


Article

Application of Deep Learning Network in Bumper Warpage Quality Improvement

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Abstract: Based on the context of Industry 4.0 smart manufacturing and for the prediction of injection molding quality of automobile bumpers, this study proposes a deep learning network that combines artificial neural networks and recognizable performance evaluation methods to better achieve the prediction and control of product quality. A pressure sensor was used to monitor and collect real-time pressure data in the mold cavity of the bumper. The quality indicators reflecting the molding quality were selected, and the correlation between these indicators and the molding quality was evaluated using recognizable performance evaluation methods and Pearson's correlation coefficient. The standard z-score was used to filter out the abnormal data in the experimental data, and the bumper critical length warpage was converted into different quality levels, and the bumper critical length warpage was defined as either "qualified" and "unqualified" in order to improve the prediction accuracy of the model. Through the experimental study of this research, the monitoring and control of bumper injection molding parameters was completed to control and improve the molding quality of the bumper.

Keywords: deep learning; molding quality; artificial neural network; recognizable performance evaluation; bumper; prediction



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1. Introduction

The main molding method for plastic products is injection molding, and many of today's injection-molded products are able to replace metal products and are lighter in weight and better in performance than metal products in many applications. Compared with high-strength metal stamping, injection molding quality plastic bumpers has many advantages: the bumper strength meets requirements; the weight of the plastic bumper is lower; the shape is more pleasing to the eye; it has the ability to absorb external force, cushioning in the event of a car accident adding a certain degree of injury reduction to passers-by and motorists; low maintenance costs; and its materials can be recycled, reducing the production cost for the automotive industry. A large number of high-tech plastics are used in the automotive industry and have become a trend [1].

Plastic parts in the production process have large warpage deformation, shrinkage and other defects which not only affect the appearance of the product, but also affect the practicality of the product. In recent years, people have used the Taguchi method, fuzzy theory, Bayes' theorem and neural networks to monitor the injection molding process parameters in real time and successfully control the molding quality of injection-molded products and reduce product defects based on the data collected from monitoring [2–5]. That is, the injection molding machine is able to use machine learning methods to understand its own real-time working status and control it by monitoring and collecting data on the real-time production process using sensors such as pressure and temperature sensors. The main contribution of this paper is to propose a new deep learning network to better achieve the

prediction and control of product quality. The model combines recognizable performance evaluation methods and class neural networks to find out the correlation between injection molding parameters and bumper molding quality during the production process and to accomplish the control and optimization of bumper injection molding parameters in order to control and improve the molding quality of bumpers.

2. Literature Review

Injection molding has a pivotal role in the manufacturing industry and, with the development of new technologies, the quality requirements for injection-molded products are becoming higher and higher. In particular, for large injection-molded parts, such as car bumpers, manufacturers are more stringent about quality control, because they are key safety components on the car body. Because manufacturers of car bumpers are increasingly pursuing more light-weight options to reduce car body weight and improve fuel economy, the car bumpers produced today are large, thin-walled, injection-molded parts with large volume and thin thickness; thus, warpage and shrinkage are more easily produced during the injection molding process. Traditionally, in order to obtain high-quality products, manufacturers set the upper and lower limits of parameters to meet the high quality requirements in the production process. However, it is often difficult to observe and control the injection molding process parameters during the production process, and it is difficult to achieve the goal of control and optimization. In order to effectively reduce the injection defects of warpage and shrinkage that often occur in injection-molded bumpers, which are large, thin-walled parts, and to ensure product quality, we need a proven method to control and optimize the parameters (temperature, pressure and speed, etc.) of the injection molding and improve the product production qualification rate.

In 2016, Kitayama et al. [6] performed a multi-objective optimization of co-process parameters, such as melt temperature, injection time, holding pressure, holding loading time, cooling time and cooling temperature, by using them as design variables and successfully verified that the application of a follower water circuit and their experimental method could shorten the molding cycle and reduce warpage by performing numerical simulations and experimental studies on the follower cooling water circuit. The effectiveness of the application of this experimental method to shorten molding cycle time and reduce warpage and other problems was successfully verified. In 2017, Kitayama et al. [7] proposed a method to determine the optimal process parameters for injection molding that could ensure product quality and productivity, taking warpage and production cycle time as key indicators of product quality and productivity and minimizing them simultaneously, determining the Pareto boundary between them and optimizing them using the order of radial basis functions. The experimental results showed that the method was successful in improving the warpage and production cycle time of the product. In 2017, Nguyen et al. [8] performed a numerical analysis based on a combination of the Taguchi method and response surface method and determined the optimal combination of process parameters for injection-molded parts through their dual optimization process, which successfully reduced the warpage problem of injection-molded products to a great extent. In 2018, Sudsawat et al. [9] applied mold flow analysis software to an injection molding machine with an experimental design based on important factors affecting product warpage, such as holding time, cooling time and melt temperature, and used a firefly algorithm to find the best combination of process parameters affecting product warpage and, finally, applied ANOVA to verify and return the product to further reduce warpage deformation. In 2019, Barghikar et al. [10] effectively controlled the warpage of the lens and improved its molding quality by conducting a full factorial design of experiments on the key factors affecting the warpage and geometric quality of the lens, including holding pressure, holding time and mold temperature, detecting the changes of these pressure and temperature parameters and analyzing and comparing the results of their simulations.

With the development of the manufacturing industry, intelligent manufacturing has begun to emerge, and artificial intelligence technology is increasingly appearing in various

aspects of injection molding production, and the injection molding industry is developing in the direction of automation and intelligence. The application of artificial intelligence technology can solve some particularly complex and uncertain problems in the injection molding production process, and, in the injection molding industry, it is used in the monitoring of the product molding process and the prediction of the molding quality. The application of artificial intelligence technology can help manufacturers record the real-time data of the injection molding production process, discover the problems in the injection molding process in time and make targeted and effective optimization adjustments to improve factory efficiency. Usually, people use machine learning and intelligent algorithms (including artificial neural networks, genetic algorithms, PID algorithms and fuzzy theory, etc.) to extract and analyze the data and realize the monitoring of the injection molding process and the effective prediction of the molding quality of the injection-molded products. This enables manufacturers to identify problems in the injection molding process and make timely and effective adjustments to their injection molding processes, improving the qualification rate of injection-molded products and the productivity of the factory to create more benefits. In 2017, Zhang et al. [11] discussed the advantages and limitations of computer intelligence technology when applied to practical fault diagnosis, as well as product quality prediction, and compared the characteristics of different intelligent algorithms, summarized the effect of these methods in practical applications and provided some guidance for subsequent researchers in the application of intelligent algorithm methods for specific production conditions. In 2017, Martowibowo et al. [12] optimized the injection molding process (e.g., injection pressure, holding pressure and holding time) of a bowl-shaped product made from PP AZ564 based on a genetic algorithm combined with mold flow analysis software and successfully verified the utility of the method for the optimization of product process parameters by comparing the results of experiments and simulations which did not differ significantly. In 2017, Li et al. [13] combined a back propagation neural network (BPNN) with a genetic algorithm (GA) to optimize the fiber-reinforced composite injection molding process with minimum warpage of the product as the objective function and process parameters, such as fiber aspect ratio, fiber content, injection time, melt temperature, mold temperature and holding pressure, as experimental design variables based on the simulation results. A directional neural network model was developed to map the functional relationship between the product warpage and its experimental parameters, optimize the experimental parameters to successfully improve the warpage of the product and achieve the purpose of optimizing the warpage deformation of the product. In 2019, Nasiri et al. [14] proposed a method based on fuzzy theory applied to artificial intelligence for the detection of faults and failures in the injection molding process which fuzzifies problems with fuzzy characteristics of attribute values and develops similarity measures for these characteristics, and the experiments successfully verified the capability and effectiveness of the method applied to the detection of faults in the injection molding process. In 2020, Song et al. [15] addressed the warpage and volume shrinkage problems commonly found in thin-walled, injection-molded parts by using process parameters, such as mold temperature, melt temperature, injection time, holding time, cooling time and holding pressure, as orthogonal and response surface experimental design parameters and applied mold flow analysis software to simulate the injection process to find the importance of different parameters for product warpage and shrinkage. The importance of different parameters for product warpage and shrinkage was found. Meanwhile, a BP neural network model was established based on the simulation results, and its weight values were optimized by applying a genetic algorithm to establish a prediction model of product warpage and shrinkage. The effectiveness of the method was successfully verified by the practical cases of the study; it could effectively reduce the warpage and volume shrinkage of thin-walled, injection-molded products. In 2020, Chen et al. [16] argued for the study of production problems of injection-molded products with large-scale, complex geometry and strict dimensional tolerances and proposed an online defect detection system based on an artificial neural network (ANN) which used sensors, such as temperature and

pressure sensors, to obtain real-time data of temperature and pressure inside the mold and establish the artificial neural network model to realize the prediction of injection-molded product problems. This research proved that the system could be applied to the optimization of injection molding process and the monitoring of molding quality in actual injection molding production, contributing to the development of intelligent injection molding. In 2019, Abdul et al. [17] proposed an artificial neural network (ANN)-model-based approach to address the common warpage and shrinkage problems in injection molding production and combined it with Taguchi's experimental design to obtain the optimal combination of product molding parameters and predict the shrinkage of molded products under different process parameters (including injection speed, holding time and cooling time, etc.). The reliability of this prediction model was verified by comparing its predicted product shrinkage with the actual product shrinkage results obtained based on Taguchi's experiments. This study showed that the ANN model had high prediction accuracy and could be used in the prediction and control of the molding quality of injection-molded products. In 2020, K. C. Ke and M. S. Huang [18] proposed a multilayer perceptron (MLP) neural network model incorporating quality metrics, which was applied to the MLP model for learning and prediction by using the relationship between data profiles obtained from pressure sensors at different locations in the injection mold during production and its molding quality, and this study successfully achieved rapid, automatic prediction of molding quality for injection-molded products. In 2020, Xu et al. [19] discussed the progress of data collection and analysis techniques applied to the manufacturing industry, where learning, and especially deep learning methods, can provide better decisions on the manufacturing production process and better automated processes of manufacturing through the provision of a large amount of production data. In 2021, Yaşar et al. [20] proposed a method for the prediction of cylinder pressure for homogeneous charge compression-ignition engines with different excess air coefficients based on deep neural networks proposed by artificial neural networks, which verified the effectiveness of this deep learning method for prediction by comparing the deep learning results with the artificial neural networks and experimental results. In 2021, Yang et al. [21] proposed a method for diagnosing and detecting new machine faults based on deep neural networks with autoencoders, which experimentally proved its effectiveness in fault diagnosis applications not only for diagnosing known types of defect but also for detecting unknown types of defect. In 2021, K. C. Ke and M. S. Huang [22] used a multilayer perceptron (MLP) neural network model and some quality metrics related to the quality of the molded product to make predictions about the conformity of the molded product quality. The prediction accuracy of the MLP model was also improved by filtering the anomalies in the data and quantifying the measured quality of the product into assessable quality levels and classifying the quality of the finished product into different quality levels. This study demonstrated the feasibility of the method by making an IC tray for experiments, which effectively reduced the cost of product quality control. In the current era of promoting smart manufacturing, data on the parameters of the machine production process can be collected and recorded, and, by applying machine learning methods, these data can now be used for the prediction and control of molded product quality.

Through the above-mentioned literature study, we found that, of the artificial intelligence algorithms currently applied in smart manufacturing, artificial neural networks are the most widely used. Artificial neural networks can play a good role in predicting the quality of injection-molded products and optimizing the process parameters, fitting the input and output data parameters that present a highly nonlinear relationship. Usually, neural network models are constructed to learn and train real-time parameters related to product quality in the injection molding process to monitor and predict the quality of the injection-molded products. With the in-depth application of artificial neural network models for training and prediction in the production process, the prediction results of models are becoming more and more accurate and close to the actual results, finally achieving adaptive control. However, in the process of building neural network models,

it is necessary to involve the weights of different molding parameters on the impact of molding quality, because different molding parameters have different degrees of impact on the product quality, such as a different amount of warpage during the molding process. This “degree” is “weight”, so the weight value must be a quantifiable value. However, different injection molding parameters have different units, different dimensions or no dimensions at all, and their impact on the molding quality of the same products cannot be directly compared, which makes it more difficult to allocate the weight values when applying neural network models. Therefore, a method is needed to quantitatively analyze and compare the impact of different injection molding parameters on product molding quality so as to obtain the weight of their impact. In 2017, Chang et al. [23,24] proposed to calculate the factorial effects of interactions based on Taguchi’s method of signal-to-noise ratio, mechanical advantage and a variable separable model to compare the performance of different five-axis machine types, and, to address the interaction effects of multi-axis motions, they also proposed to use Taguchi’s “variable separable model” to quantify the interaction values of each cutting motion, thus, solving this evaluation problem. In 2020, Chang et al. [25] applied an identifiable performance evaluation method to analyze and compare the effect and correlation between two different units and magnitudes of glass fiber and holding time on product warpage based on optimal process parameters. The interaction between different warpage directions of glass fibers was also quantified, and the evaluation of the molding quality of injection-molded products under the interaction of different parameters was successfully achieved. In 2019, Chang [26] provided quantifiable fuzziness intervals by applying the identifiable performance evaluation (RPE) method and combining it with fuzzy theory, which enabled the interaction analysis and comparison between different types of five-axis machine. Additionally, in 2021, Chang et al. [3] used the identifiable performance evaluation (RPE) method to obtain accurate reference data for the evaluation of optical components and introduced fuzzy theory to effectively quantify, measure and evaluate the residual stresses of products in different regions of the optical components.

Following the above analysis, in this study, we applied the recognizable performance evaluation (RPE) method to help us accomplish a good weight assignment when setting the weight values of the effects of different injection molding parameters, such as warpage amount, on the molding quality of bumpers. The RPE method defines an exact comparable value for the same molding quality for different injection molding parameters with “no unit, different units, multiple vector unit parameters and multiple interaction vector units” and then performs a reliable, quantitative comparison analysis to help the artificial neural network model to complete the weight assignment. This helps the artificial neural network model to assign weights. In other words, the identifiable performance evaluation method can define the non-identifiability of the factor defects in the physical experimental formulation so that a quantitative analysis can be performed between different molding parameters for the same molding quality of the product. Therefore, this study proposes a deep learning network (DLN) based on an artificial neural network model and the identifiable performance evaluation method to achieve the prediction of bumper injection molding quality (e.g., critical length warpage amount). The identifiable performance evaluation method can make the neural network model easier and more accurate in assigning weights and improve the accuracy of the deep learning network in prediction.

3. Research Methodology

3.1. Experiment Design

The quality of the injection-molded product is closely related to the flow characteristics of the melt in the mold cavity, so, in the experiments of this study, the variation of the cavity pressure of the melt in the mold cavity was used to predict the quality of the molded product, and the physical indices that reflect the quality of the injection-molded product were used to train the quality prediction model. Since cavity pressure varies with the process parameters, such as injection pressure and holding pressure of the injection molding

machine, and the warpage of the injection molded product is a function of the cavity pressure, the injection pressure and holding pressure were used as independent variables, and the warpage of the injection-molded product was used as the dependent variable in the experiments of this study so that a two-factor, full experiment could be conducted.

A typical pressure profile in the mold cavity is shown in Figure 1, which demonstrates the flow of melt in the mold cavity during the molding process. Point A indicates the start of filling, where the melt inside the cavity touches the pressure sensor and starts to transmit the pressure signal of the cavity, and the pressure inside the cavity increases steadily with the filling process until the end of the filling phase at point C. After the filling phase, the melt is compressed, and the pressure inside the cavity rises rapidly to the highest value at point D, thus, entering the pressure-holding phase. During the holding phase, the pressure inside the cavity is maintained at a certain value, and additional melt is filled into the cavity to compensate for the plastic shrinkage of the melt until the gate is cured (point E—Gate Seal) and the holding phase is over. Finally, cooling continues until the melt cures, i.e., the end of the molding cycle, when the residual stress in the mold cavity decreases at a rate determined by the rate of cooling and curing. It can be seen that the flow characteristics of the melt in the mold cavity are different at different stages of the injection molding process, so the distribution characteristics of the pressure in the mold cavity at different stages can be used to design a quality index representing the quality of the injection-molded product. In addition, $P_{P_{index}}$, $P_{H_{index}}$, $P_{R_{index}}$ and $P_{I_{index}}$ denote several different quality indicators, which will be explained in detail in the next subsection.

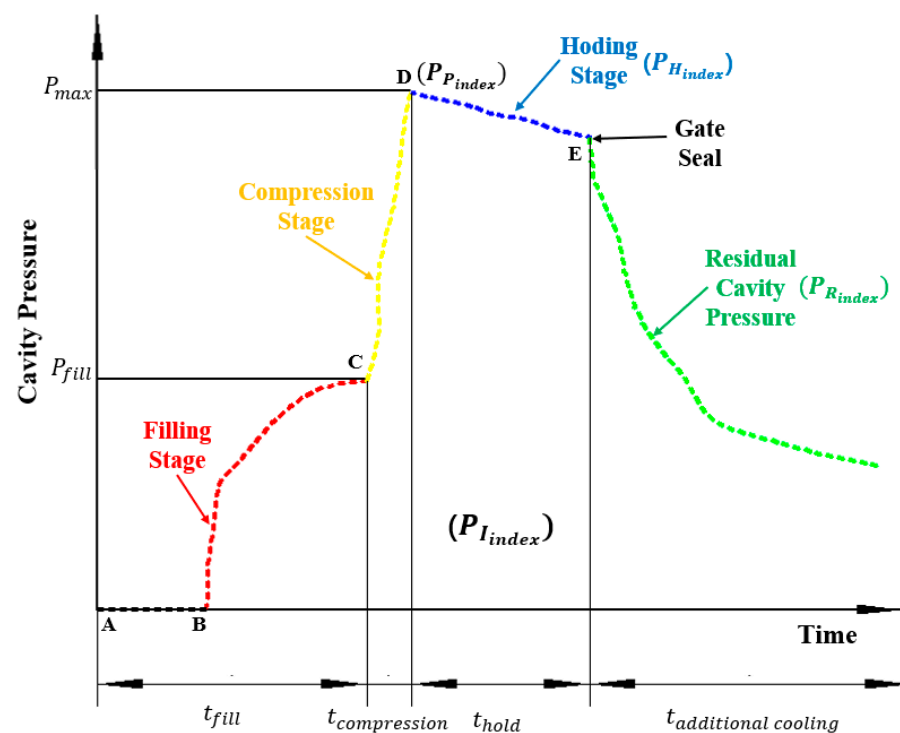


Figure 1. Typical cavity pressure profile.

3.2. Quality Indices and Pearson's Correlation Coefficient

In the injection molding process, changes to different process parameters accordingly have an impact on the quality of the molded product; therefore, the quality indicators corresponding to various process parameters were evaluated, and the quality indicators closely related to the quality of the molded product were used as input parameters for the training of the neural network model in this study to achieve the purpose of monitoring and predicting the quality of the molded product. Referring to the pressure information in the injection molding process, the quality indicators selected in this study were as follows:

1. Peak pressure index ($P_{P_{index}}$): As shown in Equation (1), $P_{P_{index}}$ indicates the maximum pressure during the filling and compression process. The molten glue is filled into the cavity under the action of pressure, so the amount of pressure determines the amount of molten glue filled into the mold cavity during the injection molding process, which has a certain impact on the quality of the molded product. Where g is expressed as a function of the curve of the pressure change in the mold during the injection process, the same occurs.

$$P_{P_{index}} = \text{Max}(g) \quad (1)$$

2. Holding pressure index ($P_{H_{index}}$): As shown in Equation (2), $P_{H_{index}}$ indicates the average holding pressure of the injection molding process, t_0 indicates the time point when holding pressure starts and t_1 indicates the time point when the holding pressure ends. The holding pressure is very important for the quality of molded products in the injection molding process, because the holding pressure stage can compensate the voids generated by the plastic shrinkage of the melt.

$$P_{H_{index}} = \frac{1}{t_1 - t_0} \int_{t_0}^{t_1} g dt \quad (2)$$

3. Residual pressure drop index ($P_{R_{index}}$): As shown in Equation (3), $P_{R_{index}}$ indicates the average residual pressure drop in the mold cavity during the cooling process, t_2 indicates the time point when cooling starts, i.e., the end of holding pressure (i.e., t_1) and t_3 indicates the time point when cooling ends. The average residual pressure drop in the mold cavity is affected by the residual stress of the melt in it, and high residual stress may cause warpage and other defects in the molded products, while low residual stress may cause over-shrinkage and other problems in the molded products.

$$P_{R_{index}} = \frac{1}{t_3 - t_2} \int_{t_2}^{t_3} g dt \quad (3)$$

4. Pressure integration index ($P_{I_{index}}$): As shown in Equation (4), $P_{I_{index}}$ represents the integration of the pressure curve in the mold cavity with time during a complete injection molding cycle, which reflects the pressure characteristics of the melt during the injection molding process.

$$P_{I_{index}} = \int_0^{t_3} g dt \quad (4)$$

In this study, Pearson's correlation coefficient (PCC) [27] was used to verify the correlation between the injection molding product quality index and its molding quality. Equation (5) is expressed as the equation of Pearson's correlation coefficient (r), which takes values in the range of $(-1, 1)$, where r denotes the value of the correlation coefficient between two variables, x_i and y_i denote the i th value of the independent variables x and y , respectively, and n is a constant, indicating that there are n pairs of two different variable values. For the correlation strength corresponding to different r values, Chang et al. [28], in 2022, applied a classification, as shown in Table 1, to help verify the degree of correlation between different quality indicators and product molding quality where a higher value of $|r|$ indicates a stronger correlation between the injection-molded product quality indicators and molding quality. Therefore, in this study, a value of correlation ($|r|$ value) between the injection molding quality and product quality indices greater than 0.75 was taken as the independent variable and used as the input layer of the neural network learning model.

$$r = \frac{\sum x_i y_i - n \bar{x} \bar{y}}{\sqrt{(\sum x_i^2 - n \bar{x}^2)(\sum y_i^2 - n \bar{y}^2)}} \quad (5)$$

Table 1. Pearson’s correlation coefficients (PCCs) related to the correlation strength.

Range of $ r $	Correlation Strength
0	No
0–0.25	Negligible
0.25–0.5	Poor
5–0.75	Moderate
0.75–1	Strong
1	Perfect

3.3. Artificial Neural Network Model

After obtaining the quality indicators that affect the key parameters of product molding quality, they need to be used as the input parameters of the neural network model for learning and training to complete the monitoring of the injection molding process and the prediction of molding quality. As a neural network model continues to input data for training and prediction in the production process, its training model will gradually improve, the more accurate the prediction results will be and the closer they will be to the actual results, i.e., it will be able to achieve adaptive process control. In this paper, the ANN learning model consisted of three main components: an input layer, a hidden layer and an output layer, which were used as a neural network model. The input layer received the input vectors and then passed each input data point to the neurons in the hidden layer. The neurons (also called neural nodes) in the hidden layer contained the summation function and the activation function. Figure 2 shows a single-neuron perceptron model, where the activation function (Equation (6)) is a nonlinear function used to map the summation function ($xw + b$) to the output value y where x, w, b and y denote the input vector, weight vector, deviation and output value, respectively, and φ denotes a constant.

$$y = \varphi(xw + b) \tag{6}$$

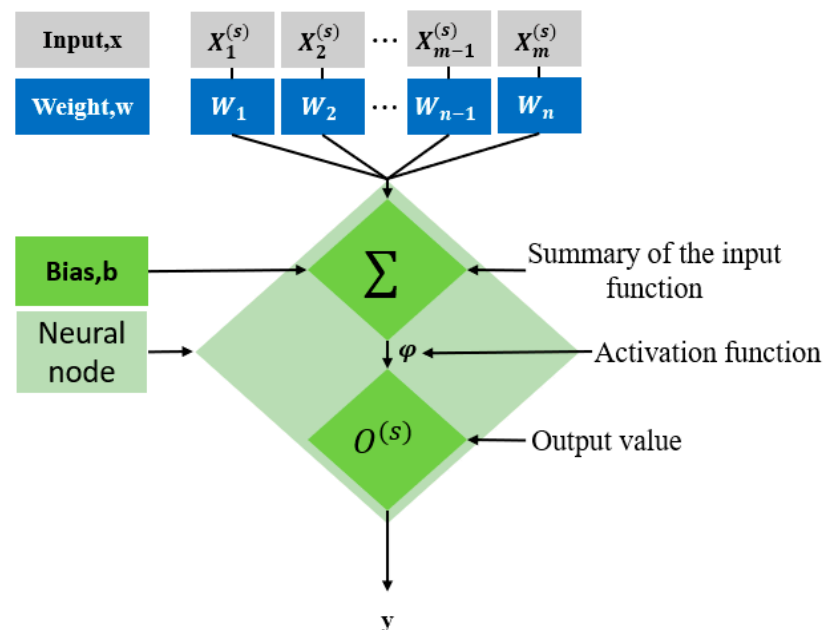


Figure 2. Single-neuron perceptron model.

Figure 3 illustrates the structure of the ANN learning model where $x_k^{(s)}$ denotes the k th input data of the s th data set, m denotes the total number of input data sets, $n_{l_r, p_{l_r}}$ denotes the p_{l_r} th neural node of the l_r th layer and N_{l_r} denotes the total number of neurons in the l_r th layer. $x^{(s)}$ denotes the vector of input data, N_{set} denotes the total number of

data points in the input data set and L denotes the total number of layers other than the input the sum of the layers.

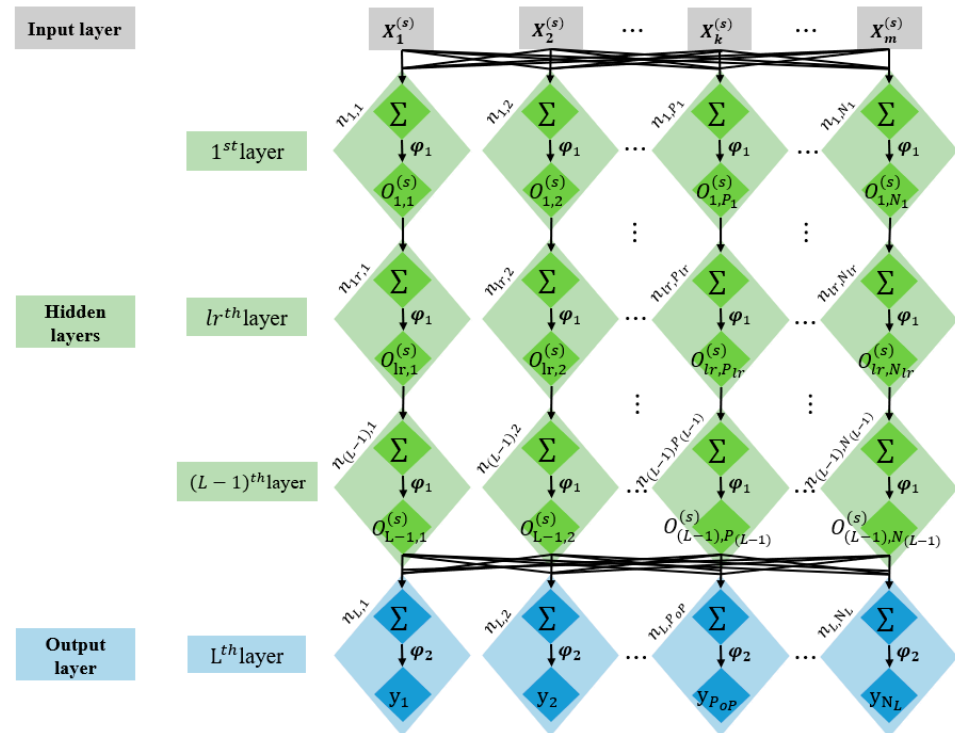


Figure 3. Structure of the ANN (Artificial Neural Network) model.

Figure 4 shows the neural network architecture of the first layer in the hidden layer. Equation (7) represents the expressions of the output vector $O_1^{(s)}$ of the first layer in the hidden and output layers, and the expressions of the other layers are the same as above. In the above equation, w_{lr} denotes the weight vector of the lr th layer. The values of the weights range between 0 and 1. These values vary with the training data and represent the memory of the neural network associated with the inputs and outputs after model training.

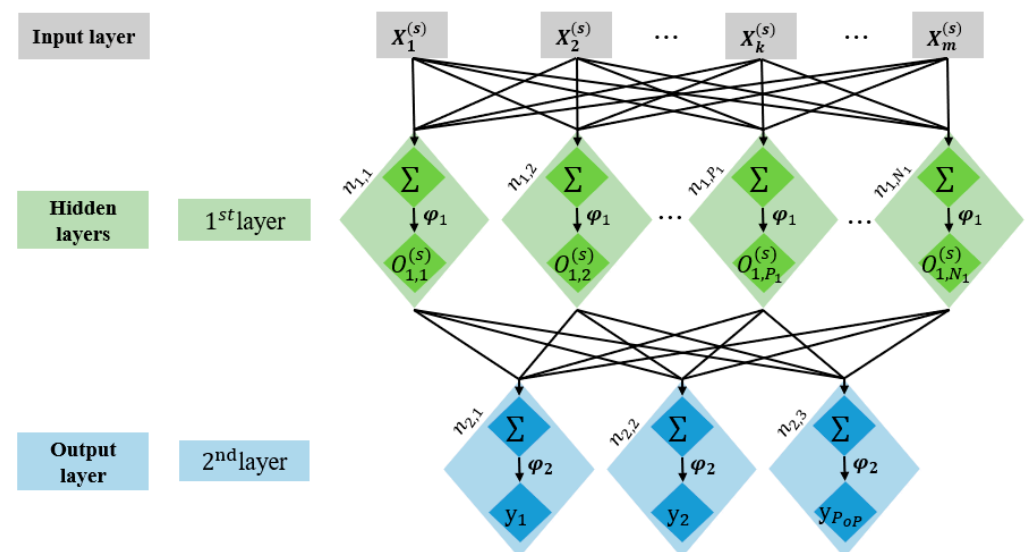


Figure 4. ANN framework used in this study.

For

$$lr = 1, O_1^{(s)} = \varphi_1(x^{(s)} \times w_1 + b_1^T)$$

where $O_1^{(s)} = [O_{1,1}^{(s)} O_{1,2}^{(s)} \cdots O_{1,N_1}^{(s)}]$

$$w_1 = \begin{bmatrix} w_{1,1,1} & w_{1,2,1} & \cdots & w_{1,N_1,1} \\ w_{1,1,2} & w_{1,2,2} & \ddots & w_{1,N_1,2} \\ \vdots & \vdots & & \vdots \\ w_{1,1,m} & w_{1,2,m} & \cdots & w_{1,N_1,m} \end{bmatrix}, b_1 = \begin{bmatrix} b_{1,1} \\ b_{1,2} \\ \vdots \\ b_{1,N_1} \end{bmatrix} \quad (7)$$

In the above equation, $O_{lr}^{(s)}$ represents the output vector of the lr th layer after training from the first data set to the s th data set. Equation (8) is the activation function used in the hidden layer of this study; the binary classification function (sigmoid function) converts the result of the input function into a probability for classification. Equation (9) is the activation function used in the output layer of this study—the normalized exponential function (softmax function) normalizes the input vector of N_L real numbers into a probability distribution consisting of N_L probabilities proportional to the exponents of the input numbers, which can be such that each element falls in the range (0,1), and the sum of all elements is 1.

$$\varphi_1(o_i) = \frac{1}{1 + e^{-o_i}} \quad (8)$$

$$\varphi_2(o_i) = \frac{e^{o_i}}{\sum_{j=1}^{N_L} e^{o_j}}, \sum_i \varphi_2(o_i) = 1 \quad (9)$$

The accuracy function A_i (shown in Equation (10)) is used to evaluate the convergence of the model training, where $N_{i_{mis}}$ denotes the number of misclassified data points in the i th training iteration, and N_{all} denotes the number of data points. The training accuracy of the model can be evaluated by comparing the predicted values with the actual output values. When the predicted and actual output values agree, the weighted values continue to be used for training the next data set; otherwise, the weighted values are adjusted. The distribution of this accuracy function converges to a constant value as the number of training iterations increases; therefore, a criterion needs to be set for it to stop training iterations to obtain higher quality results.

$$A_i = 1 - \frac{N_{i_{mis}}}{N_{all}} \times 100\% \quad (10)$$

The convergence of neural network learning models is greatly affected by the number of hidden layers and neurons. A large number of hidden layers and neurons represents a large number of calculations of weighted values, which may make the accuracy between predicted and actual values lower, but a small number of hidden layers and neurons cannot connect the input and output layers in the model well, and the data errors in actual production or experiments may also continue to model training. These are the unfavorable outcomes of the model prediction accuracy. Therefore, a high-precision injection molding machine and measurement equipment are indispensable in the experiment; otherwise, the prediction accuracy of the model cannot be guaranteed.

3.4. Recognizable Performance Evaluation

Usually, when constructing a neural network model, it is necessary to involve the determination of the weights of different molding parameters on the impact of molding quality, but the neural network model cannot directly quantify and compare the molding parameters of different units and different scales, which makes it extremely difficult to set the weights of different parameters. Therefore, a method is needed to quantify and compare the molding parameters between different units or different scales for analysis. The identifiable performance evaluation (RPE) method can define an exact comparable value for the injection parameters of “unitless, different units, multiple vector unit parameters, and multiple interaction vector units” and then perform a reliable, quantitative comparison

analysis. That is, the identifiable performance evaluation method is able to define the non-identifiability of factor defects in the physical experimental formulation, allowing quantitative analysis and comparison between different molding parameters.

Therefore, when setting up the weight values in the neural network model, the identifiable performance evaluation method can be used to help the researcher to perform quantitative comparative analysis between different parameters and to calculate the standard deviation (SD), mean square deviation (MSD) and signal-to-noise ratio (S/N) for each process parameter based on the data collected and recorded by the injection molding machine during the molding process. The definition of different injection molding defects is different, and we should not confuse the smaller-the-better characteristics, nominal-the-better characteristics and larger-the-better characteristics of different injection molding defects of the product, i.e., different injection molding defects with a larger measured value are better, closer to the target value are better and smaller are better, respectively. As shown in Table 2, the injection molding defects with the characteristics of smaller-the-better mainly include warpage, burr, dent and stress marks, etc., which are all expressed as the smaller the defect is, the better; the injection molding defects with the characteristics of nominal-the-better mainly include the geometric error of the product, the dimensional error of the product and the lack of gloss, etc., which are all expressed as the closer to the target value of the product design, the better; the injection molding defects with the characteristics of larger-the-better mainly include short shot (the more molten glue is injected into the cavity when short shot occurs, the better) and seam line angle (the larger the seam line angle is, the better), etc. The identifiable performance evaluation method in this study also had a dual identification feature, i.e., for different identifiable samples with the smaller-the-better, nominal-the-better and larger-the-better characteristics, the identifiable performance could be evaluated between two characteristics, rather than just under a single characteristic [3]. This made it easier and more accurate for the deep learning network prediction model in this study to assign weight values and improve the reliability of its predictions.

Table 2. Injection molding defects corresponding to different characteristics.

Characteristic	Injection Molding Defects
Smaller-the-better	warpage, burr, dent and stress marks, etc.
Nominal-the-better	the geometric error of the product, the dimensional error of the product and the lack of gloss, etc.
Larger-the-better	short shot and seam line angle, etc.

For this study, the warpage value of the bumper belonged to the look-ahead characteristic. Using the identifiable performance evaluation method, the standard deviation (SD), the mean square deviation (MSD) and the signal-to-noise ratio (S/N) were calculated as shown in Equations (11)–(13), respectively, and only the size of the signal-to-noise ratio needed to be compared.

$$SD = \sqrt{\frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n}} \quad (11)$$

$$MSD = \bar{y}^2 + SD^2 = \frac{1}{n} \sum_{i=1}^n y_i^2 \quad (12)$$

$$S/N = -10 \log MSD \quad (13)$$

where y_i is the i th quality characteristic; \bar{y} is the average quality characteristic; and n is the number of intercepted data.

3.5. Deep Learning Network (DLN) Model

According to the above method, the deep learning network model of this study was constructed, and its overall modeling operation procedure flow chart is shown in Figure 5, which is divided into the following seven steps: 1. Setting machine parameters and

collecting bumper process parameter data: this study performed machine setup based on a two-factor, full experiment and collected pressure signals through pressure sensors, plotted the pressure curves of different sensors and the overall pressure curve inside the injection molding machine cavity and converted them into quality indicators. The warpage of the key length of the bumper was also measured by a high-precision coordinate measuring machine, which was further used as a measure of the quality standard of the bumper; 2. Filtering and eliminating abnormal bumper warpage data: determining and filtering out abnormal bumper warpage data by the standard z-scores (1.5, 2.0 and 2.5); 3. Normalized data (RPE and PCC): different injection molding parameters have different degrees of influence on the warpage of the critical length of the bumper, and each of the above four quality indicators has a different numerical level, so they needed to be normalized and quantified (the quantization interval was (0,1)) to be used as input data for neural network model training; 4. Bumper quality classification: the warpage was converted into different levels (5, 10, 20 and 50); 5. Training and testing data: a specific set of parameters was selected as input data, and, after normalizing it, some of the data points were used for model testing and the rest for model training; 6. ANN model training: the model contained an input layer consisting of four nodes, two hidden layers (one with 100 neural nodes and the other with 75 neural nodes) and 5, 10, 20 and 50 nodes in the output layer, corresponding to the various classes, respectively; 7. ANN model test: when the test result of this model met the passing criteria of the product (bumper warpage $W \leq 1.0$ mm in this study), the class of bumper warpage could be predicted using the number of equal classes. Otherwise, we had to return to the step of bumper quality classification and redo it.

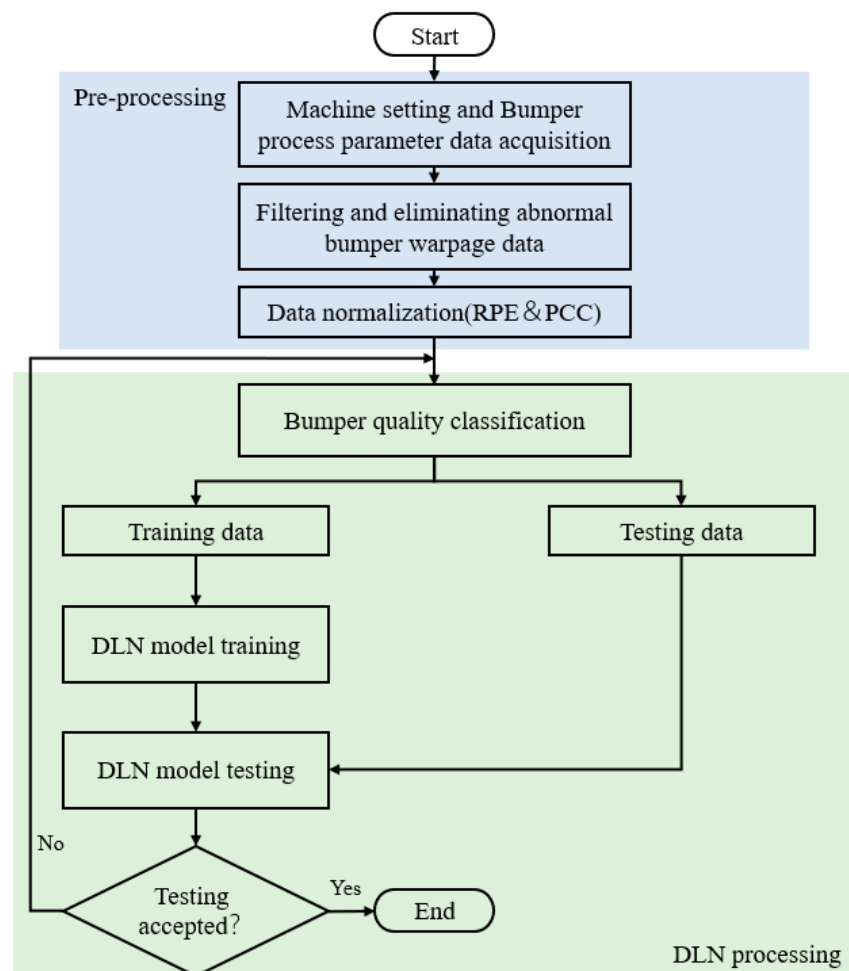


Figure 5. Flow chart of deep learning network modeling operation procedures.

In contrast to the study proposed by M. S. Huang et al. [22] in 2021, which was based on a neural network model for predicting the conformity of the molding quality of injection-molded products, this study focused on determining whether the molding quality of an IC tray fell in the qualified or unqualified region in a neural network model. The defects of an IC tray are relatively simple; they are only affected by a single weight when the neural network assigns weights. However, for most injection-molded products, the molding quality is affected by the interaction of many different defect factors, so it is necessary to assign weights to these multiple defect factors in the neural network, and, if we continue to use the neural network to assign multiple weights, we cannot identify the different degrees of influence of these different defect factors on the molding quality of the same product, while RPE can identify the impact of different defect factors on the molding quality of injection-molded products and define an exact comparable value for reliable, quantitative comparison analysis. Therefore, this study applied RPE and PCC to the neural network as a way to build a deep learning network model, which helped to assign the influence of multiple weights on the product molding quality and, thus, improved the accuracy of the deep learning network in prediction in this study. As shown in Figure 6, the deep learning network in this study applied RPE and PCC to the neural network multivariate weight assignment to effectively identify and analyze the degree of influence of the cavity pressure on its warpage value at five different locations within the mold cavity and derive the warpage prediction value of the bumper.

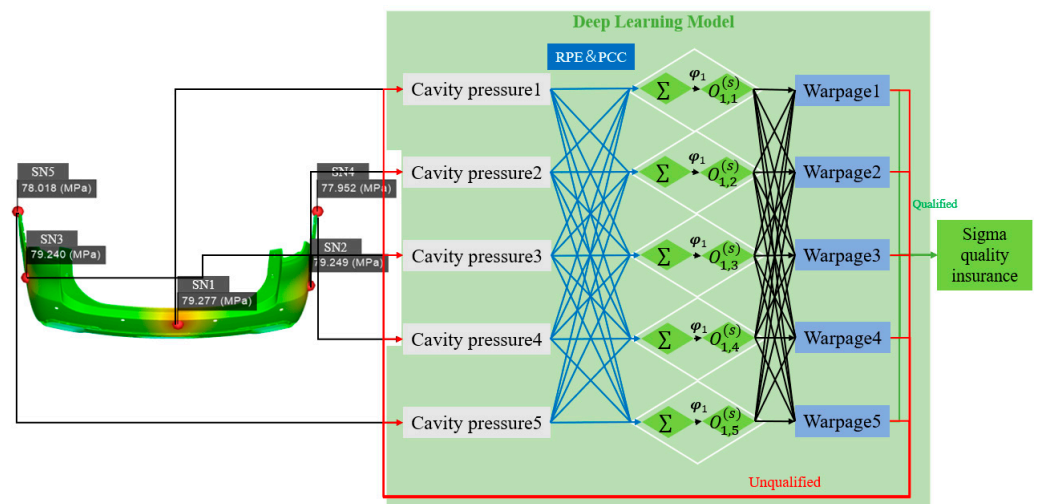


Figure 6. A simple diagram of predictive control applying a deep network model in this study.

4. Case Study

A flow chart of the DLN-based bumper quality inspection system for this study is shown in Figure 7, which includes an injection molding machine, a data acquisition module, pressure sensors and a computer for DLN modeling.

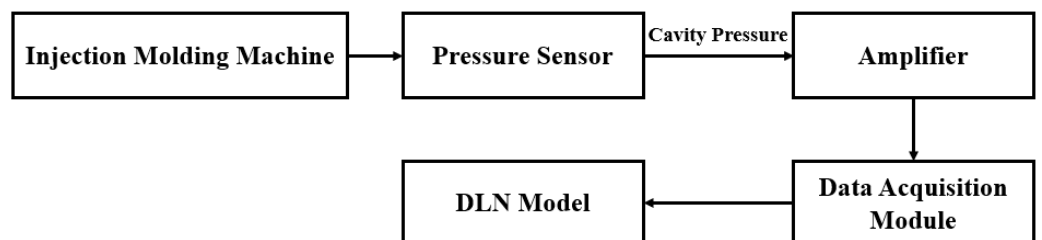


Figure 7. Flow chart of bumper quality inspection system.

The plastic bumper application material in this study was PP, and Figure 8a shows the basic geometry of the plastic bumper in this study, which was a large and thin, flesh-

thick manufacturing part, so the product as a whole was not allowed to produce a large warpage deformation. In the production process, we found that the most serious location of warpage displacement of plastic bumpers in this study was the deformation displacement of the distance between these two points of the bumper in the horizontal direction shown in Figure 8b; so, this study considered the warpage deformation (W) of this length in the horizontal direction as the key quality affecting the overall warpage deformation of the product. As shown in Figure 9, a threshold value (1.0 mm) was set for the warpage (W) of the bumper, i.e., when the warpage of the bumper was $W \leq 1.0$ mm, the bumper met the product quality requirements (qualified); when the warpage of the bumper was $W > 1.0$ mm, the bumper did not meet the product quality requirements (unqualified). The warpage values were taken to two decimal places to obtain a neural network model with higher learning accuracy and stability. The warpage in this study was defined as the value of the deformation displacement of any point on the bumper in spatial coordinates with respect to the design coordinates.

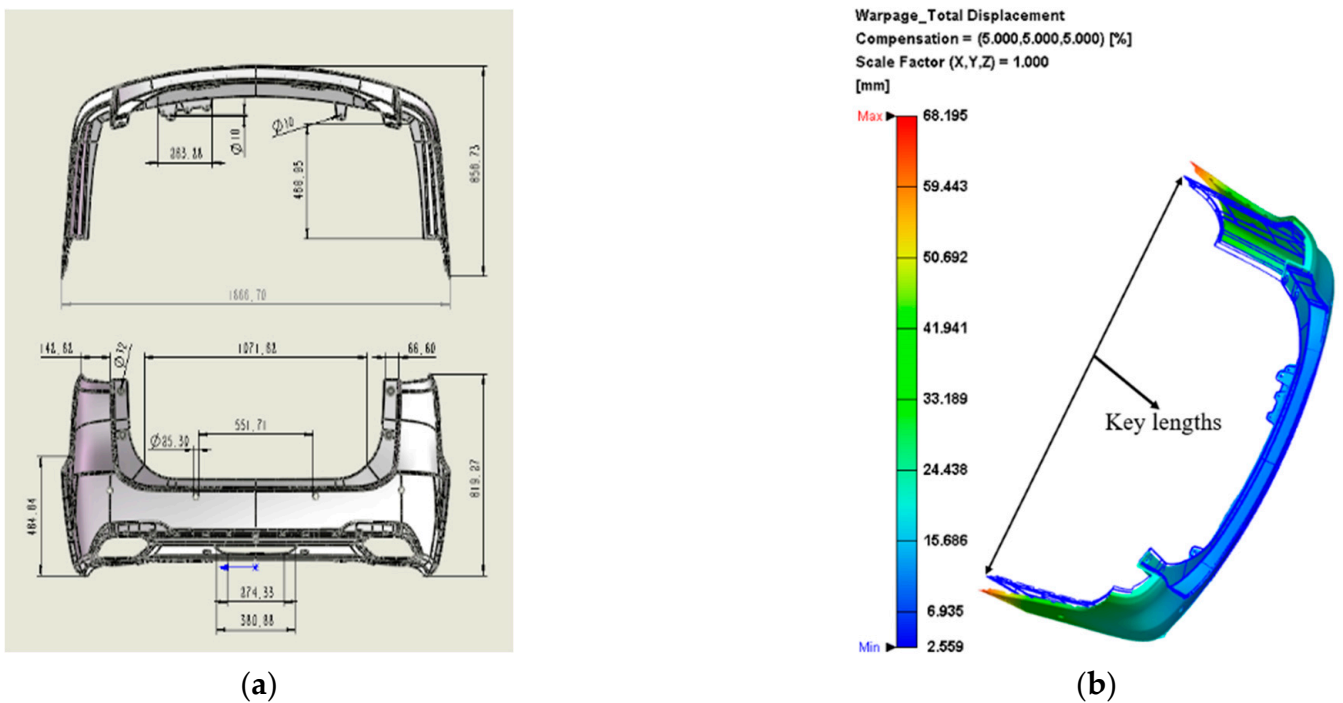


Figure 8. (a) The basic geometric dimensions of plastic bumpers; (b) warp key lengths for study.

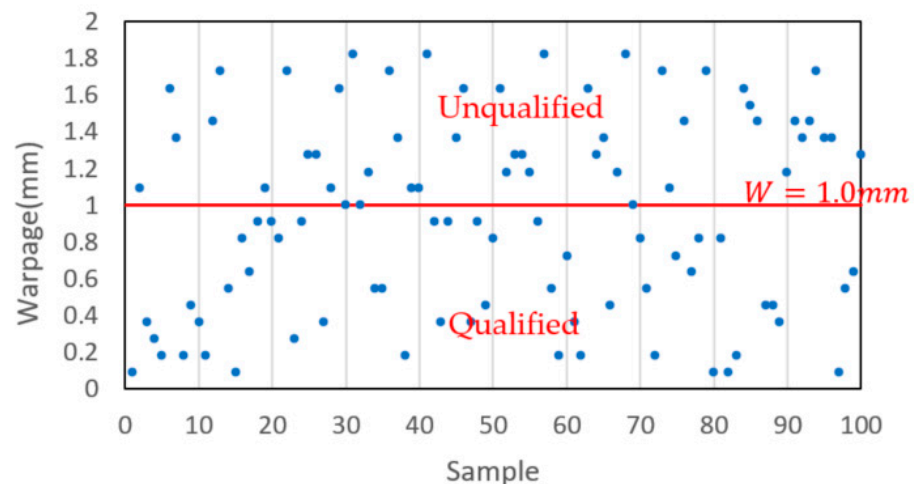


Figure 9. Classification of warpage of key length.

In this study, pressure sensors were installed at the corresponding locations in the mold cavity to detect the pressure signal in the cavity and to study the flow state of the melt and its response to the quality index. The locations of the pressure sensors are shown in Figure 10a, where SN1, SN2 and SN3 are located at the gate, and SN4 and SN5 are located at the end of the filling.

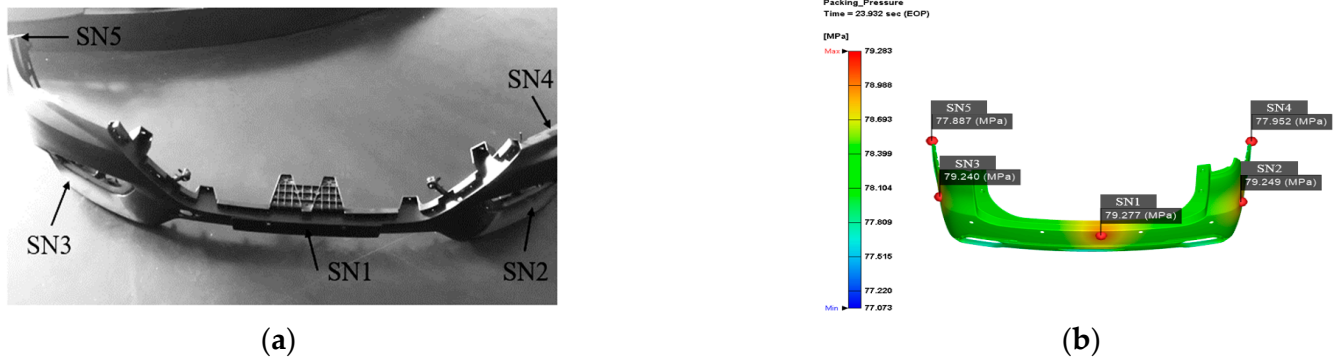


Figure 10. (a) Position of the pressure sensor in the cavity. (b) The pressure value captured by the sensor when the holding pressure was set to 80 MPa.

In this study, a two-factor, full experiment of filling pressure and holding pressure was conducted. Table 3 shows the process parameters of the bumper injection molding process, in which the injection pressure was 120–160 MPa, and the holding pressure was 60–100 MPa. The number of combinations of the two process parameters was 25, and the number of samples for each combination was six. The pressure profile in the whole cavity and the pressure profile of each sensor after each injection molding were recorded. The relationship between quality index and bumper quality (warpage amount) was investigated by adjusting the corresponding process parameters, and ANN models were constructed to predict the bumper warpage value.

Table 3. Bumper injection molding process parameters.

Item	Unit	Parameters
Melt temperature	°C	220
Mold temperature	°C	45
Injection time	s	14
V/P switchover position	Filling volume (%)	98
Cooling time	s	10.1
Holding time	s	15.5
Holding pressure	MPa	60, 70, 80, 90, 100
Injection pressure	MPa	120, 130, 140, 150, 160

In the actual injection molding process, the molding parameters we set on the injection molding machine were influenced by various factors and fluctuated during the production, i.e., the actual parameter value was not necessarily equal to the value we set. As shown in Figure 10b, when the holding pressure was set to 80 MPa, the pressure value after the end of the holding pressure was captured by the pressure sensor, which was smaller than the value we set; but, the difference was not big, around 0–3 MPa, which did not affect our subsequent experimental research. The mean, standard deviation, coefficient of variation and signal-to-noise ratio of pressure at each sensor location at different points of the molding cycle could be obtained based on the pressure data captured by the five pressure sensors during the bumper injection molding process in this study, as shown in Table 4.

Table 4. Relationship between pressure data at each sensor location.

Item	Pressure				
	SN1	SN2	SN3	SN4	SN5
Average	78.8092	78.7640	78.7446	77.2907	77.3452
SD	0.6915	0.7469	0.7625	1.0540	1.0503
Coefficient of Variation	0.0088	0.0095	0.0097	0.0136	0.0135
S/N	−37.931	−37.927	−37.925	−37.763	−37.770

The pressure integral index ($P_{I_{index}}$) and the holding pressure index ($P_{H_{index}}$) could be obtained from the overall pressure profile of the cavity. The peak pressure index ($P_{P_{index}}$) could be obtained from the pressure profile obtained from the sensor at the gate, while the residual pressure drop index ($P_{R_{index}}$) could be obtained from the pressure profile obtained from the sensor at the end of the filling. $P_{P_{index}}$ indicates the maximum pressure during the filling and compression process, and the amount of pressure during the injection molding process determines the amount of melt filled into the $P_{R_{index}}$, which indicates the average residual pressure drop in the mold cavity during cooling, which reflects the local shrinkage of the melt. The cavity pressure distribution obtained by using the sensors (SN1-SN5) is shown in Figure 11, which well illustrates the physical meaning of $P_{P_{index}}$ and $P_{R_{index}}$. $P_{I_{index}}$ represents the amount of momentum required to fill and compress the melt during the molding process. $P_{H_{index}}$ represents the average holding pressure of the injection molding process, which has sufficient influence on the molding quality (warpage amount, etc.) of the product. The pressure profile of the cavity as a whole is shown in Figure 12, which well illustrates the physical meaning of $P_{I_{index}}$ and $P_{H_{index}}$. These obtained quality indices were fed into the ANN models to assess the quality of the molded product and were further evaluated using Pearson’s correlation coefficient (PCC).

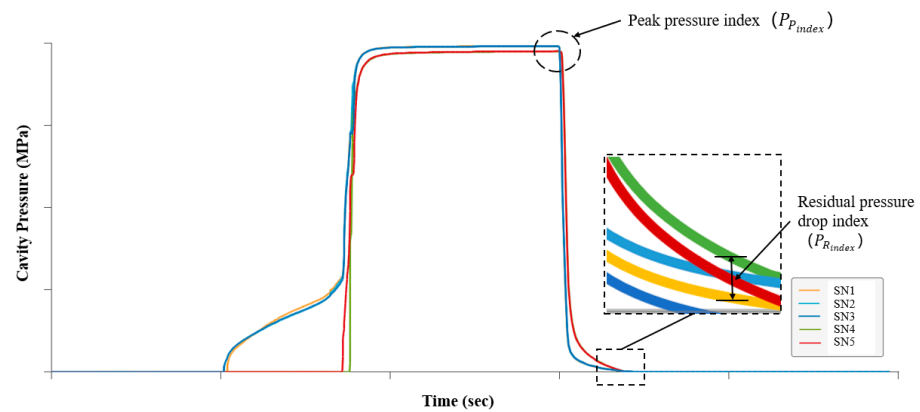


Figure 11. The peak pressure index ($P_{P_{index}}$) and residual pressure drop index ($P_{R_{index}}$).

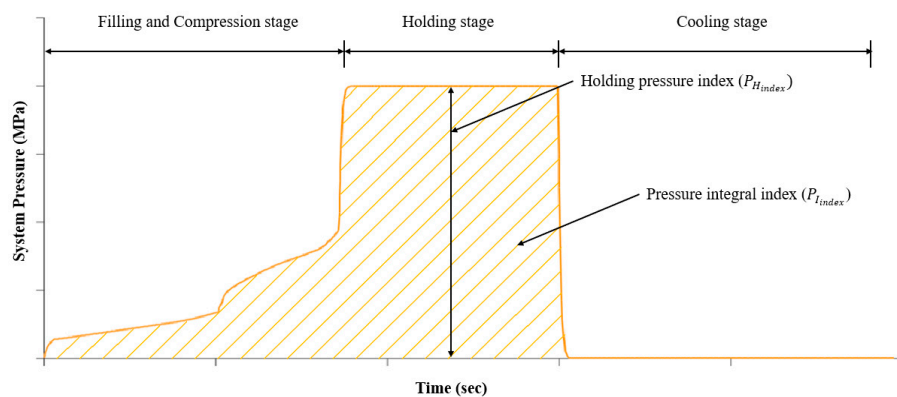


Figure 12. The pressure integral index ($P_{I_{index}}$) and holding pressure index ($P_{H_{index}}$).

As shown in Table 5, the Pearson's correlation coefficients (PCCs) [27] for the quality indicators $P_{R_{index}}$, $P_{P_{index}}$, $P_{I_{index}}$ and $P_{H_{index}}$ were all high and lay in the (0.75,1) interval, and the correlation strength was strong. Each experiment in this study used four quality indicators and output a quality classification for the amount of bumper warpage.

Table 5. Pearson's correlation coefficients (PCCs) between warpage and quality indices.

Quality Indices	Sensor Position	Sensor Symbols	Pearson's Correlation Coefficient
$P_{R_{index}}$	The end of filling	SN4	0.95
	The end of filling	SN5	0.94
$P_{P_{index}}$	Gate1	SN1	0.96
	Gate2	SN2	0.98
	Gate3	SN3	0.97
$P_{I_{index}}$	System pressure		0.92
$P_{H_{index}}$	System pressure		0.98

We use the standard z-score to identify abnormal data; $Z = \left| \frac{x-\mu}{\sigma} \right|$, where x denotes the value of a parameter data in a group of experimental parameter data, μ denotes the mean of a group of experimental parameter data and σ denotes the standard deviation. If the z-score was set to 1, the data values represented by the z-score falling outside the interval $[-1,1]$ were all outliers, and the higher the z-score, the fewer the outliers and vice versa. We filtered outliers from the experimental data using z-scores of 1.5, 2 and 2.5, respectively, and the results of the outliers are shown in Table 6. When the z-score was 1.5 (lower), we excluded a large amount of data, i.e., more outliers were determined (about 9% of the total data); when the z-score was 2, we observed six outliers in the amount of bumper warpage (about 4% of the total data); when the z-score was 2.5 (higher), we observed a small number of outliers (about 1% of the total data). When there are data filtered as outliers, to some extent, data with research value will be lost, which affects the training accuracy and prediction results of a model. So, when choosing the z-score, we had to balance the real outlier data it involved and the model training prediction accuracy. When the standard z-score was set to 2 in this study, the valid data points of bumper warpage amount were 144 at this time, 100 of them were used for model testing and the rest for model training.

Table 6. Number of outliers versus z-score.

Z-Score	Number of Outliers (Warpage)
1.5	12
2	6
2.5	3

As shown in Table 7, the number of levels of warpage of critical length of bumper was set to 5, 10, 20 and 50. When the standard z-score was set to 2, the maximum and minimum values of warpage of critical length of bumper in this study were 1.16 mm and 0.26 mm, respectively, and when the number of levels of warpage was set to 5, the width of each level was 0.18 mm, which expressed the accuracy of the bumper critical length warpage prediction model.

Table 7. Relationship between widths and z-scores of different magnitudes.

Grade Number	Z Score		
	1.5	2	2.5
5	0.15 mm	0.18 mm	0.18 mm
10	0.12 mm	0.14 mm	0.14 mm
20	0.08 mm	0.09 mm	0.09 mm
50	0.03 mm	0.03 mm	0.03 mm

5. Conclusions

In this study, we proposed a deep learning network (DLN) model based on an artificial neural network (ANN) model and a recognizable performance evaluation (RPE) method to achieve the prediction of critical length warpage of bumpers and to control and improve the quality of bumper molding. The RPE method made it easier and more accurate to assign weight values to the neural network model in this study. In addition, it had the dual recognition feature, i.e., the recognizable performance could be evaluated between two different, recognizable samples, with the characteristics of smaller-the-better, nominal-the-better and larger-the-better, instead of only under a single characteristic, which increased the reliability of this study's deep learning network model in prediction. The main results of this study are as follows:

1. Injection pressure and holding pressure were firstly identified as the key factors affecting the quality of bumper molding, and they were used as dependent variables to set up five gradients in both the intervals, (60 MPa, 100 MPa) and (120 MPa, 160 MPa), respectively, for the two-factor, full experiments, and there were six samples for each combination.
2. The mean, standard deviation, coefficient of variation and signal-to-noise ratio of the pressures at each sensor location at different points of the molding cycle were obtained based on the pressure data captured by the five pressure sensors during the bumper injection molding production process; using the identifiable performance evaluation method, the signal-to-noise ratio could quantitatively evaluate the influence of the pressure data at different sensor locations on the amount of bumper critical length warpage.
3. In addition, by observing typical, in-mold pressure curves, the pressure changes of the melt during different molding stages (filling, compression, holding pressure and cooling) in the cavity were understood, and four quality indices reflecting the molding quality of the product were selected, namely, the peak pressure index ($P_{P_{index}}$), holding pressure index ($P_{H_{index}}$), residual pressure drop index ($P_{R_{index}}$) and the pressure integral index ($P_{I_{index}}$).
4. In addition, we used Pearson's correlation coefficient (PCC) to evaluate the correlation between these quality indices and the amount of critical length warpage of the bumper and selected those with strong correlation (i.e., $|r| > 0.75$) as the input data for the deep learning network model. The in-mold pressure signals in the production process of this study bumper were obtained through five different locations, and they reflected four different quality indicators. It was calculated that all four quality indicators of the bumper in this study showed strong correlation with its critical length warpage amount, and, after normalizing them, all four quality indicators in this study could be used as the input data of the deep learning network for learning and as input data for the artificial neural network to learn and output the warpage of the critical length of the bumper.
5. In addition, the standard z-score was applied to filter and eliminate the abnormal bumper critical length warpage data, and the bumper critical length warpage in this study was converted into different levels (5, 10, 20 and 50), where more levels meant that the range of warpage in each level was reduced, and the accuracy of prediction by the bumper critical length warpage prediction model represented by different levels was different. In addition, the warpage of the critical length of the bumper was defined in the range of "qualified" and "unqualified", and, when the warpage of the critical length of the bumper in this study was $W \leq 1.0$ mm, the product met the requirements of the product specification and was qualified, while the opposite meant the product was not qualified.

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