

Article

Milling Force Prediction Based on Spindle Current Signal

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Abstract

Spindle-current-based force estimation provides a nonintrusive alternative to dynamometer-based milling-force measurement, but its accuracy is limited by the nonlinear and time-dependent relationship between spindle current and cutting force. This study proposes a CNN–ResNet–RF model for instantaneous milling-force prediction using only spindle current signals as input. In the proposed architecture, CNN layers extract local temporal features from windowed current sequences, residual blocks refine multiscale force-related representations, and a random-forest regressor performs nonlinear force regression. Milling experiments were conducted on 7075 aluminum alloy and steel 45 using a five-axis machining center. To prevent temporal data leakage, the synchronized and preprocessed current–force data were divided at the continuous cutting trial level into training, validation, and independent test subsets. On the independent test subset, the proposed model achieved an R^2 value of 0.952, an MAE of 2.793 N, and an RMSE of 4.301 N, outperforming the CNN, CNN–ResNet, and RF baseline models in terms of prediction accuracy and error reduction. These results demonstrate that the CNN–ResNet–RF framework improves test-set milling-force prediction within the tested machining range.

Keywords: spindle current signal; CNN (convolutional neural network); milling force; random forest; deep learning

1. Introduction

In milling processes, milling force constitutes a critical parameter characterizing machining dynamics, directly dictating machine tool performance, operational stability, and the surface precision of the finished workpiece. Accurately predicting these forces facilitates proactive parameter optimization and significantly minimizes the probability of machine malfunctions. Traditionally, tool force gauges are deployed for continuous monitoring; however, their prohibitive costs, restricted load capacities, and severe interference with standard machine tool kinematics render them fundamentally impractical for high-volume, dynamic industrial environments. Consequently, estimating milling forces via spindle or feed servo motor current signals has emerged as a highly pragmatic alternative. Current sensors provide non-contact, non-intrusive measurements, inherently satisfying the rigorous demands of large-scale, cost-effective factory production.

In recent years, increasing attention has been paid to the prediction of instantaneous milling forces using current signals acquired from spindle motors or feed servo motors [1]. Compared with conventional external sensors, such as dynamometers, vibration sensors, and acoustic emission sensors, motor current signals are inherently available in machine



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tool drive systems and offer the advantages of low acquisition cost, convenient online measurement, and better adaptability to harsh machining environments. Therefore, they have considerable potential for practical cutting force monitoring, especially in the machining of complex components such as impellers and integral blades. Altintas [2] experimentally verified the feasibility of using motor current signals to monitor mechanical cutting forces based on the modeling analysis of feed servo systems. Aslan et al. [3] further achieved sensorless prediction of five-axis milling forces by extracting internal feed drive current signals together with CNC communication data, thereby reducing the dependence on external force sensors. In addition, Li et al. [4] and Song et al. [5] used spindle current signals for tool breakage detection and tool wear monitoring, respectively, indicating that current signals can reflect variations in cutting load and tool condition in a timely manner. Rizal et al. [6] also identified spindle motor current as an important indirect monitoring signal, along with force, torque, vibration, acoustic emission, and temperature. Related studies have further demonstrated that spindle or feed motor current signals can be used to estimate cutting force or cutting power under appropriate modeling assumptions [7,8].

Since milling forces are affected by cutting parameters, tool geometry, workpiece material, machine tool dynamics, and tool wear, the relationship between motor current signals and cutting forces is usually nonlinear and complex. To improve prediction accuracy, neural networks and deep learning methods have been widely introduced into cutting force modeling and tool condition monitoring. Miura et al. [9] monitored the cutting power in milling by using voltage and current sensors installed on the feed-drive motors of a machining center. The proposed method was experimentally validated through two-dimensional milling tests, and its results were compared with those of dynamometer-based signals. Zuperl et al. [10] employed multiple tool, machine, and workpiece parameters as neural network inputs to predict machining forces under different cutting conditions. However, the requirement for a large amount of prior data limits the scalability of this approach in industrial applications. To improve model stability and prediction accuracy, Wang et al. [11] proposed a combined prediction model integrating multiple neural network models. Guo et al. [12] and Qin et al. [13] incorporated deep learning and tool wear models into tool condition monitoring, improving the reliability of tool state assessment during milling. Furthermore, Chao et al. [14] extracted tool degradation features from spindle current signals using advanced signal processing methods, while Xu et al. [15] proposed a hybrid milling force prediction model that integrates physical principles with neural networks. Jamshidi et al. [16] applied fractal analysis to spindle current signals for tool condition monitoring, and Yang et al. [17] demonstrated the effectiveness of spatiotemporal feature learning in capturing latent dynamic characteristics. These studies indicate that data-driven and hybrid modeling methods are effective for describing the complex relationship between current signals, cutting forces, and tool wear states.

Although existing studies have verified the feasibility of using current signals for milling force prediction, several limitations remain. On the one hand, many models require a large number of input parameters related to the tool, machine tool, workpiece, and cutting conditions, which increases the demand for training data and reduces their adaptability to changing machining conditions. On the other hand, milling forces exhibit obvious dynamic and time-varying characteristics. Therefore, models based only on static features or single-time current values may fail to accurately describe the temporal mapping relationship between current signals and instantaneous milling forces. To address this issue, Wang et al. [18] proposed a semi-supervised parallel deep factorization machine method to deal with unlabeled data, while Peng et al. [19] established a mapping relationship between milling forces and current signals through sliding-window temporal processing, highlighting the importance of strict temporal alignment. Li et al. [20] adopted neuro-fuzzy

technology to analyze the relationship between spindle and feed systems for indirect cutting force estimation. Cheng et al. [21] combined LSTM and 1D-CNN to realize real-time prediction of spindle cutting moments and tool conditions. Dong et al. [22] improved tool wear monitoring accuracy through wavelet transform and genetic algorithm optimization, while Turšič et al. [23] integrated LSTM with a consensus voting method to capture temporal characteristics in spindle current signals. These studies suggest that temporal feature extraction is essential for improving the accuracy and robustness of milling force prediction. Therefore, further investigation is still required to fully exploit the dynamic temporal characteristics of machine tool current signals and to develop a high-precision, low-cost, and robust instantaneous milling force prediction model suitable for complex machining conditions.

Direct force measurement using dynamometers is fundamentally limited in industrial settings due to high prices, spatial interference, and load restrictions; however, current transformers provide a scalable, non-contact alternative. Nevertheless, current neural network topologies utilizing these signals primarily rely on fixed machining settings and substantial prior experimental calibration. However, this approach faces notable limitations. Collecting a large number of machining parameters can be cumbersome in industrial settings, and these methods are unable to predict milling forces in real time, such as when the cutting tool engages or disengages with the material. To address these shortcomings, this research introduces a novel integrated neural network architecture—CNN–ResNet–RF. This model entirely eliminates reliance on intricate cutting parameters, utilizing solely the real-time spindle current signal of a five-axis machine tool as input to attain dynamic and precise predictions of milling force. This study initially establishes the mathematical correlation between current and milling force through torque matching during the machining process. Convolutional neural networks (CNN) are utilized to extract local temporal features from windowed spindle-current sequences, while a residual network (ResNet) is implemented to capture the profound temporal correlation between force and current. Ultimately, a random forest (RF) technique is employed to augment the model's regression resilience amid intricate dynamic disturbances.

The primary contributions of this study are outlined as follows:

1. A novel neural network-based approach for milling force prediction is introduced, which simplifies the prediction process by eliminating the need to directly incorporate cutting parameters. Instead, the method forecasts the machining milling force by solely extracting the spindle current signal.
2. By employing decision trees within the Random Forest framework for training under the tested cutting conditions, the model's susceptibility to overfitting is effectively mitigated. This enhances its adaptability, enabling the model to perform reliably within the designed experimental range.
3. A milling force prediction approach based on spindle current signals is introduced, and its predictive ability is experimentally evaluated on an independent test subset using milling data collected from 7075 aluminum alloy and steel 45 workpieces.

2. Methodology

2.1. Milling Force Modeling Based on Spindle Current Signals

The spindle drive system of a five-axis CNC machine tool comprises a servo motor, a motor shaft, and a spindle, with the current signal from the spindle motor governing the operation of the spindle. The torque output from the entire spindle drive system includes not only the milling torque but also the motor inertia, drive system inertia, load inertia, and friction torque caused by bearings. Figure 1 illustrates the transfer relationship between the current signal and milling force. The spindle motor output torque can be decomposed as:

$$T = T_a + T_c + T_f + T_d \quad (1)$$

where T represents the total torque of the motor, T_a denotes the moment of inertia, T_c refers to the cutting torque, T_f corresponds to the frictional torque, and T_d signifies the disturbance torque:

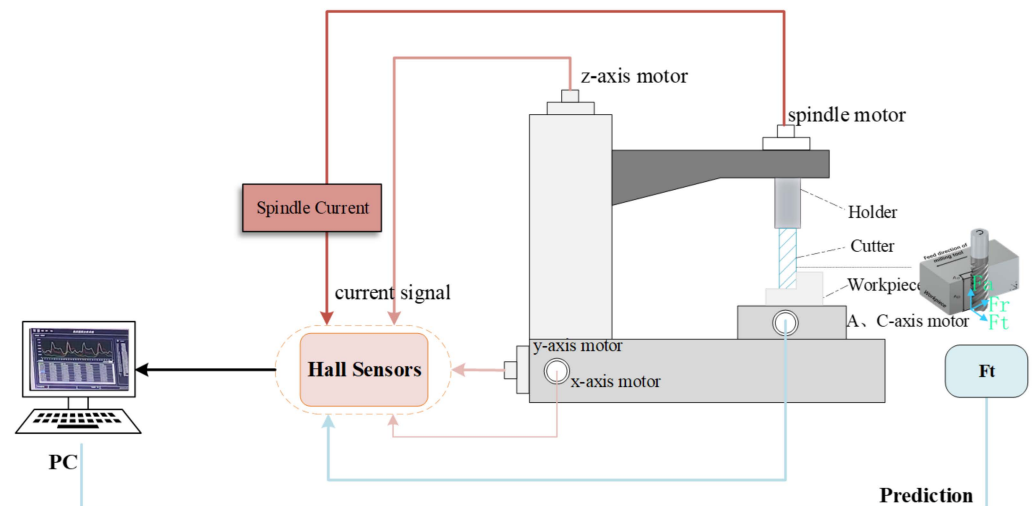


Figure 1. Schematic representation of the relationship between the spindle current signal and the milling force.

Among them:

$$T_a = J \frac{dw}{dt} \quad (2)$$

$$T_c = F_t * r \quad (3)$$

where J represents the total inertia of the rotating components, r denotes the tool radius, F_t refers to the milling force exerted by the tool during machining, and w signifies the angular velocity of the tool.

When the spindle speed remains constant, $T_a = J \frac{dw}{dt} = 0$.

When the spindle is in an idle state, $T_c = 0$.

$$T = T_a + T_c + T_f + T_d = T_f + T_d \quad (4)$$

The total output torque of the motor is the sum of the moment of inertia and the frictional torque, both of which are considered constant and denoted as A .

$$T_f + T_d = A \quad (5)$$

When the spindle rotates, the tool generates solely a tangential force, denoted as F_t .

Thus, the expression for the moment can be formulated as:

$$T = rF_t + A \quad (6)$$

In a DC servo motor system, the torque is expressed as:

$$T = K * I_{rms} \quad (7)$$

where K represents the motor torque constant, and I_{rms} denotes the equivalent current of the AC motor.

The spindle servo motors in CNC machine tools are AC motors, and the root-mean-square method is employed to convert the three-phase AC power into equivalent DC power, as follows:

$$I_{\text{rms}} = \sqrt{\frac{I_u^2 + I_v^2 + I_w^2}{3}} \quad (8)$$

where I_u , I_v and I_w represent the three-phase alternating currents of the system.

$$K * I_{\text{rms}} = r * F + A \quad (9)$$

$$F_t = \frac{\Delta T}{r} \quad (10)$$

This equation shows that the spindle current is physically related most directly to the tangential cutting-force component. In the experiments, however, the dynamometer measures the Cartesian force components F_x , F_y , and F_z . Therefore, the above derivation is used as the physical basis linking spindle current to cutting load, while the CNN–ResNet–RF model is employed to learn the nonlinear mapping from the spindle-current signal to the milling-force target used for regression. This treatment avoids a purely black-box interpretation and preserves the physical meaning of the current–force relationship.

The current I and the force F exhibit a fundamental functional relationship. Specifically, a clear proportionality exists between the increment in cutting current and the cutting force, which provides strong theoretical support for using this current increment to predict the tangential milling force. This relationship forms a critical theoretical foundation for subsequent research and practical applications. From Equation (1), it can be seen that the total torque composition is not a single one, but covers the two key elements of cutting torque as well as friction torque, that is, the cutting force affects the total torque. During machining, the tool does not operate at a constant cutting speed, and periodic tool vibrations may occur, both of which influence the cutting force. Consequently, the relationship between spindle current and cutting force is not linear, but rather a complex nonlinear one.

Therefore, the CNN–ResNet–RF architecture was selected to match the signal characteristics and the force-prediction task. CNN is used to extract local temporal patterns from windowed spindle-current sequences and to suppress redundant signal fluctuations. ResNet is introduced to preserve low-level current information through shortcut connections while enabling deeper multiscale feature learning, which is required for delayed and time-varying current–force responses. RF is used as the final regressor because ensemble decision trees reduce sensitivity to noise and single-model fitting errors during nonlinear force mapping. Compared with standalone CNN, standalone RF, and CNN–ResNet models, the hybrid structure combines local feature extraction, residual feature refinement, and robust nonlinear regression; this selection is further evaluated through the ablation comparison in Section 4.3.

2.2. Neural Network-Based Predictive Model

Given the nonlinear and time-dependent relationship between spindle current and milling force, a hybrid CNN–ResNet–RF framework was constructed to improve feature representation and regression robustness. The model uses windowed spindle-current sequences as input and predicts the corresponding milling force. First, the CNN module extracts local temporal patterns from the current signal through convolution, batch normalization, nonlinear activation, and pooling operations, thereby reducing redundant signal components and retaining force-related features. Second, the ResNet module integrates the extracted features across multiple scales by using residual blocks; the shortcut connections preserve low-level information and alleviate network degradation during deeper feature

learning. Finally, the RF regressor maps the learned features to the milling-force target by aggregating the outputs of multiple decision trees, which improves robustness to nonlinear disturbances and reduces sensitivity to single-model fitting errors. Thus, the proposed model follows a sequential architecture of CNN-based feature extraction, ResNet-based feature refinement, and RF-based nonlinear regression, as illustrated in Figure 2. The model was selected because its three components address complementary limitations: CNN alone has limited deep feature propagation, CNN–ResNet improves representation but still requires robust final regression, and RF alone cannot learn temporal features directly from raw current sequences. After the ResNet feature-refinement stage, the resulting feature maps are flattened into a one-dimensional feature vector for each sliding window and transferred to the RF stage as input variables. The synchronized milling-force value at the corresponding prediction instant is used as a continuous target label; therefore, RF operates as a regressor rather than a classifier.

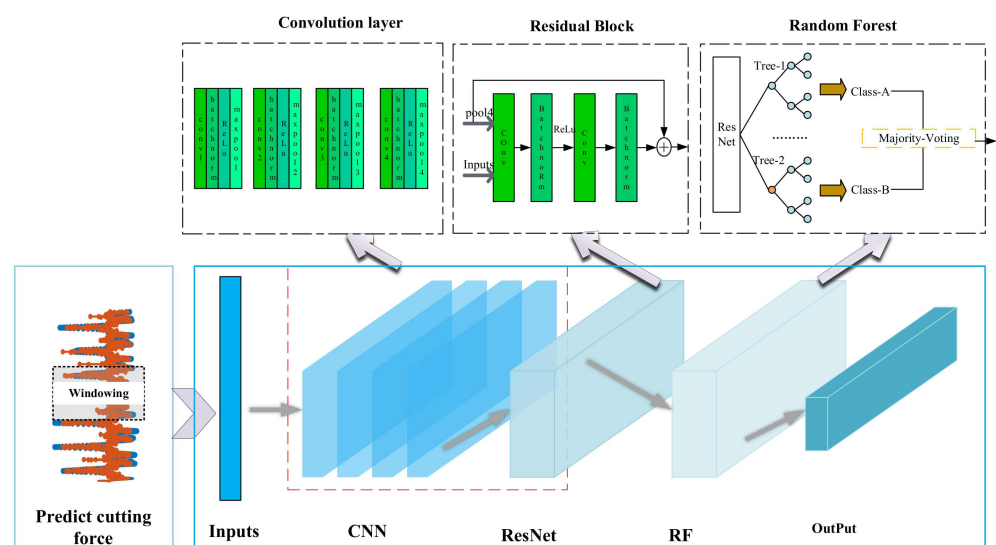


Figure 2. CNN–ResNet–RF model for milling force prediction.

The overall computational process is depicted in Figure 3.

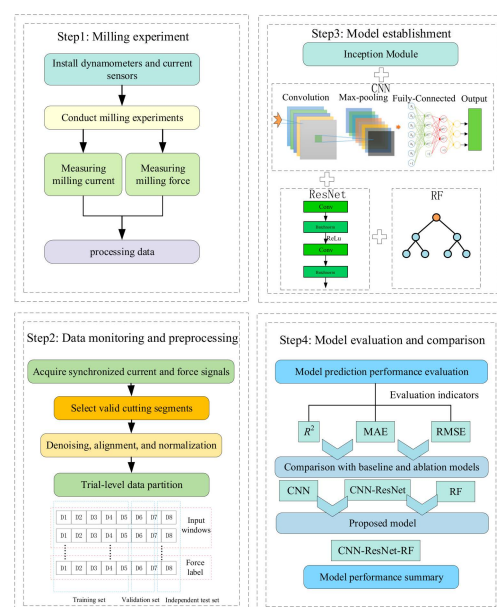


Figure 3. Overview of the computational process.

Step 1: In the first step of the cutting experiment, prior to the commencement of cutting, the rotary force meter and Hall current sensor are installed. The energy consumption meter is employed to collect the spindle current signal, while the rotary force meter is used to measure the milling force.

Step 2: In Step 2 of data monitoring and processing, data acquisition was conducted under the designed cutting conditions used in the experiments. The data collected during the process were captured using force sensors and current sensor devices. Each set of machining data was treated as an individual dataset and subsequently normalized. For the modeling phase, the processed data were divided at the continuous cutting trial level into training, validation, and independent test subsets with a ratio of 80%/10%/10%, respectively. All sliding windows extracted from the same continuous cutting trial were assigned to the same subset to prevent temporal data leakage.

Step 3: In the third step of model development, the CNN–ResNet–RF model is introduced, comprising three primary components: the CNN module, ResNet, and RF. The CNN module is responsible for extracting features from the spindle current during the cutting process, with features from different convolutional layers fused using maximum pooling. The ResNet layer consists primarily of convolutional layers and residual blocks. The RF algorithm constructs multiple regression trees and averages their outputs to generate a continuous milling-force estimate.

Step 4: In Step 4 of model comparison and evaluation, the performance of the model is assessed using three evaluation metrics: the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). To demonstrate the effectiveness of the proposed model, a comparative analysis is conducted between deep learning-based models (CNN) and machine learning-based models (RF), as well as the CNN–ResNet models.

2.2.1. CNN

CNN is a widely used deep learning framework for one-dimensional time-series signal analysis that extracts local temporal features from windowed spindle-current sequences. The CNN model proposed in this paper consists of four convolutional layers, each with different configurations, followed by a normalization layer, an activation layer, and a maximum pooling layer. The prediction task is ultimately accomplished through a regression output layer. The overall network structure, as shown in Figure 4, extracts multi-level features from the input current-sequence data, gradually reducing the dimensionality, and ultimately producing the prediction results.

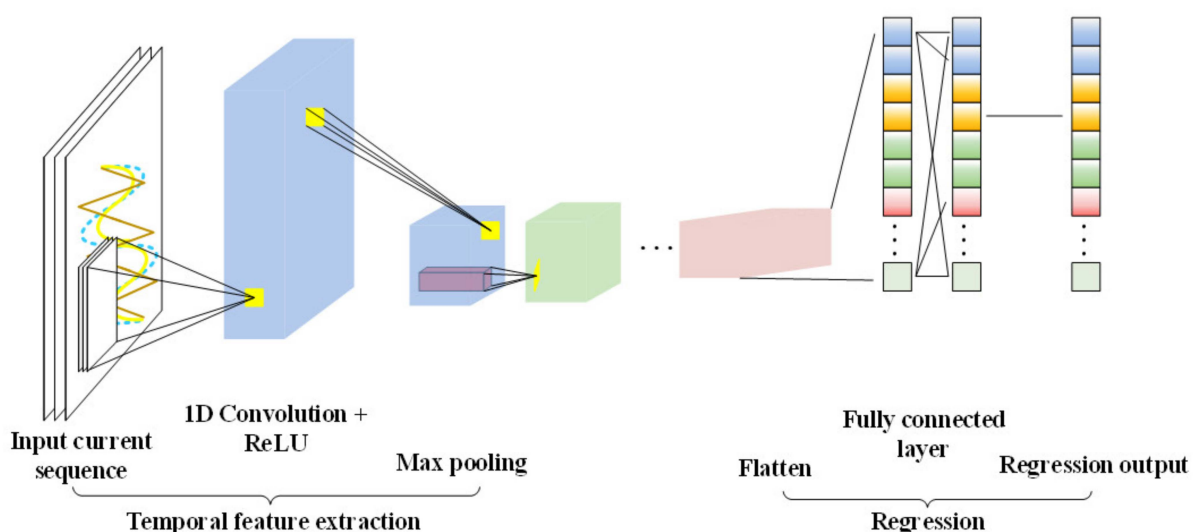


Figure 4. Structure of the 1D-CNN model for milling-force prediction based on spindle current signals.

The current signal features are extracted using the CNN network. To simulate the nonlinear relationship between the input machining current signal and the output milling force, the Rectified Linear Unit (ReLU) activation function is employed to process the output of the convolutional layers. The ReLU function is mathematically expressed as:

$$f(x) = \max(0, x) \quad (11)$$

where x is $\max(0, w^T x + b)$.

The convolutional layers extract critical features from the input current signal by applying learned filters that identify patterns and characteristics within the data. These layers are structured to progressively capture multi-level features, allowing the model to identify both simple and complex patterns at various stages. A downsampling layer (maximum pooling layer) follows the convolutional layers, combining multiple convolution operations with pooling to improve the generalization capability of the CNN model and accelerate its convergence. This downsampling layer also integrates effectively with ResNet layers. The feature values in the maximum pooling layer are derived as the maximum values from a group of neurons in the previous convolutional layer. The key parameters of the pooling layer include the pooling window length and the stride along the temporal dimension. After the final maximum-pooling operation in the CNN module, the resulting feature maps are transferred to the subsequent ResNet module for residual feature refinement. After the ResNet stage, the refined feature maps are flattened into a one-dimensional feature vector and then used as the input to the RF regressor.

In this architecture, the maximum-pooling operation is performed along the temporal dimension of the one-dimensional current-feature sequence. The pooling window length and stride are both set to 1, preserving the temporal length of the feature sequence before flattening and avoiding unnecessary loss of time-aligned current information.

2.2.2. ResNet

In general, deeper network models provide better feature representation and stronger fitting capabilities. However, excessively deep networks are prone to overfitting and face challenges such as gradient vanishing and gradient explosion, which make training increasingly difficult. To address these issues, He et al. [24] introduced ResNet, which uses residual connections to facilitate more effective information flow across layers. These connections enable efficient weight updating and parameter transmission. This structure not only mitigates problems like overfitting, weight decay, and gradient vanishing but also enhances the model's expressive power and ability to learn complex features.

For multiscale analysis of the current signal, the output from the flattening layer is used as input to the ResNet model. ResNet effectively addresses the gradient vanishing problem by introducing residual connections that allow gradients to flow directly through the network. This structure enables the training of very deep networks and supports the extraction of complex feature representations. The convolutional layers in ResNet are designed to reduce the number of trainable parameters by convolving input data with kernels, applying biases, and passing the results through activation functions before forwarding the data to subsequent layers. Additionally, skip connections in ResNet further enhance performance by transmitting information directly across layers. This mechanism combines features from earlier and later layers, improving the model's expressive power and its ability to capture intricate data patterns.

The basic structure of a residual block is shown as Residual Block A in Figure 5. GeLU denotes the Gaussian Error Linear Unit activation function, which provides smooth nonlinear activation between convolutional operations. In certain cases, the output dimensions of the two convolutional layers in the block may not match the dimensions of the block's

input. To resolve this, a 1×1 convolution is introduced to adjust the input dimensions, ensuring compatibility between input and output. This adjustment is demonstrated in Residual Block B in Figure 5, where the 1×1 convolution transforms the input shape to maintain proper functionality of the residual connections and ensure efficient information flow throughout the network.

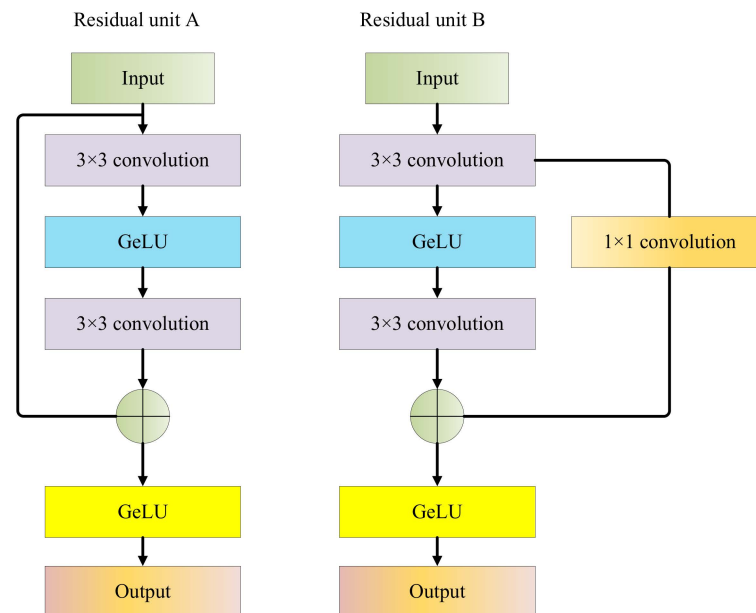


Figure 5. Structure of the residual unit.

Let the input of the residual unit be x , and let the output be x' . For Residual Block A in Figure 5, the shortcut path directly preserves the input, and the output is expressed in Equation (12). For Residual Block B in Figure 5, a 1×1 convolution is applied to the input to match the output dimensions, and the output is expressed in Equation (13):

$$x' = x + F(x, w_1, \sigma, w_2) \quad (12)$$

$$x' = w_0 x + F(x, w_1, \sigma, w_2) \quad (13)$$

where w_1 and w_2 are the 3×3 convolutional layer weights in the residual module, respectively; w_0 is the 1×1 convolutional layer weight; and σ is the activation function.

The inclusion of a residual module enables the deep network to learn features more efficiently, thus enhancing its feature extraction capability and solving the network degradation problem. A residual module consists of two paths: one is the residual path, which is obtained through convolutional operations, while the other is a shortcut path formed by two stacked kernels.

2.2.3. RF

RF, developed by Leo Breiman in 2001 [25], is an ensemble learning algorithm designed to model the nonlinear relationship between spindle current and milling force. By utilizing current signal features extracted through the ResNet network as inputs, RF effectively captures complex nonlinear interactions via its multi-decision tree framework and ensemble learning approach. The algorithm constructs multiple independent decision trees, enhancing both model performance and generalization ability. In this study, RF is implemented as a regression ensemble: each tree predicts a continuous milling-force value from the learned CNN–ResNet feature vector, and the final output is obtained by averaging the predictions of all regression trees. By randomizing sample data to build independent

decision trees, RF ensures robust and reliable outputs. Its strong generalization ability and low variance make RF highly resilient to missing features, which makes it particularly suitable for predicting milling forces.

For the feature-transfer process, each windowed spindle-current sequence first passes through the CNN module for local temporal feature extraction and then through the ResNet module for residual multiscale feature refinement. The output feature maps are flattened before entering RF, so the RF input is not the raw current sequence but a compact, learned feature vector. This design assigns temporal representation learning to CNN-ResNet and assigns the final nonlinear force mapping to the RF regressor.

The primary advantage of RF in this study lies in its robustness to data noise and missing features, ensuring consistent performance. The model's hyperparameters are configured as follows: the number of decision trees ($n_estimators$) is set to 800 to balance model complexity and accuracy, the maximum tree depth (max_depth) is limited to 10 to prevent overfitting, and the minimum samples required for node splitting ($min_samples_split$) and leaf nodes ($min_samples_leaf$) are set to their default values of 2 and 1, respectively. Random sampling with replacement ($bootstrap=True$) is applied to further improve robustness. These configurations enable RF to effectively learn the nonlinear mapping between current signal features and milling force, resulting in accurate and reliable predictions during the milling process. These hyperparameters are used for the random-forest regressor, and the regression output is the predicted milling-force value in n rather than a class label.

3. Research Methodology and Experimental Design

3.1. Experimental Design

To validate the feasibility and effectiveness of the proposed CNN-ResNet-RF neural network model, milling experiments were performed under the designed operational conditions using a five-axis machining center (VMC-C50, Shanghai TOPNC Numerical Control Technology Co., Ltd., Shanghai, China). A three-flute cemented carbide end mill with a diameter of 10 mm was used. The workpieces were 7075 aluminum alloy with dimensions of $190 \times 100 \times 70$ mm and steel 45 with dimensions of $190 \times 100 \times 100$ mm. Current signals from the spindle and feed axes were recorded using an energy consumption meter (Norma 5000, Fluke Corporation, Everett, WA, USA) at a sampling frequency of 5 kHz. The arrangement of the energy consumption meter and the placement of the current sensors are shown in Figure 6c,d. To measure instantaneous milling forces in the X, Y, and Z directions, a rotary force measurement system (5236B, Kistler Instrumente AG, Winterthur, Switzerland) was used, operating at a sampling frequency of 10 kHz. Zero-drift compensation was applied to the force measurement system to ensure data accuracy during the force measurements. The setup for the force measurement equipment is illustrated in Figure 6a, and the experimental platform configuration is depicted in Figure 6b.

During the machining process, variations in axial depth of cut, radial depth of cut, and feed per tooth significantly affect both the milling force and spindle current. To analyze these effects, the experimental program was designed using the control variable method. Three axial depths of cut and radial depths of cut were selected, while the workpiece material was varied as outlined in Table 1.

To avoid data leakage, the dataset was partitioned at the level of continuous cutting trials rather than at the level of individual sliding-window samples. All windows extracted from the same continuous sequence were assigned to only one subset. Therefore, temporally adjacent and highly overlapping samples were not simultaneously present in the training, validation, and test sets. The final dataset was divided into training, validation, and test subsets with a ratio of 80%/10%/10%, respectively. In addition, normalization parameters

were computed using the training set only and then applied to the validation and test sets to prevent indirect leakage.

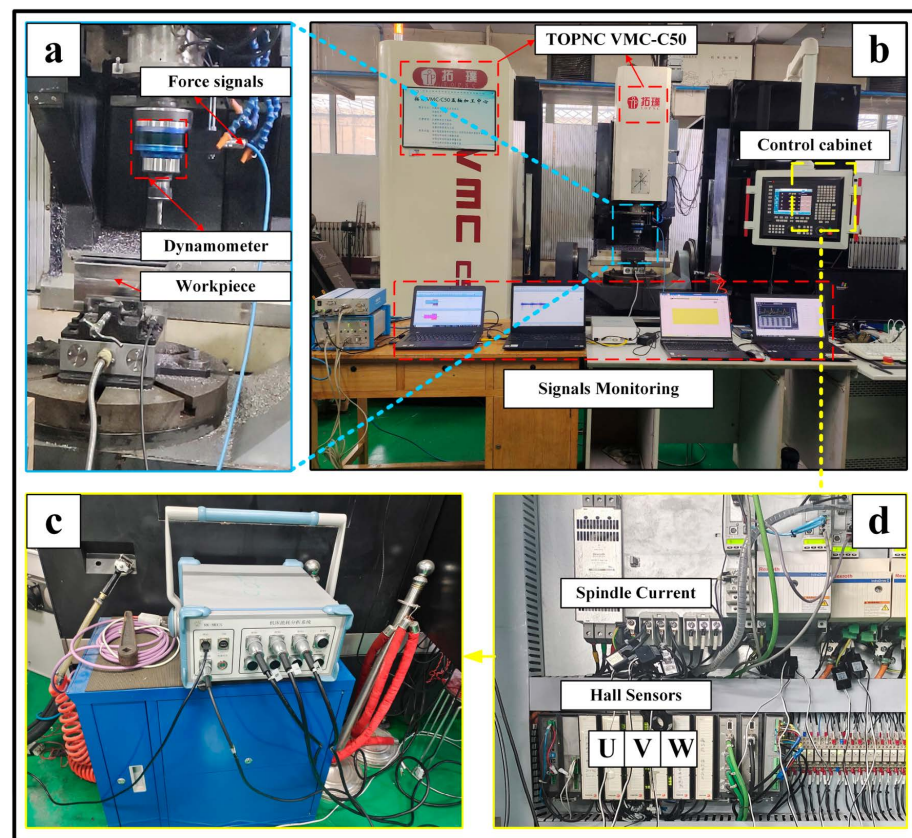


Figure 6. Experimental setup: (a) Force acquisition sensor; (b) Experimental processing platform based on the TOPNC VMC-C50 machine tool; (c) Current acquisition system; (d) Current sensor.

Table 1. Experimental cutting parameters.

Group	Workpiece Materials	Spindle Speed (n /min)	Feed Per tooth (f_z) (mm/tooth)	Axial Depth of Cut (a_p) (mm)	Radial Depth of Cut (a_e) (mm)
1	7075 aluminum alloy	2000	0.04	2	0.5
2	7075 aluminum alloy	2000	0.04	4	0.5
3	7075 aluminum alloy	2000	0.04	6	0.5
4	steel 45	2000	0.04	2	0.5
5	steel 45	2000	0.04	2	1.0

Analysis of the current and milling force signals under varying cutting conditions reveals that both signals exhibit similar fluctuation patterns. Specifically, experiments with different axial depths of cut show that variations in cutting conditions lead to corresponding changes in the current and milling force signals, as depicted in Figure 7. This observation highlights the potential of the current signal to serve as an effective predictor of milling force.

To assess the prediction accuracy and robustness of the proposed method, cutting experiments were conducted on two materials: 7075 aluminum alloy and steel 45. The 7075 aluminum alloy, being relatively easy to machine, shows minimal fluctuations in milling force, making the correlation between the current signal and milling force signal more straightforward to identify. In contrast, steel 45, a commonly used industrial material, presents a more challenging cutting environment, offering a practical and representative scenario for evaluating the method's performance.

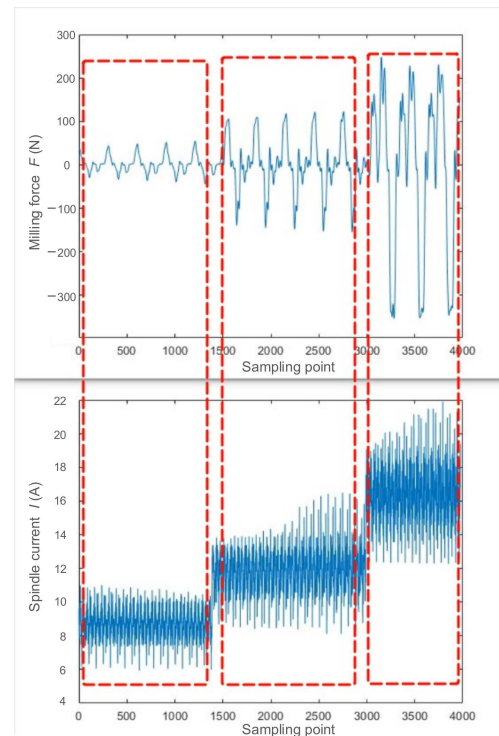


Figure 7. Comparison of experimental data for varying axial depths of cut.

3.2. Data Collection

During the experiments, a three-flute carbide end mill with a diameter of 10 mm was used to machine the workpieces. The spindle speed was set at 2000 r/min, with a feed per tooth of 0.04 mm/tooth, while the axial and radial depths of cut were varied. Milling tests were performed on both 7075 aluminum alloy ($190 \times 100 \times 70$ mm) and steel 45 ($190 \times 100 \times 100$ mm) workpieces, and changes in milling force and spindle current were continuously monitored throughout the machining process.

Cutting data under the designed experimental conditions were selected to construct the dataset. Real-time current signals were captured during the milling process using Hall current transformers installed near the spindle and spindle motor of the CNC machine, in conjunction with an energy consumption meter (Norma 5000, Fluke Corporation, Everett, WA, USA). Simultaneously, a rotary force meter (5236B, Kistler Instrumente AG, Winterthur, Switzerland) positioned near the spindle shank measured the milling forces in real time. The collected data were used to generate labels for training the CNN–ResNet–RF network.

3.3. Data Preprocessing

The simultaneously acquired current and milling force signals serve as the raw data for analysis, with preprocessing steps applied first to the milling force signal. The preprocessing begins with signal smoothing to eliminate anomalies and facilitate subsequent regularization. A low-pass filter is then applied to extract the primary information relevant to the machining process. Additionally, wavelet transform techniques are employed to compress and filter the original cutting force signal. By iteratively applying the wavelet transform, the signal is decomposed into multiple frequency bands. Through selective reconstruction, only the frequency bands containing useful information are retained, effectively reducing noise while preserving critical data. During the milling process, maintaining a one-to-one correspondence between the milling force signal and the current signal is essential to ensure no phase shift occurs. This alignment is crucial for accurate analysis, particularly when decomposing high-frequency components, as it allows for precise lo-

calized analysis. This method is especially effective for processing non-smooth signals. Signal analysis was streamlined through wavelet decomposition, and data alignment was performed to synchronize the milling force signals with the corresponding current signals. This alignment ensured the formation of a unified dataset for further analysis.

The milling current signal undergoes preprocessing, beginning with denoising through wavelet transformation using a symlet wavelet function with a filter value of 4. Bayes' thresholding is employed, with the median used as the thresholding rule across four decomposition layers. A Fourier series is then fitted to the dataset, and the fitted component is subtracted from the original spindle current signal to eliminate spurious signals unrelated to milling parameters. To address the disparity in sampling frequencies between the milling force and current signals, cubic spline interpolation is applied to expand the current signal dataset, ensuring alignment with the milling force data. After three iterations of spline interpolation, the data density is significantly enhanced, improving both reliability and accuracy. Under the designed experimental conditions, the processed data are deemed reliable and suitable for further analysis.

After wavelet packet decomposition and reconstruction, the filtered milling force and current data display smoother profiles in the time domain, with high-frequency noise effectively eliminated. The waveforms and phases of the signals remain intact, preserving their essential characteristics while minimizing the influence of noise. This preprocessing step ensures the successful extraction of key milling force and current features, enhancing data quality for further analysis.

Signal Segmentation: The raw current signal is segmented per spindle revolution, providing essential information for neural network recognition and enhancing memory efficiency during the CNN–ResNet–RF model operation.

Signal Fitting: A Fourier series is used to fit the segmented signals, modeling current signals influenced by quasi-static milling forces and machining parameters.

Signal Normalization: The extracted current and milling force signals are rescaled to the [0, 1] range, mitigating the impact of amplitude fluctuations and cutting parameters on network learning, as detailed in Equation (14).

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (14)$$

where x and x_n denote the original and normalized data, respectively; $x_{\max}$ and $x_{\min}$ denote the maximum and minimum values calculated from the training subset. The same normalization parameters were then applied to the validation and independent test subsets.

The processed current and milling-force data were partitioned at the continuous cutting trial level, with a final split ratio of 80%/10%/10% for the training, validation, and independent test subsets, respectively. The training subset was used for parameter learning, the validation subset for model selection and hyperparameter checking, and the independent test subset only for the final assessment of generalization performance. Data preprocessing, CNN–ResNet–RF model implementation, model training, and performance evaluation were performed using MATLAB R2024b.

3.4. Temporal Framing, Windowing, and Delay Handling

To explicitly define the temporal prediction framework, the spindle current signal and milling force signal were first synchronized in time. Because the two signals were acquired at different sampling frequencies, the spindle current signal was resampled to match the sampling grid of the milling force signal. After resampling, temporal alignment was performed to establish a one-to-one correspondence between the current and force sequences, thereby minimizing phase mismatch before sample construction.

The aligned time series was then converted into supervised learning samples using a sliding-window strategy. Let x_t denote the aligned spindle-current sequence and y_t denote the corresponding target milling-force sequence. For each prediction instant t , the input sample was defined as a current window of length L , $[x_{t-L+1}, \dots, x_t]$, was used to predict the force label at the same instant, y_t . Adjacent samples were generated with a stride of S , resulting in an overlap ratio of $\frac{L-S}{L}$ when $S < L$. The prediction setting was causal because only present and past current samples were used to estimate y_t , and no future current or force information was included. This design is consistent with the intended real-time application of the proposed model.

Potential time lag between spindle current variation and force response was handled at two levels. First, signal-level alignment reduced the global phase offset introduced by different acquisition channels and preprocessing operations. Second, model-level delay learning was achieved through the CNN–ResNet architecture. The convolutional layers extract local temporal patterns within each input window, while the residual connections and stacked convolutional structure enlarge the effective receptive field, enabling the network to learn delayed and multi-scale dependencies between current fluctuation and force evolution. The RF module does not model sequence order directly; instead, it receives temporally encoded features from the CNN–ResNet front-end and performs the final nonlinear regression.

To avoid information leakage and to evaluate the ability of the model to predict unseen cutting-force data, the dataset was partitioned at the continuous cutting trial level before final model evaluation. Windows originating from the same continuous cutting trial or local time neighborhood were assigned to only one subset. Therefore, temporally adjacent and highly overlapping samples were not simultaneously present in the training, validation, and test sets. The final split ratio was 80%/10%/10% for training, validation, and independent testing, respectively. The training subset was used to update model parameters, the validation subset was used for model selection and hyperparameter checking, and the independent test subset was used only once for the final assessment of predictive performance.

All performance metrics reported in the results section were calculated on the independent test subset after model training was completed. No test samples were used during CNN–ResNet training, RF training, model selection, or hyperparameter checking. This protocol ensures that the reported agreement between measured and predicted milling forces reflects prediction of new experimental force samples rather than agreement with the data used to fit the model.

4. Analysis of Results

In this section, the performance of the models is evaluated by analyzing the experimental results and predicting the milling force under varying cutting parameters and workpiece materials. The analysis is organized into three main parts.

1. The proposed CNN–ResNet–RF model can perform instantaneous milling-force prediction using only spindle-current signals as input and obtain direct force estimates without directly using cutting parameters as model inputs.
2. The hybrid model can extract local temporal features through CNN, refine multiscale feature representations through ResNet, and perform robust nonlinear regression through RF, thereby alleviating the feature-propagation and fitting limitations of the standalone baseline models.
3. The CNN–ResNet–RF model can obtain a more robust nonlinear current–force mapping than the RF baseline, and its predictive performance is quantified using R^2 , MAE, and RMSE on the independent test subset.

4.1. Evaluation Indicators

In order to validate the performance of the neural network structural milling force prediction model proposed in this study, three statistical indicators commonly used in model evaluation are selected to comprehensively evaluate the prediction performance. These three metrics are MAE, RMSE and R^2 . RMSE is used to measure the overall error by calculating the difference between the actual values and the predicted values and taking the square root of the arithmetic mean. MAE denotes the mean absolute error between the observed and predicted values. In addition, there is R^2 , which measures the fit of the model. R^2 values range from 0 to 1. The better the model fits the data, the closer the R^2 value is to 1, and the closer the other two metrics are to zero.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (15)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (16)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (17)$$

where y_i denotes the measured milling force, $\hat{y}_i$ denotes the predicted milling force, $\bar{y}$ is the mean of the measured force values, and n is the number of samples. Lower RMSE and MAE values and higher R^2 values indicate better predictive performance.

4.2. Analysis of Model Prediction Effects

In this section, the predictive performance of the proposed CNN-ResNet-RF model is evaluated on the independent test subset. These test samples were collected from the milling experiments but were excluded from model training and validation. They therefore provide a direct assessment of the model's ability to predict new milling-force results under the tested cutting conditions. Figure 8 presents the regression relationship between measured and predicted milling forces on the independent test subset, while Figures 9–11 show representative test-set predictions under different axial depths of cut, workpiece materials, and radial depths of cut. Figure 12 further compares the prediction effects of the models under different processing conditions and test datasets.

Regression plot of predicted and measured milling forces on the independent test subset

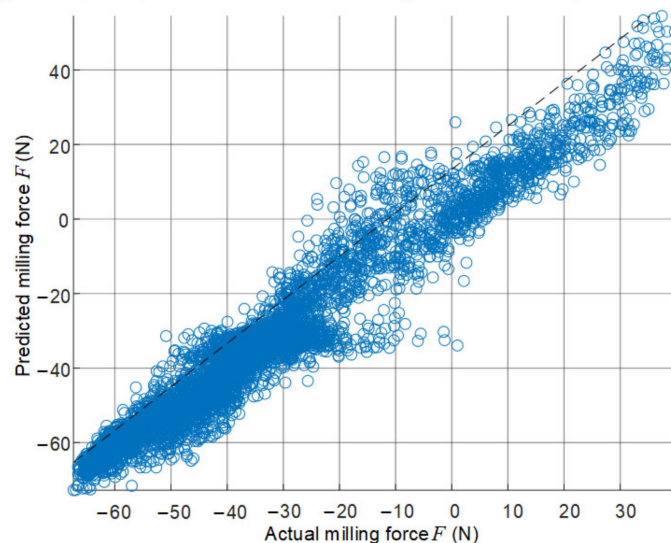


Figure 8. Regression plot of model predictions on the independent test subset.

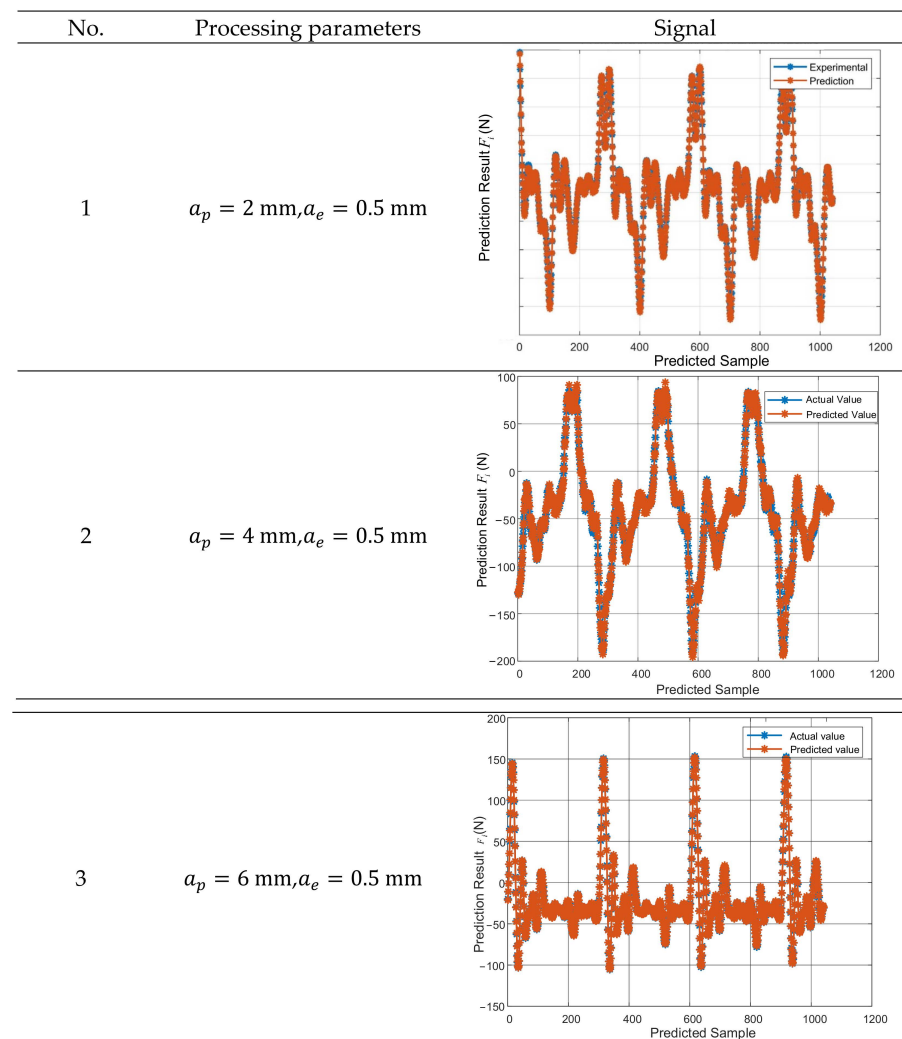


Figure 9. Predicted milling forces under different axial depths of cut.

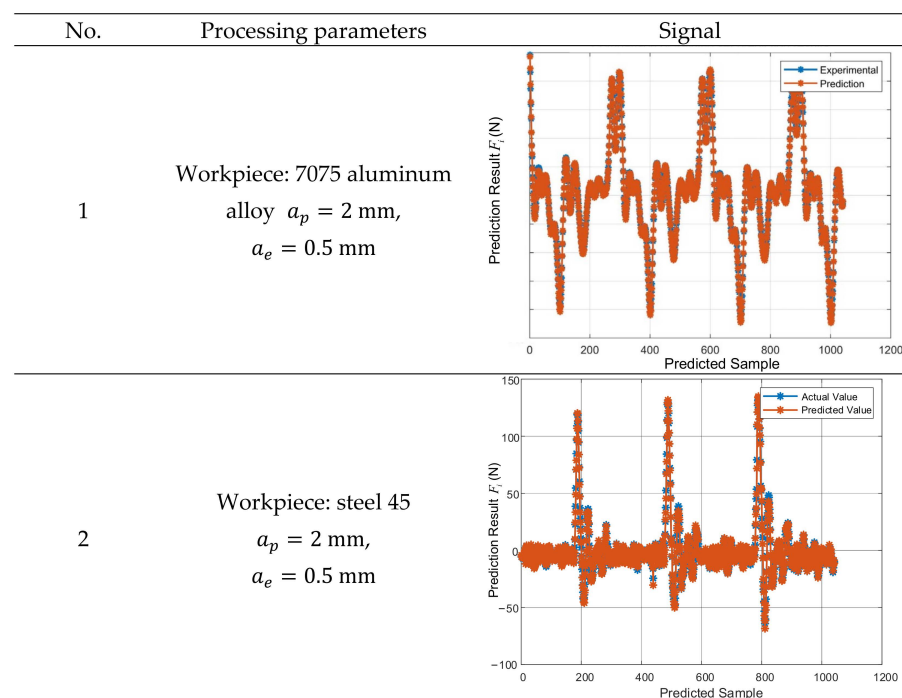


Figure 10. Predicted milling forces for different workpiece materials.

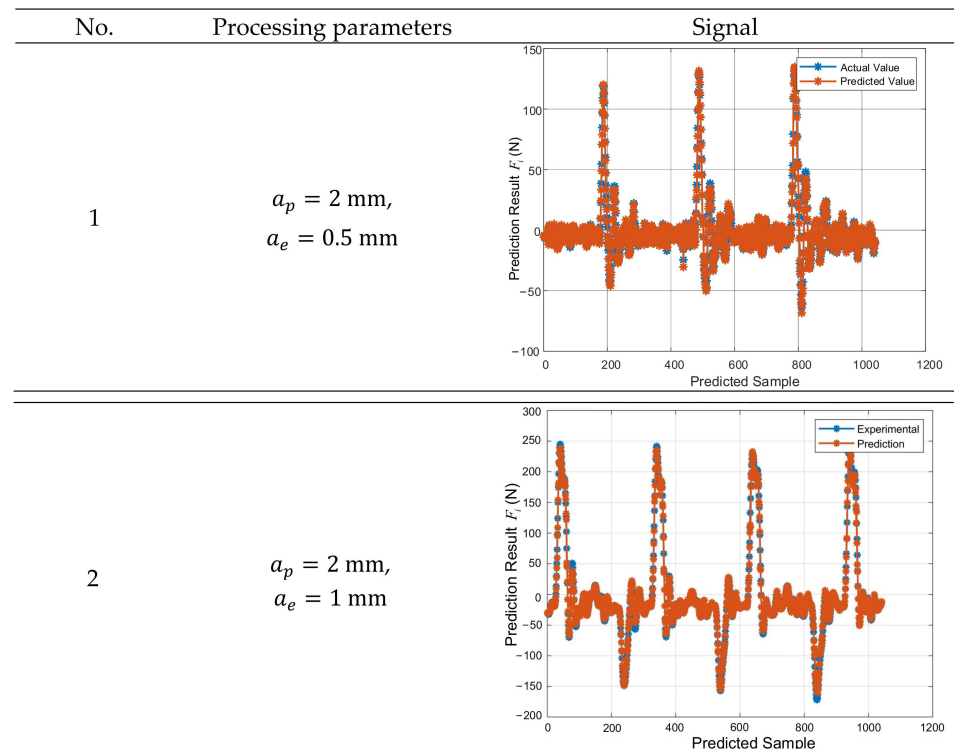


Figure 11. Predicted milling forces under different radial depths of cut.

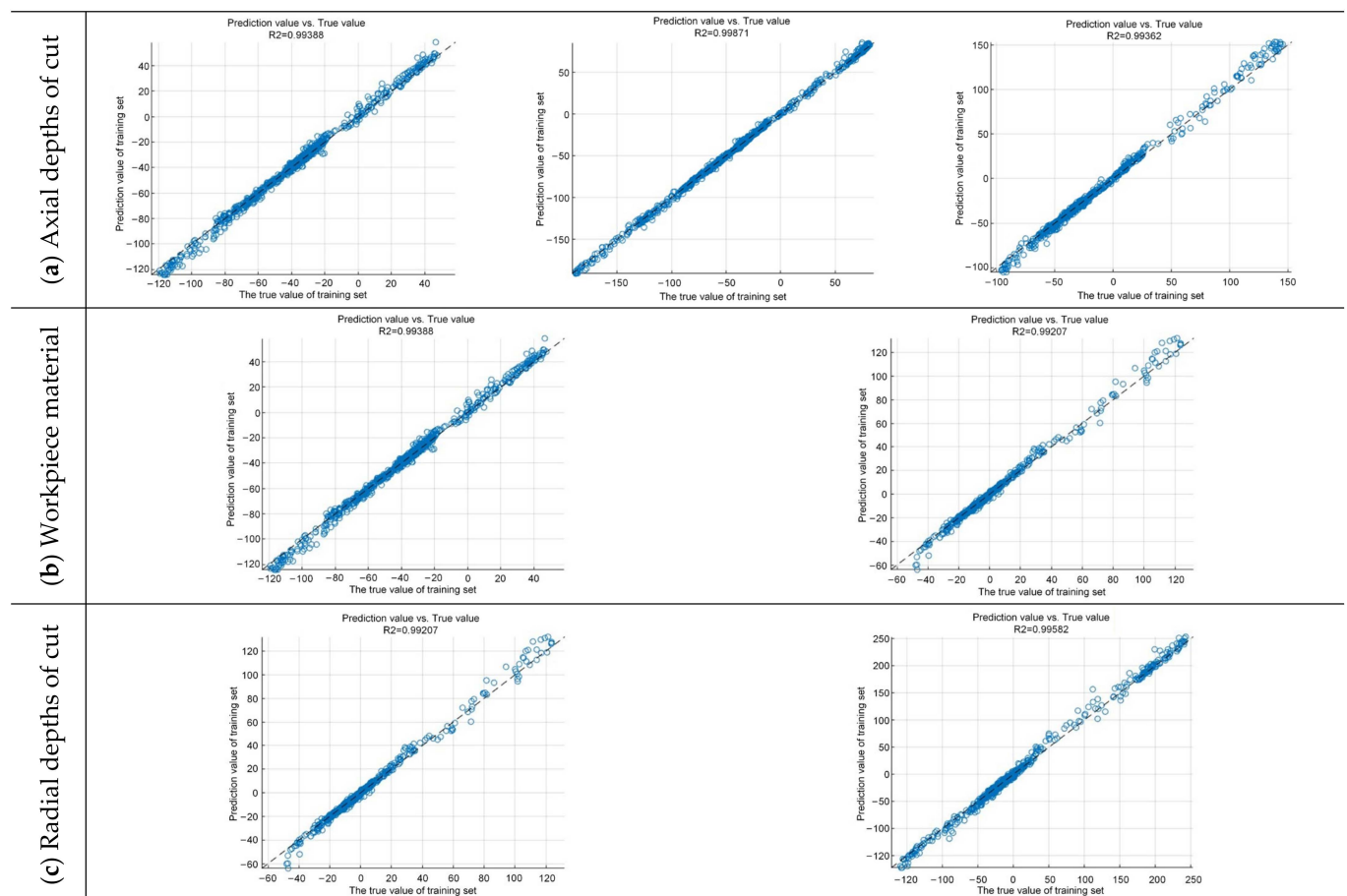


Figure 12. Comparison of the prediction effect of neural networks under different processing conditions on different test datasets: (a) different axial depths of cut; (b) different workpiece materials; (c) different radial depths of cut.

The prediction results of the CNN–ResNet–RF neural network on the independent test subset are illustrated in Figures 9–11. In these figures, the measured milling force and predicted milling force are compared for cutting cases that were not used during model training. The close agreement between the two curves indicates that the model captures the current–force mapping for unseen experimental samples rather than merely reproducing the training data. Figure 9 evaluates different axial depths of cut, Figure 10 evaluates different workpiece materials, and Figure 11 evaluates different radial depths of cut. The comparative results in Figure 12 are consistent with these observations and further support the robustness of the proposed model under the tested processing conditions. These results support the predictive capability of the proposed model within the tested experimental range.

4.3. Comparison with Other Network Models

To evaluate the effectiveness of each module combination within the CNN–ResNet–RF architecture, the CNN–ResNet–RF model is compared with the standalone CNN, CNN–ResNet, and RF models using the independent test subset. The comparison results, as shown in Table 2, provide insight into the performance improvements achieved through the integration of feature extraction, residual feature refinement, and RF-based nonlinear regression.

Table 2. Performance comparison of different prediction models on the independent test subset.

Model	R^2	MAE (N)	RMSE (N)
CNN	0.769	7.035	9.331
CNN–ResNet	0.948	2.863	4.405
CNN–ResNet–RF	0.952	2.793	4.301
RF	0.936	3.241	4.936

Table 2 presents the performance metrics of the compared models on the independent test subset. The CNN–ResNet–RF model achieves the highest R^2 value of 0.952, demonstrating a strong correlation between predicted and actual milling forces. In contrast, the CNN, CNN–ResNet, and RF models have R^2 values of 0.769, 0.948, and 0.936, respectively. Additionally, the CNN–ResNet–RF model outperforms all other models in terms of RMSE and MAE, with an RMSE of 4.301 N and an MAE of 2.793 N—significantly lower than those of the other models. The results indicate that the CNN–ResNet–RF model demonstrates superior prediction performance compared to the other architectures. By integrating the ResNet module, feature extraction is significantly enhanced, while the RF module improves prediction accuracy. This combination leverages the strengths of CNN for local temporal feature extraction from current sequences, ResNet for deep feature learning, and RF for robust prediction, resulting in a model that excels in both feature extraction and accuracy. In summary, the CNN–ResNet–RF model outperforms the CNN, CNN–ResNet, and RF models in predicting milling forces. Its superior performance highlights the effectiveness of combining CNN, ResNet, and RF, making it a robust solution for machining force prediction.

As shown in Figure 13a, the CNN–ResNet–RF predictions follow the measured milling-force curve more closely than the compared models on the independent test subset, particularly near the force peaks and valleys. This indicates that the proposed model better preserves the transient force variation associated with spindle-current fluctuations. Figure 13b provides a quantitative comparison using MAE, further showing that CNN–ResNet–RF yields the smallest prediction error among the evaluated models. Figure 14 presents the MAE distributions under three groups of tested conditions: different axial depths of cut, different workpiece materials, and different radial depths of cut. The error comparison across these subfigures supports the same conclusion that the proposed CNN–ResNet–RF model provides more stable force-prediction performance within the tested experimental range.

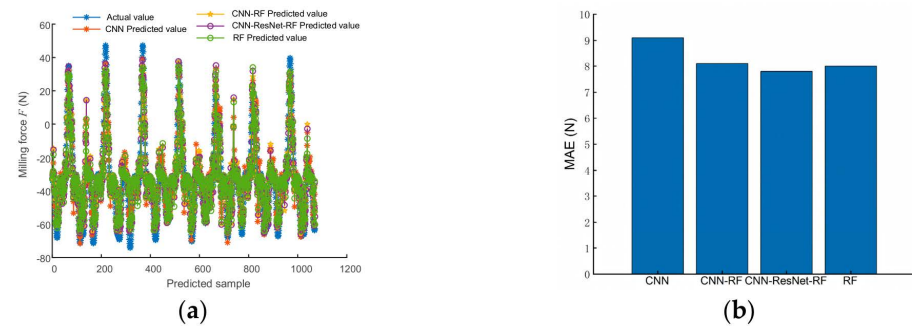


Figure 13. Comparison of the prediction results for different models: (a) predicted and measured milling-force curves; (b) MAE comparison of different models.

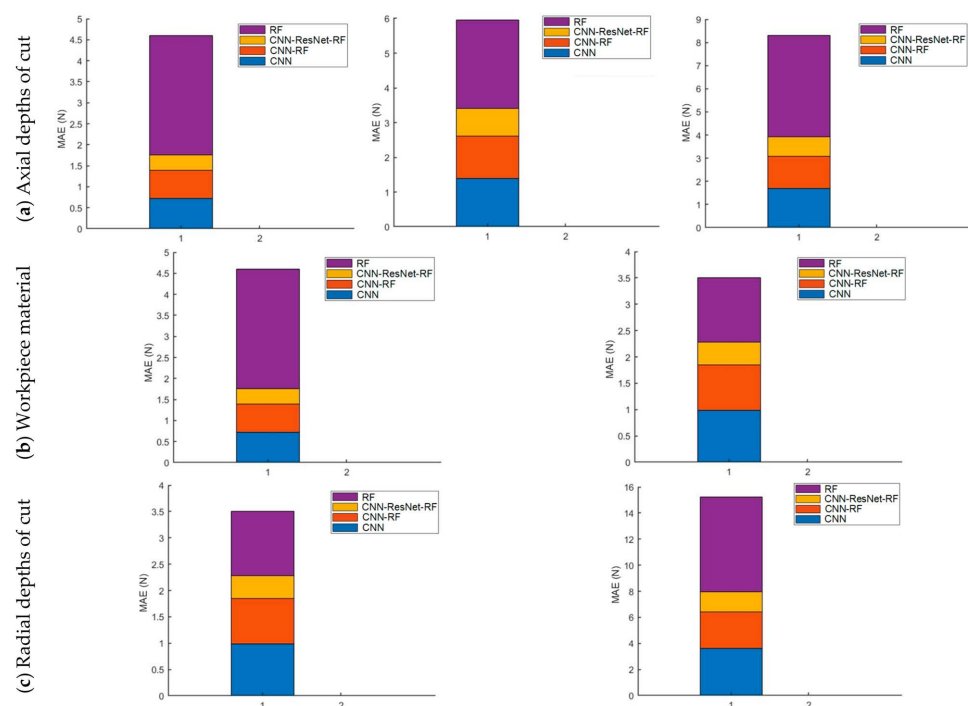


Figure 14. MAE distribution for all experimental conditions: (a) different axial depths of cut; (b) different workpiece materials; (c) different radial depths of cut.

Overall, the CNN–ResNet–RF model achieves the best prediction performance among the evaluated models, indicating its ability to capture spindle-current-related milling-force variations within the tested experimental range.

5. Conclusions

This study proposes an innovative spindle current-based milling force prediction model, CNN–ResNet–RF, which integrates CNN, ResNet, and RF. The model combines the feature extraction efficiency of CNN, the deep feature learning capability of ResNet, and the robust predictive accuracy of RF. Its effectiveness and superiority are evaluated using the collected experimental dataset, where it is used to predict milling forces based on spindle current data and compared with other neural network models on the same dataset. The key findings of the study are summarized as follows:

1. This study introduces a spindle current-driven method for predicting instantaneous milling force during the milling process. By utilizing current data collected from a five-axis machine tool operating at constant milling speed, a neural network is constructed to map the relationship between spindle current and instantaneous milling force. The

CNN–ResNet–RF model processes the collected spindle current signals to accurately predict milling forces. This indirect approach reduces the dependence on direct force measurement and enables milling-force prediction under the tested cutting conditions. The results indicate that spindle-current signals can provide useful information for estimating milling force within the designed experimental scope.

2. Comparative analysis with the standalone CNN model reveals the significant contribution of ResNet in enhancing prediction accuracy. The ResNet module strengthens the model's ability to extract complex features while mitigating the gradient vanishing problem. Furthermore, the CNN–ResNet–RF model surpasses the RF model, validating its efficiency in predicting instantaneous milling force. On the independent test subset, the CNN–ResNet–RF model achieved an R^2 of 0.952, an MAE of 2.793 N, and an RMSE of 4.301 N, confirming its ability to predict milling-force data that were not used for training within the tested experimental range.
3. When compared to other CNN–ResNet-based models, the CNN–ResNet–RF model proves superior due to its effective integration of CNN, ResNet, and RF. This architecture leverages multi-scale feature fusion and deep feature extraction, ensuring high predictive accuracy and robustness. Unlike traditional machining parameter-driven models, this current-driven neural network eliminates the need for extensive experimental determination of milling coefficients or mathematical modeling. As a result, it significantly reduces time consumption while offering current-signal-based prediction results within the tested range.
4. The CNN–ResNet–RF model demonstrates stable prediction performance on independent experimental test data from the designed milling experiments, indicating its potential for spindle-current-based force monitoring. Its applicability outside the tested materials, cutting parameters, and machine-tool configuration should be further examined using additional external validation experiments.

The present study has two experimental limitations. First, the validation dataset includes only two workpiece materials, 7075 aluminum alloy and steel 45. Second, the cutting parameters cover a limited range, with a fixed spindle speed and feed per tooth and only selected levels of axial and radial depths of cut. Therefore, the reported prediction performance should be interpreted as validation within the tested machining range rather than evidence of universal generalization. Future work will extend the dataset to additional workpiece materials, spindle speeds, feed per tooth values, axial and radial depths of cut, tool geometries, tool-wear states, and machine-tool platforms. External validation under these expanded conditions will be required to further evaluate the cross-condition generalization capability of the proposed CNN–ResNet–RF model.

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Abbreviations

The following abbreviations are used in this manuscript:

T	The total torque of the motor
T_a	Moment of inertia
T_c	Cutting torque
T_f	Moment of friction
T_d	Disturbing moment
J	Inertia of rotating parts
F	Milling force
r	Tool radius
A	Constant
K	Motor torque constant
I_{rms}	Equivalent current
I_u, I_v, I_w	Three-phase alternating currents

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