PRODUCTION ENGINEERING ARCHIVES

ISSN 2353-5156 (print)
ISSN 2353-7779 (online)

Exist since 4th quarter 2013
Available online at https://pea-journal.eu

Comparison of deep feature extraction for quality prediction in injection molding

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Article history
Received 11.09.2025
Accepted 10.01.2026
Available online 16.03.2026

Keywords
Deep feature,
Product quality,
Injection moulding,
Autoencoder,
Monitoring.

Abstract
In the context of Industry 4.0, multi-sensor data plays a pivotal role in monitoring, analyzing, and optimizing product quality in real time. The ability to capture and process data from various sensors allows manufacturers to identify deviations, detect anomalies, and improve overall production efficiency. However, raw data collected during the injection molding process often contains redundant, irrelevant, or highly correlated features that can introduce noise and reduce the efficiency of predictive models. Without proper preprocessing, such data can lead to increased computational complexity and diminished model performance. To address these challenges, effective feature extraction techniques are essential for refining the dataset, minimizing prediction errors, and enhancing the interpretability of machine learning models. In this study, we compare two widely used feature extraction methods: Principal Component Analysis (PCA) and an Autoencoder (AE). The primary objective of this research is to assess the effectiveness of these feature extraction methods in monitoring the injection molding process and predicting product quality on an advanced machine learning model LSSVM. The experimental results presented in this study are useful in determining the suitability and disadvantages of each method, with the prediction accuracy of up to 99.62% for the extracted deep feature.

DOI: 10.30657/pea.2026.32.8

1. Introduction

Injection molding is a conventional batch manufacturing process used for producing plastic parts by injecting polymer melts into a mold. Since the process relies on repeated cycles, it is expected to be highly automated. The process control consists of four stages: plasticizing, injection, packing, and cooling. The dry plastic pellet is melted via thermal energy and mechanical shear, then metered forward by the screw. During injection, the screw acts as a piston, pushing molten plastic into the mold. Cooling solidifies the material through water-cooled channels, followed by mold opening and part ejection (Bensingh et al., 2019; Rønsch et al., 2021). Consistent product quality is critical for continuous, efficient manufacturing. During the injection molding production process, product quality is affected by various factors, including irregular mold release, excessive deviations in part weight relative to the average weight, and imbalances in multi-cavity mold filling. Among these factors, product weight is widely regarded as a reliable indicator of overall quality. To ensure consistency, quality control limits are defined based on the standard deviation of product weight. If the weight of a molded part deviates beyond the established control limits relative to the average weight, the corresponding batch is classified as defective, indicating a potential issue in the molding process that requires corrective action.

The primary objective of all control strategies is to regulate machine parameters to achieve the desired product quality. However, direct measurement-based quality control strategies are often impractical in industrial settings due to the high cost of additional equipment, measurement time, and physical constraints such as limited space within the mold. As a result, the present study focuses on indirect prediction methods , (Cramer et al., 2022). These approaches can be based on either physical modeling or statistical techniques, although the former is less commonly pursued due to the complexity of fully capturing the physical behavior of the injection molding process. Process data from injection molding generate vast amounts of information for the production system, revealing the autocorrelation between various parameters and the influence of process variables on product quality. Key data points include injection pressure, melt temperature, and screw displacement or speed, all of which are essential for extracting critical process features. Data-driven methods are employed to analyze and extract meaningful characteristics of the injection molding process, enabling improved monitoring and optimization (Fan et al., 2016; Farahani et al., 2022; Nguyen et al., 2023). Before prediction can be implemented, feature extraction can be expanded by generating new characteristics to enhance the representational capacity of the original features derived from the initial collected data.

Feature extraction contributes to an overall improvement in data quality by refining and enhancing the relevant information available for analysis. This process helps reduce noise, eliminate redundant or irrelevant features, and emphasize key characteristics that influence the target variable. To our knowledge, there is currently no standardized feature extraction method for injection moulding machines to facilitate product quality prediction. In fact, the dimensionality is reduced using Mutual Information (MI) and Principal Component Analysis (PCA). PCA method is chosen due to the strong linear correlations among features, which it handles efficiently (Gao, 2012; Ge & Song, 2008). A deep learning auto-encoder (AE) network (Bengio, 2009) is employed to select features from the original data of injection molding trajectories (Bertolini et al., 2021; Mao et al., 2018; Nguyen et al., 2023). By leveraging data-driven feature extraction, these methods enhance the ability to identify patterns and correlations that influence the final product quality. In this study, we implemented two distinct feature extraction methods PCA and AE to systematically analyse and extract meaningful features from the real time data of injection moulding process. These extracted features serve as critical inputs for machine learning models, enabling the prediction of product quality based on real-time process conditions.

In the final stage, prediction model is used in the traditional way to accomplish the prediction process, that is machine learning techniques (Bertolini et al., 2021; Parizs et al., 2022; Selvaraj et al., 2022). Machine learning based approaches, such as Naive Bayes (NB), Support Vector Machines (SVM) (Zhao et al., 2020), Least Squares Support Vector Machine (LSSVM), Random Forest (RF), and K-Nearest Neighbor (KNN) classifiers, have been used to predict the production quality (Bensingh et al., 2019; Lin et al., 2024; Ribeiro, 2005). These studies aim to bridge the gap between raw process data and predictive modeling, ultimately contributing to more efficient and intelligent quality control in injection molding manufacturing. Specially, LSSVM has been successfully applied in different fields of product classification and prediction (Nguyen et al., 2023; Ribeiro, 2005; Suykens et al., 2002). The LSSVM method solves quadratic programming by converting it into a system of linear equations, using a least squares loss function. A nonlinear kernel maps inseparable data into a higher-dimensional space, where the data becomes separable. In this work, LSSVM is used to solve the problem of product quality prediction in injection molding process.

The rest of this manuscript is presented as follows: Section 2 presents the methodologies. Section 3 presents the experimental setup and data acquisition. Section 4 presents the results and discussion. Finally, Section 5 presents the conclusions.

2. Methodology

In this section, we present two distinct feature extraction techniques, each integrated with regression-based prediction models. We also detail the unsupervised training procedure employed for model development. To evaluate the effectiveness of feature extraction and its interaction with diagnostic performance, both extraction methods are systematically combined on the predictive model.

2.1. PCA method

Principal Component Analysis (PCA) applies a linear transformation to the input data with the dual objectives of reducing feature redundancy, enhancing the representational capacity of the extracted features, measured by variance. Prior to transformation, the data undergoes standardization for all attributes, thereby ensuring comparability and preventing bias due to differing numerical ranges. This prevents attributes with larger magnitudes from disproportionately influencing those with smaller ranges, thereby maintaining balanced feature representation. Following standardization, orthonormal basis vectors, known as principal components, are computed for the transformed dataset. These principal components serve as a new coordinate system that captures the most significant variance in the data while minimizing correlations among features. The components are then ranked in descending order of importance, with the first principal component accounting for the largest proportion of variance, followed by subsequent components that capture progressively smaller amounts of variance. The interpretation is that the matrix X must be centered, so that it has a mean of 0. PCA then searches for the eigenvectors of the $p \times p$ covariance matrix $X^T X$. Therefore, matrix analysis via singular value decomposition is applied, such that

$$X = UDW^T \tag{1}$$

where, U isan $n \times n$ matrix containing the eigenvectors of XX^T, D is an $n \times p$ matrix with the square root of the on the diagonal, and W is a $p \times p$ matric containing the eigenvectors of $X^T X$. The eigenvectors are sorted in decreasing order of explained variance, which is expressed as a set of p weights that can map the original variables into a new compressed space. As a result, PCA produces a transformed set of new variables that are linear combinations of the original variables and are mutually uncorrelated. This transformation not only reduces computational complexity but also enhances the interpretability of the data by eliminating redundant information.

2.2. Auto Encoder (AE) method

Figure 1 shows a single AE that is architected as a neural network. The AE consists of three layers, namely the input, hidden, and output layers. To accomplish the feature selection, the AE works as an unsupervised learning algorithm with two stages, namely the encoder and decoder. In the encoder stage, the high-dimensional input $x = \{x_1, x_2, \ldots, x_n\}$ data is mapped to low-dimensional data in the hidden layer, $h = \{h_1, h_2, \ldots, h_m\}(m \ll n)$. As the input of the decoder stage, the h data is back mapped in the output $\tilde{x} = \{\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_n\}$ with the high-level feature representation, to reconstruct the input x (Nguyen et al., 2023). The inputs of the hidden layer h are compressed into a small number of neurons. The function of activation in hidden layer k is given by Eq. (2).

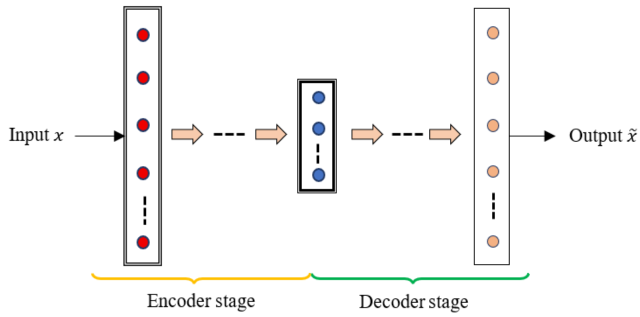


Fig. 1. Network of an AE feature extraction

$$h_i^{(k)} = f\left(\sum_{j=1}^{n} W_{ij}^{(l-1)} x_j^{(l-1)} + b_i^{(1)}\right) \quad (2)$$

Where W denotes the weight parameter, b denotes the bias parameters, and i is the unit in the hidden layer. In the first layer (i.e., the input layer), $x^{(1)} = x$, and in the last layer (i.e., the output layer), $x^{(3)} = \tilde{x}$. Then, f is the activated function used as a sigmoid function in hidden layers and a linear function in the output layer because every input example is not prescale to a specific interval such as [-1; 1].

The reconstruction error is minimized using Eq. (3) at the output. This objective function is determined with respect to the parameters W and b, which include the regularization term, and the parameter λ determines the strength of regularization. In this work $\lambda = 0.01$.

$$F(W,b) = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}x(i) - \tilde{x}(i)^2\right) + \\ + \frac{\lambda}{2}\sum_{k=1}^{n_k-1}\sum_{i=1}^{s_k}\sum_{j=1}^{s_k+1}\left(W_{ij}^{(k)}\right)^2 \quad (3)$$

where $n_{k,}$ s_k denotes the number of layers in the network and the number of units in the input layer, respectively. The AE architecture is optimally trained as the data dimensional reduction in hidden layer g. In this work, the basic encoder–decoder architecture is use to extract the feature with an input layer, a single hidden (encoder) layer, and an output (decoder) layer. The input layer consists of n neurons, where n equals the dimensionality of the dataset, with each neuron representing a discrete timestep ($n = 6000$). The hidden bottleneck layer is defined with seven neurons, which contains the most salient information from the input and form the low- dimensional AE-FS feature vector. To complete the architecture, the decoder layer mirrors the input with n neurons, allowing for accurate reconstruction of the original data structure. These extracted features are then used to predict the product quality in the predictor model.

2.3. Least Squares Support Vector Machine (LSSVM)

The least squares support vector machine (LSSVM) algorithm (Suykens et al., 2002) changed the penalty term of the slack variable in the optimization objective to quadratic constraints by introducing the linear system least squares. LSSVM solved the quadratic programming problem by a system of linear equations, which simplified the calculation process and improved the computational efficiency. The nonlinear LSSVM function can be expressed as follows:

$$f(x) = w^T\Phi(x) + b \quad \ldots\ldots(4)$$

where x_i indicates the inputs, $f(x)$ shows the relationship between the input variables and the output prediction results, w is the weight vector, $\Phi(x)$ is the mapping function, and b is the bias term. Using the estimation error, the regression problem can be expressed in relation to the principle of structural minimization as follows:

$$min\ J(w,e) = \frac{1}{2}w^2 + \frac{1}{2}\gamma\sum_{i=1}^{n} e_i^2 \quad \ldots(5)$$

$$Subject: y_i = w^T\Phi(x_i) + b + e_i (i = 1,2, \ldots, n)$$

where γ is the penalty parameter, and $e_i \in R$ are training error variables for x_i. The Lagrange multiplier optimization programming method is used to solve Eq. (4) which is constructed in Eq. (6). Thereby, the objective function is changed into an unconstraint problem (Suykens & Vandewalle, 1999).

$$L(w,b,e,\alpha) = \frac{1}{2}w^2 + \frac{1}{2}\gamma\sum_{i=1}^{l} e_i^2 - \\ - \sum_{i=1}^{l}\alpha_i(w^T\varphi(x_i) + b + e_i - y_i) \quad \ldots.(6)$$

where α_i are Lagrange multipliers. Take the partial derivatives with to w, b, $e$and α_i of Eq. (5), the optimal conditions are determined as follows

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^{n}\alpha_i\Phi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n}\alpha_i = 0 \\ \dfrac{\partial L}{\partial e_i} = 0 \Rightarrow \alpha_i = \gamma e_i \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \Rightarrow y_i = w^T\varphi(x_i) + b + e_i \end{cases} \quad ..(7)$$

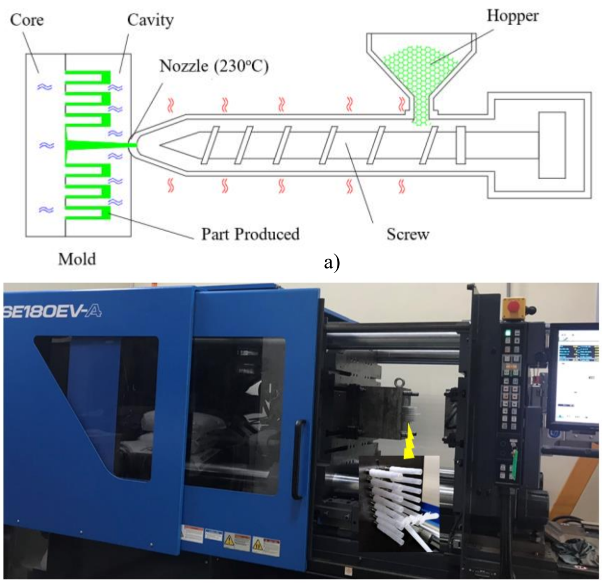
Considering the kernel function $K(x,\ x_i) = \Phi(x_i)^T \Phi(x_i)$, the output result $(\tilde{y})$ have been obtained by the LSSVM method, as follows:

$$\tilde{y} = \sum_{i=1}^{n} \alpha_i K(x, x_i) + b \tag{8}$$

where, $K(x,\ x_i)$ is the Kernel function

3. Experimental data acquisition

In the injection moulding process, the data collected from each batch run contain Injection pressure (bar) and screw position (mm) of different sub-stages. Injection pressure and screw displacement are critical variables in determining product quality, primarily due to their influence on the volume of molten material injected into the cavity and the shrinkage behaviour of the moulded part. In this study, machine data on injection pressure and screw displacement were monitored in real time to assess machine performance and the feasibility of part weight monitoring. Injection pressure serves as the driving force of the entire injection moulding process and is directly correlated with the state of the molten material within the cavity. Screw displacement, on the other hand, dictates the volume of molten material delivered into the mould. The control of displacement is achieved by regulating both the screw's rotational motion and its axial velocity, which is expressed as displacement over time. Figure 2 illustrates the experimental setup and testing equipment. All experiments were conducted using a Sumitomo SE180EV-A all-electric injection moulding machine, widely recognized for its high repeatability and exceptional process stability.



b)

Fig. 2. The experimental setup

a) injection moulding diagram; b) Experimentation on injection moulding products

The manufactured product is a multi-tube component with an approximate outer diameter of 8 mm and a length of 40 mm, as depicted in Figure 2. The material utilized in this study is a high-density polyethylene (HDPE) of specialized grade, designated as OG C140K8L104, and supplied by SK Global Chemical. This material was selected for its superior mechanical properties and processability, ensuring consistency in experimental conditions. To maintain optimal material integrity, a thermal drying system is employed to precondition the input plastic granules, preventing moisture-related defects in the final product.

During the injection moulding process, the system pressure, which directly correlates with the melt pressure at the front of the screw, is continuously monitored using the machine's integrated pressure sensor, model SA695003A3. Simultaneously, the screw position is tracked through a high-precision screw rotation encoder, enabling accurate assessment of material displacement within the injection unit. For comprehensive data acquisition, process parameters are recorded at a high-frequency sampling rate of 1000 Hz, with a sampling duration of 3 seconds, commencing from the mould-closed signal. To rigorously evaluate product quality, the mass of each moulded component is meticulously measured using a Mettler Toledo analytical balance with a resolution of 0.0001 g, ensuring exceptional precision in weight assessment. This level of accuracy is critical for detecting even the slightest variations in product weight, facilitating stringent quality control measures and ensuring process stability. This study employs three distinct experimental groups, each subjected to unique process conditions. The main variables adjusted across the groups are injection pressure and holding time, both of which have a measurable impact on the final product weight. Table 1 outlines the specific process parameters assigned to each group. The real-time data from the injection moulding process is continuously recorded on 20 to 49 production batches, respectively, to ensure statistical robustness and process traceability.

Table 1. The experimental conditions of mold injection process

Group	Injection pressure (MPa)	Holding pressure (MPa)	Holding time (s)	Holding velocity (mm/s)	Batch counts	Average weight (g)
1	70	30	2	30	49	4.813
2	65	30	1	30	44	4.659
3	50	30	1	30	20	4.732

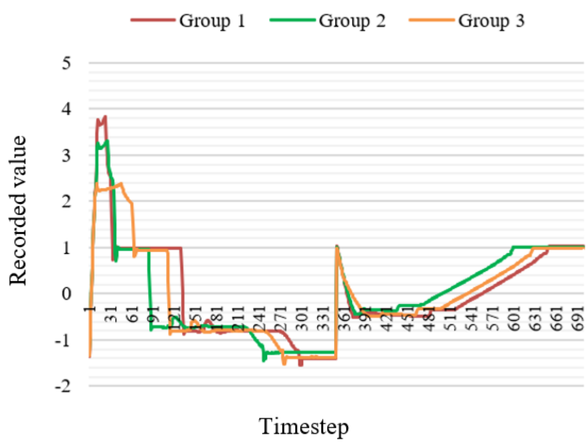


Fig. 3. Sample of pre-processed data

4. Results and discussion

Based on real-time data, the characteristics of the injection moulding process need to be extracted to predict the weight of the parts produced in each batch. First, the raw data collected from the injection moulding process is unfolded and converted into a normalized format. The two collected data sets of the injection pressure and screw position is expanded into a single flat feature vector by sequentially appending the time-points of each set. The normalization step ensures that the data is properly scaled, preserving the essential characteristics of the original signal while eliminating inconsistencies caused by different units or magnitudes. The resulting dataset retains the core information needed for subsequent analysis. Figure 3 illustrates a typical example of the data after preprocessing. The illustration shows that data are often difficult to interpret directly and that analysing such data is unnecessarily time-consuming. The feature extraction is applied to reduce complexity and enable effective prediction of product quality. Second, two advanced feature extraction techniques PCA and AE are used to identify and extract the most important features embedded in the normalized data. PCA reduces the dimensionality of the dataset by isolating the principal components with the highest variability, while AE leverages a neural network architecture to learn compressed representations of the data. Both methods aim to distil the most relevant and useful aspects of the signal, thereby improving the ability to understand and monitor the injection molding process. In this study, seven features are selected as the optimal dimension, based on both previous literature references and preliminary experiments, ensuring a balance between reconstruction accuracy and prediction performance.

Figure 4 presents the extracted feature of the injection moulding process using two proposed methods: method PCA (Fig. 4a) and method AE (Fig. 4b). Both methods produce well-separated feature sets that are suitable for further prediction.

Compared with the raw signals in Figure 3, these features are clearer and more compact, making them easier to interpret and directly applicable for product quality prediction. Third, the extracted features set is partitioned into two subsets: 80% is allocated for training, and the remaining 20% is reserved for testing. The training subset is then utilized to develop and optimize the LSSVM model, enabling it to learn the underlying patterns and relationships within the data. Finally, the LSSVM predictor model is used to forecast the testing data. The monitoring results are shown in Table 2, 3.

Overall, the two proposed feature extraction methods can accurately represent the complex relationship between the machine data of the injection moulding process and the product quality. We report that the application of the LSSVM model with two features sets is successful. The AE extracted feature set obtained the monitoring accuracy result higher than the extracted PCA feature. The average monitoring accuracy of the three groups obtained 99.31% and 99.62% for the PCA feature and AE feature sets, respectively.

The results in Tables 2 and 3 show that, although both methods can effectively represent injection moulding process characteristics, the AE extracted feature provides a more reliable basis for predicting product quality.

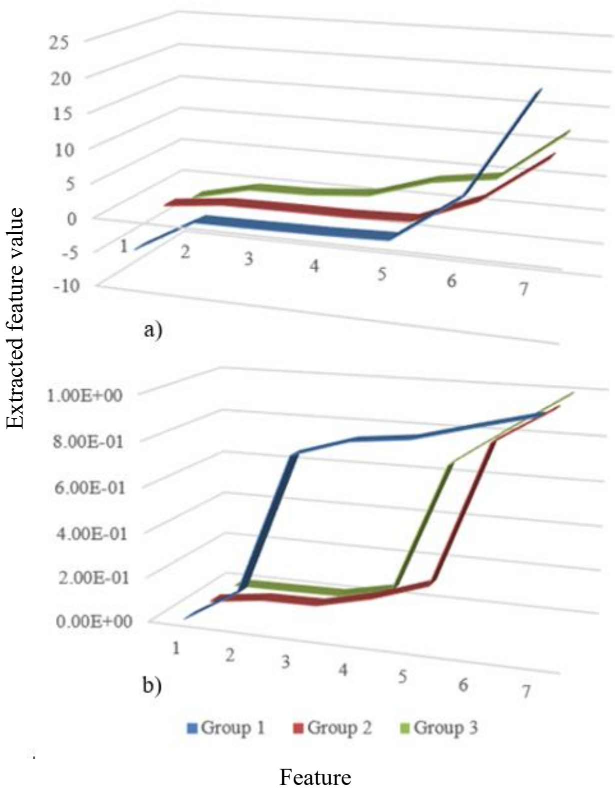


Fig. 4. Sample of extracted features: a) PCA extracted feature b) AE extracted feature

Analysis of Table 3, a small subset of test samples showed significantly higher prediction errors of AE feature dataset, sample 1 with error = 2.491%; sample 7 with error = 2.911%, which we examined to provide a balanced assessment of the model's performance. Likely contributing factors include the limited training set size, 80% of 113 samples, that increases the risk of overfitting for AE deep encoders and sample heterogeneity arising from transient operational variations or variations between processing batches. To ensure statistical transparency, we use robust summary statistics and error reporting on each sample. These results substantiate the methodological feasibility of the AE-feature approach.

Figure 5 shows the visual comparison of the results of the LSSVM predictive model based on the extracted feature set by the PCA and AE methods with the measured values. The chart highlights the superior performance of the AE-based feature extraction approach in preserving critical information for accurate prediction. It is evident that the prediction line based on AE features aligns more closely with the measured data across most points. This suggests that the Autoencoder, with its ability to capture nonlinear and latent structures within the dataset, provides a more representative feature set for the LSSVM model. In contrast, the PCA-based predictions exhibit slightly larger deviations from the actual values, likely due to PCA's linear nature and its tendency to discard subtle but relevant variations during dimensionality reduction.

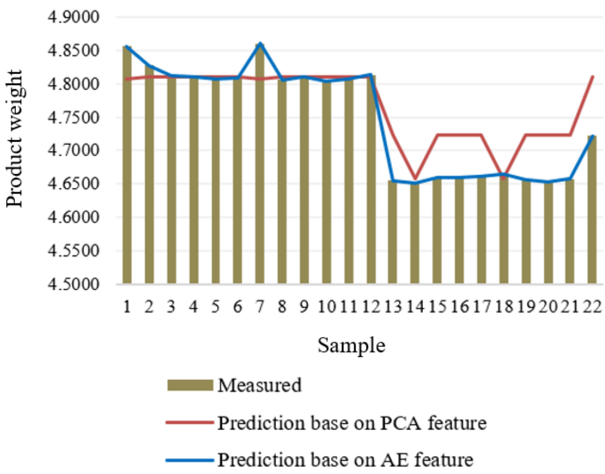


Fig. 5. The comparison of the predicted and measured results

5. Conclusion

In this study, the monitoring of product quality in the injection moulding process was experimentally compared with different feature extraction methods. High monitoring accuracy is required to reliably prevent mass defects of products and minimize production time. Two methods, PCA and Autoencoder, were proposed to extract features from real-time data. The extracted features were then used to diagnose product quality based on the LSSVM regression machine learning model. Prediction accuracy is evaluated based on the extracted features. A limitation of the present study is the relatively small dataset of 113 samples, which may constrain statistical power and the generalization capability of the trained model. The proposed methodology demonstrates feasibility of predicting production quality of injection moulding process through a machine learning-based workflow. Integrating autoencoder with LSSVR is special expected to improve performance by leveraging deep feature encoding and decoding. To address existing limitations and strengthen practical usefulness, future research will focus on validating the proposed method using more expansive and heterogeneous datasets. Systematic evaluations across diverse production batches and varying operating parameters will be conducted to rigorously quantify the model's robustness and generalizability.

Acknowledgements

This research is funded by Hanoi University of Industry under Project No. 01-2025-RD/HD-ĐHCN. The authors also acknowledge the support of School of Mechanical & Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam.

Reference

Bengio, Y., 2009. Learning Deep Architectures for AI. Foundations and Trends® in Machine Learning, 2(1), 1-127. DOI: 10.1561/2200000006

Bensingh, R. J., Machavaram, R., Boopathy, S. R., & Jebaraj, C., 2019. Influence of geometrical and injection molding parameters on optics of a bi-aspheric lens. Measurement, 134, 359–374. DOI: 10.1016/j.measurement.2018.10.066.

Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F., 2021. Machine Learning for industrial applications: A comprehensive literature review. Expert Systems with Applications, 175, 114820. DOI: 10.1016/j.eswa.2021.114820.

Cramer, S., Buschmann, D., & Schmitt, R., 2022. Comparison of Feature Extraction Algorithms for Prediction of Quality Characteristics Injection Molding. Procedia CIRP, 112, 579–584. DOI: 10.1016/j.procir.2022.09.061.

Fan, Z., Gao, R. X., Wang, P., & Kazmer, D. O., 2016. Multi-sensor data fusion for improved measurement accuracy in injection molding. In Proceedings of the 2016 IEEE International Instrumentation and Measurement Technology Conference (I2MTC 2016), Taipei, Taiwan, 23–26 May 2016, 1-5. https://ieeexplore.ieee.org/document/7520465.

Farahani, F., Saeidi, A., & Tolouei-Rad, M., 2022. A data-driven approach for predicting porosity defects in additive manufacturing using ensemble machine learning methods. Journal of Manufacturing Processes, 80, 887–897. DOI: 10.1016/j.jmapro.2022.06.013.

Gao, X., 2012. On-Line Monitoring of Batch Process with Multiway PCA/ICA. In P. Sanguansat (Ed.), Principal Component Analysis, 239–262), IntechOpen. DOI: 10.5772/38386.

Ge, Z., & Song, Z., 2008. Online batch process monitoring based on multimodel ICA-PCA method. In Proceedings of the 2008 7th World Congress on Intelligent Control and Automation (WCICA 2008), 260-264. DOI: 10.1109/WCICA.2008.4594430.

Lin, J., Ren, Z., Wu, Z., Ouyang, Z., & Yang, A., 2024. Fast and Accurate Quality Prediction for Injection Molding: An Improved Broad Learning System Method. IEEE Sensors Journal, 24(11), 18499-18510. DOI: 10.1109/jsen.2023.3346849.

Mao, G., Wang, Y., Zhao, J., & Bie, X., 2018. Multiway kernel principal component analysis for monitoring large-scale nonlinear batch processes. Computers & Chemical Engineering, 118, 77–90. DOI: 10.1016/j.compchemeng.2018.07.009.

Nguyen, V., Hoang, T., Nguyen, T., Nguyen, X., Trinh, V., Nguyen, M., Nguyen, V., & Nguyen, C., 2023. An Integrated Method in Product Quality Monitoring of the Injection Moulding Process. Industrial Engineering & Management Systems, 22(4), 503-512. DOI: 10.7232/iems.2023.22.4.503.

Parizs, R. D., Lõun, K., Lauer, A., Kadarik, V., & Frochte, J., 2022. Methodology for Establishing a Virtual Metrology System Applied to Injection Molding Processes Using Symbolic Regression. Sensors, 22(7), 2704. DOI: 10.3390/s22072704.

Ribeiro, B., 2005. Support vector machines for quality monitoring in a plastic injection molding process. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 35(3), 401–410. DOI: 10.1109/TSMCC.2004.843228.

Rønsch, G. Ø., Kulahci, M., & Dybdahl, M., 2021. An investigation of the utilisation of different data sources in manufacturing with application in injection moulding. International Journal of Production Research, 59(16), 4851-4868. DOI: 10.1080/00207543.2021.1893853.

Selvaraj, S. K., Raj, A., Rishikesh Mahadevan, R., Chadha, U., & Paramasivam, V., 2022. A Review on Machine Learning Models in Injection Molding Machines. Advances in Materials Science and Engineering, 2022, Article ID 1949061, 28 pages. DOI: 10.1155/2022/1949061.

Suykens, J. A. K., Van Gestel, T., De Brabanter, J., De Moor, B., & Vandewalle, J., 2002. Least Squares Support Vector Machines. World Scientific, Singapore. DOI: 10.1142/5089.

Suykens, J. A. K., & Vandewalle, J., 1999. Least Squares Support Vector Machine Classifiers. Neural Processing Letters, 9(3), 293-300. DOI: 10.1023/a:1018628609742.

Zhao, P., Wu, H., & Huang, D., 2020. Intelligent Injection Molding on Sensing Optimization and Quality-Reliability Evaluation. Advances in Polymer Technology, 2020, 1–9. DOI: 10.1155/2020/7654249.

Appendix

Appendix A

Table 2. Prediction results based on PCA features

No	PCA Features							Weight (g)		Error (%)
								Measured	Predicted	
1	-6.0174	-0.5863	-0.0147	0.1011	0.1521	0.3933	0.4061	4.8560	4.8065	1.019
2	-5.7491	-0.1209	-0.0812	-0.0083	0.0026	0.2477	0.3152	4.8275	4.8095	0.373
3	-5.7606	-0.1774	-0.0174	-0.0153	0.1160	0.2919	0.3550	4.8120	4.8095	0.052
4	-5.7434	-0.0955	-0.0656	-0.0196	0.0526	0.3113	0.3220	4.8100	4.8095	0.010
5	-5.7326	-0.1047	-0.0217	-0.0151	0.0145	0.2932	0.3216	4.8065	4.8095	0.062
6	-5.7965	-0.2095	-0.0046	0.0959	0.1317	0.2916	0.3049	4.8080	4.8095	0.031
7	-5.9800	-1.1570	-0.1564	-0.0243	0.0307	0.4764	0.4885	4.8605	4.8065	1.111
8	-5.7408	-0.1617	-0.1178	-0.0265	0.0330	0.2546	0.3109	4.8060	4.8095	0.073
9	-5.7616	-0.3521	-0.1663	0.0558	0.1310	0.1825	0.3924	4.8105	4.8095	0.021
10	-5.7982	-0.1865	0.0048	0.0906	0.1695	0.2640	0.2789	4.8035	4.8095	0.125
11	-5.7072	-0.1666	-0.1473	-0.0002	0.0573	0.1314	0.3524	4.8070	4.8095	0.052
12	-5.7534	-0.3653	-0.1955	0.0750	0.1325	0.2231	0.3896	4.8135	4.8095	0.083
13	-0.1854	-0.0242	0.0239	0.0344	0.3119	0.5873	7.6376	4.6545	4.7230	1.472
14	-0.4201	-0.1509	-0.0888	-0.0509	0.0313	0.6414	7.5917	4.6505	4.6585	0.172
15	0.0092	0.0689	0.1123	0.1683	0.5051	0.6502	7.6178	4.6590	4.7230	1.374
16	-0.0330	0.0242	0.0516	0.1679	0.1936	0.5650	7.5682	4.6595	4.7230	1.363
17	-0.0068	-0.0043	0.0783	0.1152	0.5157	0.5447	7.5893	4.6605	4.7230	1.341
18	-2.2786	-0.3433	-0.0467	-0.0139	0.1173	0.6816	7.2090	4.6650	4.6585	0.139
19	-0.0063	0.0033	0.0219	0.0661	0.3391	0.5488	7.5921	4.6565	4.7230	1.428
20	-0.0940	-0.0037	0.0063	0.0211	0.0460	0.5960	7.5602	4.6535	4.7230	1.493
21	-0.0090	0.0301	0.0618	0.0888	0.3247	0.5431	7.5666	4.6570	4.7230	1.417
22	-9.3322	-0.0365	-0.0228	-0.0048	-0.0039	-0.0007	1.6082	4.7220	4.8095	1.853
					Average error					0.685

Table 3. Prediction results based on AE features

No	AE Features							Weight (g)		Error (%)
								Measured	Predicted	
1	0.0004	0.0016	0.0016	0.0709	0.5028	0.8772	0.9998	4.738	4.856	2.491
2	0.0001	0.0022	0.0022	0.0161	0.1438	0.8747	0.9993	4.807	4.828	0.437
3	0.0002	0.0022	0.0022	0.0090	0.1956	0.8781	0.9993	4.807	4.812	0.114
4	0.0001	0.0021	0.0021	0.0134	0.1612	0.8708	0.9993	4.807	4.810	0.073
5	0.0001	0.0020	0.0021	0.0143	0.1668	0.8690	0.9993	4.807	4.807	0.000
6	0.0003	0.0021	0.0022	0.0104	0.2138	0.8849	0.9994	4.807	4.808	0.031
7	0.0001	0.0010	0.0011	0.0205	0.7771	0.9748	0.9998	4.723	4.861	2.911
8	0.0001	0.0023	0.0024	0.0104	0.1635	0.8760	0.9993	4.807	4.806	0.010
9	0.0000	0.0015	0.0015	0.0622	0.2110	0.8500	0.9995	4.807	4.811	0.083
10	0.0003	0.0021	0.0021	0.0166	0.1923	0.8864	0.9994	4.807	4.804	0.062
11	0.0000	0.0017	0.0018	0.0408	0.0986	0.8598	0.9994	4.807	4.807	0.000
12	0.0000	0.0015	0.0016	0.0495	0.2833	0.8416	0.9995	4.807	4.814	0.146
13	0.0000	0.0000	0.0000	0.0000	0.0006	0.0006	0.0434	4.659	4.655	0.086
14	0.0000	0.0000	0.0000	0.0001	0.0007	0.0008	0.2977	4.659	4.651	0.172
15	0.0000	0.0000	0.0000	0.0000	0.0005	0.0006	0.0080	4.659	4.659	0.011
16	0.0000	0.0000	0.0000	0.0000	0.0007	0.0008	0.0592	4.659	4.660	0.021
17	0.0000	0.0000	0.0000	0.0000	0.0006	0.0006	0.0105	4.659	4.661	0.043
18	0.0000	0.0000	0.0001	0.0006	0.0027	0.0030	0.9992	4.733	4.665	1.426
19	0.0000	0.0000	0.0000	0.0000	0.0006	0.0007	0.0296	4.659	4.657	0.043
20	0.0000	0.0000	0.0000	0.0000	0.0007	0.0008	0.1416	4.659	4.654	0.107
21	0.0000	0.0000	0.0000	0.0000	0.0006	0.0007	0.0325	4.659	4.657	0.032
22	0.0001	0.0004	0.0015	0.0016	0.9602	0.9993	0.9993	4.723	4.722	0.021
					Average error					0.378