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RESEARCH ARTICLE

Generative machine learning-based multi-objective process parameter optimization towards energy and quality of injection molding

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Abstract
The high energy intensity and rigorous quality demand of injection molding have received significant interest under the background of the soaring production of global plastic industry. As multiple parts can be produced in a multi-cavity mold during one operation cycle, the weight differences of these parts have been demonstrated to reflect their quality performance. In this regard, this study incorporated this fact and developed a generative machine learning-based multi-objective optimization model. Such model can predict the qualification of parts produced under different processing variables and further optimize processing variables of injection molding for minimal energy consumption and weight difference amongst parts in one cycle. Statistical assessment via F_1-score and R^2 was performed to evaluate the performance of the algorithm. In addition, to validate the effectiveness of our model, we conducted physical experiments to measure the energy profile and weight difference under varying parameter settings. Permutation-based mean square error reduction was adopted to specify the importance of parameters affecting energy consumption and quality of injection molded parts. Optimization results indicated that the processing parameters optimization could reduce ~ 8% energy consumption and ~ 2% weight difference compared with the average operation practices. Maximum speed and first-stage speed were identified as the dominating factors affecting quality performance and energy consumption, respectively. This study could contribute to the quality assurance of injection molded parts and facilitate energy efficient and sustainable plastic manufacturing.

Keywords Injection molding · Random forest · Multi-objective optimization · Energy consumption · Product quality · Sustainable manufacturing

Introduction

The world economic forum estimated that global market volumes would keep growing substantially from annual production of 380 million tons in 2015 and were estimated to be 12,000 tons in 2050 (Geyer et al. 2017). Injection molding is one of the primary plastics processing techniques (Liu et al. 2020) and includes four main operation phases: filling stage, holding stage, cooling stage, and demolding stage (Yen et al. 2006). These subprocesses with high-temperature heating, forced cooling, and high pressure is energy intensive and quality sensitive. The energy efficiency of injection molding is still particularly low that merely 50% to 60% of total energy contributes to the forming process (Lovrec et al. 2017). Apart from the energy efficiency issue, the injection molding process is prone to generate defects, resulting in wasted material and higher costs. Common defects in injection molded products are bubbles, flying edges, and sinkholes (Mathivanan et al. 2010). Improving the energy performance and qualification rate simultaneously is nontrivial. Currently, there are two typical promising approaches to solve such issue in practice (Arisoy et al. 2015). The first method mainly focuses on improving and upgrading the injection molding machine physically, for example, using a variable-volume pump, two-plate clamping device, and electro-hydraulic hybrid drive system for energy conservation and quality assurance (Arisoy et al. 2015). Another method

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is to optimize the processing parameters of injection molding that range from polymeric heating to parts demolding (Li et al. 2015; Liu et al. 2020). Obviously, the first approach can save energy and improve product quality directly. However, the wide application of equipment upgrading is cost-prohibitive for the majority of small enterprises. In contrast, optimizing process parameter settings is a relatively more practical and feasible way towards quality assurance and energy conservation (Madan et al. 2013; Kashyap and Datta 2015; Selvaraj et al. 2022).

There has been a body of studies that analyzed various controllable parameters to obtain the important influencing parameters and optimized process parameters to reduce energy consumption (Peng et al. 2019; Wang et al. 2021; Zhou et al. 2022). Mianehrow et al. (2017) assessed the impact of different machine-related and process-related parameters on energy consumption and provided insights into how to reduce the maximum electrical demand. Meekers et al. (2018) achieved reduce energy consumption by the impact of parameters such as cooling time on the injection process. Quantitative models were commonly established to capture the relationship between energy consumption and process parameters. Li et al. (2015) proposed a specific energy consumption (SEC) model to predict the energy consumption of an injection molding equipment by injection process parameters. The result shows that the throughput rate is the key factor. Dietmair and Verl (2008) introduced a new form of modeling to predict energy efficiency for studying the energy efficiency of machine tools. Considering the thermodynamic analysis, Chien and Dornfeld (2013) presented a semi-empirical model for predicting the energy consumption of an injection molding equipment based on the energy distribution in the injection molding process.

With the increasing production of plastic parts, striving for product quality is of increasing concern (Fernandes et al. 2018b). A series of studies have focused on identifying the relationship between process parameters and product quality to optimize the quality by the design of experiments (DOE) (Fernandes et al. 2018a). Among DOE techniques, the Taguchi method is a widely used technique to find the entire factor space based on a small number of experiments. Tang (2007) improved product quality efficiently by applying the Taguchi method. In addition, a set of numerical simulation approaches, e.g., the computer-aided engineering (CAE) technique has been applied to the injection molding process for quality improvement (Farshi et al. 2011). Additionally, due to the machine learning (ML) algorithms can construct analytic mappings from input features to output responses (Chen et al. 2008; Wang et al. 2022), some studies applied ML as a surrogate method to rapidly figure out the optimal parameters, such as artificial neural networks (ANN), support vector regression (SVR), and K means. Shen et al. (2007) proposed an ANN combined with an intelligent heuristic algorithm to optimize the process parameters of an injection molding machine. In this method, the CAE simulation data was used as the dataset to train the model between injection process parameters and volume shrinkage of parts. Luo et al. (2020) combined SVR method and particle swarm optimization algorithm to obtain optimal parameters of the machine. Ding et al. (2011) introduced a new algorithm K means of joint support vector clustering-strength Pareto evolutionary algorithm (KSVC)-SPEA to achieve multi-objective optimization.

DOE in conjunction with response surface method (RSM) is usually used in the injection molding process (Chen et al. 2012, 2016). But it cannot predict accurately when a wide range of parameters are involved (Tian et al. 2017). Additionally, most of the prior studies made a prediction of energy consumption or quality via CAE simulations or trained ML model based on a simulated dataset. Although CAE simulations can predict general correlations between trends and parameters, the simulation results do not necessarily reflect the real situation. The simulation errors cannot be ignored and may arguably result in inaccurate predictions (Hopmann et al. 2019). Most of the existing work only predicts and optimizes one single or two objectives, e.g., the energy consumption and average quality. Interestingly, in our physical experiments of injection molding, we found that the weight difference between parts in different cavities of mold is closely related to the qualification rate of products. This phenomenon recently has gained increasing attention in the domain of mold design (Gim et al. 2015; Tsai et al. 2022). To the best of our knowledge, few studies have ever incorporated this indicator into multiple objectives optimization of the manufacturing process.

To fill the above research gaps, this study proposed a data-driven model combining ML and genetic algorithms (GA) to achieve multiple objectives optimization including the energy consumption of the injection molding process, quality of the injection product, and weight difference between parts produced by multi-cavity mold. We conducted an injection molding experiment and collected 200 groups of actual operation data to train the ML model. Then, we analyzed the performance of the proposed model. Results showed that our model would improve the qualification rate of injection products and reduce the average energy use in one operation cycle. The present study would provide scientific basis for improving energy efficiency and qualification rate in injection molding practice.

The structure of this study is organized as follows: Part 2 presents the index of the dataset and procedure of dataset construction. Part 3 describes the basic methodology of the algorithm and the process of constructing the model proposed in this study. Part 4 provides a discussion of the critical results. Finally, Part 5 concludes this study.

Dataset construction

Injection molding system description

An injection molding process can be divided into four main stages: filling stage, holding stage, cooling stage, and demolding stage (Yen et al. 2006). Operation parameters influencing the injection molding process can be divided into the following categories:

- Temperature: temperature of the barrel and the temperature of the mold.
- Speed: injection speed.
- Time: injection holding time, cooling time, and cycle time.
- Pressure: holding pressure, maximum pressure.
- Stroke position: cushion position, V-P switch-over position.

Considering the influence of the process parameters on the quality of the injection product (Hassan 2013; Huang et al. 2021a, b), this study mainly selected the following seven parameters: cushion position, V-P switch-over position, cycle time, first-stage speed, second-stage speed, holding pressure, maximum pressure, and maximum speed.

The type of injection molding machine used in this study is Toyo Si-180IV, the injection molding product is the handle inner buckle of the car seat, and the number of cavities in the mold is 2, as shown in Fig. 1.

Data collection

In this study, the weight of the injection parts was used as an indicator to determine the qualification of the injection molded product. This indicator was considered to be universal because it is independent of the type of mold and material (Li et al. 2015). The weight difference between the injection molded part and standard part can reflect the existence of quality problems such as volume shrinkage, flying edges, and internal porosity. These defects are usually unacceptable but can be diminished by selecting appropriate process parameters. This study used the injection molding of inner buckle (a component in car seat) as an illustrative example. Here, the weight range for standard parts is $37.65g \leq m \leq 38.20g$. Whether the weight of injection molded part located in this range was applied as a criterion to determine its qualification.

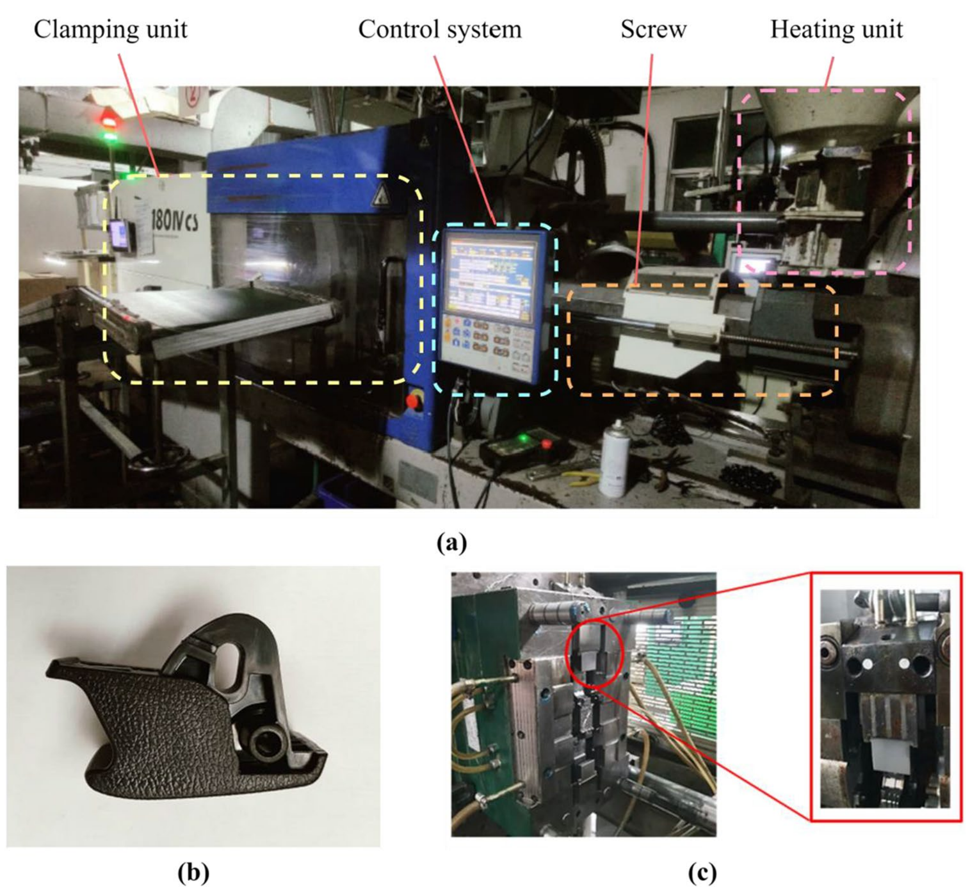


Fig. 1 **a** Injection molding machine. **b** The handle inner buckle of the car seat. **c** Multi-cavity injection mold

During the data acquisition process, the machine was set to automatic mode to obtain the corresponding 200 pairs of injection molded parts. After each random modification of the process parameters, the machine will automatically complete an injection. Notably, each pair of injection parts produced in one mold with two cavities was labeled as No. 1 and No. 2. We measured the weight of each injection molded part pair three times and adopted the average value. The weight of plastic injection parts was measured using an electronic balance (BSM-220.4).

This study used a power quality analyzer (VICTOR 5000) for energy consumption measurements in three-phase four-wire systems. Figure 2 shows the energy power curve of the injection molding machine within one cycle. Each cycle ended with the mold open and began with the mold closure, these two operations consumed energy. Furthermore, the closing operation includes the injection of the polymer, causing fluctuations in energy power. For the plasticize zone and heater zone, the machine required a large amount of energy to transport the polymer and heat material. Therefore, the energy power varied considerably among the different zones. The energy-time curve in each cycle is integrated to obtain the energy consumption corresponding to each set of process parameters. We recorded and computed the energy consumption of the 200 cycles, i.e., 400 injection molded parts.

Method

Random forest

Ensemble learning usually has better performance in completing learning tasks compared with a single learner

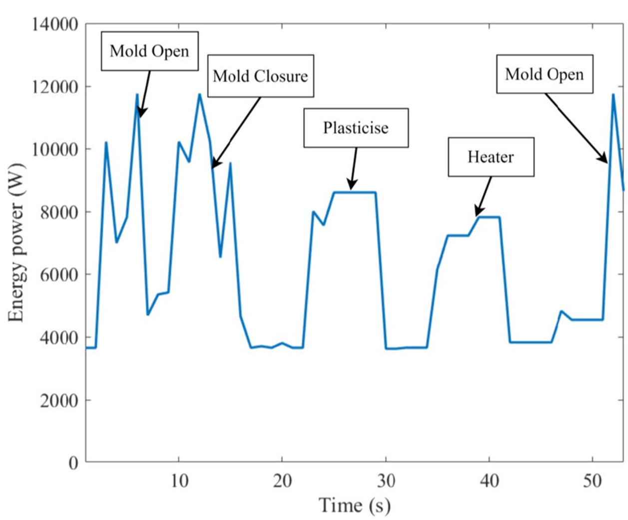


Fig. 2 Energy power-time curve in a cycle

(Dong et al. 2020). The common ensemble learning methods are boosting, bagging, and random forest (RF) (Gomes et al. 2017; Sagi and Rokach 2018; Dong et al. 2020). Bagging is a representative method of parallel ensemble learning based on bootstrap sampling. And RF is an enhanced version of bagging (Breiman 2001). RF introduces the selection of random attributes in the training process and is constructed based on decision tree. A major advantage of random forest is simplicity, high accuracy, and low computational overhead. These merits enable its wide range of applications (Akar and Güngör 2012). To initialize the RF algorithm, we defined two parameters that: number of decision trees N and number of attributes k to divide the RF. Inappropriate selection of these two parameters will lead to over-fitting or underfitting. To obtain the expected result, previous study (Geurts et al. 2006) recommended to set $k = \log_2 d$ or $k = \sqrt{d}$, where d is the number of attributes in the initial dataset. RF has classical two types: classification RF based on classification decision tree and regression RF based on regression decision tree. For each node, common division criteria include Gini index, information gain, etc. The Gini index can be calculated as follows:

$$\sum \sum_{j \neq i} \left(\frac{f(C_i, T)}{|T|} \right) \left(\frac{f(C_j, T)}{|T|} \right)$$

where C_i is a randomly selected class, T is a given training set, and $\frac{f(C_i,T)}{|T|}$ is the event probability that belongs to the C_i class (Pal 2005).

In addition, Breiman (2001) also proposed a method to calculate the importance of variables in the RF model. For each decision tree in the RF, random noise is added to one of the variables for the out-of-bag (OOB) data, such as randomly permuting the mth variable in the OOB data. A variable is proved to be important if the accuracy decreases greatly after adding random noise. The permutation-based MSE reduction has been adopted as a common approach by many researchers to evaluate the importance of variables. The corresponding equation is defined as follows (Grömping 2009):

$$\boldsymbol{OOBMSE}_t = \frac{1}{n_{OOB,t}} \sum_{i=1; i \in OOB_t}^{n} \left(y_i - \hat{y}_{i,t} \right)^2$$

where the $\hat{y}_{i,t}$ is predictions, $OOB_t = \{i$: observation i is OOB for tree $t\}$, $n_{OOB,t}$ is the number of OOB observations in tree t. For each variable x_i in each tree t, we calculated the MSE reduction after the permutation. The MSE reduction according to variable x_i for the complete forest was obtained as the average of all trees' MSE conduction. For comparison purposes, all variable importance metrics of the forest were normalized to sum to 100%. We incorporated this characteristic of RF into the importance of process variables to energy consumption, part quality, and weight difference.

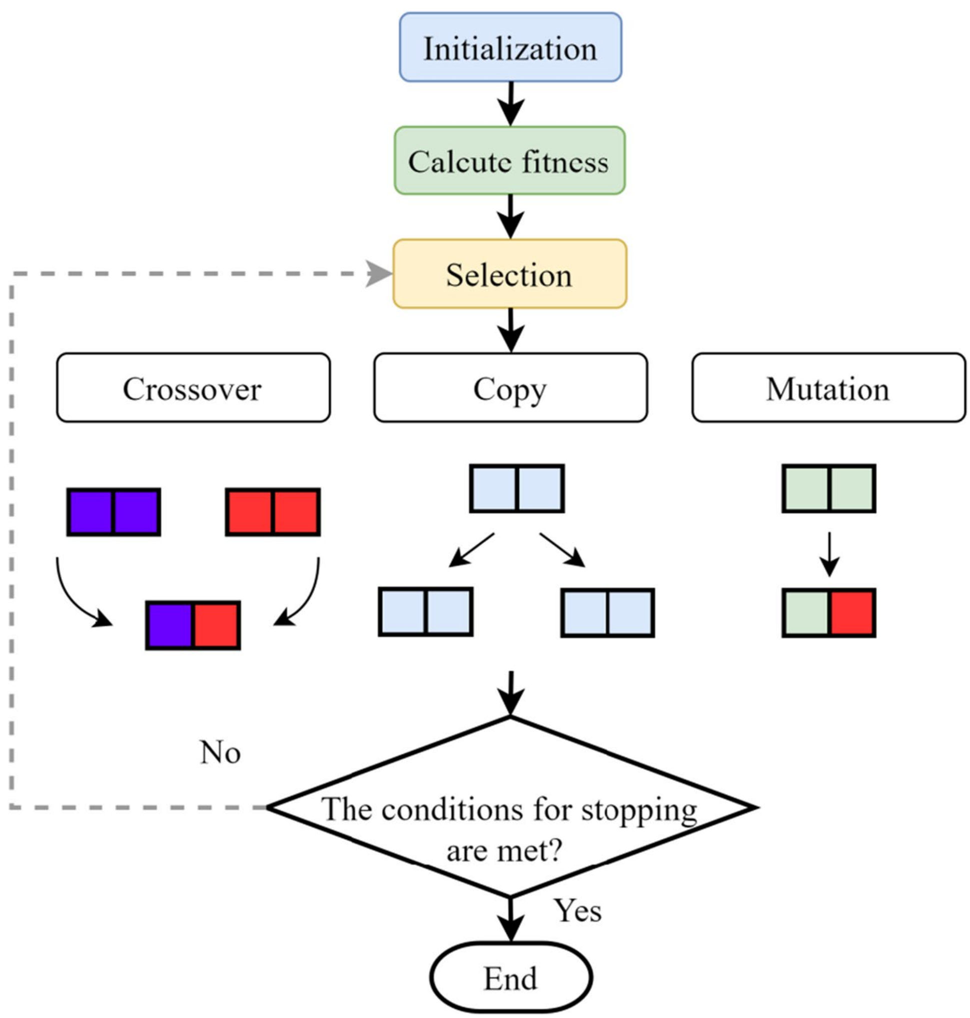
Genetic algorithm

Genetic algorithm is one of the population-based random algorithms inspired by evolutionary biology (Mirjalili 2019). It has become one of the most popular evolutionary algorithms for optimization due to its scalability, simplicity, and global optimum solutions (Kumar et al. 2020). Figure 3 presents the procedure of a typical GA algorithm. Firstly, this algorithm initializes the parameters such as number of populations, number of iterations, variation rate, and crossover rate. Those parameters affect the speed of convergence and the accuracy of the results (Lobo and Lima 2005). Then, fitness is calculated to selected chromosomes, and the selected ones were crossed, mutated, and replicated. The evolution terminated until reached the maximum of generations, or little improvement of fitness occurs in further epoch.

Generative machine learning algorithm for parameter optimization

Combining the advantages of RF and GA, this study proposed a generative machine algorithm for the multi-objective optimization, as shown in Fig. 4. Three RF models, namely, the quality prediction model, energy consumption prediction model, and weight difference prediction model were trained based on the dataset established in this study. The GA algorithm was used to continuously generate a population of chromosomes, i.e., a set of process parameters for the injection molding machine. The quality prediction model could determine the qualification of the part produced under the generated process parameters. Therefore, the model can be regarded as a first fitness function. The parameter set corresponding to the unqualified part was directly eliminated and regenerated through GA, while the parameter set with qualified part move towards the next stage. Additionally, energy consumption model can predict the energy consumption in a cycle through the process parameters. The weight difference model enabled to predict the weight difference of products generated by multi-cavity

Fig. 3 The flowchart of GA



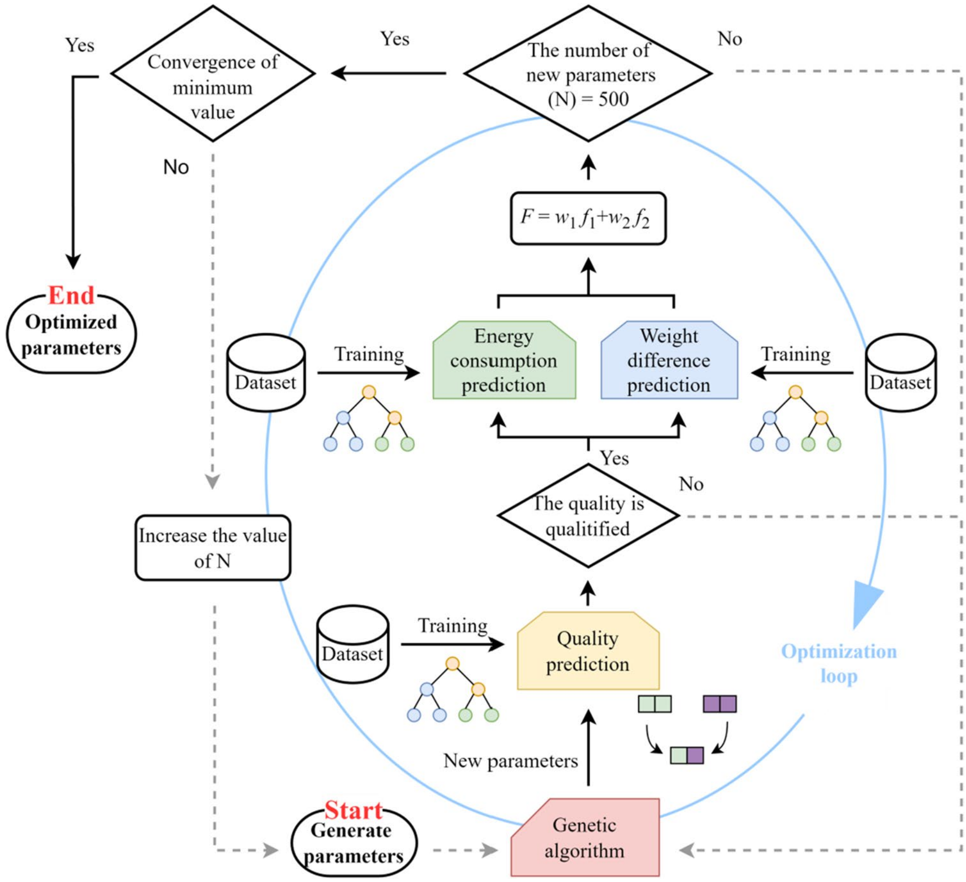


Fig. 4 The flowchart of the proposed model in this study

mold. The normalized values of energy consumption prediction and weight difference prediction were denoted as f_1 and f_2, respectively. F was the second fitness function in the algorithm proposed in this study and calculated as follows:

$$F = w_1 f_1 + w_2 f_2$$

where w_1, w_2 were the weights corresponding to f_1 and f_2, depending on the actual requirements of the engineering application, and $w_1 + w_2 = 1$. The convergence of the algorithm should be concerned when reaching the maximum iteration number. The number of iterations should be increased if the algorithm was not convergent. Otherwise, the process parameter with minimal F-value was finally selected.

Statistical assessment

To assess the quality of fit in multiple regression, we computed the most commonly used indicator R^2 (Renaud and Victoria-Feser 2010) as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \overline{y}_i\right)^2}$$

where y_i is the actual value, $\overline{y}_i$ is the mean of the actual values, and $\hat{y}_i$ is the predicted value. R^2 closer to 1 signified a better prediction model. Generally, the performance of the model can be considered as good if $R^2 > 0.8$ (Roy and Roy 2008).

For classification models, the F_1 score was selected as a measurement of classifier performance (Chicco and Jurman 2020). The equation for the calculation of the F_1 score was as follows:

$$F_1 = \frac{2 \times P \times R}{P + R}$$

where P is the accuracy of the model, R is the recall of the model, and F_1 score closer to 1 implied better performance of the classifier.

Result and discussion

Dataset analysis

Table 1 presents the basic statistical information for the dataset, including the maximum, minimum, mean, and standard deviation values of each variable.

The frequency histogram of the energy consumption dataset was shown in Fig. 5. It is worth noting that the energy consumption of over 80% is concentrated between 250,000 and 290,000 J. Besides, the mean value and standard deviation are approximately 268,940 J and 19,534 J, respectively.

The frequency histogram of the weight difference dataset was shown in Fig. 6. Over 65% of the weight difference range from 0.37 to 0.41 g, with a standard deviation of approximately 0.02 g.

Figure 7 displays a line graph of the quality dataset. The green region represented qualified areas, and the upper and lower boundary of this region indicated the tolerance of injection molded part. The red and blue curves represented the weight variation of parts in the No. 1 and No. 2 mold cavity, respectively. Notably, the trends of both curves are roughly similar. Further, the weight of the No. 1 product was basically lower than that of No. 2 product. According to this figure, 96 samples (192 parts in total) are located within the qualified region.

Performance of model

Based on the measured dataset, an RF model was constructed for prediction and using F_1 scores and R^2 metrics to measure the performance of the model. Figure 8 shows the results of quality prediction using RF. From the confusion matrix diagram, it is clear that the classification results on training set are perfectly correct. And there are only two misclassified samples on the test set. This indicated the accuracy of the quality prediction model. We also conducted ten cross-tests, and the average F_1 score on the test set was 0.96. The above analysis validated the good performance of our RF model in classifying the quality of injection molded parts.

Figures 9 and 10 show the prediction results of weight difference and energy consumption, respectively. The line with a slope of 1 in the graph was called the ideal prediction line. Sample points falling on the ideal prediction line indicate perfect prediction that the prediction value equals the true value. As shown in Fig. 9, the sample points fell roughly around the ideal prediction line, indicating that the weight difference prediction was close to the true value. The R^2 value of the weight difference prediction model on the training set and test set were 0.92 and 0.89, respectively. As the R^2 values are greater than 0.8, the RF model can be supposed to have good prediction performance of weight differences. As for the energy prediction model, the points in Fig. 10 were evenly distributed around the ideal prediction line with no significant fluctuations. The R^2 values for the energy prediction model on the training and test sets were 0.99 and 0.92, respectively. The result suggested

Table 1 Basic information of the dataset

	Cushion position (mm)	V-P switchover point (mm)	Cycle time(s)	First-stage speed (mm/s)	Second-stage speed (mm/s)	Holding pressure (MPa)	Maximum pressure (MPa)	Maximum speed (mm/s)	No. 1 weight (g)	No. 2 weight (g)	Weight difference(g)	Energy consumption(J)
Minimum	14.17	22.48	49.29	9.00	7.00	108.82	108.92	12.00	37.20	37.64	0.33	213958.80
Maximum	21.38	27.00	52.38	24.00	18.00	134.70	134.90	35.00	38.28	38.79	0.52	333775.00
Average	18.80	24.31	49.74	15.16	12.22	119.98	120.77	21.20	37.75	38.15	0.39	268940.02
Standard deviation	1.68	2.25	0.87	1.60	1.7313	6.39	6.41	1.70	0.18	0.18	0.02	19534.10

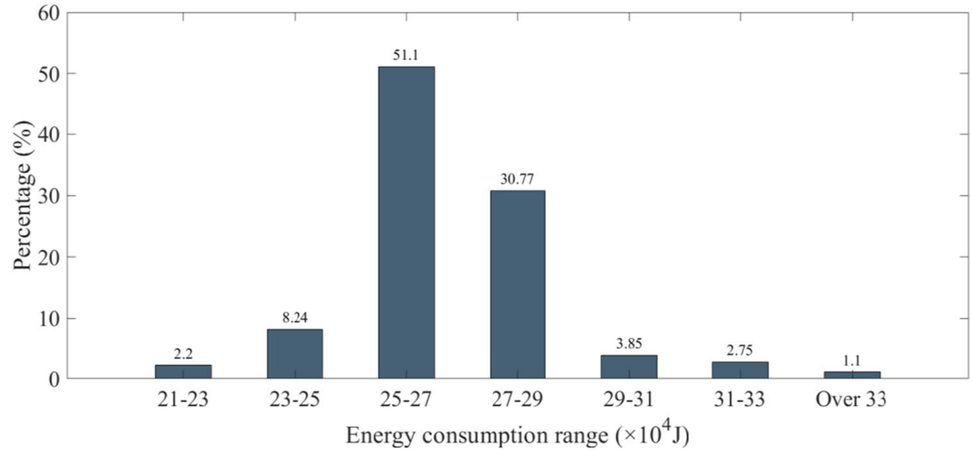


Fig. 5 The range of energy consumption dataset

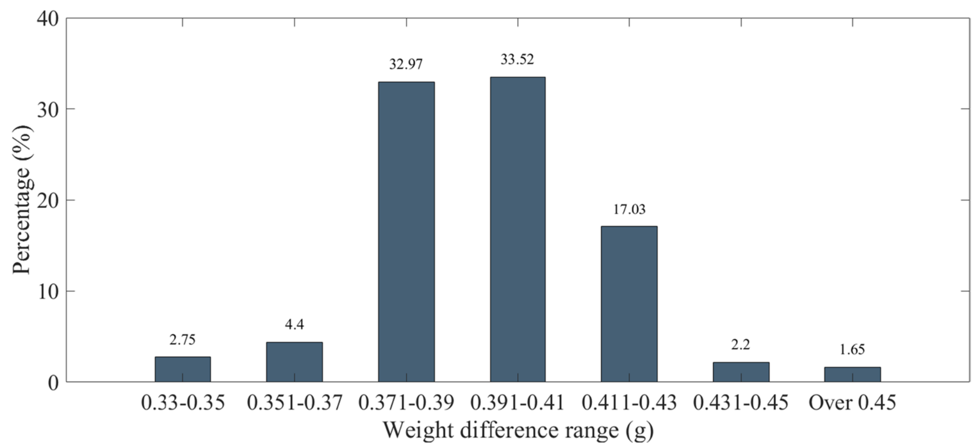


Fig. 6 The range of weight dataset

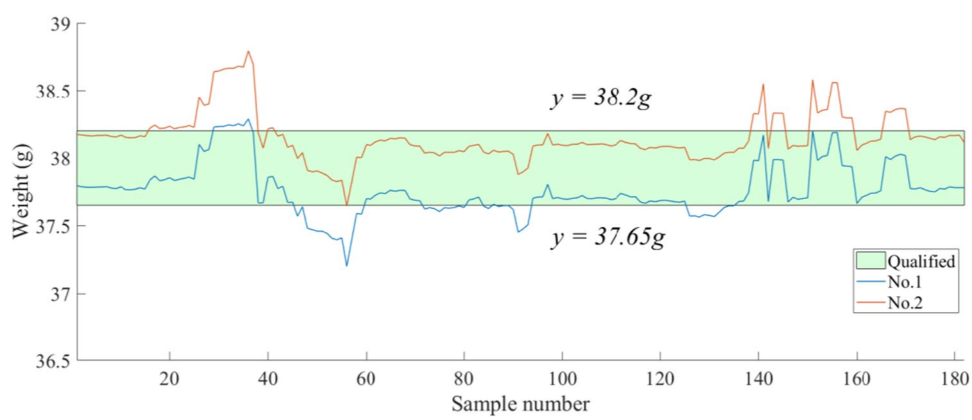


Fig. 7 Weights of each pair of injection molded products produced by the bi-cavity mold

that the model has good behavior for weight difference prediction and can accurately predict energy consumption generated during the injection molding process.

To further validate the predictive performance of the trained model on the test set, we compare the predicted values of weight difference and energy consumption with the true values, respectively. Figures 11 and 12 show residuals of the predicted values represented by histograms. The figure showed that the predicted values were in line with the true values. For the weight difference prediction model, most residuals were distributed between −0.02 and 0.02 g. The maximum and minimum residuals were 0.026 g and −0.022 g, respectively. For the energy consumption prediction model, due to the large value of the energy consumption, the average was 268,340 J. Thus, we focused on the relative error values, with maximum and minimum relative errors are 1.31% and −1.75%, respectively. In conclusion, the trained

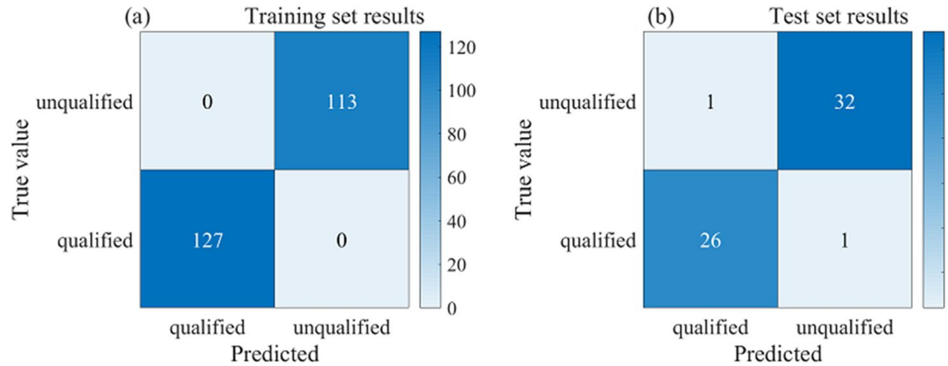


Fig. 8 **a** Confusion matrix heat map of the training set. **b** Confusion matrix heat map of the test set

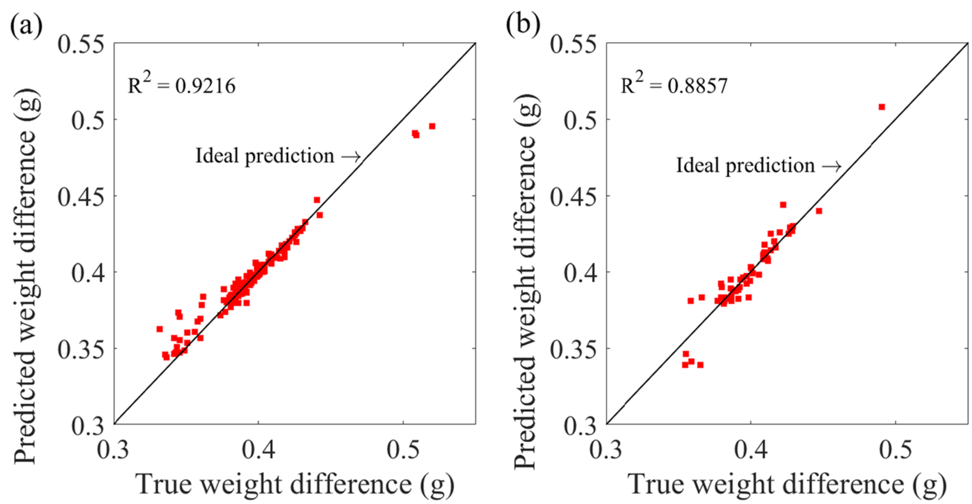


Fig. 9 **a** The performance of weight difference prediction model on training set. **b** The performance of weight difference prediction model on test set

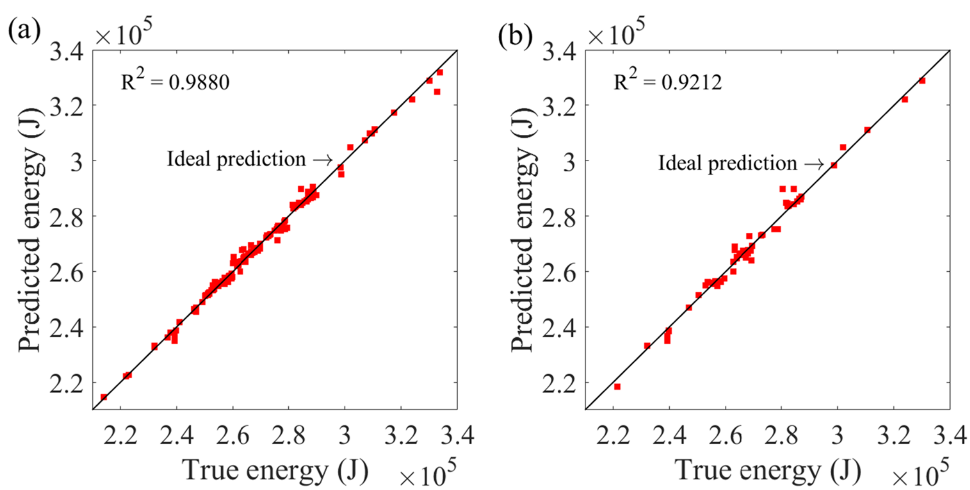


Fig. 10 **a** The performance of the energy consumption prediction model on the training set. **b** The performance of the energy consumption prediction model on the test set

model produced high-level performance in predicting the unknown sample.

Moreover, we obtained the optimal parameters by combining those ML models with GA, as shown in Table 2. Parts fabricated under this group of parameters were qualified. Clearly, the energy consumption decreased about 8% compared with the average of the original dataset. And the weight difference was 2% smaller than the mean value of the original data.

Importance analysis of input variables

To better understand the impact of each variable on the prediction results, we calculated the variable importance

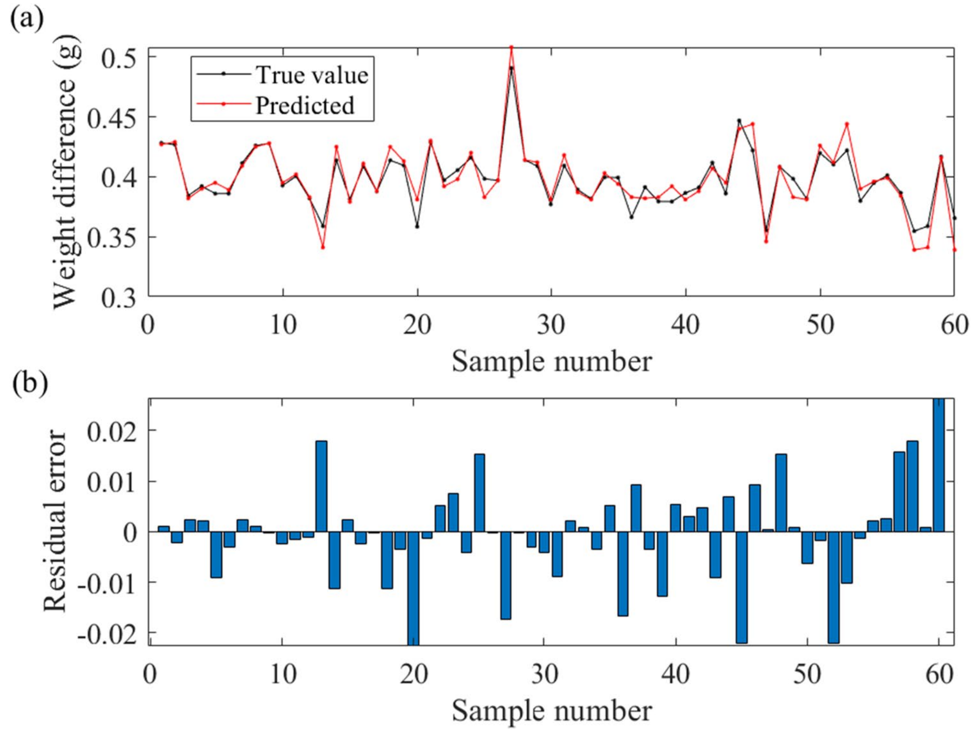


Fig. 11 **a** Comparison between true value and predicted value of weight difference. **b** The residual value between the real value and the predicted value of weight difference

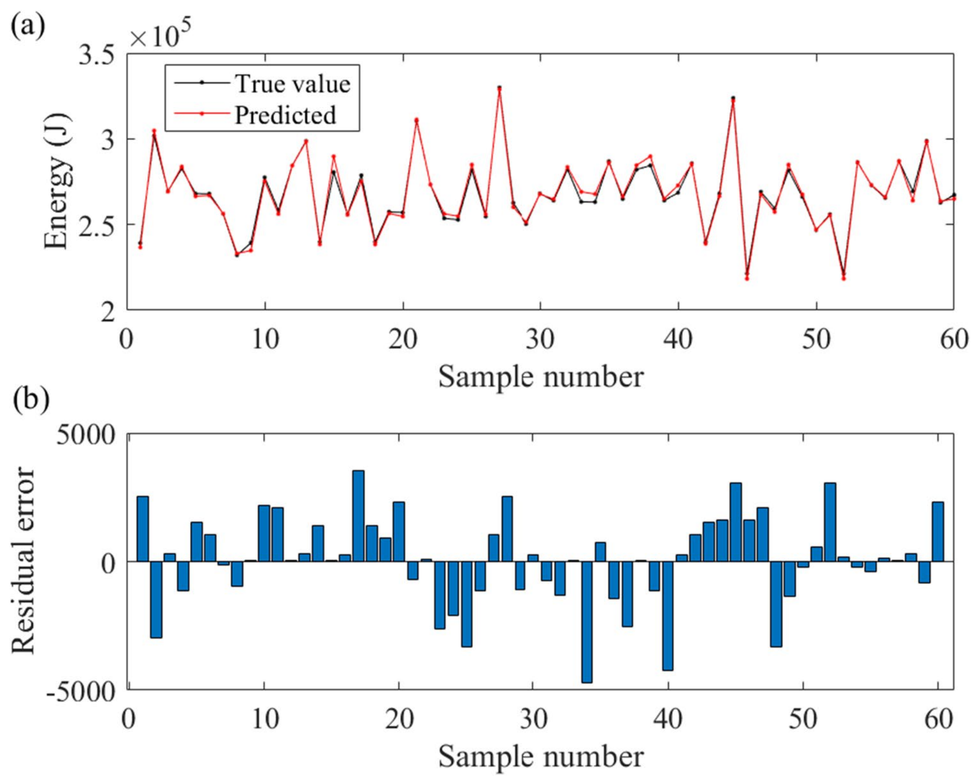


Fig. 12 **a** Comparison between real and predicted energy consumption. **b** The residual value between the real value and the predicted value of energy consumption

of all the input variables. Figures 13, 14, and 15 present the variable importance of all variables for quality prediction, weight difference prediction, and energy consumption prediction, respectively. The variables x_1 to x_8 denoted the cushion position, V-P switch-over position, cycle time, first-stage speed, second-stage speed,

Table 2 The table shows the results of optimization

ID	Variable	Value	Unit
x_1	Cushion position	14.93	mm
x_2	V-P switchover point	22.53	mm
x_3	Cycle time	50.66	s
x_4	First-stage speed	13	mm/s
x_5	Second-stage speed	7	mm/s
x_6	Holding pressure	132.25	MPa
x_7	Maximum pressure	121.27	MPa
x_8	Maximum speed	25	mm/s
Constant	Weight difference	0.38	g
Constant	Energy consumption	246914	J

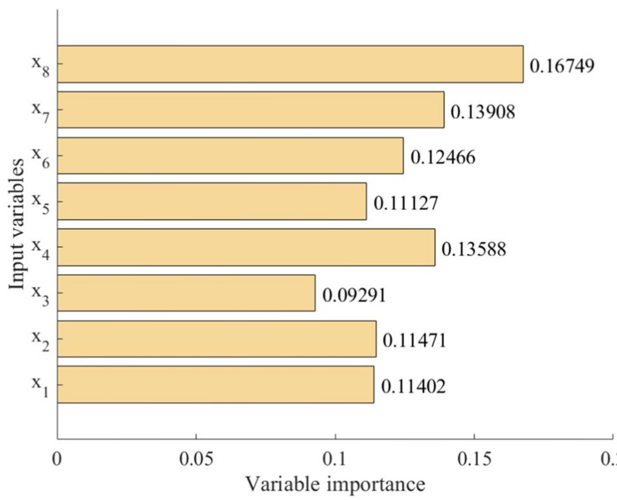


Fig. 13 Variable importance of the input variables of the quality prediction model

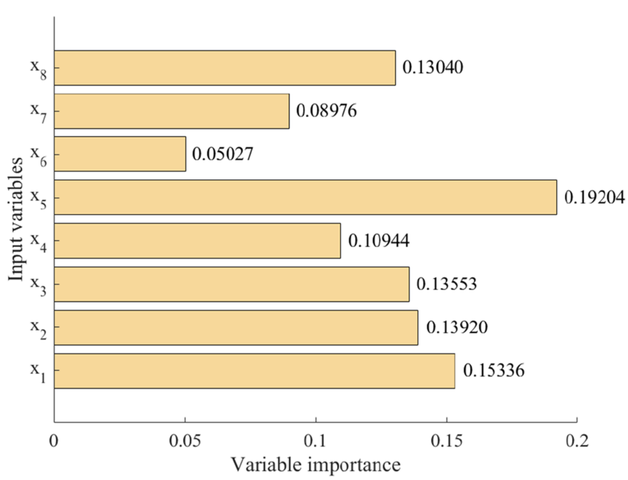


Fig. 14 Variable importance of the input variables of the weight difference prediction model

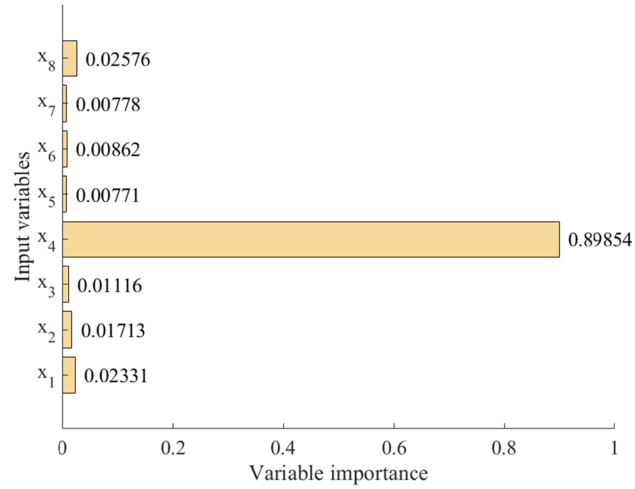


Fig. 15 Variable importance of the input variables of the energy consumption prediction model

holding pressure, maximum pressure, and maximum speed.

For the quality prediction model, the variable importance of maximum speed (x_8), maximum pressure (x_7), and first-stage speed (x_4) were the top three highest with the value of 0.16749, 0.13908, and 0.13588, respectively. The variable importance implied that the maximum speed, the maximum pressure, and first-stage speed can exert a significant impact on the quality. It is well known that the pressure and the speed were the key factors affecting the weight of injection molded products (Hassan 2013). And the weight of parts is an important metric for testing the qualification in this study; For the weight difference prediction model, the second-stage speed (x_5) had the highest variable importance of 0.19204. Aforementioned, speed is an important factor influencing the weight of parts. Therefore, it can also have an impact on weight difference. Furthermore, the variable importance of cushion position (x_1) was 0.15336. The cushion position is the position of the screw corresponding to the completion of the filling stage, having a close relationship with the filling process of injection molding. And the filling process has an essential influence on the weight difference of parts produced by different cavities; hence, the cushion position is crucial for the weight difference prediction. For the energy consumption prediction model, the variable importance was significantly discrete among the input variables, and the variable importance of the first-stage speed (x_4) reached 0.89854, indicating that the first-stage speed has a greater impact on the energy consumption of the injection molding machine. The first-stage speed refers to the speed at which the screw reaches the first specified position. Before the screw reaches the first specified position, the polymer inside the transfer unit is stationary. Therefore, the screw is subjected to greater resistance during this phase than during other phases. As the first speed increases, the more resistance the screw is subjected to and the more energy the machine needs to consume.

Conclusion

In this study, the process parameters of the injection molding machine were optimized using an active machine learning-based optimization approach. The proposed method can achieve multi-objective optimization including the qualification rate of parts, the energy consumption of the injection machine, and the weight of parts produced by multi-cavity mold. We calculated the R^2 value and F_1 score as the metrics to evaluate the performance of the trained ML model. For the quality prediction model, the F_1 score on test set was 0.96, indicating that the model can predict the quality of parts accurately. Furthermore, on the test set, the R^2 value of the energy consumption prediction model and weight difference prediction model are 0.89 and 0.92, respectively. It is suggested that the trained ML models were robust and efficient in prediction. In addition, results showed that the optimal parameters can reduce ~ 8% energy consumption and 2% weight difference compared with the average of original data. Moreover, we conducted analysis on the influence of input variables. We found that the maximum speed, the maximum pressure, and the first-stage speed have a significant impact on the quality. As for energy consumption, the impact of the first-stage speed was the dominating. For the weight difference, cushion position and second-stage speed were two key factors.

One limitation of this study was that the relationship between processing variables and energy consumption as well as the weight difference was merely obtained from the data-driven prospective. The present work failed to reveal the overall underlying mechanism of variables affecting the energy and quality in one cycle. Follow-up studies can use generative machine learning-based method to optimize other essential properties for injection molding such as deformation, size of product, and process emissions. Additionally, future study also can carry on analyzing the injection molding process based on the data in this study and establish a model to monitor the process of injection molding in real time. Alternatively, future studies can build a management system based on the proposed method to implement real-time data collection and optimization of the injection molding process.

Availability of data and materials The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Author contribution Yirun Wu: writing—original draft, visualization, formal analysis, investigation, writing—reviewing and editing. Yiqing Feng: conceptualization, methodology, software, data curation. Shitong Peng: supervision, project administration. Zhongfa Mao: methodology, software, project administration. All authors read and approved the final manuscript.

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Declarations

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