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Research on Process Quality Prediction and Control of Spindle Housings in Flexible Production Lines

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Abstract: The characteristics of flexible production lines, i.e., "multiple steps and few processes", increase the complexity of the process and the difficulty of process quality control, but are not conducive for improving the quality and efficiency of a production line. In this study, we use a flexible production line processing spindle box as the research object. Using an extensive data analysis method, we study the key influencing factors of process quality and the prediction and optimization of process quality characteristics, aiming to accurately predict the machining accuracy of flexible production line processes and to achieve efficient quality control. A fuzzy hierarchical analysis-based impact factor model is developed to obtain a process quality impact factor model consistent with the spindle box of a production line. By verifying the prediction accuracy of 24 sets of quality spindle bore data, a prediction model with a relative error of less than 0.01 is obtained, which provides a prediction sample for analyzing potential problems of process quality in a production line. The SPC control principle is used to monitor process quality by using the standard control method, and the change trends between the actual and predicted values of quality characteristics are compared to achieve predictive control of the process quality. The product qualification rate of this control scheme under this monitoring method is 96%.

Keywords: spindle housing; statistical process control; 5M1E; process quality; predictive control

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1. Introduction

The spindle box is one of the important components in a machine tool [1], which is used for machine tool processes including rotation, transmission, and other parts/auxiliary mechanisms of the installation. The role of the spindle box is mainly to support and fix, to achieve a motor-driven machine tool that can perform start, stop, commutation, and variable speed functions. In the manufacturing process, the spindle box mainly processes multiple surface parts; in general, in medium-sized machine tool manufacturing, the spindle box part of machining labor accounts for about from 15% to 20% of the overall production process [2]. Therefore, quality control of the spindle box is critical in machine tool manufacturing.

Currently, relevant technical personnel in enterprises still use quality control methods that include traditional manual paper records, tabular data collation, and numerical analysis of traditional software. However, there is a large amount of statistical data analysis in the production process, different specifications, as well as different equipment, staff, and other data classification needs, and a time lag in relevant data from recording to importing and analysis, all of which consume a lot of labor and production costs and are not predictive [3].

Foreign quality management systems have previously been developed, and numerous scientific research results have been obtained based on the process quality control of flexible production lines and related theoretical studies. In terms of critical process identification, Guo, W. et al. [4] used a topological data analysis to form a relational data network in a manufacturing process, selected critical process variables or functions that affected the system results by analyzing the shape of the network, and used predictive models to train the data to evaluate the impact of the functions. Li, A.D. et al. [5] used non-dominated ranking-based critical quality feature identification optimization and a production process whale optimization algorithm combined with an ideal point method for critical quality feature identification of unbalanced production data and prediction model building to predict critical quality feature values. Song, W. et al. [6] addressed the problem of critical variable identification in continuous annealing process operations. The authors proposed a method for classifying and identifying multiple models based on the composition of multi-scale feature variables by analyzing variable characteristics to effectively identify the key processes affecting multiple models, and thus improved the identification performance. Regarding analyzing quality influencing factors, Liu, T. et al. [7] were influenced by 5M1E, the mutual interference of quality problems, and quality characteristics, which are unavoidable in production. Based on SOV, a QC-linkage model, and coupling, a transfer model of quality characteristics variation and control was proposed, and an analysis system model applicable to different volumes of data was developed. Xu, W. [8] proposed a new method for a comprehensive quality evaluation of the product quality status of manufacturing enterprises, using similarities among characteristic quality values and a weighted comprehensive evaluation method to accurately describe the quality status of workpieces. Colledani, M. et al. [9] proposed a new specification that went beyond the traditional Six Sigma method to achieve a new integrated quality, production, and management control method that avoided the limitations of traditional quality management in an unstable production environment. In terms of quality predictive control methods, Liu, J. and Pang, J. et al. [10,11] addressed the problems of low traceability, timeliness, and unpredictability of quality control in the machining process, determined the relevance and impact weight of each impact factor on machining quality through a Bayesian network model, and established a multi-level scalable information model and correlation mechanism to form a digital double-drive processing quality dynamic control method. Based on this, many quality faults in the manufacturing process were used to train a BP neural network to improve the accuracy and practicality of the quality control system. Sikder et al. [12] proposed and validated a multi-variant process quality control method based on collaborative prediction for the manufacturing process that adjusted the process control variables according to the current response state prediction to prevent any loss of control or anomalies in the process. Radcliffe, A. J. et al. [13] addressed the measurement of real-time data during the manufacturing process based on Bayesian models applied to production process monitoring and control schemes to predict the content of non-conformities generated during the manufacturing process, and thus achieve more reliable predictions for the future through extensive data analysis. In terms of process quality evaluation and monitoring, Li, M. et al. [14] combined Industry 4.0 technology to collect and analyze large amounts of production data in real time, and used the PIL decision process approach with real-time large amounts of production data to validate the advantages of incorporating intelligent algorithms in industrial systems for quality visibility and traceability in various production scenarios. Frye, M. et al. [15] collected large amounts of quality data based on systems to make predictions, and through machine learning algorithms, performed pre-reaction to process waste and overall production rescheduling to improve production efficiency.

Domestic research on quality control technology and related theories in the manufacturing process have also been developed to some extent. In terms of critical process identification, Xu Haisheng et al. [16] established a process model of a production shop based on graph theory in order to identify the critical processes that had the most significant influence on the accurate dimensions of segments in the production process of a ship segmentation shop, and proposed an identification method of critical processes based on a comprehensive evaluation of triple elements. Wei Yun-tent et al. [17] established a complex network by using modules to divide the assembly relationship of products to improve the manufacturing and assembly efficiency of complex products. They evaluated the feasibility and rationality of manufacturing complex products by modularity and equilibrium. Zhang

Fuqiang et al. [18] established an evolutionary complex network model and through correlation relationships among part processing features realized the technical requirements of processing features and accuracy, identified key processing features through an analysis of degree and the meso index, and verified the processing feasibility of the process manufacturing process. Regarding the analysis of quality influencing factors, Yang, W [19] et al. studied the influence of rotational inertia measurement quality from the perspective of a 5M1E comprehensive analysis, and monitored the critical input factors to ensure the accuracy of the experimental results.

The methods mentioned above cover the current status of quality control research on the two core techniques of process capability assessment and control chart theory. Process capability assessment evaluates a process's ability to ensure quality by calculating a process capability index and referring to relevant criteria. Process capability indices have been extended from the traditional study of univariate process capability indices to multivariate capability indices. Control charts are an essential tool for monitoring fluctuations in quality characteristics. At present, quality control research in multi-variety and variable batch production models can be broadly divided into non-SPC methods and SPC methods. The former is a knowledge-based systems approach and an artificial neural network approach, using the experience of field workers and expert systems to analyze some complex and fuzzy process laws. Conversely, the latter method uses a large amount of sample data and does not require complex mathematical models to analyze production line quality control problems. However, traditional SPC applications are inadequate in multi-variety and variable batch manufacturing models.

In summary, research on quality control and forecasting has yielded many results. However, there is a need for more research on quality control and prediction techniques in the production environment and on process quality control in flexible production lines. There are no studies on the identification of critical control points in the process quality control target and no effective optimization of predictive control using a model with a small amount of data, and therefore further research is needed.

The thesis of this study takes the spindle housing of a high-grade CNC machine tool in a flexible production line as the research object. We investigate quality control and prediction of the critical processes of a flexible production line, focusing on the analysis and corresponding control of the quality influencing factors of the spindle housing in a flexible production line, the identification of critical quality control, and the prediction optimization and control of the quality characteristic values of the critical processes. Potential problems reflected in the quality data are accurately predicted, and an implementation plan for process quality prediction of the spindle housing in a flexible production line is finally determined.

The main work to study the process quality prediction and control of the spindle housing in a flexible production line is as follows:

(1) A fuzzy hierarchical analysis model is established for spindle housing. The index value of each scheme is analyzed and calculated, and a comprehensive analysis of various factors affecting the production line is conducted to determine the most excellent scheme for quality control.
(2) A dynamic prediction model through the GM(1,1) principle is established to obtain sample prediction values, to train the residuals of the prediction values through a BP neural network for the network model, and to verify the validity and feasibility of the combined prediction scheme by analyzing and comparing the prediction value errors of the process quality data.
(3) SPC control of the critical processes of a spindle box is used to achieve quality prediction and monitoring of each process in the production line, to complete the process quality prediction and control scheme for the flexible production line of a spindle box.

2. Flexible Production Line for Spindle Housing

2.1. Introduction of the Spindle Box Flexible Production Line

Spindle housing for an intelligent, flexible production line is integrated with some key MES and FMS system functions, mainly for different specifications of machine tool spindle box parts, to complete box surface milling processing, spindle hole processing, mounting positioning hole processing, etc. The layout of the spindle box for a flexible production line is shown in Figure 1.

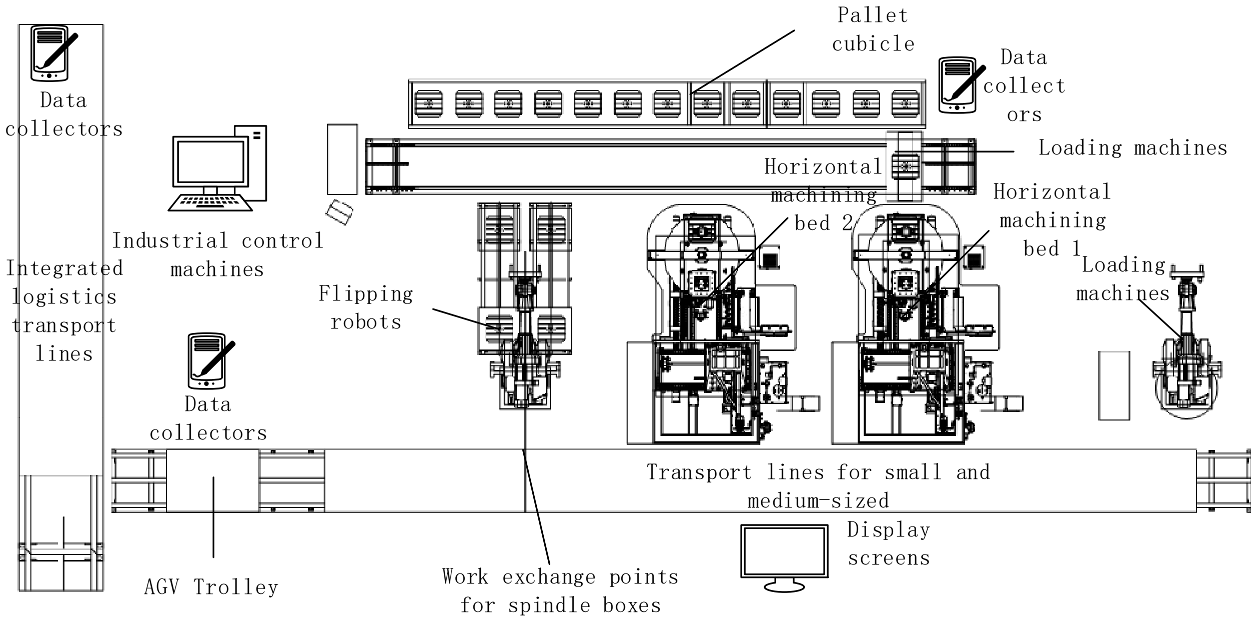


Figure 1. Layout of 1 spindle case production line.

The leading equipment of this production line consists of two H63-APC horizontal machining centers in series to complete the processing of box parts, which are equipped with handling machines such as turning robots, loading robots, material robots, and AGV carts, together with pallet stereo storage, pallet exchange devices, integrated logistics conveying lines, small- and medium-sized box transport lines, etc., to complete the whole production and processing process of parts grabbing and transportation, and its processing flow, as shown in Figure 2.

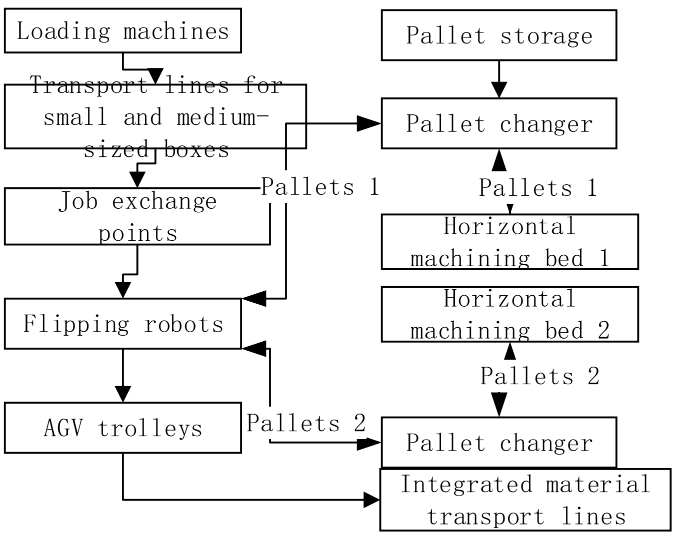


Figure 2. Processing flow of a flexible production line for 2 spindle housings.

2.2. Spindle Housing Critical Process Machining Features Model

The machining process of spindle housing mainly includes milling, drilling, tapping, and boring. Consider the machining process of the spindle housing as an example for establishing the complex network model. To visualize and express the correlations among the machining features of the spindle housing process, the machining features and their correlations are abstractly represented as a binary graph G = (V, E) to determine the machining features and the number of machining features, according to Table 1.

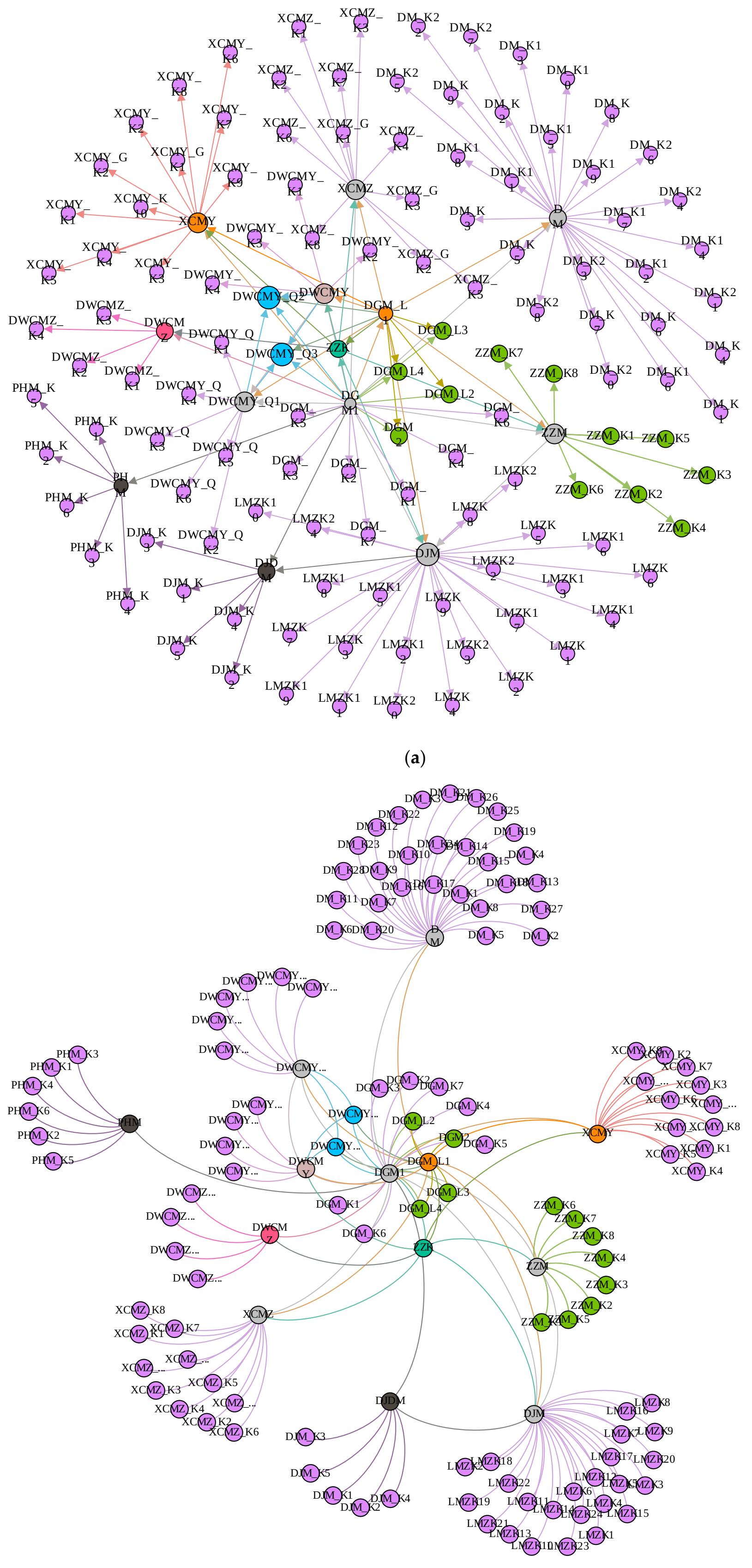
Table 1. Spindle box machining feature code table.

Feature Code	Code Meaning	Number of Features
XCMZ	The left side of the box	1
XCMY	The right side of the box	1
DWCMZ	The left side of the left rail	1
DWCMY	Right rail outer side	1
DWCMY_Q	The Notch on the outside of the right rail	3
XCMZ_K	Bottom hole on the left side of the box	8
XCMY_K	Bottom hole of the right side of the box	10
DWCMZ_K	Bottom hole of the outer side of the left rail	4
DWCMY_K	Bottom hole of the outer side of the right rail	4
DWCMY_QK	Bottom hole of the outer rail outer side notch	6
XCMY_GK	The right side of the box processes positioning holes	2
XCMZ_GK	Process positioning holes on the left side of the box	3
DM	Box top surface	1
ZZM	Spindle mounting surface	1
DGM	Guide rail mounting end face	2
DGM_L	Guide rail mounting elevation	4
DJDM	Motor base bottom surface	1
PHM	Balancing cylinder mounting end face	1
PHM_K	Balancing cylinder mounting end face bottom hole	6
DJM	The motor mount end face	1
DM_K	Bottom hole of the top surface of the box	28
ZZM_K	Bottom hole of the spindle mounting end	8
DGM_K	Bottom hole of mounting end of the guide rail	7
PHM_K	Bottom hole of the balancing cylinder mounting end	6
DJM_K	Bottom hole of the motor mounting end	5
ZZK	Spindle hole	1
LMZK	Motor mount hole	24

The machining features of the spindle housing are abstracted as points, and the correlation relationships among the machining features are outlined as edges. If the edge in the network model is expressed as vi→vj, it means that vj is processed with vi as the benchmark or that vj is evolved from vi; if there is no connection between the nodes, it means that there is no correlation between the machining features. As shown in Figure 3.

A complex network graph of machining features visualizes the relationships among individual machining features but cannot accurately determine the criticality of the nodes in the model. To further analyze the identification, the structural relationship of the complex network is abstractly represented as an adjacency matrix A, where $a_{ij} \in \{0, 1\}$, (i,j = 1,2, . . . , n), indicates whether there is an association relationship between node i and node j. If the value of a is 0, it suggests an association relationship between network node i and node j, and if the value is 1, then there is no association relationship.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$$



(**a**)

(**b**)

Figure 3. Complex network model of spindle box machining features: (**a**) Complex network model; (**b**) complex network exclusion force model.

Following the characterization principle of the adjacency matrix A, which is resolved into matrices with values of 0 or 1, the importance and criticality of the machining features in the nodes of the complex network model are identified by further analyzing and calculating the values of the feature topology parameters of the adjacency matrix.

In the established complex network-based spindle case machining feature model, the extracted nodes and the adjacency matrix are obtained according to the correlations among the machining features. By calculating the values of the node degree and meso number in the topological parameters of the network as well as the integrated centrality value, the combined weight of each importance assessment index in the model is obtained, as shown by the analysis of the calculation results of of the topological parameters of the complex network model for the spindle box body in Table 2.

Table 2. Complex network model topology parameter values.

Serial Number	Feature ID	Nodality	Number of Nodes	Centrality Mean	The Average Value of Each Index
1	DGM	12.62	15.03	32.05	20.15
2	ZZK	15.23	14.38	24.36	18.32
3	DGM_L	12.65	17.12	16.32	15.26
4	DJM	12.64	9.88	8.32	10.12
5	ZZM	7.36	7.65	10.32	8.63
6	DM	2.21	2.26	2.86	2.52
7	XCMY	2.21	1.18	2.07	1.66
8	XCMZ	1.82	0.98	1.16	1.28
9	HKM	0.56	0.92	0.96	0.88
10	LMDM	0.56	0.92	0.96	0.88
11	PHM	0.46	0.88	0.81	0.78
12	LMM	0.46	0.88	0.81	0.78
13	LMZK	0.46	0.88	0.81	0.78
14	DWCMY_K	0.21	0.31	0.22	0.26
15	DWCMY_QK	0.18	0.24	0.30	0.24
16	XCMY_GK	0.18	0.24	0.30	0.24
17	LMZK	0.12	0.22	0.26	0.20
18	DM_K	0.16	0.16	0.16	0.16
19	ZZM_K	0.12	0.12	0.12	0.12
20	HKM_K	0.09	0.09	0.09	0.09
21	PHM_K	0.09	0.09	0.09	0.09
22	LMM_K	0.07	0.07	0.07	0.07
23	ZZK	0.04	0.04	0.04	0.04
24	LMZK	0.04	0.04	0.04	0.04

Among the 24 features selected, the complex network topological parameter values of the guideway surface, spindle hole, guideway elevation, motor mounting end face, and spindle hole end face are more prominent, which indicates that they have an essential position in the complex network of the spindle box, i.e., they are the key features. In the actual production machining process, the spindle hole, guideway surface, guideway elevation, and spindle hole end face are the positioning datum for other machining steps, and the identification of crucial machining features by the complex network model is consistent with the actual key positioning datum features.

By comparing the conformity of key machining features and key positioning datum features, the rationality of the identification method of key machining features of spindle housing based on a complex network model is verified, and the correctness of the identification results is also demonstrated.

3. Influence Factor Analysis Model Based on Fuzzy Hierarchy Analysis

3.1. Analysis of Process Quality Influence Factors Based on 5M1E

In the manufacturing process of a spindle box flexible production line, each produced product quality exists within a specific range of quality characteristic value fluctuations.

The 5M1E analysis method is effective for quality management, and a 5M1E analysis of the spindle housing of a flexible production line has six factors that impact process quality, as shown in Figure 4.

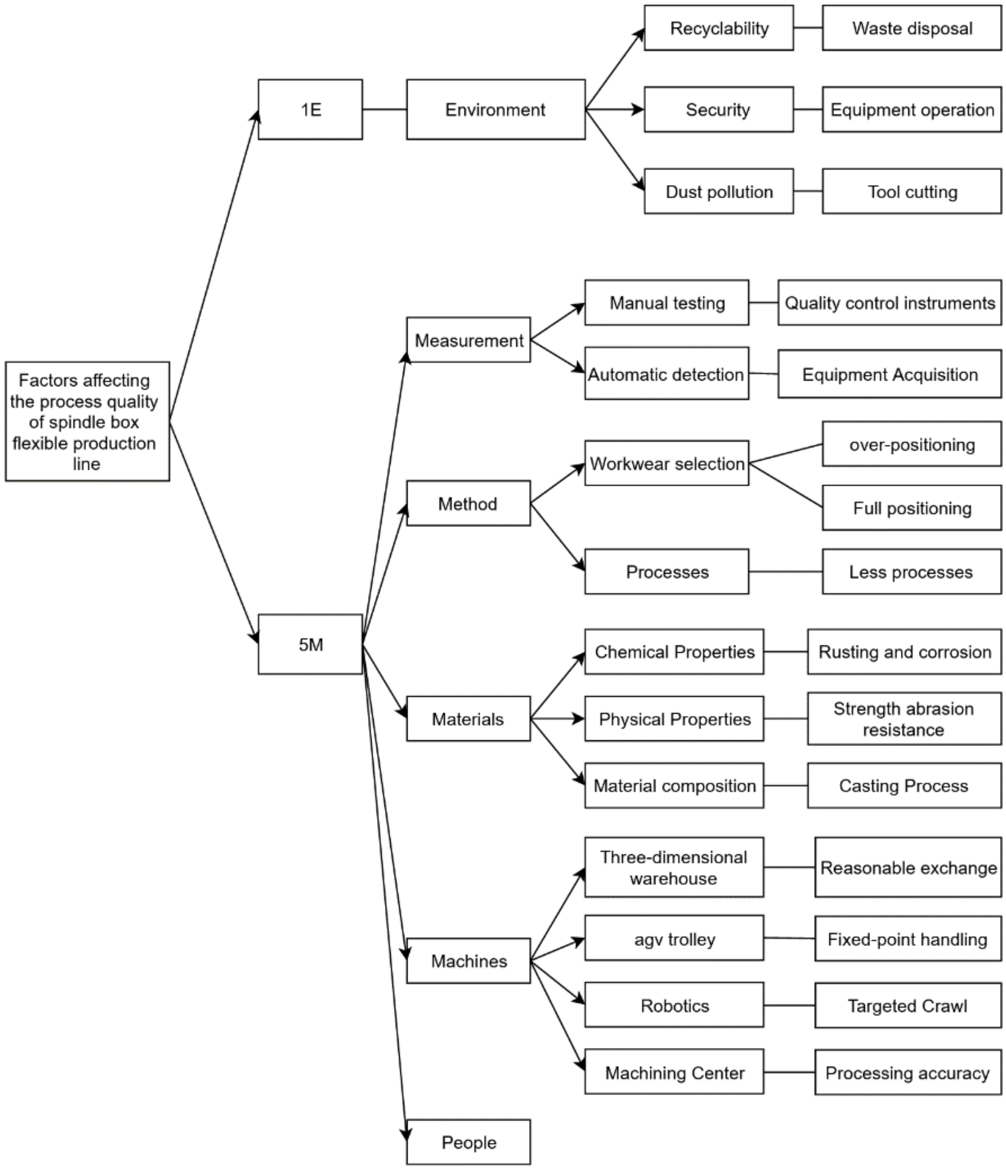


Figure 4. Factors impacting the process quality in a spindle box flexible production line.

3.2. Process Quality Impact Factor Analysis Model

From the spindle box flexible production line process quality influence factors model, it can be seen that there are multiple objectives or criteria associated with five factors that comprehensively impact the process quality of the spindle box flexible production line. The hierarchical analysis method can effectively solve a multi-objective decision-making problem; however, its test model's consistency of judgment criterion CR < 0.1 has a lack of scientific basis; therefore, in order to ensure the reliability of the analysis, this paper is based on the fuzzy hierarchical analysis method to establish the process quality impact factor analysis model. The essence of the fuzzy hierarchical analysis method is to avoid the shortcomings of the hierarchical analysis method by using fuzzy quantified indicators and conducting a two-by-two comparison.

(1) Establishment of the index optimization system

Under the condition of satisfying the production demand of the spindle box, the control measures of quality fluctuation are taken as the general target of index optimization. The flexible production line of the spindle box is evaluated comprehensively from five aspects: machine, material, method, environment, and measurement, while each evaluation index itself contains various subsets of influencing factors; the four layers of the structure model are divided into target layer, index layer, subindex layer, and program layer, as shown in Figure 5.

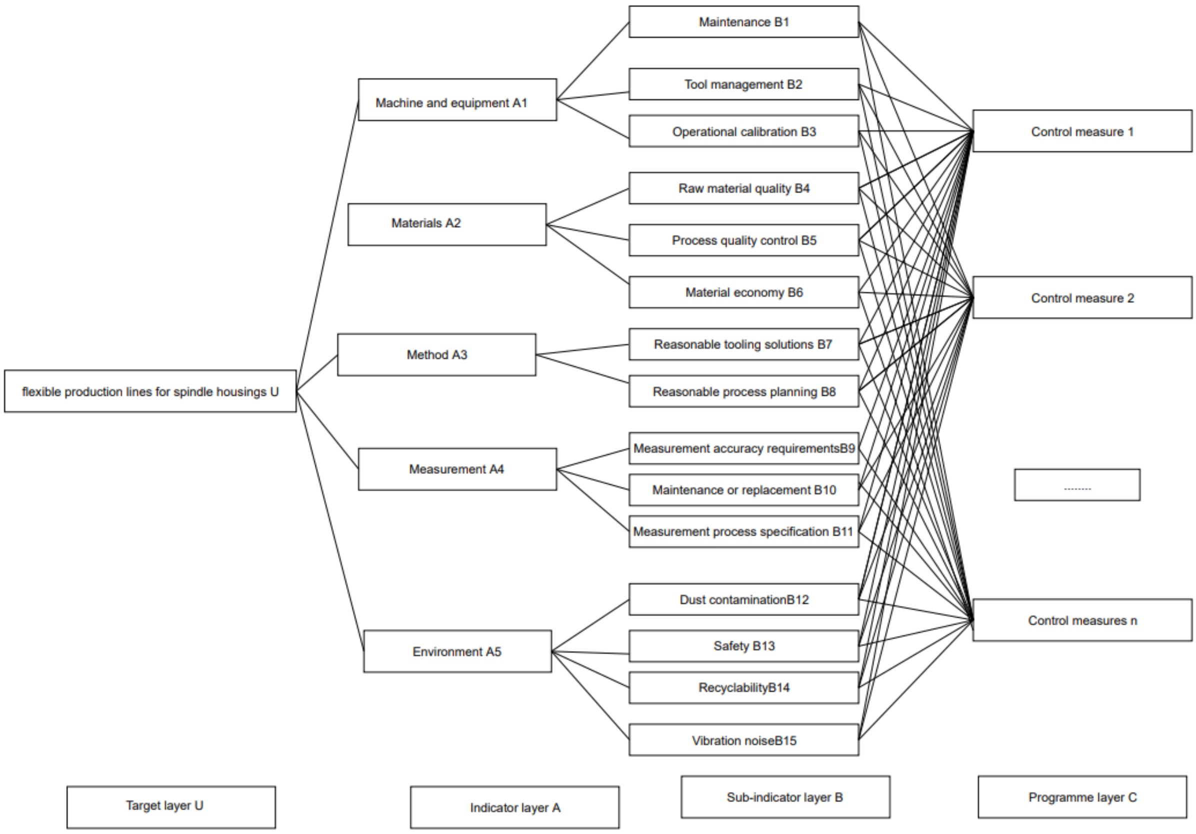


Figure 5. Hierarchical model of factors influencing the quality of the spindle housing process.

(2) Establishment of the fuzzy complementary judgment matrix

The fuzzy complementary judgment matrix quantifies the relative importance between two layers of indicators by comparing the importance between the indicator layer and the previous indicator layer, and quantifying and comparing the relative importance of each layer. In order to judge the relative importance between each indicator layer, the Satty 0.1–0.9 scaling method is usually used as the fuzzy quantification standard of the matrix, as shown in Table 3.

Table 3. Fuzzy complementary judgment matrix A.

U	A_1	A_2	…	An
A_1	a_{11}	a_{12}	…	a_{1n}
A_2	a_{21}	a_{22}	…	a_{2n}
⋮	⋮	⋮	⋮	⋮
A_n	a_{n1}	a_{n2}	…	a_{nn}

The established fuzzy complementary judgment matrix should have the following properties, as shown in Equations (1) and (2):

$$a_{ii} = 0.5; (i = 1, 2, \ldots, n) \tag{1}$$

$$a_{ij} + a_{ji} = 1; (i, j = 1, 2, \ldots, n) \tag{2}$$

where a_{ij} is a sub-indicator of indicator U, the importance of indicator A_i relative to indicator A_j.

In order to judge the relative importance among the indicator layers, the fuzzy quantification criteria of the matrix are usually adopted using the Satty 0.1–0.9 scaling method, as shown in Table 4.

Table 4. Satty 0.1–0.9 scaling method.

Scale	Definition	Meaning
0.1	Indicator i compared to indicator j	j is more important than i in the extreme
0.2	Indicator i compared to indicator j	j is more strongly important than i
0.3	Indicator i compared to indicator j	j is significantly more important than i
0.4	Indicator i compared to indicator j	j is slightly more important than i
0.5	Indicator i compared to indicator j	j is as important as i
0.6	Indicator i compared to indicator j	j is slightly more important than i
0.7	Indicator i compared to indicator j	j is significantly more important than i
0.8	Indicator i compared to indicator j	j is more strongly important than i
0.9	Indicator i compared to indicator j	j is more extremely important than i

3.3. Decision Analysis of Process Quality Influencing Factors

For the highly automated flexible production line working conditions, the degrees of influence of five factors on process quality are comprehensively analyzed. Effective control decisions on the process quality of complex production lines are realized by controlling the critical influencing factors with relevant measures.

3.3.1. Index Layer Weights

The five significant attributes of indicator layer A are compared with each other separately, and the fuzzy complementary judgment matrix of the relative importance of indicator layer A and target layer U is obtained according to the constraints of the Satty 0.1–0.9 scaling method and Formulas (1) and (2), as shown in Table 5.

Table 5. Relative importance of indicator layer A and target layer U.

U	A_1	A_2	A_3	A_4	A_5
A_1	0.5	0.7	0.7	0.6	0.8
A_2	0.3	0.5	0.4	0.3	0.4
A_3	0.3	0.6	0.5	0.6	0.6
A_4	0.4	0.7	0.4	0.5	0.6
A_5	0.2	0.6	0.4	0.4	0.5

According to its fuzzy complementary judgment matrix, its weight vector is calculated based on Equation (3) as:

$$W = (0.24 \;\; 0.17 \;\; 0.205 \;\; 0.205 \;\; 0.18) \tag{3}$$

The consistency of the fuzzy complementary judgment matrix is verified by converting it into a fuzzy consistency matrix R using Equation (4):

$$R = \begin{bmatrix} 0.5 & 0.675 & 0.5875 & 0.5875 & 0.65 \\ 0.325 & 0.5 & 0.4125 & 0.4125 & 0.475 \\ 0.4125 & 0.5875 & 0.5 & 0.5 & 0.5625 \\ 0.4125 & 0.5875 & 0.5 & 0.5 & 0.5625 \\ 0.35 & 0.525 & 0.4375 & 0.4375 & 0.5 \end{bmatrix} \quad (4)$$

The weight vector W of the fuzzy consistency matrix R is obtained from Equation (4):

$$W = (0.225 \;\; 0.181 \;\; 0.203 \;\; 0.203 \;\; 0.188)$$

3.3.2. Determination of Subindex Layer Weights

According to the expert synthesis criteria of a spindle box flexible production line of a spindle box, multiple attributes of sub-indicator layer B are compared. The fuzzy complementary judgment matrix of the relative importance of sub-indicator layer B and indicator layer A is listed according to the constraints of the Satty 0.1–0.9 scaling method and Formulas (1) and (2), as shown in Table 6.

Table 6. Relative importance of sub-indicator layer B and indicator layer A.

A_1	B_1	B_2	B_3	
B_1	0.5	0.6	0.4	
B_2	0.4	0.5	0.3	
B_3	0.6	0.7	0.5	
A_2	B_4	B_5	B_6	
B_4	0.5	0.6	0.7	
B_5	0.4	0.5	0.6	
B_6	0.3	0.4	0.5	
A_3	B_7	B_8		
B_7	0.5	0.4		
B_8	0.6	0.5		
A_4	B_9	B_{10}	B_{11}	
B_9	0.5	0.4	0.3	
B_{10}	0.6	0.5	0.4	
B_{11}	0.7	0.6	0.5	
A_5	B_{12}	B_{13}	B_{14}	B_{15}
B_{12}	0.5	0.4	0.6	0.7
B_{13}	0.6	0.5	0.6	0.8
B_{14}	0.4	0.4	0.5	0.6
B_{15}	0.3	0.2	0.4	0.5

The weight vectors of the relative importance of each sub-indicator layer with the indicator layer are calculated from Equation (3) as:

$$\begin{aligned} W^1 &= (0.333\ 0.283\ 0.384) \\ W^2 &= (0.383\ 0.333\ 0.284) \\ W^3 &= (0.45\ 0.55) \\ W^4 &= (0.283\ 0.333\ 0.384) \\ W^5 &= (0.266\ 0.292\ 0.242\ 0.2) \end{aligned}$$

3.3.3. Hierarchical Total Ranking

The results of the single hierarchical ranking between each layer are obtained by transforming the fuzzy complementary judgment matrix and matrix-vector calculation for the index layer and subindex layer; the hierarchical total weight values of each of its layers are shown in Table 7.

Table 7. Total ranking of indicators at each level.

Indicator Layer A	Indicator Weights	Sub-Indicator Layer B	Sub-Indicator Weights	Total Weights
Machinery and Equipment	0.225	Maintenance	0.333	0.075
		Tool management	0.296	0.067
		Operation calibration	0.371	0.083
Materials	0.181	Raw material quality	0.371	0.067
		Process inspection	0.333	0.060
		Material economy	0.296	0.054
Methods	0.203	Reasonable tooling solutions	0.450	0.091
		Reasonable process planning	0.550	0.112
Measurement	0.203	Measurement accuracy requirements	0.296	0.060
		Maintenance or replacement	0.333	0.068
		Measurement process specification	0.371	0.075
Environment	0.188	Dust contamination	0.261	0.049
		Safety	0.278	0.053
		Recyclability	0.244	0.046
		Vibration noise	0.217	0.041

3.3.4. Process Quality Control Scheme

Through the analysis of the total weight value in Table 7, the main factors affecting the spindle box flexible production line process quality are a reasonable tooling scheme, proper process planning, and operation condition calibration. The corresponding control methods and measures schemes are formulated for this situation, as shown in Table 8.

Table 8. Process quality control scheme for the flexible production line of a spindle case.

No.	Main Influencing Factors	Control Methods and Measures
1	Reasonable Tooling Solutions	1. Regularly check whether the horizontal machining center fixture is damaged 2. Check that the fixture is reasonable and correct before machining 3. Check that the jig adjustment top position is in place
2	Reasonable process planning	1. Regularly analyze the quality data of the spindle box for process improvement 2. Stop production to repair abnormal process problems 3. Repeatedly determine the process for different specifications of customized spindle cases
3	Equipment operation verification	1. Horizontal machining center repair and calibration 2. Calibration of fixed-point positioning of the AGV trolley operation 3. Robot gripping and placement position verification 4. Calibration of the collaboration between the three-dimensional exchange device and the transportation line

4. Optimization of Critical Process Quality Prediction Control Based on GM(1,1)-BP

The previous section identified the critical process machining characteristics of spindle housing based on a complex network model. To better investigate the data change trend and to prevent the potential problems of process quality, in this section, we conduct a predictive analysis of the quality eigenvalues of the vital process machining characteristics, establish a grey system prediction model based on the quality data obtained from the actual production line, and employ a BP neural network model for residual correction of the predicted value of the GM(1,1) model to improve the predictive control of process quality.

4.1. Process Quality Eigenvalue Prediction Model

The GM(1,1) prediction model is a standard grey system prediction model, which is based on the principle of first-order accumulation of quality data of crucial process characteristics collected through a spindle box flexible production line to generate sequences, establish differential equations, to generate accumulative prediction sequences by using a least squares transpose matrix, and finally to obtain the original sequence prediction values by accumulative reduction [20].

Usually, the original data sequence X^0 is input in a grey system prediction model, the input original sequence values must all be positive, and the original sequence data are processed non-negatively before the feasibility analysis. The input data are shown in Equation (5):

$$X^0 = \left(x^0_{(1)}, x^0_{(2)}, \ldots, x^0_{(i)}, \ldots, x^0_{(n)}\right) \tag{5}$$

where n represents that there are n sample observations, and for each data in the original sequence X^0 for the level ratio validation, all the level ratio values σ in the sequence should be within the specified range [21]. The sequence data satisfies the model building condition and the level ratio validation method, as shown in Equation (6):

$$\sigma_{(k)} = \frac{x^0_{(k-1)}}{x^0_{(k)}}, \sigma_{(k)} \in (e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}}) \tag{6}$$

In order to explore the variation pattern of the original sequence in the prediction model, sequence X^1 is generated by one accumulation process of the original data X^0, as shown in Equation (7):

$$x^1 = \left(x^1_{(1)}, x^1_{(2)}, \ldots, x^1_{(k)}, \ldots, x^1_{(n)}\right) \tag{7}$$

where $x^1_{(k)} = \sum\limits_{i=1}^{k} x^0_i, k = 1, 2, 3, \ldots, n$. In order to investigate the law of the variation of the original series, the first-order grey differential equation is established on this basis, as shown in Equation (8):

$$\frac{dx^1}{dt} + ax^1 = \mu \tag{8}$$

where a is the development coefficient and μ is the amount of grey action. As the main parameter of the GM(1,1) model function, the value of a characterizes the developmental dynamics and prediction period of the series prediction values, but when a > 1.0, the prediction period is too long and the error stack is too large to use the model for prediction [22]; μ is generated from the original series change, and its value reflects the degree of change in the data. Moreover, the effect of sample data variation on prediction accuracy is not fully taken into consideration in the case of medium- and long-term prediction by the model [22].

4.1.1. Improved Dynamic GM(1,1) Prediction Model

The principle of the dynamic GM(1,1) model is based on metabolism, where newly available prediction data or information are used as input sequences in the prediction model. The optimal length of the original sequence is selected, and based on this, the new prediction data are metabolized to remove the old data, resulting in a highly accurate prediction model.

In the prediction process, the original data sequence X^0 is predicted by the GM(1,1) model and the k + 1st data. Using the principle of the metabolic method, the first original data (stale data) in the X^0 sequence in the prediction model are removed, and (new data) are added to form a new predicted original sequence, as shown in Equation (9):

$$\hat{X}^0 = \left\{x^0_2, x^0_3, \ldots, x^0_k, \hat{x}^0_{k+1}\right\}, (k = 2, 3, \ldots, n) \tag{9}$$

On the new original sequence, there is a tendency for the kth + 1st data to change, and to predict the value of the functional relationship, the original sequence is changed by substitution. In contrast, the length of the original sequence remains the same, i.e., the dynamic model changes with the sample data. Continuous iterative replacement of the original sequence achieves a dynamic model for short-term data prediction. It keeps the original sequence with only one predicted data sequence present, which can predict the short-term data more accurately.

The dynamic GM(1,1) model needs to determine the length n, according to the prediction effect of the actual original sequence, which is determined according to the accuracy validation criteria of the GM(1,1) model. In this paper, we use the post-validation of the GM(1,1) prediction model, and the length n of the original series is selected according to the variance ratio change.

4.1.2. Verification of Dynamic Prediction of Work Process Quality Feature Values

The machining quality data of the spindle hole, an essential process feature of spindle housing, referring to the test set below the data set is divided into 24 sets of data collection.and each group measures the spindle hole diameter size three times. Among the data, there are 24 groups of mean data, as shown in Table 9.

Table 9. Training model input data.

Serial Number	Raw Date/mm	Serial Number	Raw Date/mm	Serial Number	Raw Date/mm
1	150.017	9	150.026	17	150.031
2	150.018	10	150.021	18	150.028
3	150.019	11	150.027	19	150.025
4	150.022	12	150.019	20	150.023
5	150.024	13	150.023	21	150.021
6	150.023	14	150.021	22	150.024
7	150.022	15	150.024	23	150.022
8	150.020	16	150.028	24	150.026

The MATLABR2021b software platform is used to simulate the prediction effect of different length sequences to determine the best predicted original data length n. The variance ratio C values of the prediction model are shown in Table 10, and the trend of variance ratio change is shown in Figure 6.

Table 10. Prediction model variance ratios.

n	*C*	n	*C*	n	*C*
4	0.0476	11	0.4399	18	0.4874
5	**0.0206**	12	0.6895	19	0.5003
6	0.1036	13	0.6807	20	0.5631
7	0.2491	14	0.7328	21	0.6655
8	0.5201	15	0.7012	22	0.6771
9	0.4036	16	0.6247	23	0.7252
10	0.5438	17	0.5412	24	0.7022

The n = 4–7 length original data series that meet this criterion are analyzed in Figure 6. When n = 5, the variance ratio is the smallest, and the model prediction achieves the highest accuracy. When the model length n is 6–10, the value of n gradually increases, the model is rich in information, and the model's prediction error rises steeply, so the GM(1,1) prediction model with sequence length five is chosen in this paper. This length is the original sequence length of the dynamic GM(1,1) model.

The original sequence with n = 5 was input and trained for 24 data sets, and the trend of the predicted values was obtained, as shown in Figure 7.

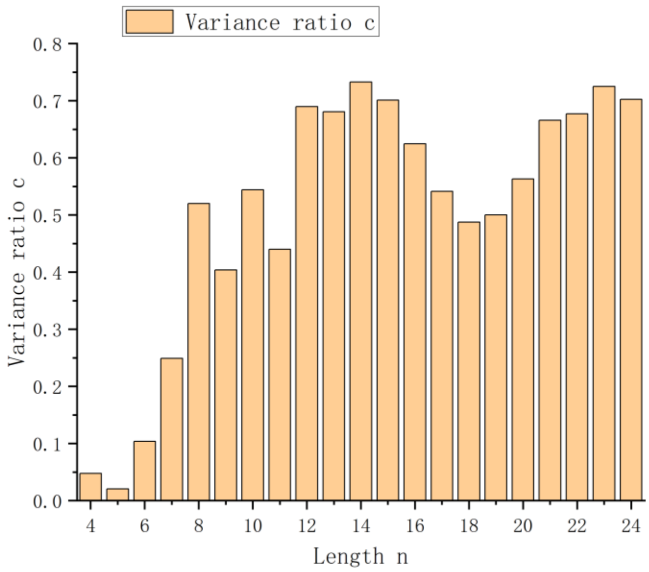


Figure 6. Variance ratio c values for different lengths.

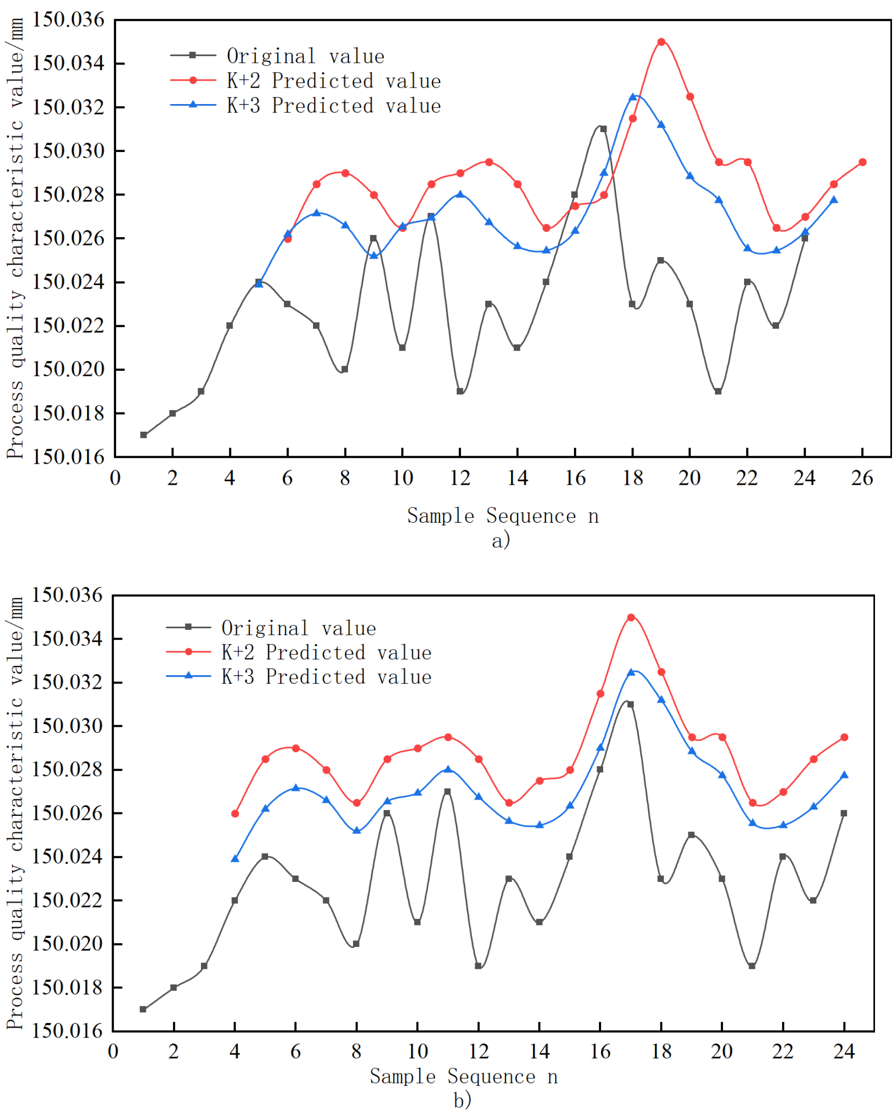


Figure 7. Dynamic GM(1,1) predicted values.

In Figure 7a, it can be seen that there is a specific difference between the curve trend of the original series and the predicted values, and by comparing the predicted values of the three series, it is found that the trend of the predicted data has a certain degree of advance. However, the analysis and comparison in Figure 7b reveal that the predicted value increases with the iteration of data error and the larger the residuals generated between the actual value. Therefore, the residuals of the dynamic GM(1,1) model prediction must be corrected.

4.2. Principle of Optimization of Neural Network Prediction Algorithm

Before using a BP neural network for prediction, the network needs to be modeled, trained, and tested. Any BP neural network model is not fixed. Based on the actual problem, the system model mapping relationship is established; the network topology is determined; the parameters for network training and testing are set; and the neuron transfer function, the training algorithm, and the relevant parameters are determined. The error between the actual output and the expected value is analyzed to determine whether the error meets the preset accuracy. The test set data are required to be brought into the completed training network model, and the error is compared with the input training set data to verify the accuracy of the model prediction and to determine the model to be used for residual correction of the predicted value.

4.2.1. Selection of Transfer Functions

A Sigmoid function has fast convergence and other characteristics; in dealing with nonlinear problems, the available choice is an S-type function such as a Sigmoid transfer function, divided into the unipolar S-type function (Log-Sigmoid) and the bipolar S-type function (Tan-Sigmoid) two. The expression of the Log-Sigmoid function is $f_{(x)} = 1/1 + e^{-x}$ and the expression of the Tan-Sigmoid function is $f_{(x)} = 1 - e^{-x}/1 + e^{-x}$. The comparative function images of the two are shown in Figure 8.

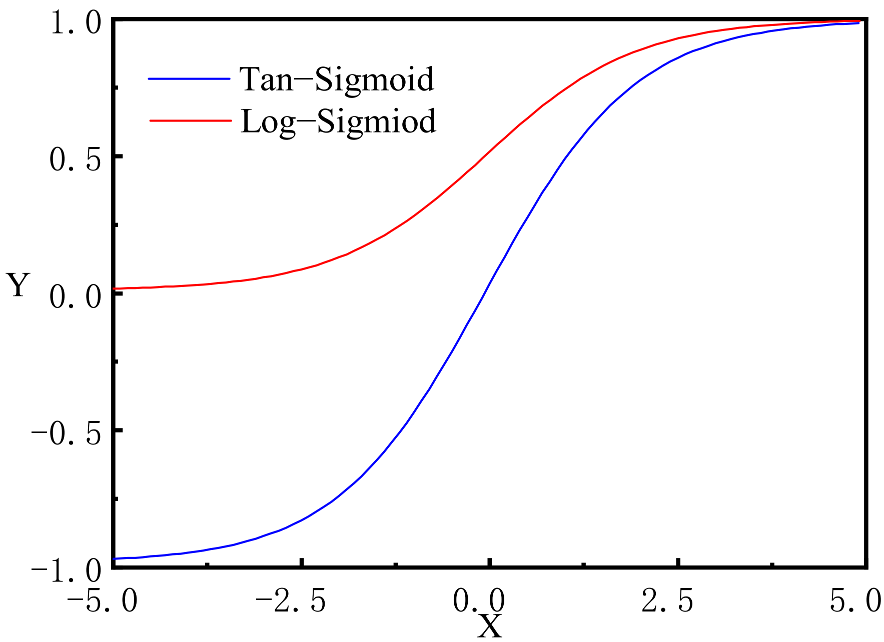


Figure 8. Comparison of transfer functions.

The Log-Sigmoid function restricts the range of output values to [0, 1], which can be used in cases where the data features are not very different or are more complex. However, the function is prone to the problem of non-gradient descent of the function during the backpropagation of the error values as the number of hidden layers increases. The Tan-Sigmoid function restricts the range of output values to [1, 1], which is suitable for cases where the differences are more prominent, and the data effect is continuously enhanced during training.

4.2.2. Pre-Feedback Propagation of the BP Neural Network

The BP neural network model is mainly feedback supervised learning where the input data are processed by the nonlinear mapping relationship in the implicit layer of the network model, and then the data are processed by the linear transfer function in the output layer, and the weights between the layers are adjusted according to the errors.

The input vector is {X(n) = [x1,x2, . . . , xn]} with input length n to the network, and let the actual output vector be {Y(m) = [y1,y2, . . . , ym]} with output length m of this network prediction model, the predicted value obtained by this model is {Z(m) = [z1,z2, . . . , z3]}, then, the error generated by the nth iteration is as shown in Equation (10):

$$e(n) = Z(m) - Y(m) \tag{10}$$

Then, its loss function is as shown in Equation (11):

$$e(n) = \frac{1}{2}\sum_{m=1}^{m} e_m^2(n) \tag{11}$$

When the error between the predicted value of the network and the actual output value does not meet the condition, i.e., the error accuracy does not meet the preset accuracy, the weights and thresholds between layers are adjusted according to the backpropagation of the output error value until the end of meeting the accuracy requirements. The vector is adjusted by feedback from the output layer to the input layer. The weights of the output layer–implicit layer and the implicit layer–output layer are adjusted, and the gradient of w_{im} is calculated as shown in Equation (12), and the suitable weights are adjusted by feedback:

$$\frac{\partial e(n)}{\partial w_{im}} = \frac{\partial e(n)}{\partial e_m} \times \frac{\partial e_m}{\partial v(n)} \times \frac{\partial v(n)}{\partial u(n)} \times \frac{\partial u(n)}{\partial w_{im}} \tag{12}$$

where e_m is the error of the ith neuron; u(n) is the input layer—hidden layer; v(n) is the hidden layer—output layer. The equation uses the chain rule to represent the transfer relationship within the network model.

The correction is made from Equation (19) to obtain the adjusted gradient values and weights as shown in Equations (13) and (21):

$$\frac{\partial e(n)}{\partial w_{im}} = -e_m v(n)\prime v(n) \tag{13}$$

$$\Delta w_{ij}(n) = \eta e_m v(n)\prime v(n) \tag{14}$$

After the above process to complete the output layer—the implied layer of the weight adjustment, the principle of the remaining layers is similar, the essence of the neural network according to the adjustment of the weight of each neuron, the input data for multiple iterations, until the error between the predicted value and the actual output value, to meet the set conditions end, to ensure the accuracy of the model prediction.

4.3. GM(1,1)-BP Combined Prediction Optimization

4.3.1. Residual Data Processing and Selection

Restricting the input data to $[-1, 1]$ to avoid differences in the magnitude of the data while processing the data with a mean close to zero can improve the convergence accuracy of the network during the training process.

In this paper, we use this method to normalize the sample data, calculated as in Equation (15):

$$X = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{15}$$

where x is the normalized value of the sample data, x_i is the sample data for network training, x_{max} is the maximum value in the sample data, and x_{min} is the minimum value of the sample data. The data normalized by this equation retain the original data's intrinsic characteristics while simplifying the data's complexity and can be used as input data for network training.

The more sample data input to the BP neural network training model, the more the training results can reflect the trend of data changes and the higher the model prediction accuracy. Therefore, selecting a reasonable amount of data and designing a reasonable model size is crucial for establishing a prediction network model with GM(1,1) prediction value residuals.

The difference between the previous process quality data1 $x^0_{(t)}$ at time t and the predicted simulated value of the original data series obtained by the dynamic GM(1,1) prediction model is called the residual at time t, as calculated in Equation ($\varepsilon_{(k)} = x^0_{(k)} - \hat{x}^0_{(k)}$, $k = 1, 2, \ldots, n$), to obtain the residual series at time t $\varepsilon^0_{(t)}$:

$$\varepsilon^0_{(t)} = \left[\varepsilon^0_{(1)}, \varepsilon^0_{(2)}, \ldots, \varepsilon^0_{(n)}\right]$$

The dynamic GM(1,1) model was optimized by training the prediction on multiple sets of prediction residuals data again. The best original sequence length was obtained from the post-validation analysis of the GM(1,1) model as 5, and the simulated value of the nth + 1st was predicted. Therefore, the residual sequence between the predicted and actual values obtained in the dynamic GM(1,1) model was chosen as the input parameter set for training and testing the BP neural network model. The predicted nth + 1st residuals were used as the output parameter set, and the collated data are shown in Table 11.

Table 11. Parameter set of residual series (parameter set unit, mm × 10^{-3}).

Group Number	Input Parameter Set					Output Parameter Set
1	0.0	0.4	−0.7	0.2	0.1	−3.0
2	0.4	−0.7	0.2	0.1	−3.0	−6.5
3	−0.7	0.2	0.1	−3.0	−6.5	−9.0
4	0.2	0.1	−3.0	−6.5	−9.0	−2.0
5	0.1	−3.0	−6.5	−9.0	−2.0	−5.5
6	−3.0	−6.5	−9.0	−2.0	−5.5	−1.5
7	−6.5	−9.0	−2.0	−5.5	−1.5	−10.0
8	−9.0	−2.0	−5.5	−1.5	−10	−6.5
9	−2.0	−5.5	−1.5	−10.0	−6.5	−7.5
10	−5.5	−1.5	−10.0	−6.5	−7.5	−2.5
11	−1.5	−10	−6.5	−7.5	−2.5	0.5
12	−10.0	−6.5	−7.5	−2.5	0.5	3.0
13	−6.5	−7.5	−2.5	0.5	3.0	−8.5
14	−7.5	−2.5	0.5	3.0	−8.5	−10.0
15	−2.5	0.5	3.0	−8.5	−10.0	−9.5
16	0.5	3.0	−8.5	−10.0	−9.5	−10.5
17	3.0	−8.5	−10.0	−9.5	−10.5	−5.5
18	−8.5	−10	−9.5	−10.5	−5.5	−4.5
19	−10.0	−9.5	−10.5	−5.5	−4.5	−1.0

In order to maximize the training accuracy of the network, all 19 sets of data obtained from the prediction of the dynamic GM(1,1) model were used as the training set, and six of them were used as the test set of the network model.

4.3.2. Selection of Residual Values to Predict Model Parameters

(1) Network initial parameters and the expected error value

The BP neural network adjusts the initial parameters by way of feedback iteration. Before the neural network makes a prediction, it needs to initialize the weights between each layer and the threshold value of each layer, whose practical value range is (−2.4/F, 2.4/F), and F is the number of neurons at the input of the weights. The expected error and the number of nodes in the hidden layer determine the prediction accuracy of the network model. Choosing a reasonable value of the expected error can change the network's convergence, shorten the network's training time, and improve the accuracy of the model prediction.

(2) Transfer function and training algorithm

The BP neural network's input–implicit layer of the nonlinear relationship is generally a selected S-type transfer function, and the implicit–output layer of the linear relationship is generally a selected Purelin linear transfer function.

As shown in Figure 8, the S-type transfer function is selected as the transfer function of the input–implicit layer because the input sample data of this paper needs to be mapped in the interval [−1, 1].

The network model determines the network learning algorithm between layers according to the training object and requirements. Backpropagation training algorithms commonly used for BP neural network models mainly include gradient descent (TRAINED), Newton's (TRAINBFG), the conjugate gradient method, and the Levenberg–Marquardt algorithm. The experimental comparison by MATLAB in illustrates that without considering memory, the LM algorithm can be used as the model training learning algorithm in this paper due to its fast convergence and high prediction accuracy, as it avoids the direct calculation of the Hessian matrix.

(3) Learning rate and determination of hidden layer nodes

The role of the network model learning rate lr is to constantly adjust the weights and thresholds between the layers. If the learning rate is too low to update the weights in the network at a microscopic level, the training rate will become slow; conversely, it may lead to undesirable divergence behavior in the loss function, failing convergence of the data. In the BP network established by the TrainLm function, the learning efficiency is generally taken as 0.001–0.1. According to the number of nodes in the hidden layer there is a relationship with the number of input and output nodes and the number of nodes is selected as small as possible within a certain range. A smaller number of nodes is chosen as far as possible within a specific range. To ensure that the values obtained are suitable for the learning rate and the number of nodes in the hidden layer in this paper, a combination of simulated training with a learning efficiency interval [0.001, 0.5] and several nodes in the hidden layer interval [3,12] was performed with a fixed constraint of 1000 iterations, a root mean square error of 0.000001, and a training function for the LM learning algorithm, using the average error of the output values from the six test sets as the comparison ratio. The presented calculations are shown in Table 12

Table 12. Average error values of the network training output.

Learning Rate	**Number of Implicit Layer Nodes**							
	5	**6**	**7**	**8**	**9**	**10**	**11**	**12**
0.001	3.609	2.686	2.689	4.391	1.872	3.390	**1.020**	1.970
0.01	5.599	1.770	6.091	3.886	2.993	3.714	2.433	3.274
0.1	6.183	1.585	2.846	3.430	2.339	3.189	5.540	3.626
0.2	3.563	2.079	2.551	2.381	2.459	9.471	3.7587	3.139
0.5	5.054	6.004	3.377	3.120	1.477	5.903	1.714	4.540

The role of the network model learning rate lr is to adjust the weights and thresholds between layers continuously, and the learning efficiency is generally taken between 0.001 and 0.1. Table 13 shows that the learning rate and the number of implied nodes have no enduring influence on the average error value, and the randomness of the BP neural network due to the reverse calculation of the error adjustment weights leads to a certain magnitude of fluctuation in the average error value. However, it is known that when the learning efficiency is 0.001, the average error value of the network training is relatively small, therefore, we chose the learning rate value of lr = 0.001. Comparing the conditions of this learning rate, the average error value is the smallest when the number of implied nodes M = 11, so the BP neural network model structure is finally determined.

Table 13. Test set data sheet (vector units, mm $\times$ 10^{-3}).

Number of Groups	Test Set Input Vector					Test Set Output Vector	
1	−3.0	−6.5	−9.0	−2.0	−5.5	−3.0	−1.5
2	−9.0	−2.0	−5.5	−1.5	−10.0	−9.0	−6.5
3	−2.0	−5.5	−1.5	−10.0	−6.5	−2.0	−7.5
4	−0.7	0.2	0.1	−3.0	−6.5	−0.7	−9.0
5	3.0	−8.5	−10.0	−9.5	−10.5	3.0	−5.5
6	0.0	0.4	−0.7	0.2	0.1	0.0	−3.0

4.4. Example Illustration of Residual Value Prediction

(1) Training and capability verification of the BP neural network model

In the BP neural network program run by the MATLAB platform, during the training of sample data, the network model continuously adjusts the connection weights between the layers until the results meet the target expectation value, and then stops training and selects some samples of data for testing. The model's performance after training and the training state performance are shown in Figure 9.

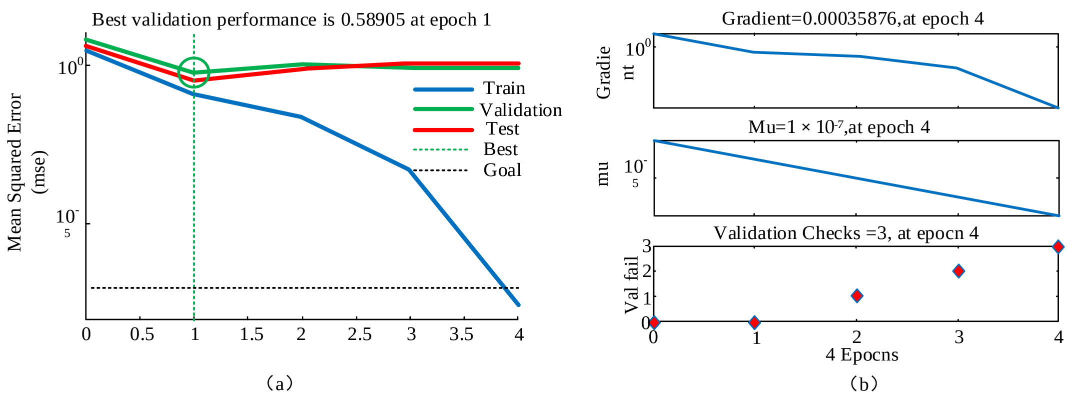


Figure 9. The BP neural network training performance. (**a**) shows the number of network training iterations; (**b**) shows the ge'lei of the algorithm.

Figure 9a shows that the model proceeds to the fourth generation to complete the network training and converges to the set error value range; the validation process shows the best performance of the first generation network training. Figure 9b shows that, when training to the fourth generation, the algorithm gradient is 3.5876×10^{-4} and the momentum parameter is 1×10^{-7}. Testing the first generation as usual, in order to examine the complete training network quality, further testing of the network model is required.

In order to test the prediction effect of the BP neural network model, the last six random sets of data were selected from the sample data as the test set, as shown in Table 13. The simulated prediction of the test set data is called with the sim() function to obtain the output value, and the output value is inverse normalized to obtain the prediction value of the model.

To test the predictive ability of the BP neural network model and the trend of the predicted data, the residual prediction values of the BP neural network model were compared with the residual values of the GM(1,1) model, as shown in Figure 10.

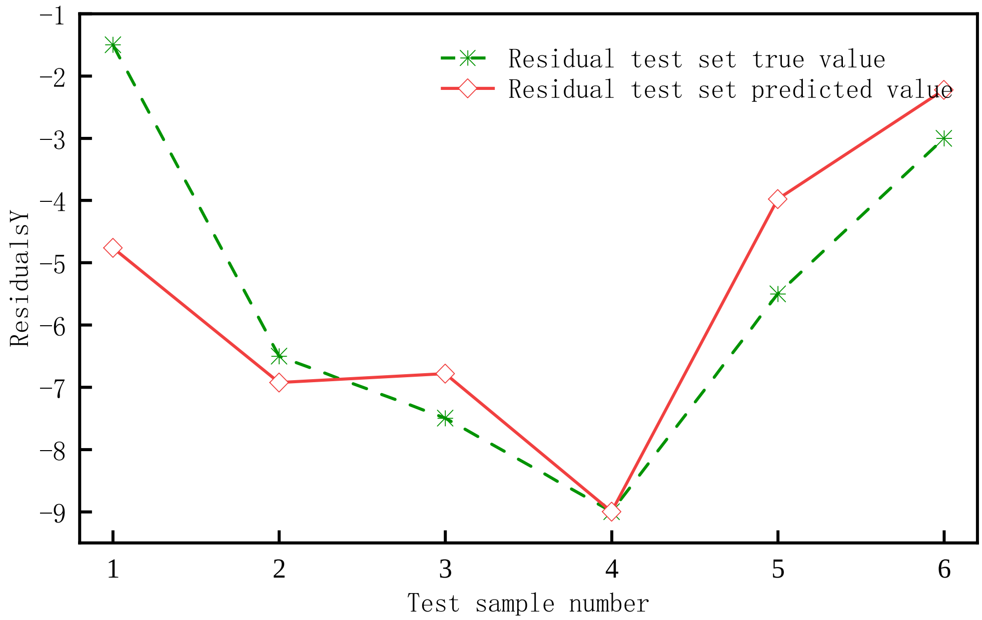


Figure 10. Prediction results of the residual test set.

As can be seen from the figure, the actual value of the residual series set has the same trend as the predicted value, and the difference between the two data sets is slight. It can be seen that this BP neural network model is feasible for predicting the corrected residual values, indicating that the model can respond to the nonlinear relationship of the change in the residuals predicted by the GM(1,1) model and can be used as the objective function for correcting the predicted values.

4.5. Combined Prediction Validation of BP-GM(1,1)

The combined prediction method is a combination of two or more prediction methods to build a prediction model. Taking into consideration that a dynamic GM(1,1) model can update the prediction in real time and can reflect a particular trend of data changes, samples of data selected in a previous paper show an irregular distribution and the BP neural network model helps to correct and predict nonlinear data functions, making full use of the advantages of both to improve the process quality characteristic values prediction accuracy. Therefore, based on a dynamic GM(1,1) prediction model, the BP neural network prediction model is added to predict and correct the critical process quality characteristic values.

The BP-GM(1,1) combined prediction model replaces the predicted residuals with the corrected residuals and calculates the combined predicted values as in Equation (16), i.e., the corrected residuals are obtained:

$$\widetilde{x}^0_{(k)} = \hat{x}^0_{(k)} + \hat{\varepsilon}^0_{(k)}, (k = 1, 2, \ldots, n) \tag{16}$$

Comparing the original data, the predicted data of the dynamic GM(1,1) model, and the data after correcting the residuals, as shown in Figure 11, it can be seen that the predicted data curve after correcting the residuals is significantly closer to the original data curve and has higher prediction accuracy than the predicted data curve of the dynamic GM(1,1) model, which is more consistent with the actual situation.

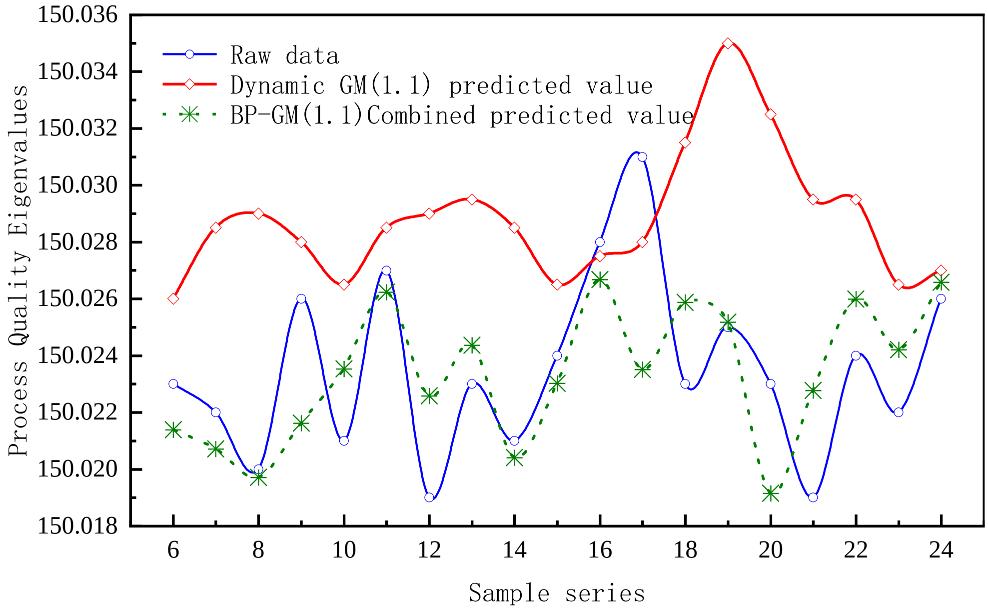


Figure 11. Comparison of combined prediction results.

In order to judge the effect of combined prediction optimization, the relative average error is used to compare and analyze the prediction effect of the dynamic GM(1,1) model and the GM(1,1)-BP combined prediction model, as shown in Table 14.

Table 14. Prediction results of sample data.

Sample Number	Original Value/mm	Dynamic GM(1,1) Predicted Value/mm	Dynamic GM(1,1) Δ	Combined Predicted Value/mm	Combined Forecast Δ
6	150.023	150.0260	0.00200%	150.0214	0.00107%
7	150.022	150.0285	0.00433%	150.0207	0.00086%
8	150.020	150.0290	0.00600%	150.0197	0.00019%
9	150.026	150.0280	0.00133%	150.0216	0.00291%
10	150.021	150.0265	0.00367%	150.0235	0.00169%
11	150.027	150.0285	0.00100%	150.0262	0.00051%
12	150.019	150.0290	0.00667%	150.0226	0.00239%
13	150.023	150.0295	0.00433%	150.0244	0.00091%
14	150.021	150.0285	0.00500%	150.0204	0.00040%
15	150.024	150.0265	0.00167%	150.0230	0.00065%
16	150.028	150.0275	0.00033%	150.0267	0.00088%
17	150.031	150.0280	0.00200%	150.0235	0.00499%
18	150.023	150.0315	0.00567%	150.0259	0.00192%
19	150.025	150.0350	0.00667%	150.0252	0.00012%
20	150.023	150.0325	0.00633%	150.0190	0.00256%
21	150.019	150.0295	0.00700%	150.0230	0.00252%
22	150.024	150.0295	0.00367%	150.0260	0.00133%
23	150.022	150.0265	0.00300%	150.0240	0.00147%
24	150.026	150.0270	0.00067%	150.0266	0.00039%
			$\overline{\Delta}$ = 0.00396%		$\overline{\Delta}$ = 0.00154%

The analysis in Table 14 shows that the average relative error of the dynamic GM(1,1) prediction value is 0.00375% and the average relative error of the combined prediction model prediction value is 0.00146%; comparing the average relative error values of both shows that the accuracy of the combined prediction model is 61% better than the dynamic GM(1,1) prediction model. Therefore, the response shows that the combined prediction model based on GM(1,1)-BP has a better prediction effect.

5. Process Quality Monitoring and Evaluation of Flexible Production Line for Spindle Housing

5.1. Joint Control Based on EWMA

An SPC control chart is a tool to monitor process quality and record quality data to achieve control. However, a control chart application analysis requires many data samples to support it, and there are problems such as weak detection ability and leakage due to the influence of data changes in time and space. Compared with the principle of a conventional control chart, an exponentially weighted moving average (EWMA) control chart is a control chart constructed using time weights and the number of restricted S, which can achieve the detection and analysis of any size offset in the process. Therefore, a joint EWMA and process quality control method is adopted to effectively improve the SPC quality control method.

The quality data are organized into subgroups, and each subgroup's mean and extreme deviation R are calculated. The control chart is built according to the principle to monitor the production line's processing quality status. Let this sample subgroup's total number of observations be n and the individual observation be x, as shown in Equation (17):

$$\overline{X} = \frac{\sum_{i=1}^{n} x_i}{n}; R = x_{\max} - x_{\min}; (n = 1, 2, \ldots, n) \tag{17}$$

where x_i is the sample detection value, x_{max} is the maximum value in subgroup samples, and x_{min} is the minimum value in subgroup samples. Then, in order to obtain the control line of the mean control chart, it is necessary to calculate the average value of the subgroup mean and the average value of the subgroup extreme difference, as in Equation (18):

$$\overline{X} = \frac{\sum_{i=1}^{n} \overline{X_i}}{n}; \overline{R} = \frac{\sum_{i=1}^{n} \overline{R_i}}{n}; (n = 1, 2, \ldots, n) \tag{18}$$

Then, the control line of the control chart is drawn as shown in Equation (19):

$$\begin{cases} UCL_{\overline{x}} = \overline{\overline{X}} + A_3\overline{R} \\ CL_{\overline{x}} = \overline{\overline{X}} \\ LCL_{\overline{x}} = \overline{\overline{X}} - A_3\overline{R} \end{cases} \tag{19}$$

Then, the control line of the control chart is drawn as shown in Equation (20):

$$\begin{cases} UCL_s = D_4\overline{S} \\ CL_s = \overline{S} \\ LCL_s = D_3\overline{S} \end{cases} \tag{20}$$

A3, D3, and D4 are unbiased constants corresponding to the sample mean or extreme deviation.

In order to more precisely identify minor deviations of the quality data in the monitored area, the exponentially weighted moving average method is used to weigh the measured values for each data set to build the EWMA control chart. To construct an attribute-specific control chart applicable to the spindle box based on this principle, first, it is necessary to calculate the statistic Zi that determines the control chart, as shown in Equation (21):

$$Z_i = \lambda X_i + (1 - \lambda) Z_{i-1} \tag{21}$$

where λ is the weight constant, which is usually 0 < λ < 1. The initial value Z_0 takes the target value of process quality control, which is Z_0 = E(x) = μ_0.

When the observations are independent random variables, the EWMA statistic's variance is as shown in Equation (22):

$$\sigma_{zi}^2 = \sigma(\frac{\lambda}{2-\sigma})\left[1-(1-\lambda)^{2i}\right] \quad (22)$$

where σ is the standard deviation of the sample data.

The control chart is constructed based on the statistics of EWMA and its variance, where the control line of the control chart is as shown in Equation (23):

$$\begin{cases} UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2i}\right]} \\ CL = \mu_0 \\ LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2i}\right]} \end{cases} \quad (23)$$

where L is the width coefficient of the control line, which generally takes the value L = 3; and $0.05 \leq \lambda \leq 0.25$, the smaller λ value in the range applies to smaller offsets.

5.2. Spindle Box Process Quality Case Analysis and Verification

Take the case of a spindle box flexible manufacturing line for the processing of the spindle hole as an example; analysis of the processing quality requirements for the diameter of φ precision boring machining of the spindle hole, a micrometer measuring tool to obtain the data of the spindle hole, as shown in Table 15.

Table 15. Spindle bore measurement data.

Serial Number	Measured Value/mm	Deviation Conversion Value/mm	Serial Number	Measured Value/mm	Deviation Conversion Value/mm
1	150.017 150.015 150.021	0.017 0.020 0.021	13	150.021 150.022 150.027	0.021 0.022 0.027
2	150.018 150.024 150.028	0.018 0.024 0.021	14	150.027 150.016 150.022	0.027 0.016 0.022
3	150.019 150.016 150.021	0.019 0.016 0.021	15	150.019 150.025 150.032	0.019 0.025 0.032
4	150.022 150.018 150.025	0.022 0.018 0.025	16	150.023 150.029 150.030	0.023 0.029 0.030
5	150.024 150.028 150.018	0.024 0.028 0.018	17	150.021 150.015 150.017	0.021 0.015 0.017
6	150.023 150.015 150.019	0.023 0.015 0.019	18	150.024 150.021 150.023	0.024 0.021 0.023
7	150.022 150.024 150.031	0.022 0.024 0.021	19	150.028 150.019 150.021	0.028 0.019 0.021
8	150.020 150.027 150.016	0.020 0.027 0.016	20	150.031 150.033 150.027	0.031 0.033 0.027
9	150.026 150.027 150.030	0.026 0.027 0.030	21	150.023 150.023 150.025	0.023 0.023 0.025

Table 15. *Cont.*

Serial Number	Measured Value/mm	Deviation Conversion Value/mm	Serial Number	Measured Value/mm	Deviation Conversion Value/mm
10	150.025 150.019 150.022	0.025 0.019 0.022	22	150.024 150.023 150.017	0.024 0.023 0.017
11	150.023 150.015 150.017	0.023 0.015 0.017	23	150.022 150.016 150.018	0.022 0.016 0.018
12	150.019 150.021 150.023	0.019 0.021 0.023	24	150.026 150.023 150.031	0.026 0.023 0.031

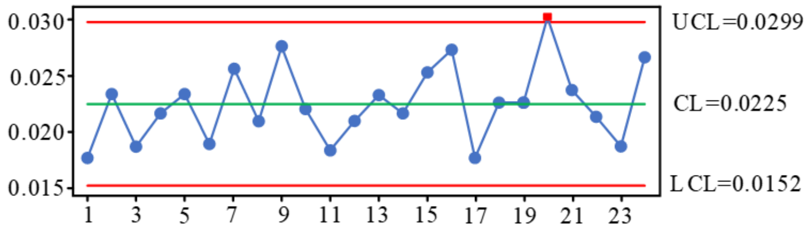
In order to further predict potential process quality problems in the current production line, the characteristic quality values in Table 15 are predicted and simulated using the GM(1,1)-BP combined prediction model based on machining characteristic quality spindle bore data, the actual data and the predicted data are analyzed for statistical process control, and the corresponding control charts are drawn from the actual and predicted samples of the process quality data, as shown in Figure 12.

As can be seen from Figure 12 in Figure 12a the actual sample, in the control chart, there is an abnormal sample point outside the control range, that is, it predicts that in the production process there is an out-of-control quality trend. However, at this time, Figure 12b shows the EWAM control chart without the appearance of abnormal samples, which predicts that, with the weighted passage of time, the quality of production processing does not show the some out-of-control quality trend, that is, there is no severe loss of control as the process progresses.

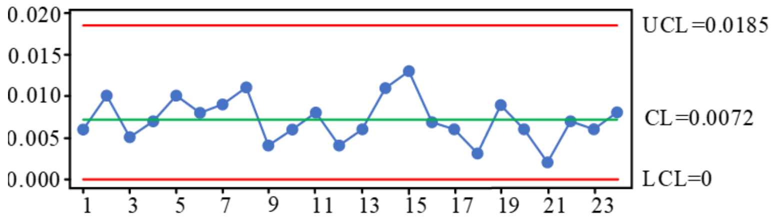
At this point, the process quality prediction analysis can be performed for out-of-control samples to ensure the product's quality and the production task's regular operation. In Figure 12d, the EWMA control chart of the second and third data samples appears to be out of control, but in the predicted data samples of the Figure 12c control chart, all the data samples are within the control range, and with the weighted passage of time, the data samples in the control range are increasing, indicating that, as the processing process of the production line progresses, processing quality could have a specific adjustment, i.e., with an increase in the time of processing there is a risk of out-of-control quality. The staff should pay attention to processing quality changes in the production line.

The visualization solution based on Echarts is chosen to monitor better the process quality of the spindle housing flexible production line. According to the platform framework and monitoring function model, the development of this monitoring platform is completed based on Web remote service technology. The visualization interface of electronic signage is developed for the real-time display of quality data. Workers and quality inspectors can view the current processing status of the production line in real-time through electronic signage, as shown in Figure 13. Through the visualization interface, the changes in SPC control charts, the distribution of errors expressed in process capability analysis charts, whether the data distribution belongs to a normal distribution, and the statistics of product data information of the production line can be observed intuitively and in real time. Display the current production line equipment processing status and product quality pass rate to help enterprises better manage the production line production quality conditions.

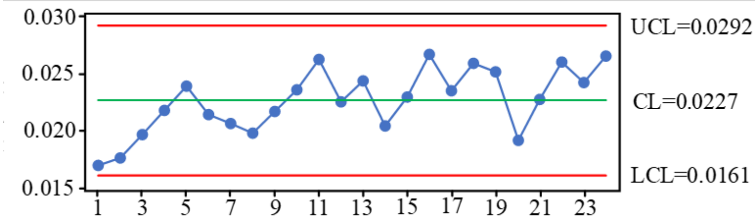
Through the long-term use of a visualization monitoring platform, enterprises verified the method described in this paper for continuous monitoring and early warning of the process quality of the machining parts in a spindle housing production line. Under the same production line processing test conditions, using the traditional process quality control of the state of the spindle housing, the product qualification rate is only 89%, while, under the real-time monitoring platform used in this paper, the spindle box flexible production line product qualification rate is up to 96%.



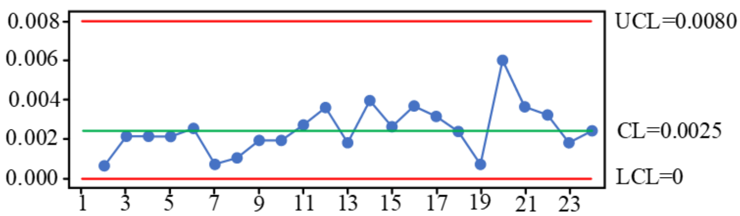
(**a**) Sample mean of the sample



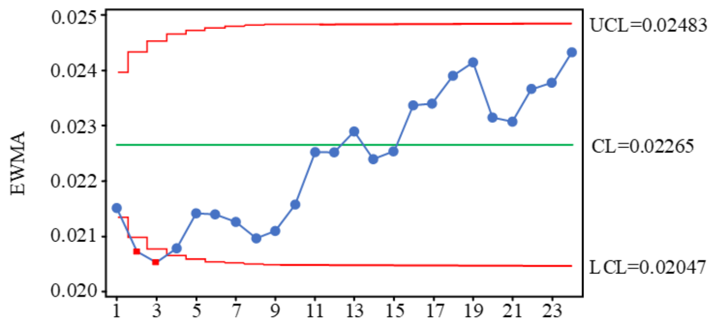
Sample extreme deviation of the sample



(**b**) Sample mean of the predicted sample

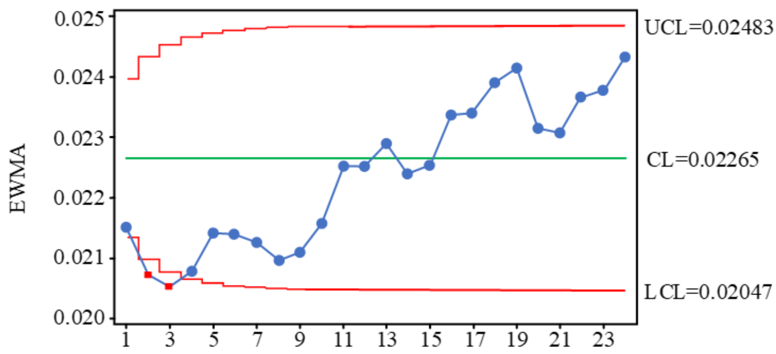


Sample extreme deviation of the predicted sample



(**c**) EWMA Sample

Figure 12. *Cont*.



(**d**) EWMA Sample Predictions

Figure 12. Spindle bore diameter error control: (**a**) Actual $\overline{X} - R$ control chart; (**b**) predicted $\overline{X} - \mathrm{R}$ control chart; (**c**) actual EWMA control chart; (**d**) predicted EWMA control chart.

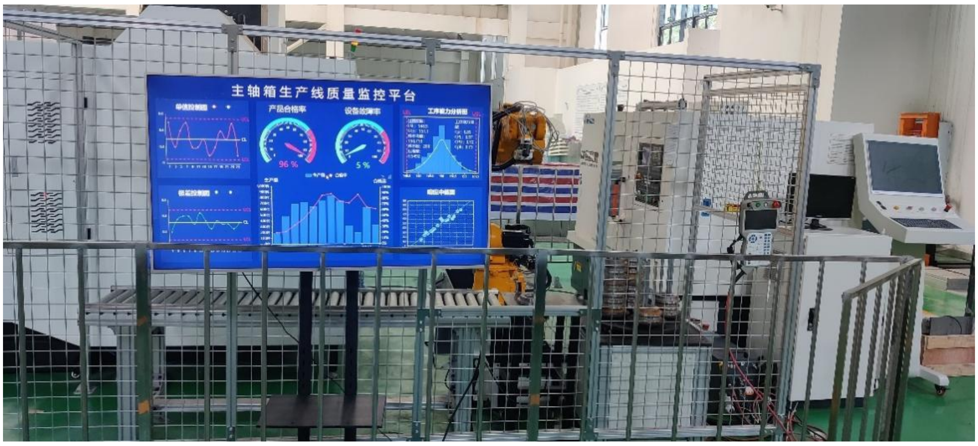


Figure 13. Production line process quality monitoring platform interface.

6. Conclusions

The high degree of automation in the manufacturing process of a flexible production line can easily cause product quality to be reduced due to uncontrolled process quality. In addition, flexible production lines have variations of "multiple steps and few processes", and the process quality needs to consider the comprehensive influence of many factors. There is no predictive control of the process quality. Therefore, in this study, we investigated variations in quality characteristics of key process features in a flexible production line and the control method, to determine a model that could effectively predict variations in process quality characteristics.

In this study, we used a spindle box flexible production line as the research object and studied process quality control. A decision analysis model of process quality influencing factors, a combined prediction model of process quality characteristic values, and a process quality monitoring and capability assessment model of a spindle box flexible production line was established. The research findings of the paper are as follows:

(1) A decision analysis model of process quality influencing factors of a spindle box flexible production line is established, and process quality control decisions are formulated. Through a comprehensive analysis of the process quality influencing factors, a hierarchical model of the spindle box process quality influencing factors is established, combined with the "5M1E" analysis method and fuzzy hierarchical analysis method, to analyze and make decisions on the influence of multiple factors. The fuzzy weight ranking value of each influencing factor is used to improve the process quality control decision of the spindle box flexible production line.

(2) A combined prediction model of process quality characteristic values is established. The dynamic GM(1,1) predicts the fundamental process quality characteristic values and obtains the potential change trend of process quality. In order to avoid prediction failure due to large residual values, a BP neural network is used to correct the residuals of the predicted values. A model is obtained with predicted data close to the actual data variation. The average relative error is improved by 61% compared with dynamic GM(1,1), effectively reflecting the trend change of process quality characteristic values.

(3) A process quality monitoring and process capability assessment model is established for a spindle box flexible production line of spindle cases. Using the principle of statistical process control (SPC), the process quality control process of a spindle box flexible production line is developed, and multiple control charts are used to jointly determine whether there is an uncontrolled state or trend in process quality. The actual and predicted values of the process quality characteristics are analyzed by combining multiple control charts. Based on the actual data and predicted changes in quality characteristics, we use time weighted EWAM control charts in conjunction with average and extreme difference control charts to determine the production line's current process quality status and to analyze the production line's quality problems. The process quality is again monitored for potential out-of-control trends based on predicted data using multiple control charts jointly.

Two points should be noted for future research. First, the quality control of the spindle housing of a flexible production line is easily affected by several factors. As the equipment is used for a more extended period during the manufacturing process, the aging of the equipment increases, and the wear and tear of the equipment itself also affects quality control; therefore, the impact of aging equipment on quality control should be studied in future experiments, for preventive process quality control. Second, compared to the small amount of data in this paper, the data generated in enterprise production processes are extensive. Subsequent research should be based on actual production line data for massive iteration, to achieve more realistic control optimization, and therefore, improve the optimization effect and accuracy.

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