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Research on the Optimization of Data-Driven Predictive Maintenance Algorithms for CNC Machine Tools

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SUMMARY: *Big data technology progress has led to improved precision of machine tool failure prediction. This paper utilises geometric data such as the structure and assembly relationships of CNC machine tools, combined with digital twin technology, to construct a multi-body kinematic/dynamic model. This enables simulation of the corresponding parts during machine tool operation, providing data support for predictive maintenance. Gray rough sets are introduced to optimise the BP neural network prediction algorithm. The predictive maintenance accuracy of CNC machine tools may be improved through the creation of an initial decision table, the use of grey relational analysis, and the processing of discrete information. The findings show that the BP neural-network prediction model based on grey rough sets has loss values of 0.099, 0.059 and 0.018 at three different iteration settings. In five different signal-to-noise ratio datasets, the loss function values are all less than 0.15, and the prediction accuracy exceeds 90%. This enables precise prediction and maintenance of CNC machine tool failures.*

KEYWORDS: *multibody kinematics/dynamics; grey rough set; BP neural network; predictive maintenance; CNC machine tool; digital twin*

1 Introduction

Machine tools are the mother machines of industry. Modern industrial production requires machine tools to operate stably over the long term, without sudden failures, and to maintain precision within the permissible range [1, 2]. Based on this, researchers are working hard to adopt new methods to avoid various losses and material waste caused by equipment failures. Regular monitoring of machine tool operating conditions can maximise the avoidance of sudden failures. Currently, machine tool maintenance is primarily reactive [3]. However, reactive machine tool maintenance methods have numerous drawbacks. First, reactive maintenance methods cannot promptly capture equipment status information and can only rely on experience or faults for assessment [4, 5]. Second, scheduled inspections consume significant human and material resources, and the absence of emergency response plans can directly impact production schedules when sudden equipment failures occur [6, 7]. Additionally, equipment failures can lead to frequent batch quality issues, affecting pass rates, meaning that sudden downtime events are unacceptable [8, 9].

Due to the aforementioned problems, predictive maintenance (PM) has been one of the

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factors contributing to the development of contemporary smart manufacturing. Predictive maintenance is able to predict vital performance indicators based on the constant monitoring and data analysis, such as the remaining useful life of machine parts. Critical operating parameter data can help in making decisions, assessing equipment operating environment, and optimizing maintenance scheduling [10-13]. The main principle of predictive maintenance in CNC machine tools is to perform regular servicing on equipment and facilities in order to keep them functioning normally and reduce the rate of damage [14]..In addition to special maintenance jobs, predictive maintenance also includes routine inspection, lubrication, testing, and equipment adjustment even when the condition of the equipment is not predetermined [15, 16]. It also offers a structure to all planned maintenance operations, such as creating work orders to address any potential issues found through inspection[17, 18]. A well-designed and properly developed predictive maintenance programme can balance equipment ownership and operational profits by balancing maintenance costs and equipment costs, as well as related production losses, thereby maximising benefits [19-21]. In summary, a predictive maintenance plan is absolutely essential for efficient, reliable, and safe production processes. Since the foundation of predictive maintenance is diagnostic algorithms, designing and implementing intelligent algorithms to enhance the detection efficiency of predictive maintenance tasks can fully leverage the direct and practical maintenance advantages of predictive maintenance [22-24].

Currently, due to the sustained economic development, CNC machine tools have become popular in most enterprises. In turn, there is a lot of research on predictive maintenance of CNC machine tools to make sure that they work safely. Reference [25] introduces a predictive maintenance algorithm targeting cutting tools and main spindle motor system components of machine tools. By establishing an artificial intelligence-based model for predicting tool wear and bearing failures, it aims to prevent downtime caused by equipment failures. Reference [26] develops a decision-making application for detecting the remaining service life of industrial processing tools. Through data-driven predictive maintenance analysis, it effectively addresses issues arising from the processing process and machine tool maintenance. Literature [27] establishes a machine tool maintenance decision support system that integrates multiple types of information. By statistically analysing fault phenomena in machine tool linear axes and combining the results with manufacturing enterprise performance and cost estimates, it formulates predictive maintenance strategies tailored to the condition of machine tool linear axes. This not only reduces the frequency of machine tool failures but also lowers maintenance costs.

A hybrid predictive maintenance strategy of machine tools implemented through digital twins was explored in literature [28] .Through developing an intelligent model-based and data-centered framework, such a system can allow precise and timely determination of the service life of CNC machine tools. Literature [29] concentrated on the drawbacks of the conventional method of predictive maintenance in most manufacturing environments and has given a predictive maintenance approach that uses digital twin technology (PdMDT). The method aims at meeting the changing needs of equipment maintenance by providing the specific steps of how equipment maintenance should be performed.Literature [30] indicates that the effective application of machine learning methods can help collect high-value information and knowledge generated in industrial production systems, providing useful technical support for predictive maintenance of production line equipment in factory workshops. Literature [31] explores a predictive maintenance scheme for grinding machine bearings, introducing fault classification detection methods and remaining life prediction content for bearings, providing important guidance for predictive fault detection and maintenance based on machine learning technology. Literature [32] argues that identifying and analysing the exponentially growing data from industrial production systems is the foundation for predictive maintenance of equipment such as CNC machine tools. It proposes a predictive maintenance concept based on artificial intelligence tools, effectively improving the operational efficiency and decision-support capabilities of maintenance departments. Literature [33] emphasises that predictive maintenance schemes are methods for making adaptive decisions by predicting the exact time when manufacturing equipment requires maintenance. It proposes an artificial intelligence algorithm-based milling tool monitoring framework to effectively monitor the wear and tear of general-purpose manufacturing tools and prevent their failure. Literature [34] introduces IoT methods for condition monitoring and maintenance of manufacturing equipment. This predictive maintenance method helps address the lag effects and inaccuracies associated with traditional manual maintenance methods, thereby improving system production efficiency, product quality, and profitability. The aforementioned research indicates that a predictive maintenance system for CNC machine tool tools can visualise data such as the operational status and historical operational conditions of CNC machine tool tools, enabling real-time monitoring and early warning of equipment status, promptly identifying equipment abnormalities. This facilitates the provision of more comprehensive manufacturing decision-optimisation technologies for the industry, achieving the goals of zero equipment downtime and maximised production capacity.

The proposed research will create a combined model of predictive maintenance of CNC machines that satisfies common fault-maintenance needs through integration of geometric modelling and algorithmic prediction. Multi-body structural model of CNC machine tools is considered then. The STEP-format component models and XML description files of the assembly and constraint relationship are created subsequently. Then multi-body kinematic and dynamic model with rigid-flexible coupling are established and fully connected and the corresponding parameters are refined and the effectiveness of multi-body model is validated. Ultimately, a BP neural-network prediction model based on grey rough sets is constructed and verified in several stages using historical operational fault data, which allows precise fault prediction of CNC machine tools

2 Analysis of CNC machine tool modelling and predictive maintenance steps

2.1 Analysis of common faults in CNC machine tools

2.1.1 Bearing failure

Rolling bearings, as important mechanical components, convert the sliding friction generated between the shaft and the bearing seat into rolling friction, thereby reducing friction losses. Specifically, they include the following common faults:

1) Fatigue spalling. Although there are many types of fatigue, rolling bearings are likely to produce small fragments, or even broken metal fragments, due to contact stress, which can cause cracks and lead to fatigue spalling. In addition, pitting corrosion is caused by material fatigue, but due to its small size, the larger the corrosion area, the more likely it is to cause cracks.

2) Wear. Based on the working process of the bearing, rolling and sliding occur between the rolling elements and the inner raceway, and sliding also occurs between the retainer and the guide surface. This easily causes the working surface of the bearing to continuously lose metal. The wear of the bearing's working surface causes changes in its dimensions and shape, thereby

increasing the bearing's meshing clearance, reducing the shape accuracy of the machined surfaces, lowering rotational precision, and resulting in higher temperatures, greater noise, and increased vibration. Ultimately, this prevents the bearing from functioning properly, which is referred to as wear failure. This phenomenon is closely related to various factors, including lubrication adequacy, contact stress, material properties, surface friction intensity, and environmental medium conditions.

2.1.2 Unbalanced faults

Due to the inability to achieve completely uniform distribution of materials, errors are likely to occur during processing, resulting in eccentricity between the rotor of the rotating mechanism and other rotating centres. This is known as eccentricity. If the degree of eccentricity is low, it will not affect the operation of the rotating mechanism or the machine.

If there is a large eccentricity, it will inevitably cause unbalanced failure. There are two types: dynamic imbalance and static imbalance. Due to the deviation, even if the consistency of quality and rotation centre cannot be guaranteed, strict inspection of the eccentric vibration of the equipment must be carried out to ensure the safety and reliability of the equipment during use.

2.2 Construction of mechanical multi-body kinematic/dynamic models

The creation of models of CNC machine tools enables realizing the process of data mapping of physical entities. Together with predictive maintenance algorithms, such a solution allows tracking the changes in CNC machine tool parts during the operation at relatively low cost, which supports predictive maintenance. The CNC machine tool Digital Twin geometric model stated above considers the machine tool as a rigid body.

The geometric model may be applied to direct component manufacturing, check design viability, and perform three-dimensional visualization. A Digital Twin is an accurate copy of a real device and can reflect the kinematic and dynamic properties of the machine tool. It needs to consider the mass, inertia, material properties, friction, and damping properties of the mechanical system. At high speed, structural elastic deformation, vibration, and dynamic loading are the primary reasons behind tool wear and performance reduction. It is therefore important to integrate the physical properties, elastic deformation, and dynamic loading of the CNC machine tool into the Digital Twin and develop rigid-body and flexible-body models to analyze the coupled dynamic behavior of the tool. Due to this fact, this section presents a multi-body kinematic/dynamic model of the Digital Twin based on the CNC machine tool Digital Twin geometric model proposed earlier.

2.2.1 Multi-body kinematics/dynamics model construction process

The multi-body kinematics / dynamics modeling is done using the Digital Twin geometric model developed in the previous section, and the relevant construction process is presented in Figure 1.

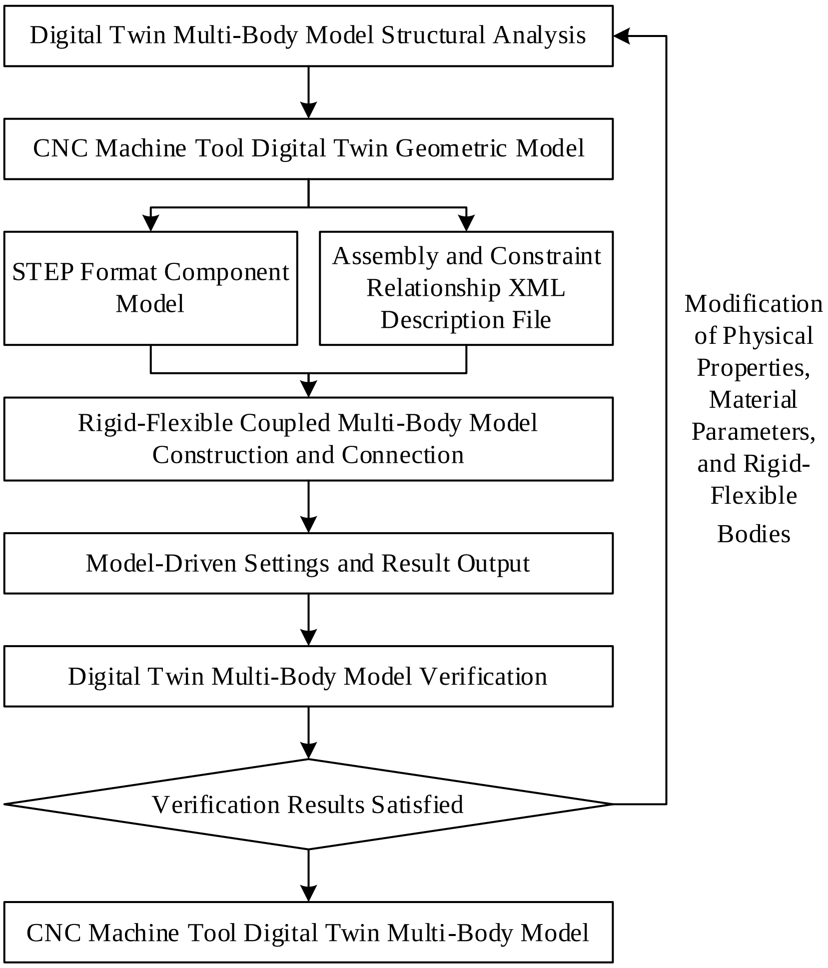


Figure 1: Dynamic modeling process

1) Analyse the structure of the kinematic and dynamic models of the Digital Twin multi-body system.

According to the relationship between the structures and assembly of the CNC machine tools, categorize and give a summary of the appropriate entities, joints, and constrains that could be defined in the multi-body model of the Digital Twin. At the same time, consider the forces, torques, and loads between parts or connection points.

2) Generate generic neutral files for parts and assembly and constraint relationship description files.

In order to allow automatic calculation of component moment of inertia and center of gravity, the geometric model of the CNC machine tool Digital Twin is converted into a neutral file in STEP format and the assembly and constraint relationships described in the Digital Twin geometric model are transformed into XML-based relationship description files.

3) Construction of multi-body kinematic and dynamic models with rigid-flexible coupling for digital twins

In the multi-body dynamics modeling setup, imports are made in the STEP format of component models and in the form of XML assembly constraint relationships, component properties are changed, additional part coordinate systems are introduced to link other objects and constraints, and forces and torques are specified within the model. Depending on the actual application purpose, define and construct components as rigid or flexible bodies. Modify and add kinematic pairs to accurately reflect the actual connection relationships between machine tool components. Simultaneously define the physical properties of kinematic pairs, such as stiffness, damping, and friction coefficients. In the Digital Twin multi-body kinematics and dynamics model, kinematic pairs primarily include fixed pairs, rotational pairs, translational pairs, spherical pairs, and gear pairs.

During the construction process, each component needs to be assigned one or more part coordinate systems. The spatial connection between components in a multi-body system is achieved through translation and rotation relationships between coordinate systems.

4) Model-driven settings and simulation result output

Based on the real-world operation of the machine tool, determine the external loads, driving forces, and driving torques of the Digital Twin multi-body model, choose a suitable solver that can carry out the kinematic and dynamic simulation, and produce the time-series information of force, torque, displacement, velocity, and acceleration.

5) Digital Twin multi-body kinematics and dynamics model verification

Once the simulation has been done, the outcomes of the Digital Twin multi-body system model should be checked. When the acquired results do not match the theoretical calculations, it is necessary to adjust the connection relationships, physical properties, physical parameters, and rigid-flexible body settings in the multi-body model. Through simulation, the CNC machine tool Digital Twin multi-body model may be applied to motion planning, dynamic characteristic testing, and deformation analysis, thus contributing to the improvement of machine-tool structure design. In the present research, the servo feed system, spindle system, and tool-processing system in the CNC machine tool Digital Twin geometric model will be presented as an example of how their dynamic models can be constructed, and after that, the dynamic/kinematic model of the overall machine-tool Digital Twin will be created.

2.2.2 Servo Feed System Digital Twin Multi-Body Kinematics/Dynamics Model Construction

The servo feeding system has the ability to convert the rotation of the motor into linear displacement and consequently provides a feed movement of the work table in the process of CNC machining such that the machining operation can be undertaken at the workpiece site. The mechanical model of the servo feed system used in this research has been depicted in Figure 2 as a simplified version. The ball screw drive is directly coupled to the servo motor shaft to convert the rotary motion into feed motion of the work table. The output torque of the motor shaft in the feed system is marked as T , the motor rotation angle as θ_1 , the rotational inertia of the motor shaft as J_1 , the screw rotational inertia as J_2, motor shaft and screw torsional stiffnesses are expressed as K_1 and K_2 respectively, and the rotational damping coefficients of motor shaft and screw are marked as B_1 and B_2 respectively; the mass of the workbench is indicated as m .The stiffness coefficient of the workbench is set to K_m, the moving damping of the workbench is set to B_m, and the displacement of the workbench is set to $x_0\left(t\right)$.

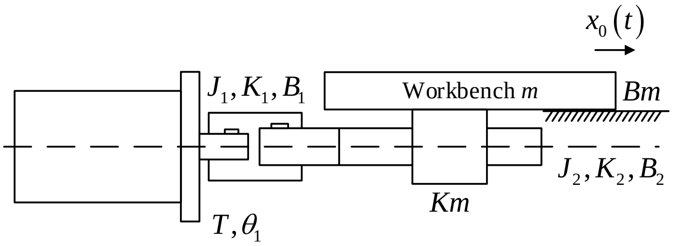


Figure 2: Servo feed system simplified model

If the lead of the lead screw is set to L, then the formula for converting the workbench displacement of $x_0(t)$ to the lead screw angle is

$$\theta_m(t) = \frac{2\pi}{L} x_0(t) \tag{1}$$

If the angle of rotation of the servo motor is set to $\theta_1(t)$, then the torque formula is satisfied.

$$J\frac{d^2\theta_m(t)}{dt^2} + B\frac{d\theta_m(t)}{dt} + K\left[\theta_m(t) - \theta_1(t)\right] = 0 \tag{2}$$

The values J, B, and K represent the equivalent rotational inertia, damping, and stiffness coefficient of each component of the transmission chain converted to the motor. The calculation formula is as follows:

$$J = J_1 + J_2 + \left(\frac{L}{2\pi}\right)^2 m \tag{3}$$

$$B = B_1 + B_2 + \left(\frac{L}{2\pi}\right)^2 B_m \tag{4}$$

$$K = \frac{1}{\frac{1}{K_1} + \frac{1}{K_2} + \frac{1}{\left(\frac{L}{2\pi}\right)^2 K_m}} \tag{5}$$

After proportional transformation, the dynamic parameters in the system can be converted to one side of the transmission system, which facilitates calculation. Then, the equilibrium equation of the workbench movement displacement can be expressed as

$$J\frac{d^2x_0(t)}{dt^2} + B\frac{dx_0(t)}{dt} + Kx_0(t) = \frac{L}{2\pi}K\theta_1(t) \tag{6}$$

According to the above equation, the servo-feed-system workbench movement can be explained using the second-order differential equation with oscillatory behavior. This paper uses an incremental modeling strategy to formulate the kinematic/dynamic model of the CNC machine tool Digital Twin. To start with, idealized assumptions, including the absence of dampening and lack of friction at the connection points of each moving pair are made and then the simulation model is compared with the results of real experiments and finally, the model is constantly augmented with the details of the model until it approximates the actual physical features of the machine tool.

The feed system of a CNC machine tool provides connection between the worktable and the base by means of four sliders and guide rails. The coupling is used to rotate the ball screw with an AC servo motor. Connection of the ball screw to the front and rear support bearings is made via a rotating joint. The combination of the ball screw and the nut attached to the worktable constitutes a helical transmission pair.

2.2.3 Spindle Digital Twin Multi-Body Kinematics/Dynamics Model

In the spindle Digital Twin multi-body kinematic/dynamic model, the spindle motor is fixed to the spindle box of the Z -axis feed system. The spindle motor and spindle shaft are defined as a rotating pair. The spindle shaft is assembled with the support bearing on the spindle sleeve through two rotating pairs. The spindle shaft is assembled with the tool holder and tool through a fixed connection.

2.2.4 Digital Twin Multi-Body Kinematics/Dynamics Model for Tool Machining Systems

The multi body system model that describes how the milling tool relates to the workpiece is quite simple, as it primarily includes the rotation rate of the tool, the relative position of the tool and workpiece, and the contacting relationship between the two.

2.2.5 Digital Twin Multi-Body Kinematics/Dynamics Model of CNC Machine Tools

The Machine Tool Digital Twin multi-body kinematic/dynamic model consists of numerous mechanical subsystems such as the machine tool base, the $X/Y/Z$ -axis feed system, the spindle system, the automatic tool changer, and the machine-tool housing. The machine-tool base is immovably attached to the tool housing. This base is linked with the Y -axis feed system and the Z -axis feed system with the help of ball screws which are driven by servo motors. The X -axis feed system is linked to the Y -axis feed system using a ball screw. The spindle system and the automatic tool changer are installed on the spindle housing of the Z -axis system.

2.3 BP neural network prediction model based on grey rough sets

The implementation of predictive maintenance of CNC machine tools requires processing a large volume of historical operating information gathered by the machines. Once the required data is obtained and treated, the fault-prediction model may be trained and optimized over time, and simulation and prediction can offer digitalized and precise results of processing. First of all, an early decision table of CNC machine tools is created and the grey relational analysis is employed to remove redundant information. Next, the rest of the data is discretized and irrelevant factors are discarded based upon rough-set theory, which leads to the creation of a simple decision table of mining equipment data. The resulting simplified table is then taken as the training input into the BP neural-network prediction model. Lastly, the predicted outputs are compared with the desired accuracy to decide the efficacy of the developed prediction model. The construction process of the BP neural-network prediction model considering the use of grey rough sets is shown in the Figure 3.

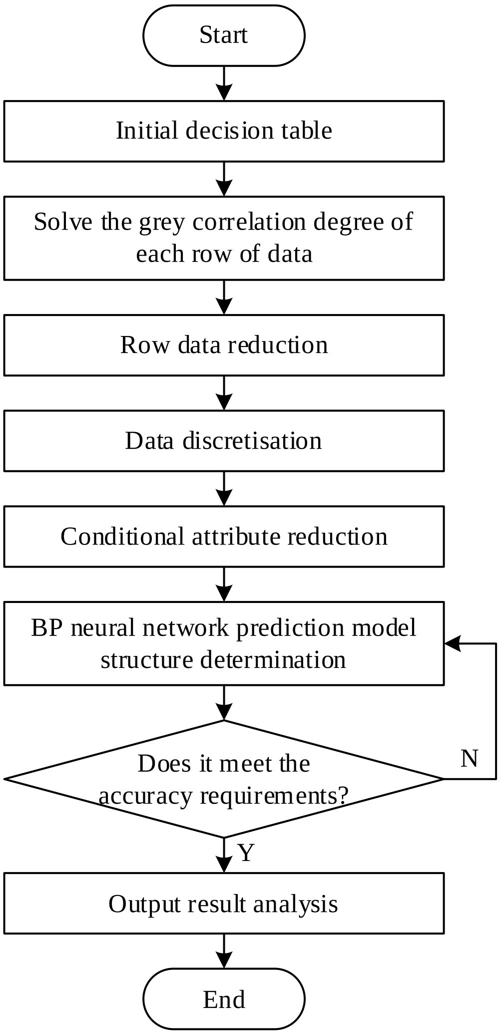


Figure 3: BP Neural Network Prediction Model Based on Grey Rough Set

Using a dataset of operational faults from CNC machine tools as the training set, where: λ represents the fault status of mining equipment, $\lambda = 1$ represents the fault status, $\lambda = 0$ represents the normal status; $a \sim f$ represents six possible factors that may cause faults in mining equipment.

1) Grey correlation analysis

Let the feature sequence of the CNC machine tool fault state be X_0, and define the fault state sequence as $X_i = (x_i(1), x_i(2), \cdots, x_i(n)), i = 1, 2, \cdots, m)$. Then, the calculation steps for the grey correlation degree $\gamma(X_0, X_i)$ between the feature sequence and the fault state sequence are as follows:

a) Solve for the mean image of sequence X_i as X_i';

b) Solve for the mean image X_0' of the characteristic sequence X_0, calculate the difference between it and the corresponding component X_i', take the absolute value, denote it as $\Delta_i(k)$, and find its maximum value M and minimum value N:

$$\Delta_i(k) = \left| x_0'(k) - x_i'(k) \right| \tag{7}$$

c) Calculate the correlation coefficient $\gamma(x_0(k), x_i(k))$:

$$\gamma(x_0(k), x_i(k)) = \frac{N + \xi M}{\Delta_i(k) + \xi M}, \xi \in (0,1) \tag{8}$$

In the formula: ξ is the discrimination coefficient, and ξ is usually taken as 0.5.

d) Calculate the grey correlation degree:

$$\gamma(X_0, X_i) = \frac{1}{n}\sum_{k=1}^{n} \gamma(x_0(k), x_i(k)) \tag{9}$$

If the grey correlation degree is low, it is considered that these data cannot effectively reflect the fault characteristics of CNC machine tools and should be screened out.

2) Coarse set reduction

For the initial decision table DT, the processing steps of the vertical attribute reduction algorithm are as follows:

a) Calculate the lower triangular matrix of the difference matrix $M_{n\times n}\left(DT\right) = \left(c_{ij}\right)_{n\times n}$;

b) Perform a conjunction operation on the disjunctive normal form to obtain the difference function Δ;

c) Transform the form to $\Delta' = \underset{k}{\vee} \Delta_k$, and create a vertical reduction decision table for CNC machine tool faults based on the corresponding constraint terms.

The data table obtained after lateral reduction by grey correlation analysis is discretised using the equal frequency packing method, and the attributes of the data set are reduced using a difference function. The remaining factors are the fault influencing factors of CNC machine tools.

3) Construction of BP neural network prediction model

The BP neural network consists of an input layer, a hidden layer, and an output layer. In this case, the input layer has the same number of nodes as the number of factors of influence on faults, which is denoted by k; the hidden layer size is determined by trial and error, which is denoted by j; the output layer only has the λ fault-state output, thus the number of nodes it has is set to 1. In turn, the three-layered BP neural network form can be formulated as $k - j - 1$.

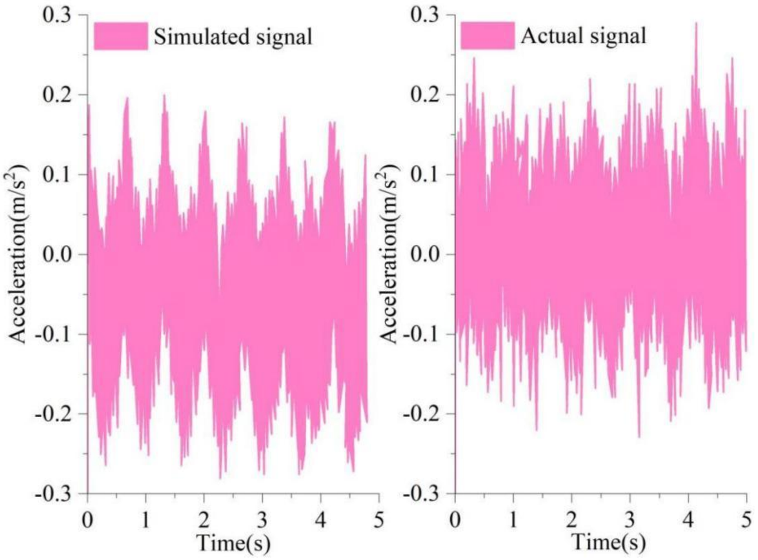
3 Effectiveness analysis of predictive maintenance models for CNC machine tools

3.1 Verification of the availability of simulation signals for multi-body models

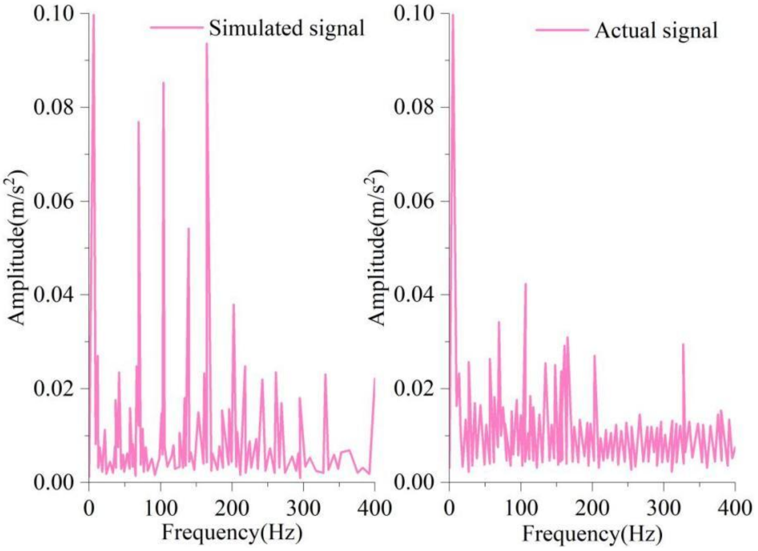
3.1.1 Comparison of simulated signals and actual signals for lead screw pitting faults

The accuracy of the simulation signals of the multi-body kinematic/dynamic model constructed for CNC machine tools is closely related to the actual prediction accuracy of the subsequent prediction model. Therefore, this section uses simulation signals of two types of faults, namely lead screw pitting and outer ring failure of support bearings, as examples to compare the errors between the simulation signals and the actual signals, and to determine the usability of the constructed model.

Figure 4 shows the simulation and actual time-domain waveforms and envelope spectra of lead screw pitting faults. Taking a pitting fault at a rotational speed of 400 rpm as an example, calculations show that the characteristic frequency of lead screw pitting faults is theoretically 40.67 Hz. In normal conditions, the defects in lead screws occur most commonly in the form of pitting that is very vulnerable to impact. Since the fault location keeps changing as the screw rotates, the fault patterns that occur during the operation of a lead-screw are generally irregular and hard to track. The impact wave forms of the simulated signal and measured signal are very similar based on the time-domain waveforms. The envelope spectrum shows that the predominant frequencies of the simulated and measured signals are 41.79 Hz and 43.16 Hz, respectively and their respective deviations of the theoretical characteristic frequency of lead-screw pitting are 2.75 and 6.12 percent. Therefore, there is little difference between the simulated outcome and the measured outcome.



(a) Time-domain waveform



(b) Envelope spectrum

Figure 4: Simulation and actual signals of screw pitting fault

Moreover, discrepancies between the probability distributions of simulated signals and measured signals can also decrease the accuracy of fault prediction. This is why, prior to the utilization of simulated signals, signal transferability must be studied based on the standpoint of probability-density distribution, and the probability-density properties of the two types of signals associated with lead-screw raceway pitting faults must be evaluated in detail. Figure 5 shows the probability-density distributions of lead-screw pitting-fault signals. It can be seen in the figure that due to the fact that the simulated signals contain a small number of influencing factors, their data distribution is more compact. Most of the vibration signal values are within the range [- 0.15, 0.15] and the probability density has its peak in the range [0.0,4.5] which is 4.20. Conversely, in the presence of a large number of random factors, the measured signals have less peak probability density with a peak of 2.93. However, despite these differences between the simulated signal and the measured signal, the two probability-density distributions are still quite alike. More significantly, they both maintain important fault-feature information, which means that simulated lead-screw pitting-faults signals can be transferred to predict the lead-screw faults in the real world.

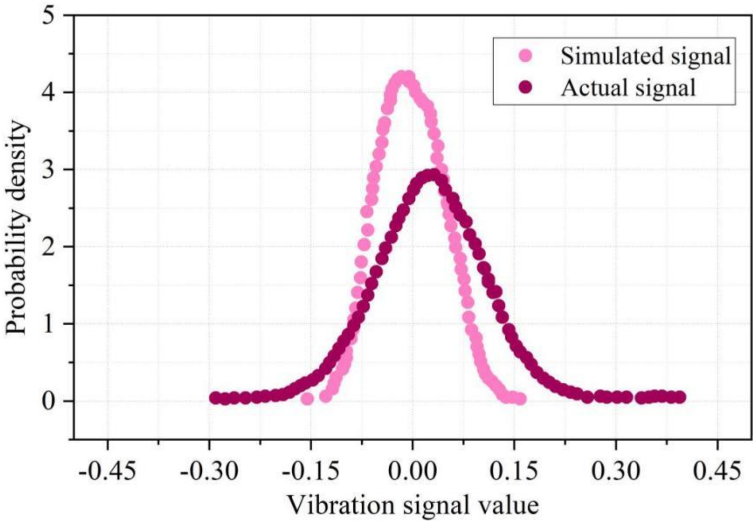
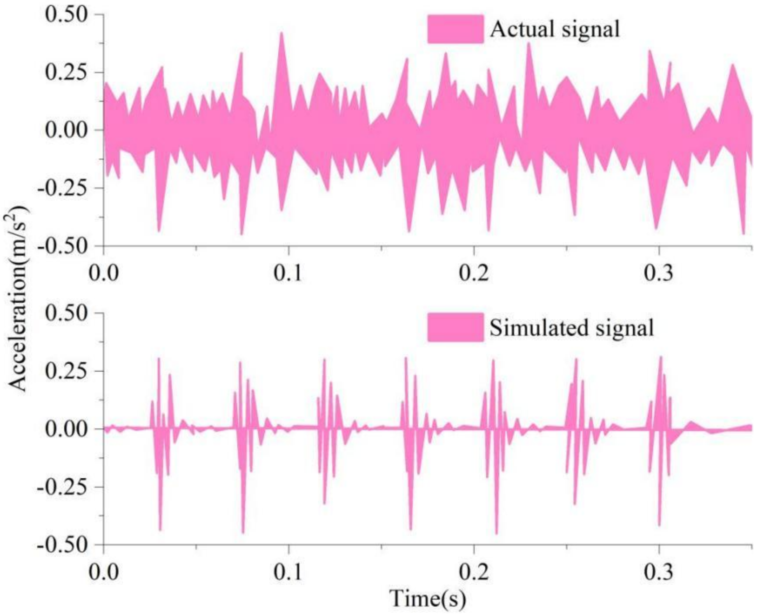


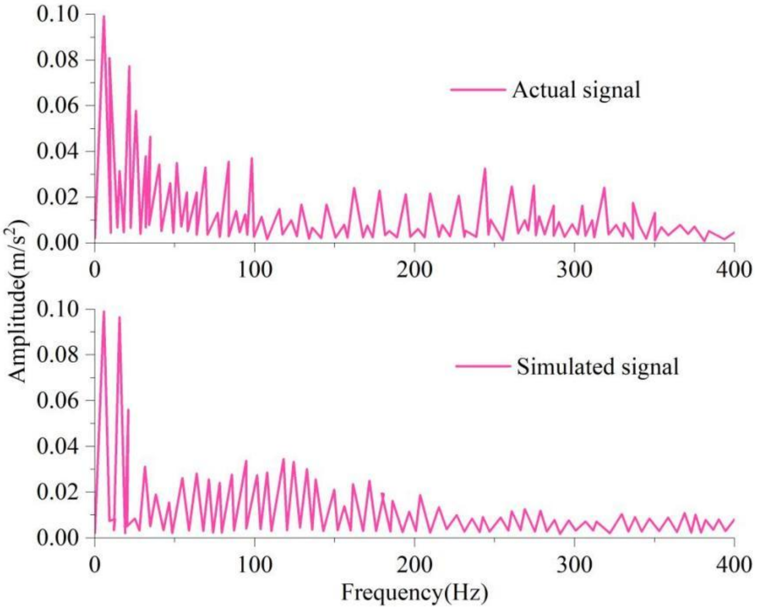
Figure 5: Probability density curve of screw pitting fault signal

3.1.2 Comparison of simulated signals and actual signals for outer ring failure of support bearings

Using the outer-ring fault of a support bearing at 400 rpm as an example, calculations reveal that the theoretical characteristic frequency of this fault is 9.21 Hz. Time-domain waveforms and envelope spectra of the simulated and measured signals of the bearing outer-ring pitting failure are given in Figure 6. As it can be seen in the figure, the variations in contact force cause impact responses as the rolling elements move across the defective area. The time-domain waveforms of the simulated and measured signals are found to be close, as shown in the figure. On the envelope spectrum the major frequency components of the simulated and measured signals are 9.22 Hz and 9.23 Hz respectively with relative deviations of 0.11 percent and 0.22 percent respectively of theoretical characteristic frequency of the bearing outer-ring fault. These findings suggest that simulated signal has good agreement with measured signal in time-frequency dynamics.



(a) Time-domain waveform



(b) Envelope spectrum

Figure 6: Simulation and actual signals of outer ring fault of support bearing

Additionally, Figure 7 shows the probability density distribution of the fault signals for the outer ring of the support bearing. As can be seen, the probability density distribution of the simulated signals is relatively concentrated with a high peak. The main vibration signal values are distributed between -0.25 and 0.25, with the peak reaching as high as 50. However, the actual signal, influenced by various random factors from other components, exhibits a lower probability density peak (5.12) and a smoother probability distribution (vibration signal values ranging from -0.5 to 0.5). Although there are differences between the simulated signal and the actual signal, the probability density distributions of the two under the same fault condition are relatively close, enabling the migration of the simulated signal to actual fault diagnosis.

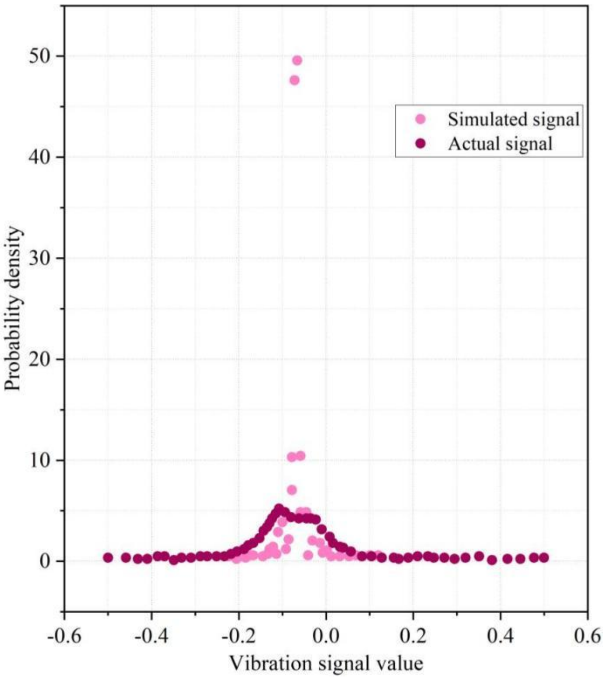


Figure 7: Probability density curve of outer ring fault signal of support bearing

3.2 Performance evaluation of BP neural network fault prediction model

3.2.1 Comparison of model iteration changes

To ensure that this paper fully leverages the advantages of grey rough sets in optimising BP neural networks, two comparison methods were selected: the weight decay-based BP neural network (WD+BP) and the dropout-based BP neural network (DO+BP). These methods were trained simultaneously to compare the fault prediction performance of the three approaches for CNC machine tools. Figure 8 shows the error performance of the three methods at different iteration counts. In training with 10, 20, and 30 iterations, the loss function value of the grey rough set + BP neural network prediction model remained the smallest. At 10 iterations, the model's loss function stabilised at 0.099 by the 6th iteration; at 20 iterations, the model stabilised at 0.059 by the 11th iteration; and at 30 iterations, the model stabilised at 0.018 by the 16th iteration. Across different iteration counts, the grey rough set + BP neural network prediction model consistently achieved more accurate predictions of potential faults in the multi-body model of CNC machine tools.

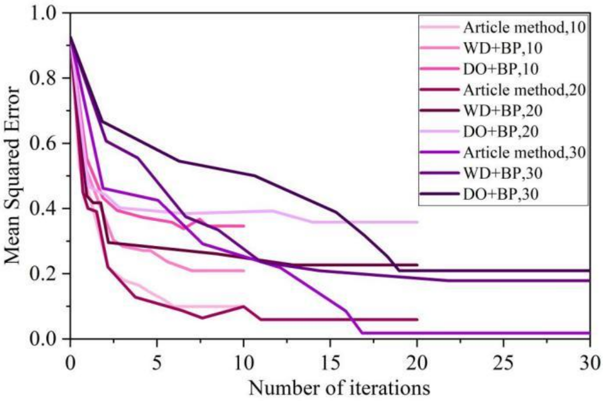
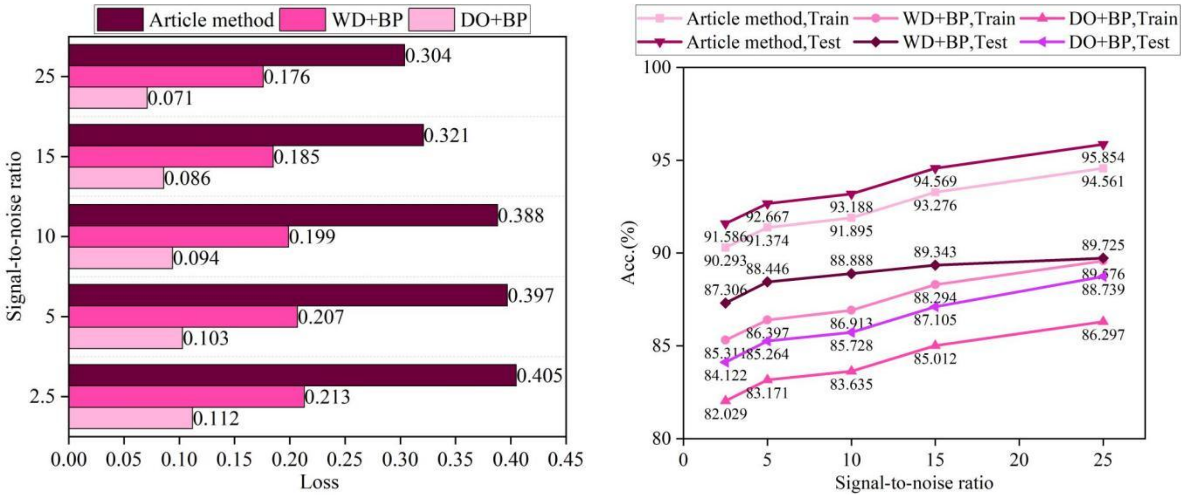


Figure 8: The errors of 3 methods under different numbers of iterations

3.2.2 Comparison of model prediction accuracy

Three BP neural networks were examined through their performance with a fault dataset under support-axis underfeed conditions that were artificially contaminated by Gaussian white noise. The signal to noise ratio (SNR) of the dataset was set at 25, 15, 10, 5, and 2.5 and the dataset was split into training subset and testing subset in the ratio of 7:3. They then measured the loss functions, training accuracy and testing accuracy of the three predictive models. Figure 9 shows how the outcomes of the three models vary depending on signal to noise ratio. With varying levels of signal to noise ratios, the loss values of the BP neural-network prediction model built on the concept of gray roughness are 0.112, 0.103, 0.094, 0.086 and 0.071 respectively, all less than those of the comparison model. Also, its training accuracies are 90.293, 91.374, 91.895, 93.276 and 94.561 respectively whereas its testing accuracies are 91.586, 92.667, 93.18, 94.569 and 95.854. All the accuracy rates are above 90 percent and are also higher than that of the comparison model. Consequently, the BP neural-network prediction model formulated on the principle of gray roughness has lesser loss and better accuracy of fault prediction of CNC machines.



(a) Loss

(b) Accuracy of the training set and the test set

Figure 9: Results of 3 prediction models vary with change of signal-to-noise ratio

4 Conclusion

This paper improves the accuracy of CNC machine tool fault prediction by constructing a multi-body model of the machine tool and optimising the BP neural network prediction model using grey rough sets. The deviation between the simulated signal and the theoretical frequency for lead screw pitting faults is only 2.75%, with a probability density peak of 4.20. The deviation for outer ring bearing faults is 0.11%, with a density peak as high as 50. The model exhibits signal transferability with actual faults. In 10, 20, and 30 iterations, the optimised BP neural network training loss values are the lowest among the three models, at 0.099, 0.059, and 0.018, respectively. In training with different signal-to-noise ratios, the loss function values of this model are 0.112, 0.103, 0.094, 0.086, and 0.071, with accuracy exceeding 90% in all cases, enabling precise fault prediction and providing a basis for maintenance. Given the diverse types of CNC machine tools, to enhance the model's generalisation capability, it can be trained using grey rough set-based regularisation algorithms of the same type, thereby expanding the model's applicability.

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