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Prediction of Gear Deviations in Dry Hobbing Process Based on CNN-BiLSTM

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Abstract: Dry hobbing is an advanced gear machining technology widely used in automotive manufacturing due to its high efficiency, cost-effectiveness, and environmental benefits. As the demand for high-precision gear production continues to rise, achieving consistent machining accuracy remains a critical challenge. To address this issue, this paper proposes an in-situ deviation prediction model for dry hobbing, integrating machining parameters and vibration data. First, time-frequency domain dynamic features of spindle vibrations during dry hobbing are extracted, while machining parameters such as hob rotational speed and axial feed rate are incorporated as static features. These fused features are then used to train an in-situ prediction model based on a CNN-BiLSTM architecture. Furthermore, Bayesian optimization is employed to fine-tune the hyperparameters of the model. The proposed approach is validated using test and verification datasets, with results demonstrating that the fusion of static and dynamic features significantly enhances prediction accuracy. This in-situ prediction model provides manufacturers with a valuable tool for real-time monitoring and control of gear deviations in industrial production.

Keywords: Dry hobbing; Gear deviations; Feature fusion; long short-term memory.

1. Introduction

Gears are fundamental mechanical components essential for power and motion transmission. They play a critical role in various industries, including instrumentation, automotive manufacturing, shipbuilding, and railway transportation. As the demand for high-precision gears continues to grow [1], ensuring machining accuracy has become increasingly important.In high-speed dry hobbing, the combination of large machining parameters and the absence of metal cutting fluids leads to elevated workpiece temperatures, resulting in significant dimensional errors, particularly in tooth thickness [2]. Traditional gear accuracy inspection relies on offline measurements conducted at dedicated metrology centers, which are time-consuming, costly, and unsuitable for real-time monitoring. However, advancements in intelligent manufacturing, in-situ measurement, and machine learning have significantly improved inspection accuracy, efficiency, and automation. These developments make in-situ measurement a promising alternative to conventional inspection methods. Therefore, developing rapid and precise gear accuracy inspection techniques is essential for achieving high-efficiency, high-precision dry hobbing.

Gear accuracy is a critical indicator of machining quality and transmission performance, encompassing geometric accuracy, meshing accuracy, and surface quality. Compared to offline measurement, on-machine measurement eliminates clamping errors, enhancing assessment reliability. Kong et al. [3] improved the accuracy of flank deviation measurement for face gears by compensating for probe motion direction errors (PMDE).Mathematical analytical modeling and data-driven approaches are the two primary methodologies for in-situ gear quality assessment [4]. In the domain of analytical modeling, Luo et al. [5] investigated the effects of different pitch deviations and random pitch deviations on the vibration acceleration and dynamic transmission error (DTE) of gear pairs. Wang et al. [6] applied reverse engineering techniques to reconstruct gear models and simulated the variation curve of the gear center distance to calculate total radial composite deviation and inter-tooth radial composite deviation. Chen et al. [7] developed a mathematical model to simulate tooth flank topography in high-speed dry hobbing and analyzed its sensitivity to process parameters and hob geometry. In addition to mathematical modeling, Klocke et al. [8] introduced the SPARTApro® software, which predicts gear deviations by simulating the dry hobbing process based on geometric penetration calculations. Ding et al. [9] analyzed the impact of machine tool geometric errors on gear accuracy, establishing an analytical mapping between gear deviations and machine tool geometric errors. Deng et al. [10] explored the correlation between force-induced errors and tooth profile deviations in dry hobbing using numerical simulation methods.

Although physics-based modeling and simulation-driven approaches offer improved interpretability in gear deviation prediction, accurately modeling gear deviations remains challenging due to the complexity of evaluation metrics and the uncertainty of model inputs [11]. Consequently, mathematical analytical modeling alone is often insufficient for assessing gear geometric deviations in real-world production environments.Data-driven approaches leverage large-scale monitoring data to capture the complex relationships between machining parameters and gear deviations. Vibration monitoring has proven to be an effective technique for evaluating machining quality, as gear deviations are closely linked to the dynamic behavior of the machining process. Jia et al. [12] employed vibration signals as input to develop a capsule neural network-based classification model for hobbing accuracy prediction, enabling real-time evaluation of hobbing precision. Lin et al. [13] proposed an improved PSO-BP-PSO algorithm based on measured geometric deviations to establish a predictive model linking honing parameters to gear geometric deviations. Wang et al. [14] integrated mechanistic and data-driven models in a parallel structure using digital twin (DT) technology to construct a DTM model. By comparing DTM model predictions with measurement results, their work provided a reference for non-contact dynamic gear measurement methods. In milling, Lu et al. [10] utilized Gaussian process regression to develop a predictive model for workpiece surface accuracy and analyzed correlations between cutting speed, feed rate, cutting depth, and surface accuracy. Wu et al. [15] constructed an improved correlation analysis random forest model based on experimental data, using inherent parameters (e.g., gear diameter, module) and hobbing process parameters as inputs to predict hobbing accuracy.Radial composite deviation is a key indicator for evaluating gear transmission accuracy. However, existing studies struggle to adapt to variations in actual machining conditions, posing challenges for real-time assessment of machining accuracy.

This paper is the first time to predict gear deviations by fusing the dynamic features from in-process vibration signals and the static features of hobbing process parameters, achieving better prediction accuracy compared to the models merely with process parameters or monitored vibration data.Then, a novel in-situ gear deviations prediction model based on CNN-BiLSTM is proposed based on the fused dynamic and static features.Finally, experiments on dry hobbing verify that the developed model is significantly better than traditional data-driven models. It provides a promising solution for substituting the "post-process" inspection step with the in-situ inspection of gear deviations.

After that, Section 2 provides a brief introduction to the dry hobbing process, feature extraction and fusion methods, and the development of the CNN-BiLSTM-based gear deviation prediction model. Section 3 presents a detailed description of the hobbing experiment. Section 4 reports the prediction results and compares them with other commonly used data-driven methods. Section 5 concludes our study and discusses potential future research directions.

2. Research Methods

Dry hobbing is widely employed for the tooth shaping of external cylindrical gears with high efficiency, low machining cost, and environmentally friendliness. In the dry hobbing process, the hob is meshed with the gear workpiece in crossed axis in a way similar to a pair of worm and gear set, as shown in Figure . The gear workpiece rotates synchronously with the hob rotation in accordance with the strict transmission ratio to form the involute tooth profile. Simultaneously, the hob feeds in the workpiece axial direction to generate the entire tooth profile with the workpiece width.

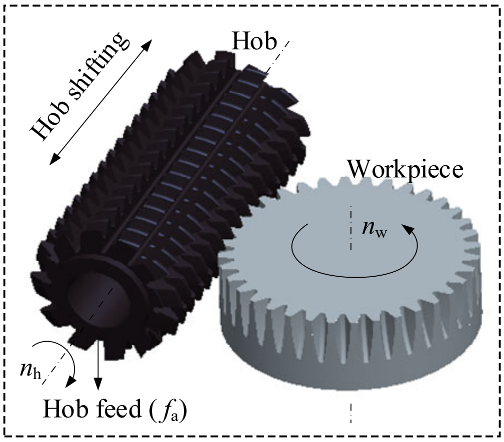

Figure 1. Kinematic relationship of hobbing

Theoretically, due to the kinematic coupling of the hob and workpiece, feed marks and generated cuts, collectively known as envelope error at the tooth flank, are inevitably resulted, The envelope error mostly depend on the hob feed rate, hob diameter, and the number of hob flutes and threads [13], which do not need to be considered in the standard gear inspection procedure. cumulative pitch deviation (F_p), and radial runout (F_r), are adopted as the key deviation indicators to assess the geometrical accuracy of the hobbed gear.

According to the short-period and long-period properties of gear deviation items, analyzing time-series vibrations is more effective for the gear deviation prediction. the variations in the hobbing parameters, such as the hob rotation speed and feed rate, will change the cutting forces, and these have a direct impact on gear deviations. Thus, real-time monitored vibration data and hobbing process parameters should be simultaneously adopted to effectively estimate gear deviations in the dry hobbing process.

The prior knowledge of machining information of hobbing parameters can help to improve the prediction accuracy and generalization ability of the data-driven models. After determining the design parameters of hob and gear processing, the static processing parameters to be adjusted by gear hobbing machine include: Fa (feed rate) and S (speed). The monitored cutting vibrations, resulting from nonlinear cutting forces and machine tool dynamics, are closely related to gear geometrical deviations. However, vibration signals are often contaminated by industrial noise and exhibit varying data lengths under different hobbing parameters. Thus, denoising and temporal alignment of vibration signals are crucial for accurate dynamic feature extraction, as shown in Figure.

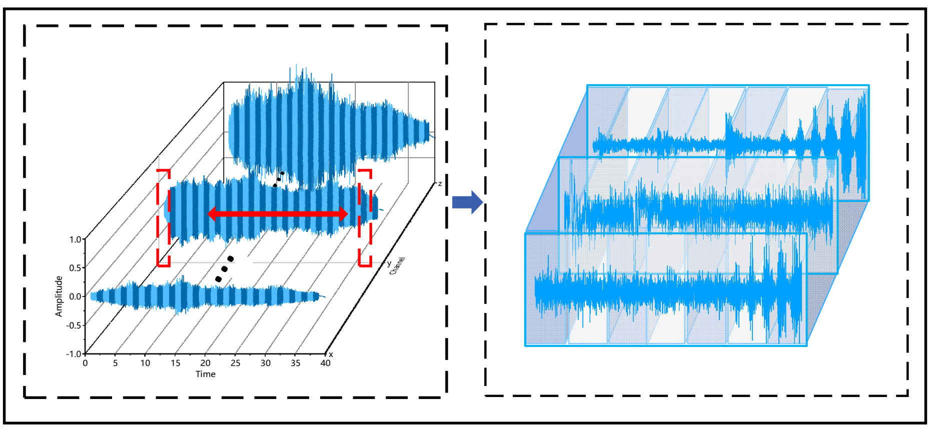

Figure 2. The vibration signal.

Compared to directly acquired raw vibration signals, extracted dynamic features reveal intrinsic patterns and characteristics from multiple dimensions. Integrating this information significantly enhances the model's ability to recognize complex patterns, thereby accurately mapping gear deviations to vibration signals in a high-dimensional space. Specifically, time-domain features intuitively reflect the temporal evolution of vibration signals, while frequency-domain features reveal the distribution of different frequency components. The selected features are shown in Table.To effectively reduce noise interference, this study employs a denoising method combining improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) and power spectrum analysis, ensuring signal purity and the reliability of analytical results. Additionally, to prevent feature degradation due to long-term signal variations, the signal is segmented into fixed-length segments (1024 points) to capture local variation patterns. Ultimately, the extracted machining features consist of static features representing machining parameters and dynamic features characterizing cutting vibrations. To structurally represent hobbing features, the extracted features are arranged in vector form, as shown in formula (1):

$$\psi_{i,j} = \begin{bmatrix} (\varphi_{st}^{fa}, & \varphi_{st}^{s} & , & \varphi_{dy}^{t} \ldots, & \varphi_{dy}^{f} \cdots)^{1} \\ \vdots & & , & \vdots & \\ (\varphi_{st}^{fa}, & \varphi_{st}^{s} & , & \varphi_{dy}^{t} \cdots, & \varphi_{dy}^{f} \cdots^{n} \end{bmatrix} \quad (1)$$

Here, i represents the gear sample, j denotes the number of sample segments, st and dy correspond to static and dynamic features, respectively. fa and s indicate feed rate and spindle speed, while t and f represent time-domain and frequency-domain features. n denotes the number of data segments.

Table 1. The selected features

Static Fearture	Dynamics Fearture	
Fa	mean	Shape factor
S	std	Crest factor
	var	skewness
	peak	kurtosis
	peak2peak	energy

Convolution (Conv) serves as the foundation of the CNN architecture[16]. During forward propagation, it utilizes convolution kernels of various sizes and stride movements to learn multi-level feature representations from raw features, establish connections, share weights across channels, and pass them to the next layer of the network. Its classic architecture is illustrated in FigureThe convolution operation is defined as follows in formula (2):

$$Z_i^l = f \times (w_i^l * x^{l-1} + B_i^l) \quad (2)$$

where Z_i^l represents the convolution output, f is the Rectified Linear Unit (ReLU) activation function, w_i^l is the ith convolution kernel in the lth layer, denotes the convolution operation, x is the output from the l-1th layer, and Bil is the corresponding bias term.

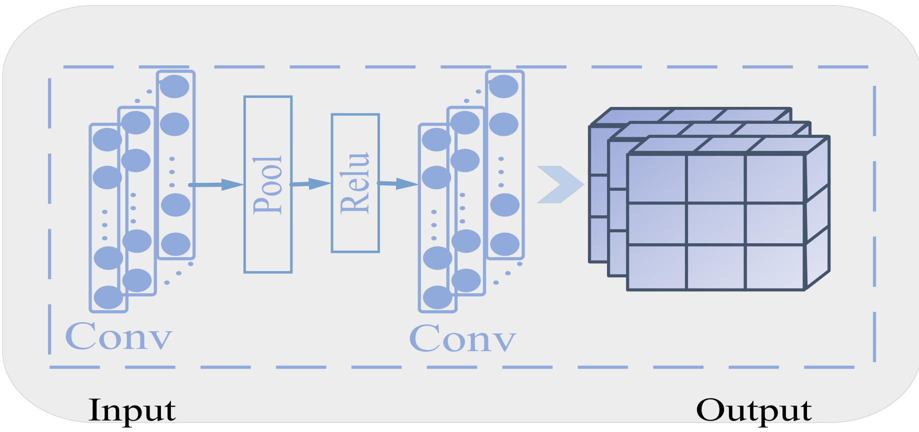

Figure 3. The CNN architecture

The selection of convolution kernel size is crucial in convolutional neural networks. In the gear hobbing process, convolution kernels of different sizes can capture information at different scales, enabling the identification of subtle precision variations caused by changes in machining parameters and vibration characteristics. If only a single convolution kernel size is used in the network, some information may inevitably be lost during representation learning, thereby affecting prediction accuracy. To enhance CNN's ability to capture global information, multiple convolution kernels of different sizes are employed to process feature maps, along with nonlinear activation functions for feature transformation. Subsequently, a Dropout layer is applied for random feature dropping to enhance the model's generalization capability. Since the generated tooth surface along the machining path exhibits strong temporal dependence, omitting the pooling operation is a reasonable choice to preserve the time dimension of hobbing process features.

As a complement, BiLSTM leverages its memory mechanism to capture dynamic changes in the time dimension along the machining path. The sequential feature maps extracted by the CNN are fed into the BiLSTM network layer to capture their dynamic characteristics, significantly improving prediction accuracy. This provides strong support for achieving high precision and stability in the hobbing process. Figure illustrates the LSTM unit model. Long Short-Term Memory (LSTM) introduces a gating mechanism that enables handling long-sequence dependencies. However, LSTM processes data dependencies only in a single direction—i.e., from past data. Bidirectional LSTM (BiLSTM) extends LSTM by adding a backward propagation path, allowing sequential features to be processed in both forward and backward directions. This bidirectional mechanism enables the network to comprehensively capture dependencies between time steps, thereby preserving critical information in sequential data more effectively.

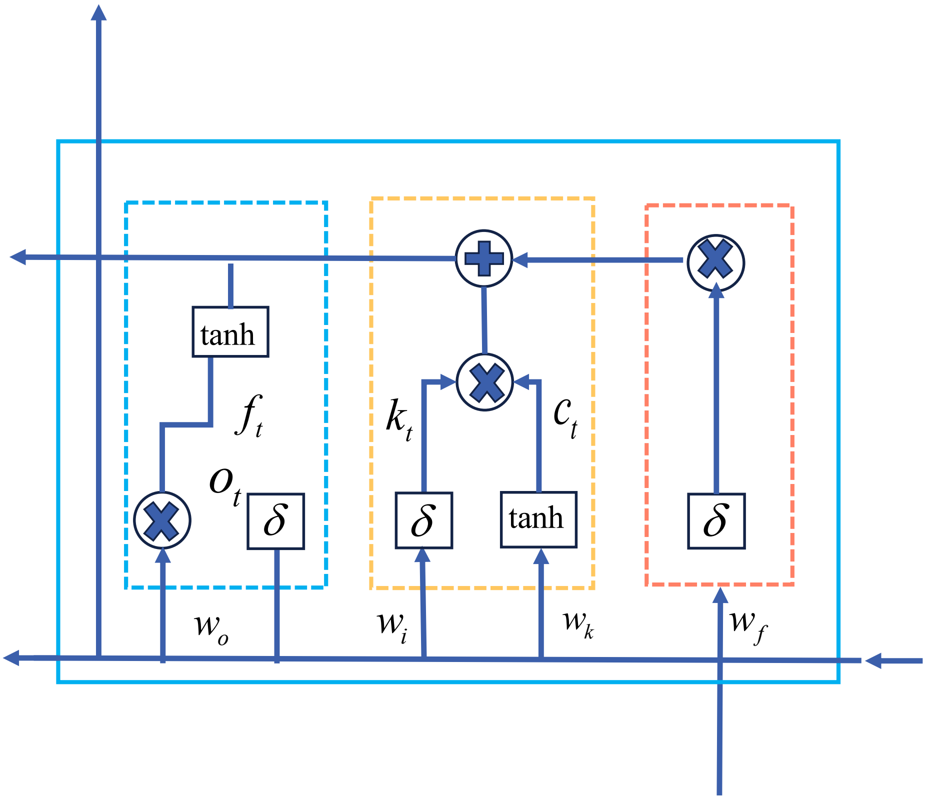

Figure 4. The LSTM network structure

Figure illustrates the BiLSTM network structure. Have input weights, cycle weights, and deviations for input gates, forget gates, and output gates. Where f k. I and o are forgetting gate, unit state, input gate and output gate respectively. The expressions for these doors are as follows in formula (3).

$$\begin{cases} f_t = \delta(W_f x_t + R_f h_{t-1} + B_f) \\ k_t = \tanh(W_k x_t + R_k h_{t-1} + B_k) \\ i_t = \delta(W_i x_t + R_i h_{t-1} + B_i) \\ o_t = \delta(W_o x_t + R_o h_{t-1} + B_o) \end{cases} \tag{3}$$

Then, the unit state and output state at time step T are obtained in formula (3) and (4):

$$c_t = f_t \bullet c_{j-1} + k_t \bullet o_t \tag{4}$$

$$h_t = o_t \bullet \tanh(c_t) \tag{5}$$

Where ct is the unit state of LSTM, σ is the activation function, and the Sigmoid function with an output range of (0-1) is selected to indicate the opening degree of the gate unit; The operator “.”esents the pointwise multiplication of two vectors. The final output of bilstm can be expressed as in formula (6):

$$\begin{aligned} A_i &= f_1(w_1 x_i + w_2 A_{i\text{-}1}) \\ B_i &= f_2(w_3 x_i + w_4 B_{i\text{-}1}) \\ h_i &= f_3(w_5 A_i + w_6 B_i) \end{aligned} \tag{6}$$

Where, f_1、f_2 *and* f_3 are the activation functions of each layer respectively, $\boldsymbol{x_i}$ is the input of $\boldsymbol{t_i}$ （i = 1, 2, … , t） , $\boldsymbol{h_i}$ and $\boldsymbol{h'_i}$ are the LSTM hidden states of forward and backward iterations respectively, y_i is the output, and ω_i is the weight of each layer. The extracted content is encoded into the hidden output state sequence y. Finally, the output results are regressed and predicted through the full connection layer, which is used to determine the machining error caused by the change of machining parameters and machining vibration, and then represent the machining accuracy of the gear, that is, the tag.

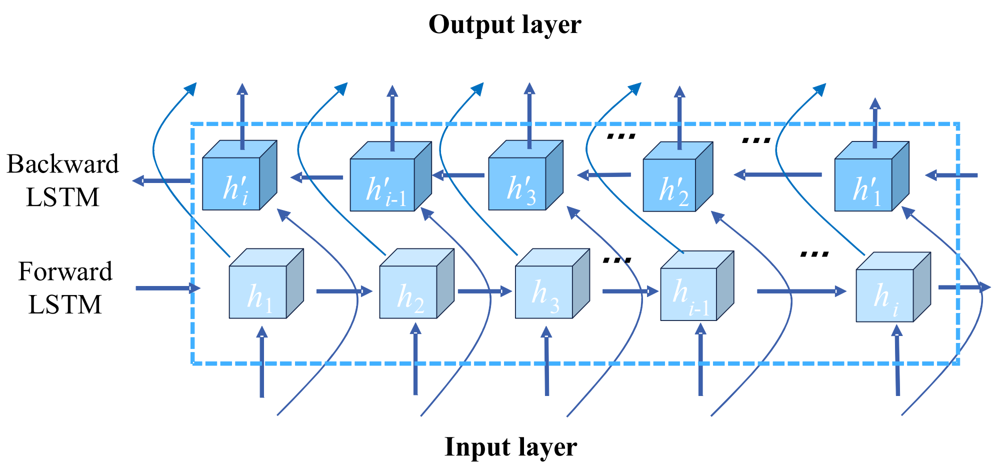

Figure 5. The BiLSTM network structure

To effectively mitigate the overfitting problem during model training, this study employs the Dropout technique to optimize the neural network. Dropout randomly deactivates a portion of neurons during training with a certain probability, reducing the model's dependence on specific neurons and thereby enhancing generalization ability. In this study, the Dropout probability is set to 0.25. Figure illustrates the network structure of the CNN-BiLSTM hybrid prediction model.

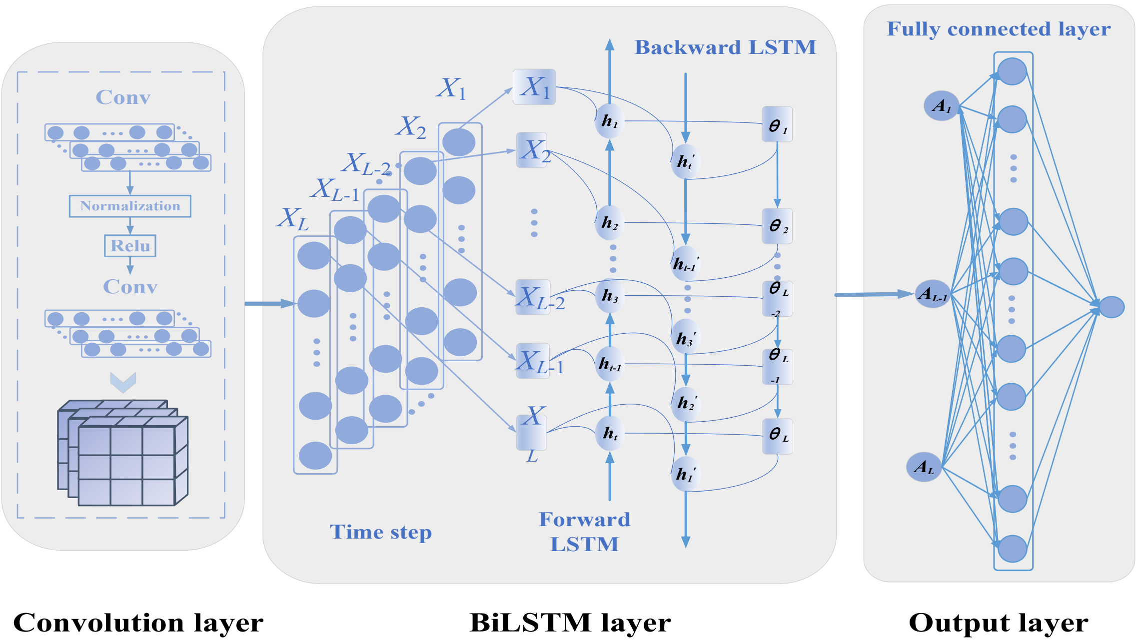

Figure 6. The CNN- BiLSTM network structure

3. Gear Hobbing Experiment

Due to the staggered structural design and cutting characteristics of the hobbing machine, it is extremely difficult to place sensors inside the machine to obtain vibration data at the ideal cutting point. To capture the vibration data along the x-direction of the hob spindle, the measurement point was set at the spindle-end bearing, simulating the vibrations of the hob during the cutting process. In this paper, a high-speed dry hobbing machine (YE3115CNC) is used, which is manufactured by Chongqing machine tool plant. According to ISO 1328, it has a maximum processing capacity of 6 levels. As shown in Figure, the hob is mounted on the tool holder, and a tri-axial accelerometer (PCB-356A16) is installed at the spindle-end bearing. The sensor's orientation corresponds to the machine tool's coordinate system (x, y, z). Data acquisition was performed using an NI 9231 data acquisition card to facilitate signal collection and processing. The parameters of the processed gear are shown in Table.

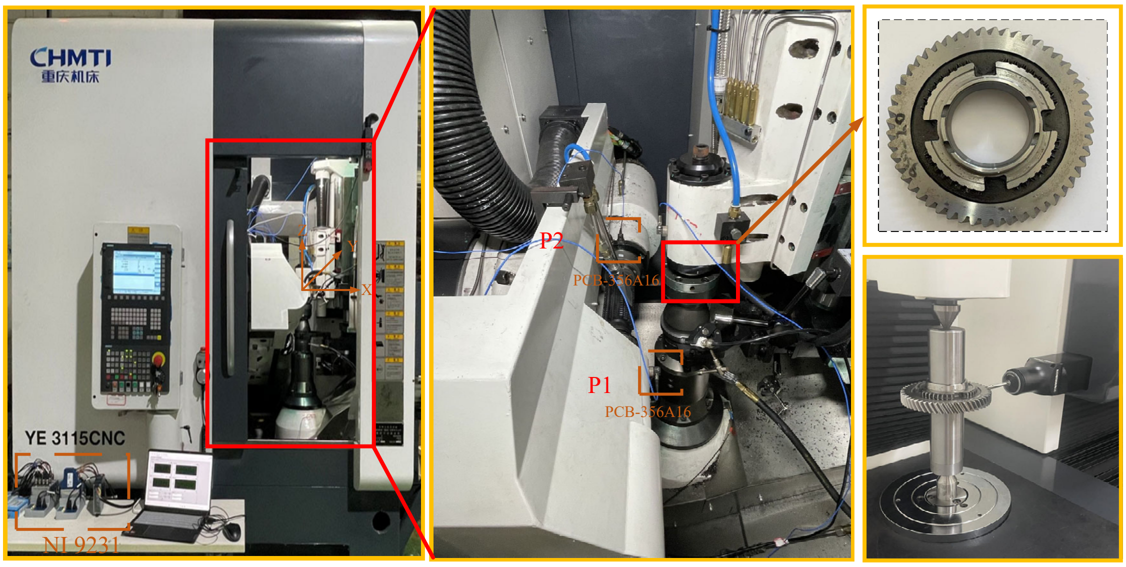

Figure 7. The experimental frame

It is important to note that during the cutting-in and cutting-out phases, the hob teeth do not fully engage in the cutting process, resulting in signal characteristics that differ significantly from those observed during full cutting engagement. Additionally, useless signals from the pre-start and reset phases can negatively impact model training and prediction. To address this issue, this study employs the root mean square error (RMSE) of the machining current signal to identify and extract the complete cutting process.

Table 2. Experimental parameters of gear hobbing

Gear number	Feed	Speed
1:30	0.5:0.5:3.0	550:100:950

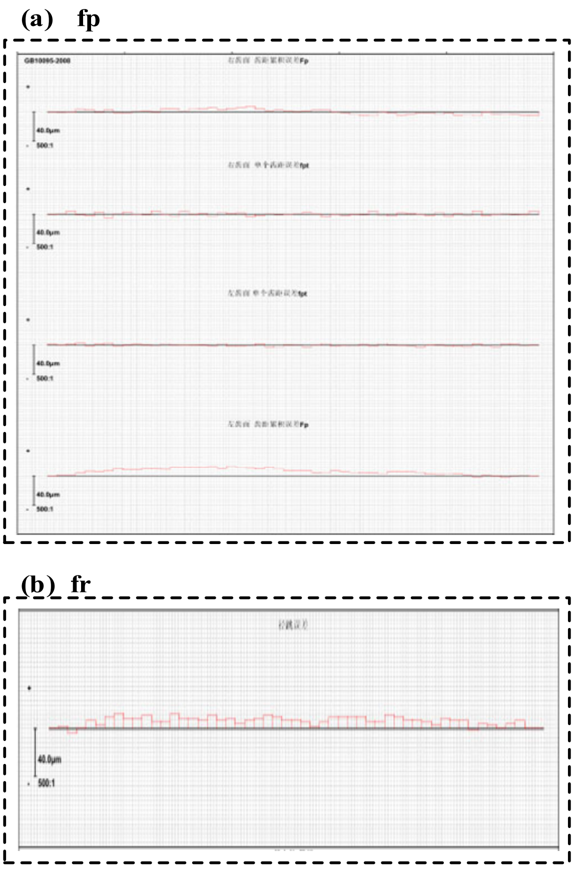

Figure 8. The precision inspection results about Fp and Fr

In this paper, the vibration data in X and Z directions of P1 and P2 points are obtained respectively. The hobbing vibration sequence is sliced by sliding algorithm. Under the condition of time window length L and length n, samples data are produced from 30 hobbing vibration sequences.In order to accurately measure the cumulative pitch error (Fp) and radial runout error (Fr) of gears, a three-dimensional gear tester is used for measurement. The measurement data is then used to generate accuracy level labels, as shown in Figure.In order to prevent the uneven distribution of features in different dimensions, leading to the reduction of prediction accuracy and slow training convergence, the data must be normalized before being sent to the neural network model. The dataset will be normalized. In the prediction of hobbing quality, Bayesian optimization algorithm is used to optimize the super parameters in the model, which overcomes the subjectivity and empiricism of manual selection, and takes into account the prediction accuracy and calculation amount.

The proposed framework is constructed using MATLAB 2024a. The network structure of the model includes sequence input layer, convolution layer, bidirectional LSTM layer, complete connection layer, drop layer and classification layer. In the sequence input layer, the sample matrix is controlled according to the time step L and the selected time-frequency characteristics. The label of each matrix is predicted in the classification layer.The matrix is marked according to the gear number, so the number of hidden states of the LSTM network is set to 2. In order to study the effectiveness of static and dynamic feature fusion strategy, two evaluation models were developed using different data sets A1 (static and dynamic fusion feature) and B1 (vibration feature).

4. Results and Discussions

Based on the above theoretical basis, the CNN-Bilstm framework is proposed in this study, and the gear classification model is constructed for the accuracy indexes FP and fr. The model is trained and tested using the data set integrating static and dynamic features. In order to verify the effectiveness of this method, the input sample matrix is extracted from the gear machining feature sequence and used as the network input. The data set was divided into training set, verification set and test set. In order to ensure the uniform distribution of categories, samples were taken for each accuracy category as the test. The confusion matrix of the model in the X direction of A1 and B1 data sets is shown in Figure .

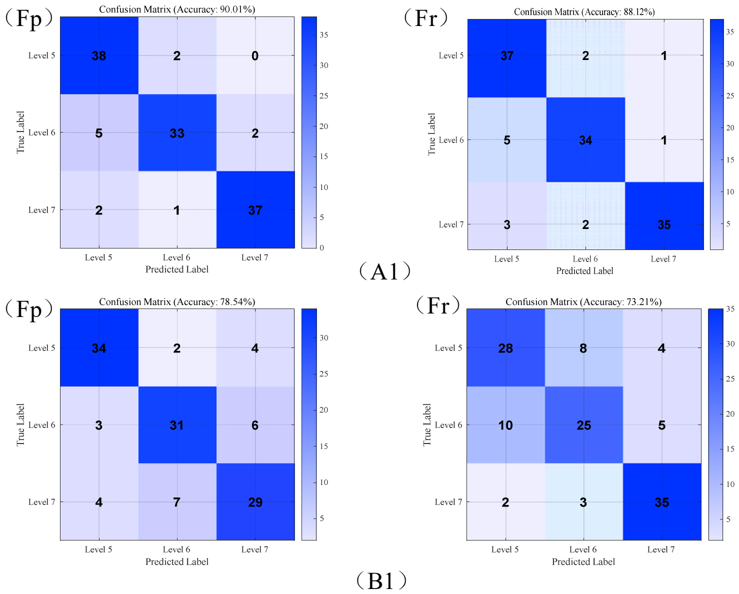

Figure 9. The Confusion Matrix of Prediction Results in the X Direction

Table illustrate the accuracy of accuracy classification, respectively. The evaluation results show that the proposed evaluation framework is usually effective. The prediction results at P1 and P2 are different, which may be that the vibration signal at P1 is more ideal, with less noise and interference, and it is an ideal data acquisition point. In addition, the prediction performance of the model in the X direction is higher than that in the Z direction, and Fr and Fp have the same sensitive vibration direction. For a given evaluation index Fr and Fp, the effectiveness of the vibration signal changes with the sensor acquisition point and channel direction. Tables.3 Model evaluation results

Table 3. The evaluation results

Data Set	Deviations	P1 Accuracy(%)		P2 Accuracy(%)	
		x	z	x	z
A1	Fp	90.01	86.34	79.24	76.54
	Fr	88.12	84.57	84.16	78.47
B1	Fp	78.54	76.24	77.14	74.23
	Fr	73.21	69.75	65.21	64.86

The maximum prediction accuracy of cumulative pitch error and radial runout is 90.01% and 88.12% respectively. It should be noted that the accuracy varies with the time window L and the vibration direction. As shown in Figure.

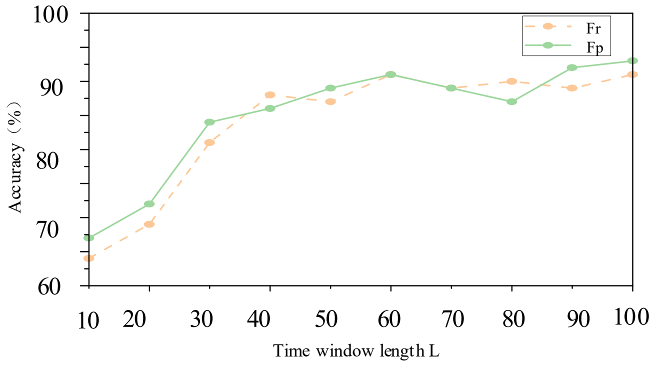

Figure 10. The prediction accuracy under different time window lengths

To comprehensively evaluate the feasibility and advantages of the proposed CNN-BiLSTM framework, we conduct a comparative analysis of its predictive performance against several classic models, including CNN and GRU. The experimental results indicate that the CNN-BiLSTM model exhibits superior capability in processing vibration sequence data, significantly outperforming other models in terms of accuracy, robustness, and generalization ability. This improvement can be attributed to the complementary strengths of CNN and BiLSTM, where CNN effectively captures spatial features, while BiLSTM enhances temporal dependencies by processing sequential data bidirectionally.

The combination of these two architectures enables the model to extract more informative representations from complex vibration signals, leading to more precise and reliable predictions.

5. Conclusion and Future Work

In this study, a gear deviation prediction model is proposed by integrating the dynamic features of hobbing vibration signals with the static features of hobbing process parameters. Compared to models that rely solely on machining parameters or vibration signals, the proposed approach significantly enhances prediction accuracy. Based on this, a CNN-BiLSTM model is developed to effectively capture the spatiotemporal bidirectional features of hobbing vibrations, addressing the limitations of traditional network architectures (such as CNN and GRU), which are restricted to local feature extraction. This approach substantially improves the model's predictive accuracy during training.

The experimental results demonstrate that:

(1) The proposed method effectively evaluates the cumulative errors of gear pitch and radial runout.

(2) The fusion of static and dynamic features improves the model's predictive performance.

(3) The cumulative errors of gear pitch and radial runout exhibit sensitivity to specific vibration directions.

While the proposed approach demonstrates promising results, several areas warrant further investigation. Future research will focus on the following aspects: Feature Enhancement: The inclusion of additional sensor data, such as acoustic signals or cutting force measurements, could provide a more comprehensive understanding of the hobbing process and further improve prediction accuracy. Model Optimization: Exploring advanced deep learning architectures, such as attention mechanisms or Transformer-based models, may enhance the model's ability to capture long-range dependencies and refine feature extraction. Real-time Implementation: Developing an efficient real-time monitoring and prediction system for gear manufacturing could enable early detection of deviations, improving production efficiency and reducing defect rates.

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References

[1] Li Q, Liang S Y. Weak Crack Detection for Gearbox Using Sparse Denoising and Decomposition Method[J]. IEEE Sensors Journal, 2019, 19(6): 2243-2253.

[2] Cao H, Zhu L, Li X, et al. Thermal error compensation of dry hobbing machine tool considering workpiece thermal deformation[J]. The International Journal of Advanced Manufacturing Technology, 2016, 86(5-8): 1739-1751.

[3] Kong W, Dong J, Xiao Y, et al. A novel method to improve on-machine measurement accuracy for face gear tooth flank deviation[J]. Journal of Manufacturing Processes, 2024, 128: 19-40.

[4] Ren H, Yin A, Song W, et al. Vibration Monitoring With Dependencies Attention for Gear Hobbing Quality Evaluation[J]. IEEE Sensors Journal, 2020, 20(22): 13726-13733.

[5] Luo Y, Xu L. Contact dynamic modeling and corner contact analysis of the spur gear pair with pitch deviations[J]. Mechanical Systems and Signal Processing, 2025, 227: 112377.

[6] Wang Y, Wang G, Fan Y, et al. A virtual measurement method for evaluating the gear radial composite deviation based on point cloud data[J]. Results in Engineering, 2024, 22: 102380.

[7] Chen Y, Liu X, Yang X, et al. Investigation on Geometrical Morphology of Tooth Surface Finished by Green High-Speed Dry Hobbing for Gear Precision Machining[J]. International Journal of Precision Engineering and Manufacturing-Green Technology, 2023, 10(5): 1141-1154.

[8] Klocke F, Brecher C, Löpenhaus C, et al. Calculating the Workpiece Quality Using a Hobbing Simulation[J]. Procedia CIRP, 2016, 41: 687-691.

[9] Ding S, Chen Z, Zhang H, et al. Gear evaluation deviations-based crucial geometric error identification of five-axis CNC gear form grinding process[J]. Journal of Manufacturing Processes, 2023, 99: 663-675.

[10] Deng F, Tang Q, Li X, et al. Study on mapping rules and compensation methods of cutting-force-induced errors and process machining precision in gear hobbing[J]. The International Journal of Advanced Manufacturing Technology, 2018, 97(9-12): 3859-3871.

[11] Attia H, Sadek A, Altintas Y, et al. Physics based models for characterization of machining performance – A critical review[J]. CIRP Journal of Manufacturing Science and Technology, 2024, 51: 161-189.

[12] Jia Y, Li G, He K. Classification prediction of gear hobbing precision and iterative adjustment of process parameters[J]. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 2022, 44(11): 517.

[13] Lin X, Liu Y, Sun S, et al. Prediction and optimization of gear skiving parameters and geometric deviations[J]. The International Journal of Advanced Manufacturing Technology, 2022, 121(5-6): 4169-4185.

[14] Wang Y, Wang G, Xu H, et al. A prediction model of gear radial composite deviation based on digital twin mesh[J]. Measurement, 2025, 240: 115619.

[15] Wu D, Yan P, Guo Y, et al. Integrated optimization method for helical gear hobbing parameters considering machining efficiency, cost and precision[J]. The International Journal of Advanced Manufacturing Technology, 2021, 113(3-4): 735-756.

[16] Arbib M A. The Handbook of Brain Theory and Neural Networks[M]. 2nd ed. The MIT Press, 2002.