Deep Learning Network in Injection Molding

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Based on Industry 4.0 smart manufacturing and for the prediction of injection molding quality of automobile bumpers, the deep learning network is proposed 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.

deep learning | molding quality | artificial neural network

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][3][4][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.

2. Current Works

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, a proven method is needed 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 propagationneural 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 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. 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 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. 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 studies, 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.

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