the potential to lead to further advancements in the field of Industry 4.0.

References

[1] X. Zhu, S. Ge and N. Wang, Digital transformation: A systematic literature review. *Computers & Industrial Engineering*, 2021, Vol. 162, 107774.

[2] M.C. Chiu, H.Y. Tsai and J.E. Chiu, A novel directional object detection method for piled objects using a hybrid region-based convolutional neural network. *Advanced Engineering Informatics*, 2022, Vol. 51, 101448.

[3] I. Castelo-Branco, M. Amaro-Henriques, F. Cruz-Jesus and T. Oliveira, Assessing the Industry 4.0 European divide through the country/industry dichotomy. *Computers & Industrial Engineering*, 2022, 108925.

[4] Z. Rajnai and I. Kocsis, Assessing industry 4.0 readiness of enterprises. *2018 IEEE 16th world symposium on applied machine intelligence and informatics (SAMI)*, 2018, pp. 000225-000230.

[5] G. Schuh, R. Anderl, R. Dumitrescu, A. Krüger and M. ten Hompel, *Industrie 4.0 maturity index. Managing the digital transformation of companies–Update 2020*, acatech STUDY, 2020, 64.

[6] D. Ulas, Digital transformation process and SMEs. *Procedia Computer Science*, 2019, Vol. 158, 662-671.

[7] A. Garzoni, I. De Turi, G. Secundo and P. Del Vecchio, Fostering digital transformation of SMEs: a four levels approach. *Management Decision*. 2020, Vol. 58, No. 8, pp. 1543-1562.

[8] S. Peillon and N. Dubruc, Barriers to digital servitization in French manufacturing SMEs, *Procedia CIRP*, 2019, Vol. 83, pp. 146–150.

[9] N. Urbach and M. Röglinger, Introduction to digitalization cases: how organizations rethink their business for the digital age. In: N. Urbach, M. Röglinger (eds.) *Digitalization cases: how organizations rethink their business for the digital age*, Springer International Publishing, Cham, 2018, pp. 1-12.

[10] N.S. Mhlungu, J.Y. Chen and P. Alkema, The underlying factors of a successful organisational digital transformation. *South African Journal of Information Management*, 2019, Vol. 21(1), pp. 1-10.

[11] T. Chen and C. GuestrinXgboost: A scalable tree boosting system. *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, 2016, pp. 785-794.

[12] A. Ogunleye and Q.G. Wang, XGBoost model for chronic kidney disease diagnosis. *IEEE/ACM transactions on computational biology and bioinformatics*, 2019, Vol. 17(6), pp. 2131-2140.

[13] C.P. Hsieh, Y.T. Chen, W.K. Beh and A.Y.A. Wu, Feature selection framework for XGBoost based on electrodermal activity in stress detection. *2019 IEEE International Workshop on Signal Processing Systems (SiPS)*, 2019, pp. 330-335.

[14] V. Vapnik, Pattern recognition using generalized portrait method. *Automation and remote control*, 1963, Vol. 24, pp. 774-780.

[15] S. Huang, N. Cai, P.P. Pacheco, S. Narrandes, Y. Wang and W. Xu, Applications of support vector machine (SVM) learning in cancer genomics. *Cancer genomics & proteomics*, 2018, Vol. 15(1), 41-51.

[16] D.J. Leinweber, Stupid data miner tricks: overfitting the S&P 500. *Journal of Investing*, 2007, Vol. 16(1), 15.

[17] S. Farahani, B. Xu, Z. Filipi and S. Pilla, A machine learning approach to quality monitoring of injection molding process using regression models. *International Journal of Computer Integrated Manufacturing*, 2021, Vol. 34(11), pp. 1223-1236.

[18] R.D. Párizs, D. Török, T. Ageyeva and J.G. Kovács, Machine Learning in Injection Molding: An Industry 4.0 Method of Quality Prediction. *Sensors*, 2022, Vol. 22(7), 2704.

[19] H. Jung, J. Jeon, D. Choi and J.Y. Park, Application of machine learning techniques in injection molding quality prediction: Implications on sustainable manufacturing industry. *Sustainability*, 2021, Vol. 13(8), 4120.

[20] N. Kumar and J. Kumar, Efficiency 4.0 for Industry 4.0. *Human Technology*, 2019, Vol. 15(1), 55.

[21] F. Guo, X. Zhou, J. Liu, Y. Zhang, D. Li and H. Zhou, A reinforcement learning decision model for online process parameters optimization from offline data in injection molding. *Applied Soft Computing*, 2019, Vol. 85, 105828.

[22] Z. Dong, P. Zhao, J. Zheng, K. Ji, Y. Chen and J. Fu, Intelligent injection molding: Parameters self‐learning optimization using iterative gradient‐approximation adaptive method. *Journal of Applied Polymer Science*, 2021, Vol. 138(29), 50687.

[23] I.R. Dănuţ‐Sorin, C.G. Opran and G. Lamanna, Lean manufacturing 4.0 of polymeric injection molding products. *Macromolecular Symposia*, 2020, Vol. 389, No. 1, p. 1900109.