Research Article

Control Method of Nanomaterial Numerical Control Electronic Processing Based on RBF Neural Network

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Abstract

With the rapid development of social economy and modern industry, the performance requirements of some important nanomaterials in various fields are constantly improving. The processing of these nanomaterials will have a direct impact on the development level of some core industries, such as aerospace, medical devices, and automobile manufacturing. In the early stage of the machining process, the BP neural network is generally used to control the CNC machining. However, it also has some shortcomings, such as the inability to determine the initial parameter weights according to the errors in the processing process, which limits its application in processing control. Therefore, this paper used RBF neural network to solve the problems in the process of CNC machining of nanomaterials and, at the same time, integrated RBF neural network technology into CNC electronic machining control, so as to improve the precision of CNC electronic machining of nanomaterials and avoid the occurrence of errors to the greatest extent. The method proposed in this paper used the self-learning and self-adaptive ability of RBF neural network to adjust the parameters of CNC machining control and relied on its fast convergence speed and strong approximation ability to achieve better CNC machining control effect. The experimental results showed that, after integrating the control technology of RBFNN in the CNC machining process of nanomaterials, the roundness error and roughness error of the machined workpiece were reduced by 70% and 50%, respectively. The control method proposed in this paper has high precision and strong stability.

1. Introduction

Along with the rocketing development of petrochemical industry and modern machinery industry, the process of CNC machining has become more and more complex, random, and uncertain, which also makes the processing of nanomaterials difficult to control. Therefore, it is necessary to make a breakthrough in the control method of CNC machining, so as to effectively solve a series of problems caused by the variety of nanomaterials. In the past, people used the BP algorithm in the process of CNC machining, but the learning and convergence speed of this algorithm were slow. RBF neural network can solve this problem very well. It has strong versatility and has no local minima. Therefore, this paper considered using this neural network to control the NC machining of nanomaterials. The purpose is to prove that it is an effective method to use RBF neural network to process and control nanomaterial CNC electronics [1, 2].

The processing control of nanomaterial CNC electronics can optimize and improve the comprehensive application performance of nanomaterials. In response to this topic, some scholars have conducted a lot of research and analysis. Zhang et al. constructed a dynamic balance control system, which is mainly used for control under low pressure environment. In the case of continuous operation of the vacuum pump, the system can automatically adjust the opening of the intake valve through proportional calculus [3]. Mimura introduced functional field emission arrays and vacuum nanoelectronics devices under development, such as field emitters for integrated vertical field effect transistors.
and field emitters with electrostatic lenses. And it described the expectations for vacuum nanoelectronics. That is, it can provide stable and high frequency power output under harsh conditions [4]. Zhu and Schmidt have studied the contents of miniature smart devices, including nano-energy systems, micro batteries, micro supercapacitors, micro wind harvesters, and micro saturable memristors, which can meet multipurpose application scenarios, such as automatic systems and medical equipment [5]. Based on the error compensation model and simulation experiment analysis, Gong proposed an improved nine-line method. The experimental results showed that the improved nine-line method can effectively improve some problems of the traditional nine-line method, such as the accuracy of the roll angle [6]. The above-mentioned scholars have carried out a series of extended researches on the control of CNC electronic processing of nanomaterials, which have enriched this topic. However, they have not been applied to specific practical problems and lack certain practicality.

RBF neural networks can improve the accuracy and stability of predictive models and objects. Regarding the RBF neural network, some scholars have conducted a lot of experimental analysis. Zhang et al. combined principal component analysis and independent component analysis to obtain characteristic parameters of wind farms. The results showed that the RBF neural network model can significantly reduce the fluctuation of the wind speed sequence and achieve the purpose of the research [7]. Aiming at the external disturbance and model uncertainty of MEMS gyroscopes, Fei and Wu proposed an adaptive control scheme based on fully tuned radial basis function (RBF) neural network to improve the dynamism and stability of MEMS gyroscopes. The simulation studies have verified the effectiveness of the proposed scheme [8]. Qu et al. used RSM model and radial basis function (RBF) neural network model to approximate the relationship between experimental factors and experimental data and established an approximate model. The experimental factors are analyzed and optimized based on different approximate models. In the verification experiments with different sample heights, it is proved that the RBF neural network model is a better model. The research results can provide reference for the parameter optimization of the improved air-assisted orchard sprayer [9]. Wentao et al. proposed an adaptive block inversion control strategy based on an improved RBF neural network for the complexity of uncertainty, nonlinearity, and strong coupling of high-speed motorized spindles. The parameter update law and inversion control law are obtained by Lyapunov theory, which can ensure the stability of the entire electrospindle control system. Finally, the simulation results have verified the rationality and effectiveness of the proposed control scheme [10]. The above scholars compared the RBF neural network with other neural network algorithms and verified the superiority of the neural network to a certain extent. But they did not apply it to solve practical problem; thus, the data lacked credibility.

A series of experimental data results showed that the error of the surface roughness of the workpiece based on the method in this paper is between 1 and 1.5, while the error range of traditional CNC machining methods is between 1.5 and 4. The roundness error of the workpiece based on the method in this paper is between 1 and 2.3, and the error range of the traditional CNC machining method is between 2.5 and 8.5. It can be seen that the two errors of the workpiece based on the method proposed in this paper are much lower than those of the traditional CNC machining method. After the control technology of the RBFNN, the precision of the workpiece has been greatly improved. In addition, the mean absolute error and root mean square error based on RBF neural network are both less than 0.005, and both are smaller than those of other traditional methods. This showed that it has the highest precision and the best control of CNC electronic machining workpieces. In eight stability testing experiments, the RBF-based CNC machining control method for nanomaterials maintained good stability. Among them, in the first four experiments, the stability of the RBF-based neural network is maintained above 15%, and the highest is even close to 30%. During the next four experiments, although the stability of the CNC machining control method based on SVM has been increasing, the stability based on the RBFNN has always maintained a good momentum, and the stability of CNC machining control was up to 42%.

2. RBF Neural Network and Control Method for Numerical Control Electronic Machining of Nanomaterials

2.1. RBF Neural Network. The English full name of RBF is radial basis function, and the Chinese name is radial basis function. It was proposed in the late 1980s and is one of the categories of artificial intelligence algorithms. The RBF algorithm is a feed-forward network, which is usually divided into a three-layer structure. The RBF neural network is divided into three layers in total, namely, the input layer, the hidden layer, and the output layer [11]. The input layer of the RBF neural network is composed of signal source nodes, which are mainly connected to each learning network and input data; the function of the hidden layer is to transform and analyze the input data; the output layer performs linear response output. What the RBF neural network needs to learn is the weight matrix from the hidden layer to the output layer. The main architecture of the RBF neural network is shown in Table 1.

The excitation function in the RBF neural network is a Gaussian function, which simulates some neural network structures in the human brain, such as mutually covering the receptive field. Thus, it also belongs to a local approximation network (multiple adjustable parameters have an impact on the output layer). That is, it can approximate any continuous function with arbitrary precision [12]. The general BP network is a global approximation (a small number of weights affect the output layer), which leads to the need to readjust the weights of the BP network in the learning process of each sample. So, it is extremely easy to fall into the situation that the local area is small, and the real-time performance of the control system is insufficient. The
between RBF and BP neural network is shown in Table 2.

For any BP neural network, there is always an RBF neural network that can replace it, and vice versa. Therefore, it can greatly improve the speed of convergence and learning and can effectively avoid the local small situation, so as to achieve the high real-time requirements of the control system [13]. For any BP neural network, there is always an RBF neural network that can replace it, and vice versa. The comparison between RBF and BP neural network is shown in Table 2.

The basic principle of the RBF neural network structure is as follows: the RBF is regarded as the center of the hidden layer, and the structure is centrosymmetric, locally distributed, and a nonlinear function [14]. Therefore, after the center point of the hidden layer is determined, the input layer can be directly mapped to the hidden layer. At this time, the mapping weight from the hidden layer to the output layer is the basic parameter of the neural network. And the most important thing is that these parameters can be adjusted at any time. RBF neural network has excellent performance and compact topological structure. Its parameters in the structure can be learned separately, and its cluster analysis ability, generalization ability, antinoise ability, repair ability, and parallel information processing ability are strong. Thus, the acquisition of the optimal solution is relatively easy, and it has also widely used because of these characteristics. Its main application fields include image processing, speech recognition, radar origin location, medical diagnosis, pattern recognition, time series analysis, and data classification. It inherits the nonlinear mapping ability of neural network and also has the characteristics of self-learning and fault tolerance. It can perform cluster analysis and learning from massive historical data and then obtain the basic laws of behavior changes [15]. Studies have shown that, among all feedforward networks, it can achieve the best performance in the completion of the mapping function. Figure 1 shows the basic topology of the RBF neural network.

The parameters and topology of the RBF neural network can be explained by the following theories: first, the RBF neural network can map the entire process from the input layer to the output layer; second, regularization can make generalization and exact matching to obtain balance. Thirdly, the Bayesian rule can calculate the postprobability based on the preprobability. Bayesian rule is a standard method of applying observed objects in probability and statistics to make corrections about prior probabilities. The basis of the hidden layer is the radial basis function, which transfers the data in the low-dimensional model to the high-dimensional model. The learning process of RBFNN is generally divided into two stages: first, the Gaussian function center of each node in the hidden layer is determined according to the input sample data. Several methods commonly used in this stage include random selection of fixed center method and self-organized selection center method; second, the least squares method is used to obtain the weights of the output layer, and the center supervised selection method and regularization strict difference can also be used [16]. Finally, the relevant parameters are corrected according to the sample information, thereby further improving the accuracy of the neural network.

### Table 1: Main structure of RBF neural network.

| Structure          | Characteristic                                      |
|--------------------|----------------------------------------------------|
| Input layer        | Composed of signal source nodes                    |
| Hidden layer       | A locally distributed nonlinear nonnegative function with symmetrical attenuation to the center and radial direction |
| Output layer       | Composed of output nodes                          |

### Table 2: Differences between RBF and BP neural network.

| Items                  | BP neural network                  | RBF neural network                  |
|------------------------|------------------------------------|------------------------------------|
| Activate function      | Sigmoid activation function        | Radial basis function              |
| Approximation mode     | Global approximation               | Local approximation                |
| Number of network layers | Unlimited                         | 3 layers                           |
| Running speed          | Slow                               | Fast                               |
| Hidden layers          | Multiple                           | 1 piece                            |

mapping process of the RBF network from the input layer to the output layer is nonlinear, and the mapping process from the hidden layer to the output layer is linear. Therefore, it can greatly improve the speed of convergence and learning and can effectively avoid the local small situation, so as to achieve the high real-time requirements of the control system [13].

2.2. Nanomaterials. Nanomaterials are solid ultrafine materials, also known as ultrafine particle materials [17]. It was discovered in the 1980s and has been called one of the most promising materials of the 21st century. With the development of science and technology, the application of nanomaterials has become more and more extensive. The particle size of nanomaterials is generally less than 100 nanometers. The classification of nanomaterials generally recognized by scholars is shown in Figure 2. But it also has different classification methods. For example, according to the structure, it can be divided into three-dimensional, two-dimensional, one-dimensional, and zero-dimensional nanomaterials. The structures of these four nanomaterials are shown in Figure 3. Zero-dimensional nanomaterials are represented by atomic clusters and atomic beam structures. One-dimensional materials and two-dimensional materials have been widely used in the electrical industry, such as nanotubes, nanorods, and superlattices. Nanomaterials are neither a microscopic system nor a macroscopic system, but a mesoscopic system.

Due to the extremely small grains and extremely large surface areas, the fraction of atoms arranged disorderly on the surface of the grains is much larger than the percentage of atoms on the surface of crystalline materials, which leads
to the surface and interface effects, small size effects, quantum size effects, optical effects, dielectric confinement effects, and macroscopic quantum tunneling effects [18]. At the same time, it also has a series of properties, such as high surface activity, strong oxidation, superparamagnetic, and reducibility. Among them, the small size effect is also called the volume effect, which lays an important foundation for the wide application of nanomaterials. Table 3 shows the particle size and surface effects of the nanomaterials. The ability of nanoparticles to penetrate the potential barrier is called tunneling effect.

Nanomaterials come in a variety of shapes, including granular, linear, flake, and tubular. It is precisely because nanomaterials have many plastic forms that they have a wide range of applications in many fields. In the medical field, nanomaterials have been widely used in biological detection, Uighur medicine transportation, cell separation, gene therapy, artificial transplantation of animal organs, etc. It is also widely used in commercial fields, such as fillers, sunscreens, catalysts, semiconductors, and cosmetics [19]. Table 4 summarizes the applications of nanomaterials in different fields.

2.3. RBF Control Method for CNC Machining of Nanomaterials. With the development of aerospace industry, nuclear industry, and modern manufacturing industry, people have put forward more and more requirements on the material properties and processing technology of product parts, especially the popular
nanomaterial products. Nanomaterials are dense in structure and high in purity but generally have low thermal conductivity. In addition, nanomaterials can still maintain very high strength and hardness within a certain temperature range. The atomic particle bonding process of this material is very stable and difficult to process [20, 21]. In the specific production process, the precision of nanomaterials will be affected by a series of factors, such as its own basic characteristics, the performance of the control system, and the selection of parameters.

In the CNC electronic machining control system, all parameters are generally determined before machining. However, the working condition parameters are easily affected by the material, so it is necessary to give a machining parameter that can be adjusted in real time according to the actual situation, so as to make the processing effect the best and stable. The RBF neural network can solve this problem very well. By adding this network to the numerical control system, its ability to process information in parallel and the characteristics of continuous learning can be maximized, and the running speed of the numerical control system can be improved. This method is simple and effective. The CNC electronic processing system is extremely complex, and its mechatronics is extremely significant. Some modules in the system can establish simple mathematical models, and they rely on classical control theory, which takes input and output characteristics as the mathematical model of the system for process control [22, 23]. Figures 4 and 5 show the numerical control system and its basic principle for real-time monitoring of nanomaterial neural network.

From the basic principle of the RBF control method for NC machining of nanomaterials, we can see that the RBF control method reduces the cost of NC machining by shortening the control time. In the nanomaterial neural network numerical control system, we have added an additional controller to realize the dynamic adjustment of the numerical control system. In this process, if the CNC system receives the initialization signal, it will mobilize the controller to send out corresponding commands to change the processing parameters and realize the system adaptive control. At the same time, the use of RBF control method can also improve the efficiency of CNC machining at the software level and help the CNC system achieve automatic control and automatic adjustment. Based on the prewritten instructions, different control methods can also be simulated to achieve optimal control.

### Table 3: Surface and Interface Effects of Nanomaterial Particles

| Nanoparticle size/nm | Total number of atoms contained | Proportion of surface atoms/% |
|----------------------|---------------------------------|------------------------------|
| 15                   | $6 \times 10^5$                 | 10                           |
| 10                   | $3 \times 10^4$                 | 30                           |
| 5                    | $2 \times 10^2$                 | 70                           |
| 1                    | 85                              | 95                           |

### Table 4: Application Areas of Nanomaterials

| Properties       | Application                                                                 |
|------------------|-----------------------------------------------------------------------------|
| Optics           | Antireflective coating                                                      |
|                  | Light-based sensor for cancer diagnosis                                     |
| Magnetism        | Increase storage density                                                    |
|                  | Magnetic nanoparticles to improve the details and contrast of MRI images    |
| Machinery        | Small components, such as the capacitance of electronic devices             |
|                  | Monitors                                                                    |
|                  | Highly conductive materials                                                 |
| Biomedicine      | Antibacterial silver coating for wound dressings                            |
|                  | Disease monitoring sensors (quantum dots)                                   |
|                  | Automatic drug delivery system                                              |
| Environmental protection | Clean up contaminated soils and pollutants, such as oil                  |
|                  | Biodegradable polymer                                                        |
|                  | Industrial exhaust gas treatment                                             |
|                  | Effective filtration of water                                               |
| Personal care    | Inorganic sunscreen                                                          |
|                  | Emulsification technology                                                    |

2.4. NC Machining Control of Nanomaterials Based on RBF Neural Network. The implementation steps of the control method proposed in this paper mainly include the following points: first, initialize the parameters; then, use the RBFNN to train the data; finally, actual output value and the judgment result of the performance index are obtained.

In the process of NC machining of nanomaterials, the accuracy of materials and processing procedures sometimes need to be adjusted immediately. At this time, a good NC machining control method can save resources to the greatest extent. RBF neural network has multiple layers, so it can
realize dynamic adjustment of parameters. According to the actual situation of nanomaterial processing, this paper resets the basis function of the RBF neural network:

\[
\delta_i(y) = \exp\left[-\frac{\|y - c_i\|^2}{2\sigma_i^2}\right],
\]

\[
x^H = \sum_{i=1}^{m} \delta_i \times \mathcal{Y}/2_i.
\]

In those formulas, \(y\) represents the center vector of the basis function. In this paper, this basis function actually reflects the input and output process of nanomaterial processing. At the same time, the weight of the input layer is the sum of the total number of neurons in each layer of the basis function. \(x^H\) depicts the output of the CNC machining control process.

In order to determine the process of nanomaterial processing, we need to calculate the corresponding output layer in advance:

\[
e_i = \min \mathcal{F} + \frac{\max \mathcal{F} - \min \mathcal{F}}{2\varepsilon},
\]

\[
d_{ij} = \sqrt{\frac{1}{\mathcal{F}} \sum_{i=1}^{m} (\mathcal{F}_{i}^m - e_i)}.
\]

Among them, \(e_i\) represents the center after initialization, and there is a certain quantitative relationship between it and the center vector \(y\). In the process of initialization, we can also make the uncertain nanomaterial processing information respond near the center, which can improve the accuracy of nanomaterial CNC machining. And \(d_{ij}\) represents the width vector of the central region of the RBFNN.

In the process of CNC machining of nanomaterials, the role of the hidden layer of the RBF neural network cannot be ignored. Among them, the hidden layer mainly deals with the temporary adjustment of materials in the CNC machining process, and its function is expressed as follows:

\[
u_j = \left(\frac{\|y - d_{ij}\|^2}{\|c_i + d_{ij}\|^2} \cdot y^2\right),
\]

\[\varepsilon = \frac{1}{2} \|\mathcal{F} - c\|.
\]

Among them, \(v_j\) represents the output result of the hidden layer, which describes the dynamic adjustment process of CNC machining of nanomaterials. \(\varepsilon\) refers to the number of layers, which will determine the number of iterations of the RBF neural network. It also directly affects the running speed of the RBF control method.

After determining the number of layers and the corresponding hidden layer, we can update and adjust the parameters according to the actual CNC machining process. The parameter update process is as follows:

\[W_{ij} = w(m - 1) - u \frac{\partial \mathcal{F}}{\partial \omega (m - 1)},\]

\[C_{ij} = e_{ij} (\nu - 1) - \tau \frac{\partial E}{\partial C_{ij} (\nu - 1)} + \sigma (e_{ij} (\nu - 1)) - e_{ij} (\nu - 2).\]

In these formulas, \(W_{ij}\) and \(C_{ij}\) respectively describe the situation of parameter update in the process of CNC machining control. In this process, the adjustment process of CNC machining of nanomaterials directly acts on the
adjustment of parameters. Next, in order to evaluate the CNC machining control method, this paper defines the performance evaluation function:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - x_i^*)^2},$$

$$\text{AAE} = \frac{1}{N} \sum_{i=1}^{N} |x_i - x_i^*|.$$ \hspace{1cm} (5)

Among them, AAE and RMSE respectively represent the mean absolute error (the average of the absolute values of the deviations of all individual observations from the arithmetic mean) and the root mean square error (the positive square root of the variance), which describe the actual performance of the CNC machining control method. From the above analysis, it can be concluded that the control method designed in this paper can ensure that the error converges to a small value with arbitrary precision. Next, the stability and control effect of the algorithm in this paper will be visually verified through simulation experiments and comparisons.

3. Application Effect of Nanomaterial CNC Machining Control Method Based on RBF

To better verify and analyze the influence of the method proposed in this paper and the traditional CNC machining method on the precision of nanomaterial CNC machining workpieces, this paper adopted the nanomaterial CNC machining RBF neural network monitoring system and randomly selected 24 nanomaterial CNC machining workpieces. The data results were arranged from large to small, and the first 8 pieces of data were too out for comparison. The specific results of the experiment are shown in Figure 6.

According to the experimental data in Figure 6, we can clearly see that the error of the surface roughness of the workpiece based on the method in this paper is between 1 and 2.3, while the error range of the traditional CNC machining method is between 2.5 and 8.5, and the average reduction in error was as low as 70%. It can be seen that the two errors of nanomaterial CNC machining workpiece based on RBF neural network are much lower than those of traditional CNC machining methods. After the control technology of the RBFNN, the precision of the workpiece has been greatly improved.

Next, in order to verify the effectiveness and superiority of CNC electronic machining based on RBFNN, we selected the common CPSO neural network, BP neural network, and SVM to compare them with the RBFNN in this paper and analyzed their average absolute error (AAE) and root mean square error (RMSE), and the experimental results are shown in Figure 7.

According to the experimental data in Figure 7, we can clearly see that the mean absolute error and root mean square error based on the RBF neural network are both less than 0.005 and are smaller than those of the other three methods. This showed that it has the highest precision and the best control of CNC electronic machining workpieces.

Then, in order to explore the stability of the CNC electronic machining process under different methods, we continued to carry out 8 experiments on the basis of the above experiments. In these 8 experiments, the steps and materials used in each experiment are always the same. In the test process, the article used Stab Net software, which is an advanced analysis system that can automatically measure the thermal stability of polymer materials to detect the stability of the CNC electronic machining process, and the results are shown in Figure 8.

According to the experimental data in Figure 8, we can clearly see that the RBF-based CNC machining control method for nanomaterials maintained good stability in the eight stability testing experiments. Among them, in the first four experiments, the stability of the RBF-based neural network was maintained above 15%, and the highest was even close to 30%. During the next four experiments, although the stability of the CNC machining control method based on SVM has been increasing, the stability based on the RBFFNN has always maintained a good momentum, and the stability of CNC machining control was up to 42%. 

\[\text{Surface roughness error}\]

\[\text{Roundness error}\]

\[\text{Traditional} \quad \text{Ours} \quad \text{Traditional} \quad \text{Ours}\]

\[\text{Error} \quad \text{Number of times}\]

\[\text{Error} \quad \text{Number of times}\]

\[\text{Figure 6: Comparison of application effect between RBF neural network control and traditional method in NC machining of nanomaterials.}\]
Figure 7: Error comparison of four kinds of neural networks.

Figure 8: Stability of CNC electronic machining.

Figure 9: Running speed of CNC machining control system.
In the actual CNC machining control, the running speed of the system is extremely important. Therefore, this paper explored the running speed of the CNC machining control system under the action of different methods, and the experimental results are shown in Figure 9.

According to the experimental data in Figure 9, we can clearly see that, with the continuous increase of the operation cycle of the CNC machining control system, the speed of the system was also getting faster and faster. Among them, in the first three periods, because the CNC machining control system needed to be familiar with the machining process and hardness of the processed material, the speed of the system was relatively slow, with an average of 31.3 seconds. In the latter three periods, the CNC machining control system has been completely familiar with the machining process and related processes, so the CNC machining control speed of the four methods was decreasing. Among them, the nanomaterial CNC machining control system based on RBF neural network has the highest running speed, with an average time of 25.1 seconds.

4. Conclusion

The CNC machining process of nanomaterials has the characteristics of strong interference, uncertainty, and difficult modeling, and the RBF neural network can solve this problem very well. It can control this process in real time and enhance the intelligent processing degree of this process. This paper briefly introduced the application characteristics of RBF neural network and also used the neural network technology to construct the system structure of nanomaterial CNC machining control. A series of experimental data showed that the method proposed in this paper can basically complete the task of CNC machining of nanomaterials. Due to some characteristics of the RBF neural network itself, such as high fitting accuracy and strong real-time performance, its application and development prospects in the field of nanomaterial CNC electronic processing control are very broad. However, there are still some deficiencies in this paper that need to be improved. The properties and types of nanomaterials are complex; thus, there are many influencing factors in the processing process. In the future, the role of these influencing factors in the processing process will be analyzed in detail. In addition, the selection of relevant parameters of the RBF neural network still needs to be further optimized and debugged, so that the control effect can reach the optimal value.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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