

Machine learning for enhancing manufacturing quality control in ultrasonic nondestructive testing: A Wavelet Neural Network and Genetic Algorithm approach

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ABSTRACT

With the rapid development of the global manufacturing industry, an efficient and accurate quality control system has become key to enhancing competitiveness. Ultrasonic Nondestructive Testing (NDT), as an efficient means of quality inspection, plays a crucial role in improving manufacturing quality through the precision of its data analysis. This study aims to explore the application of ultrasonic NDT data in manufacturing quality control by integrating machine learning technologies, with a specific focus on the Wavelet Neural Network optimized by Genetic Algorithms (GA-WNN). This study achieved significant prediction and evaluation results by applying a GA-WNN to quality control in manufacturing. Compared to traditional Wavelet Neural Network (WNN) models, the GA-WNN more effectively identifies and predicts potential quality issues, especially in noisy data and complex production environments, demonstrating higher accuracy and stability. When predicting possible defect types in the manufacturing process, the GA-WNN showed a notable improvement in accuracy over other models. Additionally, in quality stability evaluation, GA-WNN was able to capture production fluctuations more accurately, providing more valuable results for decision-making. The methodologies and discoveries of this study offer new perspectives and tools for quality control in manufacturing and the analysis of ultrasonic NDT data, presenting broad application prospects.

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1. Introduction

In the context of rapid global manufacturing industry development, ensuring manufacturing quality is not only the cornerstone of enterprise survival but also the key to enhancing competitiveness [1, 2]. With technological advancements, ultrasonic NDT, known for its efficiency and non-destructiveness, has been widely applied in quality control within the manufacturing sector [3-5]. However, traditional analysis of ultrasonic testing data largely relies on experienced operators, which is not only inefficient but also struggles to detect complex and minute defects [6, 7]. Therefore, efficiently and accurately analysing ultrasonic NDT data becomes a crucial issue for improving the level of manufacturing quality control.

The rapid development of machine learning technologies in recent years has offered new solutions to the aforementioned problems. By utilizing machine learning algorithms for in-depth

analysis of ultrasonic NDT data, it's possible to significantly improve the accuracy and efficiency of defect detection [8-11]. More importantly, this approach allows for automated detection under complex conditions, greatly enhancing the quality control capabilities of the manufacturing process. However, existing research primarily focuses on the improvement and optimization of algorithms, with less attention given to their application and effect evaluation in the actual manufacturing process, limiting the widespread application of machine learning in manufacturing quality control [12-14].

Although existing research methods have improved detection efficiency and accuracy to some extent, there are still some flaws and deficiencies [15-18]. Firstly, the algorithm models used in many studies are complex and require substantial computational resources, which is not conducive to application in resource-limited production environments. Secondly, some research lacks consideration of the variability in manufacturing processes, making it difficult to adapt to changing production conditions [19, 20]. Moreover, existing methods often overlook the interpretability of models, which is disadvantageous for problem diagnosis and decision support in practical applications [21].

This paper aims to introduce machine learning technology, specifically the GA-WNN, to build a comprehensive system suitable for manufacturing that includes quality prediction, stability assessment, and control optimization. Firstly, the study focuses on a manufacturing quality prediction model based on GA-WNN, aimed at providing a basis for early intervention through accurate prediction of potential quality issues in the manufacturing process. Secondly, a quality stability assessment system for the manufacturing process is established, evaluating production stability by analysing data fluctuations during the production process to provide references for quality control. Finally, an optimization model for manufacturing process quality control is researched, aiming to improve product quality and production efficiency by optimizing production parameters through algorithms. This study not only improves the level of quality control in manufacturing but also provides a new methodology for the efficient utilization of ultrasonic NDT data, having significant theoretical and practical value.

2. Construction of a manufacturing process quality prediction model based on GA-WNN

This paper proposes a model based on the GA-WNN (Fig. 1), designed to overcome the limitations of traditional quality prediction methods when faced with complex manufacturing stages, achieving accurate prediction of quality characteristic values throughout the entire manufacturing process. Based on its excellent generalization ability and noise resistance, the WNN's initial parameters are optimized using GA, not only speeding up the model's convergence but also significantly enhancing its predictive accuracy. Unlike models specifically for other assembly processes, the GA-WNN model considered in this study encompasses the entire chain from raw material processing to final product assembly. The model's input vector $A = \{a_1, a_2, \dots, a_l\}$ includes the actual values of quality characteristics from raw materials through each manufacturing step and their deviation from process standards, while the model output $B = \{b_1\}$ aims to predict the quality characteristic values of a specific manufacturing stage or the final product. This approach enables the model to provide real-time, accurate predictions of the quality condition of downstream processes or final product quality based on actual quality data and its fluctuations from upstream processes, offering strong support for early detection of potential quality issues and timely adjustment of production strategies.

WNN is a composite model that combines wavelet transform and neural networks. Its primary feature is the ability to decompose input signals into different frequency components through wavelet transforms, capturing both time and frequency characteristics of the signal. Compared to traditional Artificial Neural Networks (ANN), WNN not only handles nonlinear relationships but also effectively processes time-varying and noisy signals. For example, while ANN often requires signal preprocessing or manual feature extraction, WNN can automatically extract key features through adaptive multi-scale analysis, overcoming the limitations of traditional meth-

ods. In ultrasonic non-destructive testing data analysis, WNN can accurately capture subtle fluctuations in the signal and predict potential quality issues, while ANN may fail in such applications due to its insufficient ability to process time-frequency features. When constructing the manufacturing process quality prediction model based on GA-WNN, the design of the model's structure and the selection of parameters decisively impact its performance. To adapt to the complexity of quality control in manufacturing, this paper adopts a three-layer structure of the WNN, designed to fully capture and analyse the complex quality information contained in ultrasonic NDT data. In determining the optimal number of nodes in the hidden layer, a crucial parameter in the network structure, this study employs a trial-and-error method due to the absence of a unified standard. By continuously adjusting the number of nodes and evaluating model performance, the aim is to achieve optimal quality characteristic prediction effects. Assuming the number of input layer nodes is represented by l , and the number of output layer nodes is represented by j , with a constant ranging from 1 to 10 represented by s , the formula is:

$$v = \sqrt{l + j} + s \quad (1)$$

Moreover, selecting an activation function is another crucial parameter setting. This paper chooses the Morlet wavelet function as the activation function $\psi(a)$ for the hidden layer, due to its good anti-interference capability and computational stability when processing ultrasonic NDT data. This is crucial for improving the model's adaptability and predictive accuracy in complex manufacturing environments. The expression for $\psi(a)$ is:

$$\psi(a) = \cos(1.75a)e^{\frac{-a^2}{2}} \quad (2)$$

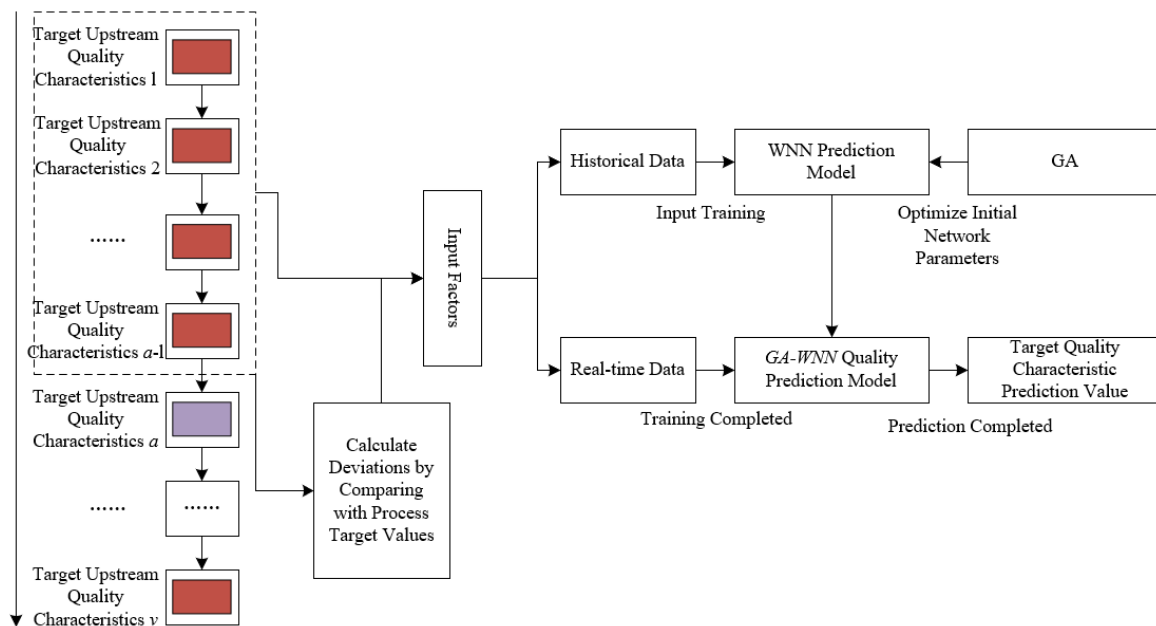


Fig. 1 Schematic diagram of the manufacturing process quality prediction model

This study introduces initial optimization parameters in the WNN, including connection weights μ_{uk} and μ_{kj} , translation factors y_k , and scale factors x_k . To adapt to this high-dimensional data structure and simplify the coding process, this paper employs a real-number encoding strategy, using floating-point numbers to represent the network's weights and factors. Additionally, considering the two-dimensional nature of the weight matrix and the one-dimensional nature of chromosomes, this study unfolds the two-dimensional weight matrix into a one-dimensional array and concatenates it with translation and scale factors, forming a complete chromosome representation for the implementation and calculation of GA. The total length of individual encoding is represented by $u \times k + k + k + k \times j$. Fig. 2 shows the schematic diagram of the encoding strategy.

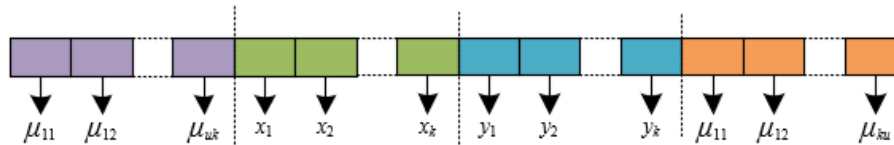


Fig. 2 Encoding strategy schematic diagram

In the implementation of the GA, the reciprocal of the error between the predicted values and actual values serves as the fitness function to measure the performance of the prediction model, where a higher fitness value indicates higher model prediction accuracy and superior solution quality. Assuming the prediction output error of the WNN is represented by r , the expression for the fitness function d is as follows:

$$d = \frac{1}{r} \quad (3)$$

To ensure that individuals with high fitness are prioritized for selection, this study employs the widely used roulette wheel selection method to determine the probability of an individual being selected, ensuring the inheritance and optimization process's effectiveness of high-quality solutions. Assuming the fitness value of the u -th individual is represented by D_u , and the coefficient is represented by j , with the total number of individuals in the population represented by V , the calculation formulas are as follows:

$$d_u = \frac{j}{D_u} \quad (4)$$

$$o_u = \frac{d_u}{\sum_{u=1}^V d_u} \quad (5)$$

For two chromosomes X and Y of length m , assuming a random number between $[0,1]$ is represented by e , the crossover operation process is as follows:

$$x_j = (1 - e)x_j + ey_j \quad (6)$$

$$y_j = ex_j + (1 - e)y_j \quad (7)$$

When a mutation operator mutates the j -th gene of chromosome X with a certain probability, assuming the upper and lower bounds of gene value are represented by x_{MAX} and x_{MIN} , the current iteration number by H , the maximum number of network iterations by H_{MAX} , and a random number between $[0,1]$ by e_1 and e_2 , the mutation operation expression is as follows:

$$x_j = \begin{cases} x_j + (x_{MAX} - x_j) \cdot e_1 \cdot \left(1 - \frac{H}{H_{MAX}}\right)^2 & e_2 > 0.5 \\ x_j + (x_{MIN} - x_j) \cdot e_1 \cdot \left(1 - \frac{H}{H_{MAX}}\right)^2 & e_2 \leq 0.5 \end{cases} \quad (8)$$

3. Construction of a quality stability assessment system for the manufacturing process

To construct a reasonable quality stability assessment system for the manufacturing process, it's first necessary to determine multiple influencing factors. This study is not limited to a specific purpose but extends the view to multiple factors that may affect quality stability throughout the manufacturing process. Therefore, the factor set N is defined as a collection of quality characteristics encompassing all stages from raw material selection, processing technology, assembly process, to final inspection, i.e., $N = \{n_1, \dots, n_u, \dots, n_l\}$, where l represents the number of quality characteristics being assessed in the manufacturing process. For the evaluation set I , this study uses the degree of deviation of quality characteristic values from process standards as a key indicator to measure the quality stability of the manufacturing process. The evaluation set I is defined as three levels: $I = \{i_1, i_2, i_3\} = \{\text{significant deviation, general deviation, minor deviation}\}$,

reflecting the degree of deviation of various quality characteristics from their specified standards in the manufacturing process.

In the construction of the quality stability assessment system for the manufacturing process, selecting appropriate membership functions to quantify the degree of deviation of various quality characteristics is crucial. This step aims to transform ultrasonic NDT data and other quality characteristic data into dimensionless values that can reflect quality stability. Unlike assessments in other assembly processes that may only focus on specific dimensions or characteristics, the assessment of quality stability in the manufacturing process needs to consider comprehensive quality characteristics from raw material inspection, intermediate process control, to final product inspection, which may include dimensions, strength, surface roughness, and other dimensions.

To quantify the reasonableness of these quality characteristic deviations, this study uses normalization to convert data into values within the $[0,1]$ interval. The closer the normalized value is to 1, the closer the quality characteristic of the process is to the set standard value, indicating a smaller actual deviation and higher quality stability. Conversely, the closer the value is to 0, the larger the actual deviation and the lower the quality stability. Since quality characteristics in manufacturing often include various types, and each type of characteristic may have different levels of acceptability and standards, traditional normalization methods may not meet the needs of all situations. Therefore, this paper proposes a flexible normalization method that considers the upper and lower deviations from the standard values of quality characteristics in the manufacturing process, more comprehensively and accurately reflecting the quality stability of the manufacturing process. Assuming the normalized quality characteristic value is represented by a^* , the actual quality characteristic value by a , the standard value of the quality characteristic by i , the maximum upper deviation of the quality characteristic value by i_G , and the maximum lower deviation of the quality characteristic value by i_M . The following is the normalization equation:

$$a^* = 1 - \frac{|a - i|}{i_G - i_M} \quad (9)$$

Assuming the membership degree corresponding to parameter a is denoted by $e(a)$, the expected value of the distribution is denoted by i , and the width of the curve is denoted by δ , then the membership function expression is as follows:

$$e(a) = \exp\left[\frac{-(a - i)^2}{2\delta^2}\right] \quad (10)$$

Further assuming the distribution expected values for the three intervals are denoted by i_x , ω_y , and i_z , with i_x and i_z being the maximum and minimum values of that parameter attribute, and ω_y being the given expected value under the *general deviation* condition, the specific function expressions are as follows:

$$e(a) = \begin{cases} 1 & a \leq i_x \\ \exp\left[\frac{-(a - i_z)^2}{2\delta_x^2}\right] & i_x < a \leq i_z, \delta_x = \frac{i_y - i_x}{3} \end{cases} \quad (11)$$

$$e(a) = \begin{cases} \exp\left[\frac{-(i_y - a)^2}{2\delta_{y1}^2}\right] & i_x < a \leq i_z, \delta_{y1} = \frac{i_y - i_x}{3} \\ \exp\left[\frac{-(a - i_y)^2}{2\delta_{y2}^2}\right] & i_y < a \leq i_z, \delta_{y2} = \frac{i_z - i_y}{3} \end{cases} \quad (12)$$

$$e(a) = \begin{cases} \exp\left[\frac{-(a - i_z)^2}{2\delta_z^2}\right] & i_x < a \leq i_z, \delta_z = \frac{i_z - i_y}{3} \\ 1 & i_z \leq a \end{cases} \quad (13)$$

Assuming the number of quality characteristics involved in the assessment is denoted by l , a quality stability fuzzy matrix for the manufacturing process can then be established as:

$$E = \begin{bmatrix} e_{11} & e_{12} & e_{13} \\ e_{21} & e_{22} & e_{23} \\ \vdots & e_{u2} & \vdots \\ e_{l1} & e_{l2} & e_{l3} \end{bmatrix} \quad (14)$$

4. Optimization modelling for manufacturing process quality control

In the entire production process of manufacturing, the complexity of quality control far exceeds that of a single manufacturing stage, as it encompasses multiple stages, from raw material processing and component manufacturing to final product assembly. Each stage can introduce quality deviations, which may accumulate along the production chain, affecting the final product's quality stability. Especially when using high-precision techniques such as ultrasonic NDT for quality assessment, even minor deviations can have a significant impact on the final product's quality. Therefore, traditional quality control thresholds based on manufacturing standards often fail to manage the entire manufacturing process's quality stability comprehensively and effectively. Addressing this issue, this paper aims to optimize quality control thresholds by real-time prediction of quality characteristics at various stages of the manufacturing process and comprehensive assessment of the entire manufacturing process's quality stability. Fig. 3 shows the schematic diagram of the optimization model for manufacturing process quality control.

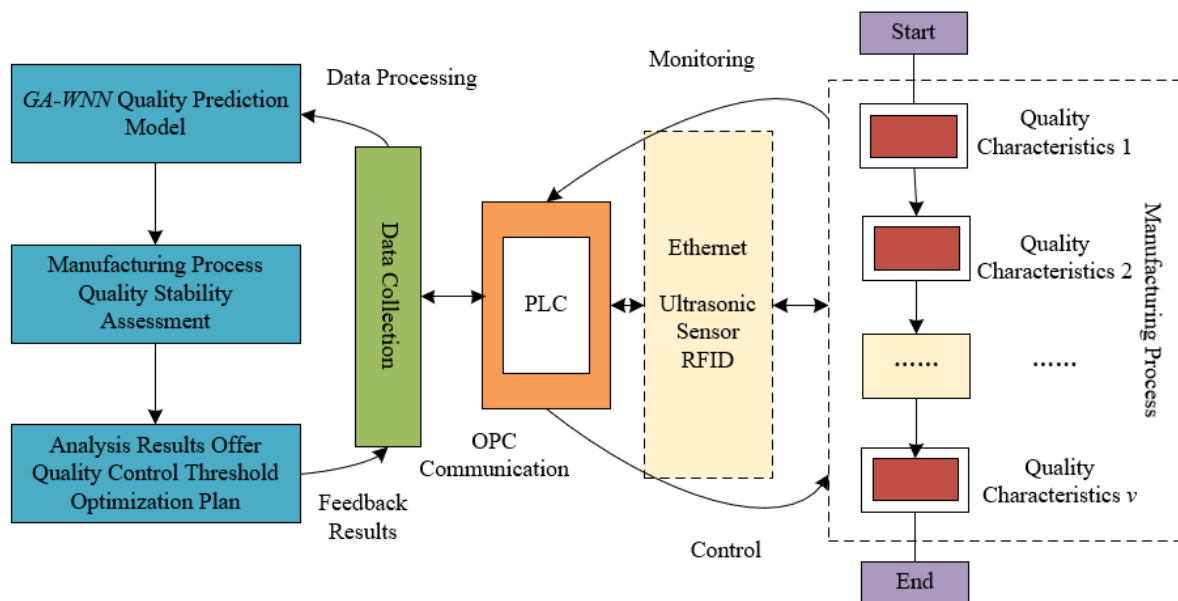


Fig. 3 Schematic diagram of the optimization model for manufacturing process quality control

In the manufacturing process, due to the diversity and complexity of the involved processes, the impact of each process's quality characteristics on the overall product quality stability varies. Especially when high-precision quality assessment technologies such as ultrasonic NDT are introduced, quality deviations in each process and their impact on the final product quality can be identified more accurately. In this context, controlling all quality characteristics of every process to the same extent would lead to a tremendous waste of resources and may not achieve effective real-time quality control. Therefore, this paper proposes a quality control optimization principle, which prioritizes controlling those quality characteristics of processes that have a significant impact on overall quality stability.

Assuming the initial process requirements for quality characteristics are represented by $H \pm e$, the process target value by H , and the permissible range within the process by $[H-e, H+e]$. Meeting the initial process requirements, the control threshold is divided into j levels, with the quali-

ty characteristic control threshold at the j -th level represented by H_j , and the threshold change degree at the j -th level by S_j , where $S_j \in [0,1]$, then there is:

$$H_j = [H - H \times S_j, H + H \times S_j] \quad (15)$$

In the optimization modelling for quality control in the manufacturing process, optimizing the quality characteristic thresholds is a key step aimed at precisely controlling the quality characteristics of each production stage to improve the overall manufacturing process's quality stability. Below are the five key steps for optimizing quality characteristic thresholds in the manufacturing process:

- **Data Collection and Model Training:** First, collect ultrasonic NDT data and the quality characteristics data of corresponding processes from the real-time database of the Manufacturing Execution System (MES). This data reflects the historical quality situation in the manufacturing process and is used to train the constructed GA-WNN model. Through this training, the model learns the relationship between quality characteristics in the manufacturing process and the final product quality, providing a basis for subsequent quality predictions.
- **Quality Characteristics Prediction and Assessment:** Next, use the real-time collected manufacturing process data as input to predict the quality characteristics of target control points using the trained GA-WNN model. By comprehensively assessing these prediction results using the established manufacturing process quality stability assessment method, a quantified score about the entire manufacturing process's stability can be obtained.
- **Optimization Adjustment of Quality Control Thresholds:** If the assessment results do not meet the preset quality stability standards, it indicates that optimization adjustments of quality control thresholds are needed. Priority is given to adjusting the quality characteristics with greater weight and currently showing larger deviations in their predicted values. By progressively narrowing the range of control thresholds, i.e., adjusting from looser to stricter standards, quality deviations are reduced, and quality stability is improved.
- **Cyclical Optimization Process:** If the quality stability still does not meet the standards even after adjusting to the strictest control threshold range, the same adjustment process is applied to the quality characteristics with the next highest weight. This cyclical process ensures that by sequentially optimizing the control thresholds of key quality characteristics, the entire manufacturing process's quality stability can gradually improve to meet the assessment standards.
- **Real-time Feedback and Process Adjustment:** Finally, the optimized quality control threshold results are promptly fed back to the Programmable Logic Controller (PLC) on the manufacturing floor to guide actual manufacturing operations. This step ensures that the optimizations of quality control thresholds can be quickly implemented, impacting the manufacturing process, and effectively improving the manufacturing process's quality stability and product quality.

To validate the practical application of the GA-WNN model, we collaborated with an automotive parts manufacturing company and implemented the GA-WNN model on their production line. The company uses ultrasonic non-destructive testing technology to monitor product quality during production, and we applied the GA-WNN model to analyse the data from this process. The experimental results demonstrated that GA-WNN significantly improved the accuracy of quality predictions and was able to identify potential quality issues in advance. In terms of quality stability assessment, GA-WNN accurately captured production fluctuations, enabling the management team to adjust production parameters in time, thus preventing large-scale production losses. Specifically, within two months of implementing GA-WNN, production efficiency increased by 10 %, and the product rework rate decreased by 15 %. This case study validates the effectiveness of GA-WNN in real manufacturing environments.

5. Experimental results, analysis, and discussion

Comparing the manufacturing process quality prediction results shown in Fig. 4, differences in predictive performance between the GA-WNN and the traditional WNN are observable. It's evident from the experimental data that GA-WNN provided closer to actual value predictions for most samples. For instance, on sample 3, the GA-WNN predicted a value of 24.3, while the actual value was 24.6, resulting in a small difference of only 0.3. In comparison, the WNN predicted 24, showing a discrepancy of 0.6 from the actual value. Similarly, for sample 6, the GA-WNN's prediction of 23.4 was very close to the actual value of 23.8, whereas the WNN predicted 23, resulting in a larger discrepancy. Overall, GA-WNN consistently showed lower prediction errors across all samples than WNN, indicating higher accuracy in manufacturing quality predictions. These experimental results highlight the effectiveness of the GA-WNN model in predicting quality in the manufacturing process. Through GA optimization, GA-WNN can more accurately adjust network parameters, better capturing the patterns of quality variation in the manufacturing process, and providing more precise prediction results. This improvement in accuracy is crucial for early identification of potential quality issues in the manufacturing process, offering strong data support for timely intervention measures.

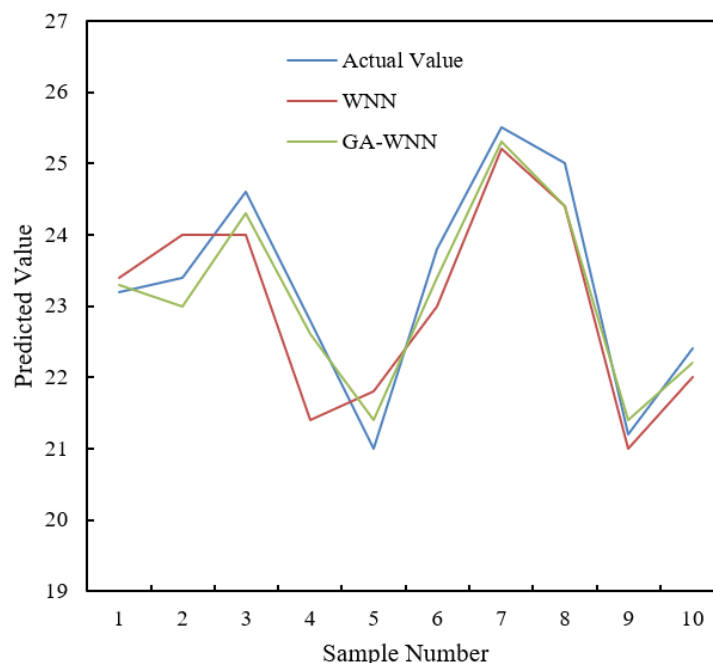


Fig. 4 Comparison of quality prediction results for manufacturing process test set

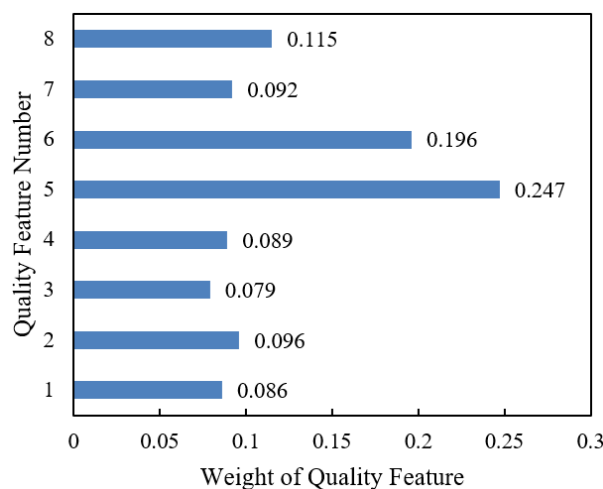


Fig. 5 Weight distribution for quality characteristics in manufacturing process

Fig. 5 shows the weight distribution data for various quality characteristics in the manufacturing process, indicating that among all considered quality characteristics, the fifth and sixth quality characteristics occupy significantly higher weights of 24.7 % and 19.6 % respectively, which are noticeably higher than other quality characteristics. This suggests that these two quality characteristics have a greater impact on the final product's quality within the manufacturing process; therefore, their stability and accuracy should be prioritized during quality control and optimization. Conversely, the third quality characteristic holds the lowest weight at 7.9 %, indicating its relatively minor impact on the final product's quality. Such weight distribution helps identify key quality characteristics that significantly affect the final product's quality in the manufacturing process, providing a basis for the rational allocation of resources and optimization adjustments. Through precise allocation of quality characteristic weights, the proposed optimization model for quality control in the manufacturing process can guide quality management activities more effectively during the production process. This optimization strategy, based on weight distribution, ensures that limited resources are focused on key stages that most significantly affect the final product's quality, thus improving the efficiency and effectiveness of quality control throughout the manufacturing process. Furthermore, real-time feedback of optimization measures to the production line's PLC further ensures real-time monitoring and adjustment of the manufacturing process, enhancing the production process's flexibility and responsiveness.

Table 1 presents the final evaluation vectors for 100 sets of quality characteristic data in the manufacturing process, reflecting the membership degrees of three different quality characteristics (Characteristic 1, Characteristic 2, Characteristic 3) across various sample groups. It can be observed that Characteristic 3 has higher membership degrees in most groups, such as 0.784 in Group 1, 0.784 in Group 3, and 0.725 in Group 100, showing that Characteristic 3 deviates from its target values more frequently compared to Characteristics 1 and 2 throughout the manufacturing process. In contrast, Characteristic 1 generally has lower membership degrees, indicating higher stability and lower likelihood of deviation during the manufacturing process. Characteristic 2's membership degrees are at a medium level, indicating its probability of deviating from target values falls between Characteristics 1 and 3. Analysis of this data demonstrates the effectiveness of the proposed optimization model for quality control in the manufacturing process. Firstly, the analysis of the final evaluation vectors for quality characteristic data accurately identifies quality characteristics prone to deviation during the manufacturing process, providing a clear basis for optimizing adjustment of quality control thresholds.

Table 1 Final evaluation vector for quality characteristic data in manufacturing process

Group	Characteristic 1	Characteristic 2	Characteristic 3
1	0.021	0.134	0.784
2	0	0.265	0.562
3	0.002	0.153	0.784
...	...	...	...
48	0.095	0.314	0.445
49	0.115	0.258	0.451
50	0.223	0.178	0.432
51	0	0.101	0.835
52	0	0.162	0.784
...	...	...	...
99	0.124	0.332	0.421
100	0	0.124	0.725

Table 2 Stability scores for the manufacturing process

Group	Characteristic 1	Characteristic 2	Characteristic 3
1	83.25	51	58.94
2	71.24	52	86.25
3	82.36	53	82.31
...	...	...	...
48	65.25	99	63.21
49	62.39	100	77.89

Table 2 provides stability scores for various groups of data concerning three different quality characteristics (Characteristic 1, Characteristic 2, Characteristic 3) in the manufacturing process. The data shows significant differences in stability scores for different quality characteristics across groups, reflecting the quality fluctuations during the production process. For instance, Characteristic 1 scored 83.25 in Group 1 and 62.39 in Group 49, illustrating variability in its stability across different production batches. Characteristic 2 scored relatively high in some groups, such as 100 in Group 49, indicating higher stability in these specific production batches. In contrast, Characteristic 3's scores vary greatly across groups, such as 86.25 in Group 2 and 63.21 in Group 48, showing notable variations in stability during different production processes. These findings suggest that the developed quality stability assessment system for the manufacturing process effectively evaluates and reflects the stability of various quality characteristics during production. Through this assessment system, potential quality fluctuation issues in the production process can be accurately identified, providing a scientific basis for optimizing adjustment of quality control thresholds and formulating corresponding quality improvement measures.

6. Conclusion

This paper has successfully developed a comprehensive system for quality prediction, stability assessment, and control optimization in the manufacturing industry by integrating machine learning technology, particularly the GA-WNN. The research focuses on three core aspects: firstly, developing a manufacturing quality prediction model based on GA-WNN, achieving precise prediction of potential quality issues in the manufacturing process; secondly, constructing a quality stability assessment system for the manufacturing process, evaluating production stability through the analysis of production data fluctuations; and lastly, studying an optimization model for manufacturing process quality control, enhancing product quality and production efficiency through algorithmic optimization of production parameters.

The experimental results demonstrate the comprehensiveness and depth of this research. Analysis of the training set error convergence graph for different manufacturing process quality prediction models, test set quality prediction results, weight distribution of quality characteristics, final evaluation vectors for quality characteristics, stability scores for the manufacturing process, predicted results and comprehensive scores for actual manufacturing process quality characteristic data, and levels of quality control thresholds not only proves the effectiveness of the GA-WNN model in quality prediction and control within the manufacturing industry but also shows the feasibility of improving manufacturing process stability and product quality consistency through optimized control thresholds and real-time feedback adjustment measures.

Although the GA-WNN model demonstrates excellent performance in quality prediction and stability assessment, there are still some limitations. Firstly, the performance of the GA-WNN model is highly dependent on the quality of the input data. In cases where there is significant noise or missing data, the model may experience a decrease in accuracy. Secondly, the training process of the GA-WNN model requires a considerable amount of time, especially when the dataset is large. The computational complexity of the genetic algorithm can be high, which may impact the real-time performance in practical applications. Additionally, GA-WNN is highly sensitive to high-frequency noise in ultrasonic signals, which means that more data preprocessing work may be needed when dealing with complex noise environments. Future research could focus on the following aspects for improvement: exploring more efficient algorithms to reduce training time, developing robust optimization methods for noisy data, and further enhancing the model's adaptability to ensure stable operation even when data quality is poor.

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