A Time-Aware CNN-BiLSTM-Attention Model for Short-Term Track geometry irregularity deterioration

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Abstract. Track geometry irregularity deterioration is a key factor affecting railway operation safety, and its accurate prediction is of great significance for guiding maintenance departments in scientifically formulating maintenance plans. The short-term prediction of track geometry irregularity deterioration faces three main challenges. These include coordinated analysis of multiple parameters, handling non-fixed detection intervals, and extracting spatiotemporal features. This study proposes a CNN-BiLSTM-Attention-based method for short-term prediction of track geometry irregularity deterioration. The method addresses parameter coupling effects via a coordinated modeling framework of key parameters, captures non-fixed detection interval features using a time-aware attention mechanism, and enhances spatiotemporal feature analysis by combining CNN spatial feature extraction with BiLSTM temporal modeling.
The study selected a 47.6 km section of China's Jin-Shan Line and validated the method using 21 months of track geometry cars data. Results indicate that the R^2 values for track cross level attained 0.993, with MAPE for all parameters maintained within 5%, demonstrating quantifiable improvement in evaluation metrics compared to baseline models. The research results can provide technical support for railway maintenance departments to monitor track conditions and optimize maintenance plans.

Keywords: Track geometry, Time-aware attention, Deterioration.

1 Introduction

The railway transportation system, recognized as one of the most sustainable transportation infrastructures globally, serves as a fundamental pillar in national economic development. Track geometry undergoes progressive deterioration due to multifaceted factors, with resultant deviations impacting safety and comfort [1]. Industry analytics [2] indicate the global railway sector allocates over $32 billion annually toward track maintenance. To ensure safe operations while controlling costs, railway departments are shifting toward condition-based proactive maintenance, requiring high-frequency detection. Railway practitioners use Track Geometry Cars (TGC) for inspections [3], but due to high costs, inspection intervals are long—twice monthly in China, while Dutch lines are inspected biannually [4]. Under existing detection conditions, studying deterioration patterns and predicting development trends has practical significance for maintenance strategies, optimizing costs, and ensuring safety [5,6].

In addressing the critical challenge of track geometry irregularity deterioration prediction, contemporary research frequently employs composite indicators such as Track Quality Index (TQI) or Track Geometry Index (TGI) for quantitative assessment of track geometry conditions. These comprehensive metrics synthesize multiple fundamental parameters, including left/right longitudinal level (left/right LL), left/right alignment, rail gauge, track cross level, and twist parameters. Empirical investigations have established that each constituent parameter independently contributes significant diagnostic value to overall track condition assessment [7], necessitating multivariate modeling approaches. Track geometry deterioration prediction methods can be broadly classified into traditional models and machine learning models [8]. Traditional models include statistical regression models and stochastic process models. Hamid [9] used a stepwise regression model to predict TQI, Chang et al. [10] established personalized multi-stage linear models of track geometry state deterioration for each section to predict TQI, and An et al. [11] proposed an improved track geometry deterioration model using Weibull distribution to accurately estimate the tamping cycle for each track section. Quiroga and Schnieder [12] evaluated the probability distribution of deterioration through Monte Carlo simulation. However, in engineering practice, track geometry irregularity deterioration is essentially a complex spatiotemporal process driven by multiple parameter coupling and heterogeneous factors (traffic loads, environmental conditions, line geometric features) [13]. Existing research indicates that traditional models still have room for further optimization when dealing with multi-source heterogeneous factors and their non-linear relationships [14].

With advances in computer science, machine learning-based prediction techniques have been widely applied in the field of track engineering [15]. Research progress is mainly reflected in two levels: At the traditional machine learning level, scholars have successively proposed TQI prediction accuracy improvement methods integrating grey model GM(1,1) with probabilistic support vector machine (PSVM) [16], and random forest algorithms applied to rail gauge prediction [17]. Additionally, to address data imbalance issues, Wang et al. [18] employed data oversampling techniques and gradient boosting methods to predict geometric defect occurrence rates. In terms of deep learning methods, existing research includes spatiotemporal neural network models for rail break prediction based on ResNet-Transformer architecture [19], deep learning systems for rail surface defect prediction and track quality assessment [20], and deep learning methods extended to turnout detection [21]. Notably, Han et al. [4] achieved long-term prediction of longitudinal level irregularities, while the CNN-LSTM model proposed by Wang et al. [13] significantly improved track geometry parameter prediction performance through spatiotemporal feature extraction.

Liu et al. [22] indicated that there are certain differences between track geometry irregularity detection data and the data requirements for machine learning: on one hand, the relatively large sampling intervals result in a limited total number of samples. On the other hand, the detection data exhibits a degree of temporal non-uniformity, which does not fully align with the characteristics of large-scale and uniformly sampled data typically required by conventional machine learning methods. For processing non-equidistant time series data, researchers have proposed various approaches, including weight conversion methods based on decay functions [23], direct prediction models using improved gated recurrent units [24], and time-aware LSTM architectures specifically designed to handle irregular intervals [25]. Notably, CNN-BiLSTM models that combine CNN's feature extraction capabilities with BiLSTM's time series modeling advantages have demonstrated promising performance in multiple fields, including bearing fault diagnosis [26], power load forecasting [27], residential electricity consumption prediction [28], and sea level height prediction [29].

Based on these findings, we propose a time-aware CNN-BiLSTM-Attention model for short-term track geometry deterioration prediction. This approach aims to overcome limitations in existing research, such as focusing on single parameters, ignoring coupling effects between parameters, assuming track inspection data as equally-spaced time sampling, and neglecting non-equidistant detection characteristics. The main contributions of this method are as follows:

(1) Construction of a joint prediction framework for seven key parameters, achieving coordinated modeling of these parameters through feature sharing mechanisms and parameter-specific prediction layers.

(2) Proposal of a non-equidistant sequence modeling method based on time-aware attention mechanisms, enhancing the model's adaptability to irregular time intervals in track detection data.

(3) Application of a combined CNN and BiLSTM structure to process track geometry irregularity data, providing empirical research for deep learning applications in this field.

The structure of this study is arranged as follows: The second section elaborates on the short-term prediction problem of track geometry irregularity deterioration. The third section details implementation details of the prediction method. The fourth section provides validation using the Jin-Shan Line engineering case, and the fifth section summarizes the research findings and discusses prospects for engineering applications.

2 Problem Description

This research focuses on the short-term prediction problem of track geometry irregularity deterioration. Within China's railway maintenance protocols, track infrastructure is systematically segmented into standardized 200-meter sections, as illustrated in Fig. 1. For any track section i ($i = 1, 2, ..., N$)at time point t_j , the track geometry irregularity state vector can be represented as a seven-dimensional vector:

$$X_i(t_j) = [h_l(t_j), h_r(t), a_l(t_j), a_r(t_j), l(t_j), g(t_j), d(t_j)]^T \in \mathbb{R}^7 \tag{1}$$

Where $h_l(t_j), h_r(t_j)$ represents left/right LL, $a_l(t_j), a_r(t_j)$ represents left/right alignment, $l(t_j)$ represents track cross level, $g(t)$ represents rail gauge, and $d(t_j)$ represents twist. The lower half timeline of Fig. 1 shows the observational data characteristics of a typical track section in the time window $T = \{t_1, t_2, ..., t_n\}$: (1) Non-equidistant sampling characteristics, with adjacent detection intervals $\Delta t_j = t_{j+1} - t_j$ showing significant time-varying properties, ranging from days to months. (2) Dynamic evolution complexity: the seven parameter sequences exhibit coupled associations and differentiated evolution patterns. Based on the above analysis, given the historical observation sequence $\{X_i(t_j), \Delta t_j\}_{j=1}^{n}$ as model input, the prediction target is the track geometry state at the next detection time, which can be expressed as the mapping:

$$\{X_i(t_{j-n+1}), ..., X_i(t_j) \to X_i(t_{j+1})\} \tag{2}$$

Where the time interval Δt_j needs to satisfy $\Delta t_j \sim \mathbb{P}_{train}$ (distribution of historical observation sequence intervals).

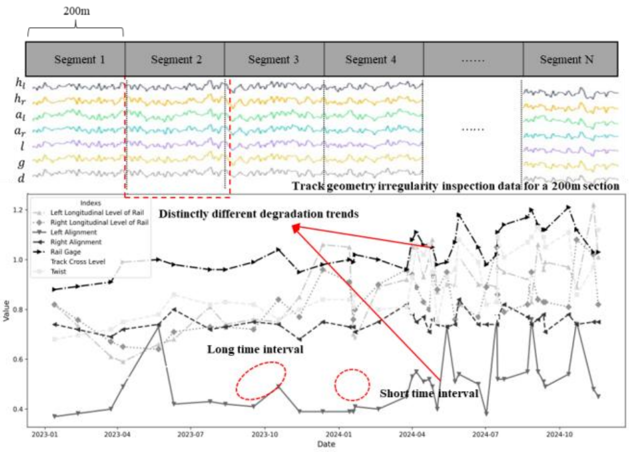

Fig. 1. Track geometry irregularity deterioration prediction problem

3 Methodology

3.1 CNN Feature Extraction Module

This research introduces a comprehensive multi-task learning architecture predicated on a CNN-BiLSTM-Attention model for the concurrent prediction of seven track geometry irregularity parameters, as depicted in Fig. 2. The framework implements a hard parameter sharing paradigm, comprising a unified feature extraction backbone network coupled with multiple task-specific prediction modules. The CNN-BiLSTM-Attention architecture, functioning as the shared feature encoder, extracts generalizable latent representations from historical temporal sequences, thereby capturing inherent cross-parameter correlations and dependencies among the seven geometric parameters; the specialized prediction heads subsequently generate parameter-specific forecasts aligned with the distinctive evolutionary characteristics of each geometric indicator.

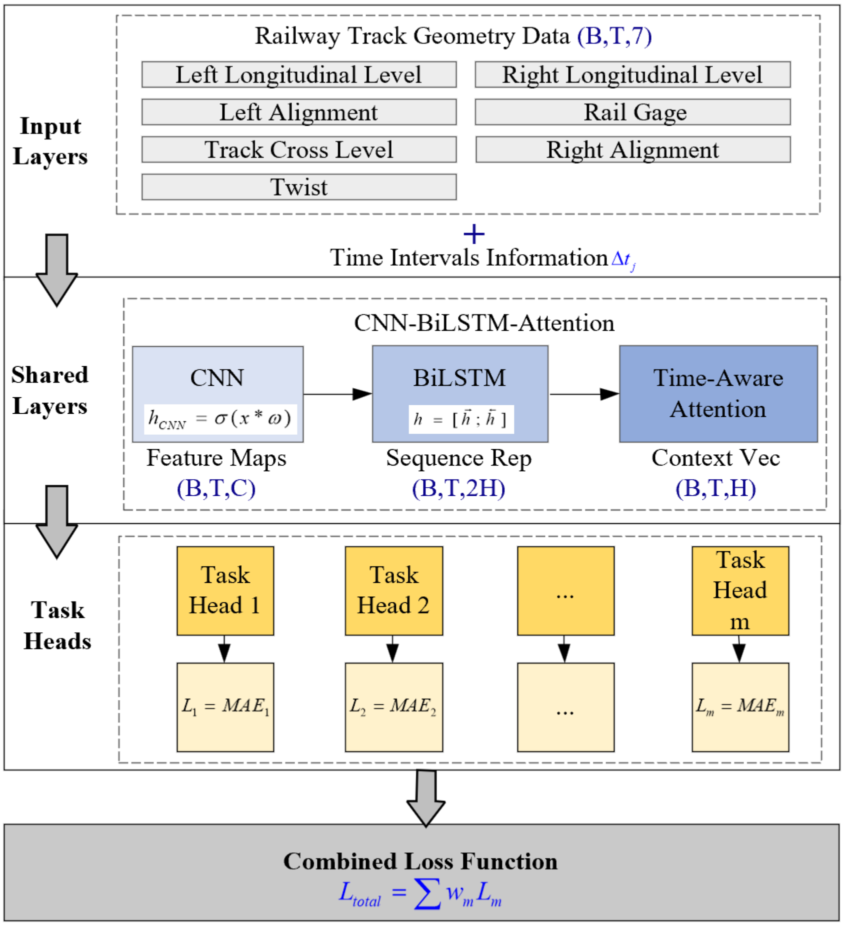

Fig. 2. Multi-task prediction framework for track geometry irregularity deterioration

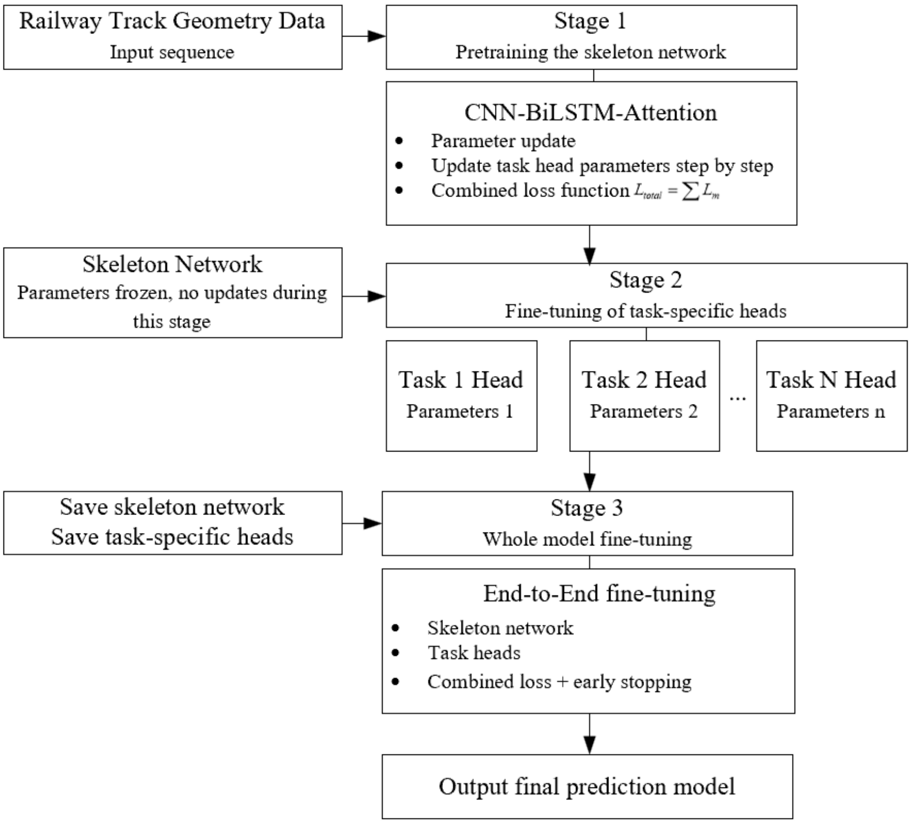

Fig. 3. Hierarchical training strategy for the multi-task learning framework

3.2 CNN-BiLSTM-Attention Model

The multi-task learning framework implemented in this study leverages a CNN-BiLSTM-Attention architecture as its foundational feature extraction mechanism, facilitating the collaborative representation learning of interdependent track geometry irregularity parameters. This hybrid neural architecture effectively captures complex spatiotemporal patterns and long-range temporal dependencies inherent in track geometry parameter evolution through the synergistic integration of convolutional neural networks for spatial feature extraction, bidirectional long short-term memory networks for temporal sequence modeling, and time-aware attention mechanisms for adaptive temporal weighting, as illustrated in Fig. 4.

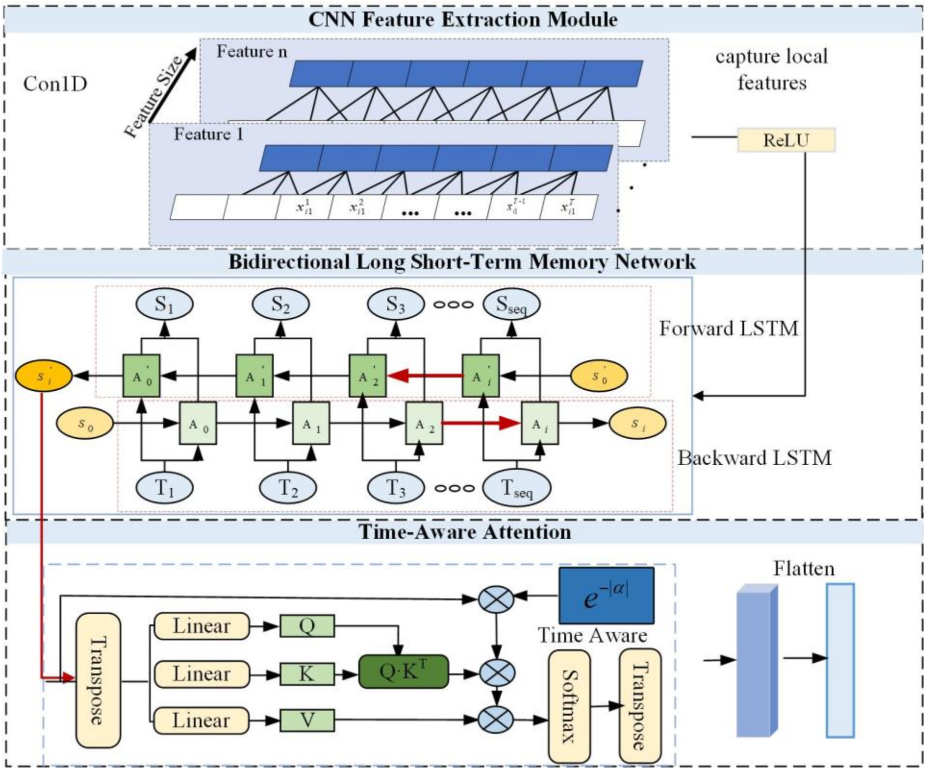

Fig. 4. CNN-BiLSTM-Attention

CNN Feature Extraction Module. A one-dimensional convolutional neural network is employed for local feature extraction, performing feature transformation on the input sequence through sliding convolution windows, effectively identifying local patterns and spatial correlations in track geometry parameters. The convolution operation can be represented as:

$$F_{conv} = ReLu(Conv1D(X_{input})) \tag{3}$$

Where, X_{input} represents the input time series features, $Conv1D$ denotes the one-dimensional convolution operation, and $ReLU$ is the activation function.

Bidirectional LSTM Network. Based on the features extracted by CNN, a bidirectional LSTM network is applied to capture long-term temporal dependencies. The bidirectional structure enables the model to utilize both historical and future contextual information simultaneously. The output of BiLSTM can be expressed as:

$$H_{bilstm} = BiLSTM(F_{conv}) \tag{4}$$

where integrates the $BiLSTM$ outputs from both forward and backward directions, and contains the hidden states for each time step.

Time-Aware Attention Mechanism (TAAM). To address the issue of irregular intervals in track inspection data collection, the model introduces TAAM. This mechanism transforms time interval information into attention weight adjustment factors:

$$\Delta t_{ij} = | t_i - t_j | \tag{5}$$

$$w_{time} = exp(-\Delta t / \lambda) \tag{6}$$

$$\alpha_{ij} = softmax(Q_i K_j^T / \sqrt{d} \cdot w_{time}) \tag{7}$$

$$O = \sum_j \alpha_{ij} V_j + H_{bilstim} \tag{8}$$

Where, Δt_{ij} is the interval matrix between time points, λ is a learnable time scale parameter, Q, K and V are the query, key, and value matrices respectively, represents the attention weights after time adjustment, and is the final output with residual connections added.

Mean Absolute Error (MAE) is adopted as the primary objective function due to its robustness against outlier observations and L1 regularization properties, characteristics particularly advantageous for track geometry parameter prediction where measurement anomalies may occasionally manifest in inspection data.

$$L_m = \frac{1}{n} | y_i^m - \hat{y}_i^m | \tag{9}$$

The overall loss for the multi-task framework is a weighted sum of task losses:

$$L_{total} = \sum_{m=1}^{M} w_m L_m \tag{10}$$

Where, w_m is the weight for task m, with equal weights adopted in this research.

4 Case Study

This investigation selects a 47.6-kilometer segment spanning from K193 to K240+600 of the Jin-Shan railway line under the jurisdiction of Beijing Railway Bureau as the experimental domain, systematically partitioned into standardized unit sections of 200 meters each. The dataset encompasses comprehensive track inspection records and maintenance intervention data spanning the period from March 2023 to October 2024. The maintenance documentation incorporates temporal timestamps, spatial coordinates, and intervention methodologies, thereby providing the predictive model with authentic maintenance event information that enhances prediction fidelity and alignment with operational engineering practices. Through Pearson correlation analysis, different degrees of correlation between parameters were found: the correlation coefficient between left/right LL and alignment parameters is 0.59, and the correlation coefficient between rail gauge and twist parameters is 0.68 (as shown in Fig. 5). This correlation indicates that there are interactions among various geometric parameters, while each parameter also exhibits different distribution characteristics, which poses requirements for the multi-parameter prediction capability of the model.

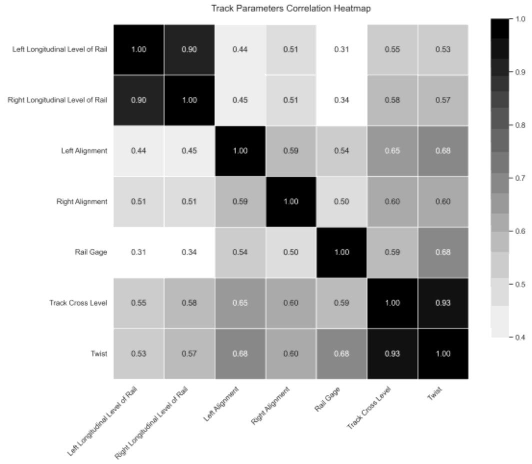

Fig. 5. Heatmap of correlation among track geometry irregularity

In the experimental process, data was indexed according to unit section numbers and was randomly divided into 70% training set and 30% validation set; key hyperparameters of the CNN-BiLSTM-Attention model are determined through optimization algorithms until the loss function converges; historical data is used to predict the track geometry state of the target month, which is then compared with actual detection data to evaluate the model's prediction performance.

4.1 Model Performance Analysis

To systematically evaluate predictive performance metrics and identify the optimal architectural configuration, this investigation conducted a comprehensive comparative analysis of state-of-the-art deep learning architectures within the single-task prediction paradigm, including CNN-BiLSTM hybrid networks, Deep Neural Networks (DNN), and Bidirectional Temporal Convolutional Networks (BiTCN). Throughout the model benchmarking process, the Optuna hyperparameter optimization framework was employed for automated hyperparameter tuning across all architectural variants to ensure methodological consistency and comparative validity. All models used the same L1 loss function as the optimization objective and employed consistent training, validation, and test dataset division schemes. Through hyperparameter optimization techniques, the optimal configuration of the CNN-BiLSTM-Attention model proposed in this study was determined, with Table 1 showing the results of the hyperparameter optimization experiments.

Table 1. Hyperparameter Optimization Results

Parameter Category	Parameter	Optimized Value
Model Structure	Hidden Layer Dimension	192
	Number of LSTM Layers	1
	Convolution Kernel Size	5
	Dropout Rate	0.34
Optimizer	Learning Rate	0.0001
	Weight Decay	0.002

Table 2 shows the performance comparison of four deep learning models in predicting seven track geometry parameters, evaluated through four metrics: RMSE, MAE, MAPE, and R^2. The results indicate that the CNN-BiLSTM-Attention model performs best overall, achieving the lowest errors and highest R^2 values for most parameters, particularly in left rail longitudinal level prediction with an RMSE of 0.067 and R^2 of 0.947. CNN-BiLSTM ranks second, while BiTCN and DNN also perform well on certain specific parameters. Although the DNN model ranks lower overall, it performs excellently in track gauge prediction (R^2 0.970), approaching the level of the optimal model. These results demonstrate the effectiveness of the attention mechanism in improving prediction accuracy and indicate that model selection should be based on specific prediction tasks.

Table 2. Model comparison results table

	CNN-BiLSTM-Attention				CNN-BiLSTM			
	RMSE	MAE	MAPE	R2	RMSE	MAE	MAPE	R2
Left LL	0.067	0.048	4.69%	0.947	0.070	0.050	4.95%	0.941
Right LL	0.080	0.058	5.72%	0.940	0.083	0.060	5.94%	0.935
Left Alignment	0.064	0.044	6.16%	0.941	0.068	0.048	7.18%	0.932
Right Alignment	0.069	0.044	5.89%	0.925	0.080	0.054	7.61%	0.901
Rail Gage	0.065	0.040	3.79%	0.970	0.079	0.049	4.90%	0.956
Track Cross Level	0.075	0.049	6.42%	0.954	0.074	0.053	8.10%	0.955
Twist	0.061	0.042	4.97%	0.977	0.065	0.048	6.51%	0.973
	BiTCN				DNN			
	RMSE	MAE	MAPE	R2	RMSE	MAE	MAPE	R2
Left LL	0.079	0.054	5.16%	0.924	0.075	0.056	5.65%	0.932
Right LL	0.094	0.065	6.18%	0.916	0.090	0.066	6.49%	0.922
Left Alignment	0.074	0.050	7.08%	0.921	0.066	0.047	6.99%	0.937
Right Alignment	0.081	0.051	6.69%	0.897	0.069	0.046	6.35%	0.925

Rail Gage	0.074	0.043	4.16%	0.962	0.066	0.045	4.44%	0.970
Track Cross Level	0.079	0.050	6.72%	0.949	0.075	0.053	7.98%	0.954
Twist	0.065	0.043	5.13%	0.973	0.067	0.050	6.81%	0.971

To empirically validate the efficacy of the proposed multi-task learning paradigm against conventional single-task modeling approaches, this study executed a series of controlled ablation experiments while maintaining architectural consistency and optimizing for identical convergence criteria. Table 3 shows that models using the multi-task learning framework demonstrate superior performance on all tasks. Based on correlation analysis between different parameters in the dataset, the track geometry irregularity deterioration prediction tasks were divided into three groups: Task 1 for Left/Right LL, Task 2 for Left/Right Alignment, and Task 3 for the remaining 3 parameters. Specifically, the RMSE, MAE, and MAPE values under the multi-task framework are generally lower, especially in Track Cross Level and Right Alignment tasks, where RMSE and MAE are significantly reduced and MAPE is effectively improved. Additionally, R^2 values are enhanced in most tasks under the multi-task framework, particularly in Left Alignment and Twist tasks, where the improvement in R^2 values is more significant. These comparisons indicate that the multi-task learning framework can effectively share feature information between tasks, thereby enhancing prediction accuracy and model generalization ability for each task. Overall, the experimental results support the effectiveness of multi-task learning in improving model performance, reducing training errors, and enhancing prediction accuracy.

Table 3. Multi-task framework comparison results table

	Single-task Learning Framework				Multi-task Learning Framework			
	RMSE	MAE	RMSE	MAE	RMSE	MAE	MAPE	R2
Left LL	0.067	0.048	0.067	0.048	0.052	0.037	4.01%	0.964
Right LL	0.080	0.058	0.080	0.058	0.069	0.047	4.52%	0.953
Left Alignment	0.064	0.044	0.064	0.044	0.041	0.029	4.18%	0.971
Right Alignment	0.069	0.044	0.069	0.044	0.032	0.023	3.37%	0.981
Rail Gage	0.065	0.040	0.065	0.040	0.051	0.036	3.74%	0.981
Track Cross Level	0.075	0.049	0.075	0.049	0.027	0.018	2.30%	0.993
Twist	0.061	0.042	0.061	0.042	0.035	0.024	2.67%	0.992

As shown in Fig. 6, the proposed hierarchical multi-task learning model exhibits distinct phase characteristics during the training process. The backbone network training phase demonstrates good convergence properties, with loss values decreasing from 1.4 to 0.2, validating the applicability of the CNN-BiLSTM-Attention hybrid architecture in time series feature extraction. The training curves of the three task heads display differentiated characteristics: the training and testing losses for Task 1 and Task 2 show insignificant downward trends, while the loss value for Task 3 stabilizes at 0.08. Experimental data indicate that the performance of each task on the test set is close to that on the training set, confirming the model's generalization performance.

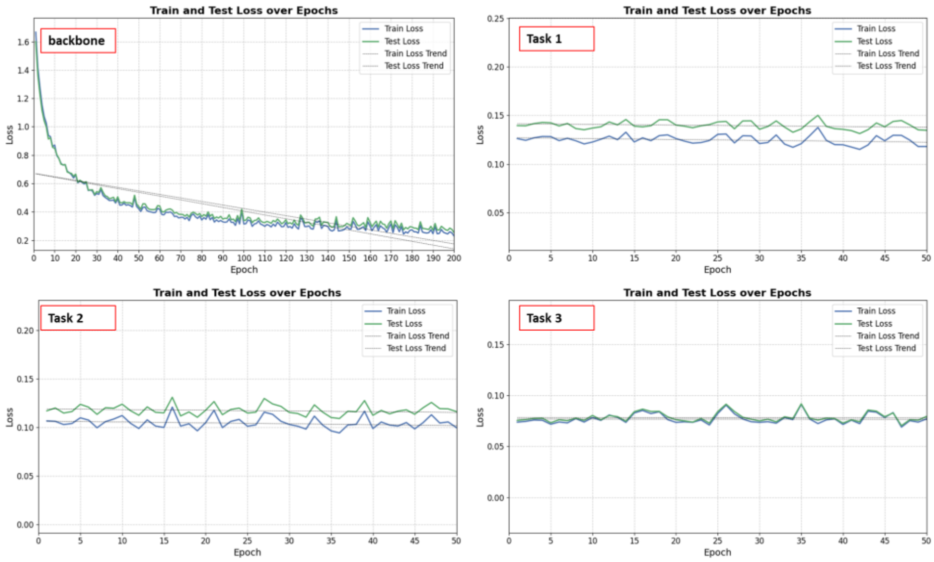

Fig. 6. Track geometry irregularity deterioration prediction loss

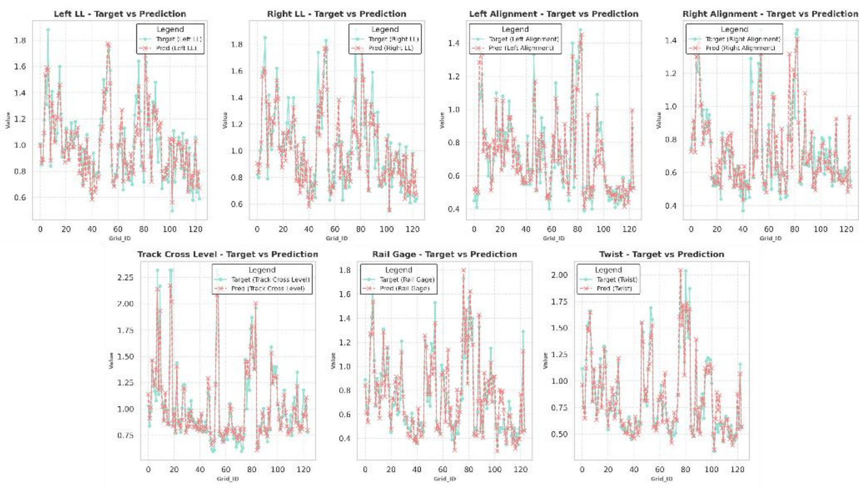

Fig. 7. Track geometry irregularity deterioration prediction fitting

Fig. 7 displays the prediction results of the CNN-BiLSTM-Attention multi-task model on the validation set of the Jin-Shan line, presenting a comparison between actual values (blue) and predicted values (red) for seven key track geometry parameters. The model predictions highly align with actual measurements, accurately capturing the peak and valley features of each parameter, which is crucial for identifying potential track geometry anomalies. Different parameters exhibit various change patterns: Left/Right Longitudinal Level shows larger amplitude fluctuations; Left/Right Alignment displays significant peaks in multiple locations; Track Cross Level, Rail Gage, and Twist are relatively stable but with local mutations. Notably, the model maintains good prediction accuracy even in areas where data exhibits nonlinearity and sudden changes.

4.2 Experimental Results

The proposed predictive framework demonstrates dual capabilities in forecasting deterioration trajectories and quantifying the ameliorative effects of maintenance interventions on track geometric conditions. Analyzing inspection and maintenance records from a representative 6-kilometer segment, with Left/Right Longitudinal Level (LL) parameters serving as primary analytical indicators, as visualized in Fig. 8, the post-maintenance effects following the April 2024 intervention are clearly observable through significant amplitude reduction in both Left/Right LL parameters, accompanied by a measurable deceleration in deterioration rates, as evidenced by the gradient transitions in the spatiotemporal heatmap visualization. This indicates that the model can learn the impact of maintenance interventions, providing a basis for evaluating the effectiveness of maintenance measures. By comparing the actual post-maintenance track condition with the predicted results, the rationality of maintenance decisions can be verified, and data support can be provided for the optimization of subsequent maintenance strategies.

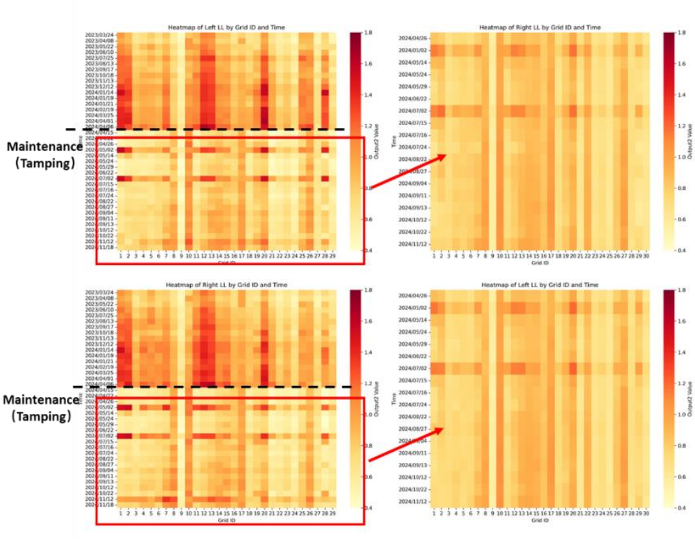

Fig. 8. Spatiotemporal distribution heat map of Left/Right LL before and after maintenance

5 Conclusion and Discussion

This research introduces a novel multi-task CNN-BiLSTM-Attention framework for short-term track geometry irregularity deterioration prediction within railway systems.

Empirical validation utilizing operational engineering data from China's Jin-Shan railway corridor demonstrates that the proposed multivariate parameter modeling approach exhibits enhanced congruence with the underlying physical deterioration mechanisms of track infrastructure compared to conventional univariate methodologies. The time-aware mechanism enables the model to learn the distribution patterns of non-equidistant inspection data, enhancing the modeling capability for irregular time series. Comparative experiments confirm that CNN-BiLSTM-Attention demonstrates advantages in predicting key parameters compared to existing time series prediction models.

Notwithstanding the methodological advancements presented in this investigation, certain limitations warrant acknowledgment. The current research utilizes a 21-month monitoring dataset, representing a temporal window that remains relatively constrained when contextualized within the comprehensive lifecycle of railway track infrastructure. The predictive framework primarily addresses near-term state forecasting for subsequent inspection intervals, with limited extension to long-horizon deterioration trajectory analysis across extended temporal domains. Future research can be conducted in the following aspects: first, expanding the scope of data collection for long-term monitoring of the line; second, studying in depth the interaction mechanisms between various geometric parameters to further enhance the model's ability to capture the coupling effects of multiple parameters. Overall, the method proposed in this study provides a feasible solution for short-term prediction of track geometry irregularities. Its attempts in collaborative modeling of multiple parameters and processing of non-equidistant time series provide a reference for research in related fields and are expected to provide technical support for the daily maintenance work of railway engineering departments.

References

1. Peinado Gonzalo, A., Horridge, R., Steele, H., Stewart, E., Entezami, M.: Review of data analytics for condition monitoring of railway track geometry. IEEE Transactions on Intelligent Transportation Systems 23(12), 22737-22754 (2022)
2. Rempelos, G., Ognibene, G., Le Pen, L., Blainey, S., Preston, J., Powrie, W.: Railway track deterioration models: a review of the state of the art. Transportation Geotechnics 49, 101377 (2024)
3. Li, C., He, Q., Wang, P.: Estimation of railway track longitudinal irregularity using vehicle response with information compression and Bayesian deep learning. Computer-Aided Civil and Infrastructure Engineering 37(10), 1260-1276 (2021)
4. Han, L., Liao, Y., Wang, H., Zhang, H.: Long-term prediction for railway track geometry based on an optimised DNN method. Construction and Building Materials 401, 132687 (2023)

5. Allah Bukhsh, Z., Saeed, A., Stipanovic, I., Doree, A.G.: Predictive maintenance using tree-based classification techniques: a case of railway switches. Transportation Research Part C: Emerging Technologies 101, 35-54 (2019)
6. Wang, X., Liu, X., Bian, Z.: A machine learning based methodology for broken rail prediction on freight railroads: a case study in the United States. Construction and Building Materials 346, 128353 (2022)
7. Lasisi, A., Attoh-Okine, N.: Principal components analysis and track quality index: a machine learning approach. Transportation Research Part C: Emerging Technologies 91, 230-248 (2018)
8. Soleimanmeigouni, I., Ahmadi, A., Kumar, U.: Track geometry deterioration and maintenance modelling: a review. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit 232(1), 73-102 (2018)
9. Hamid, A., Gross, A.: Track-quality indices and track-deterioration models for maintenance-of-way planning. Transportation Research Record 802, 2-8 (1981)
10. Chang, Y., Liu, R., Tang, Y.: Segment-condition-based railway track maintenance schedule optimization. Computer-Aided Civil and Infrastructure Engineering 38(2), 160-193 (2022)
11. An, R., Jia, L., Tang, Y., Tian, Y., Wang, Z.: Railway track tamping maintenance cycle prediction model based on power-time-transformed Wiener process. Applied Sciences 14(13), 5867 (2024)
12. Quiroga, L., Schnieder, E.: Monte Carlo simulation of railway track geometry deterioration and restoration. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 226, 274-282 (2012)
13. Wang, X., Bai, Y., Liu, X.: Prediction of railroad track geometry change using a hybrid CNN-LSTM spatial-temporal model. Advanced Engineering Informatics 58, 102235 (2023)
14. Guler, H.: Decision support system for railway track maintenance and renewal management. Journal of Computing in Civil Engineering 27(3), 292-306 (2013)
15. Liao, Y., Han, L., Wang, H., Zhang, H.: Prediction models for railway track geometry deterioration using machine learning methods: a review. Sensors 22(19), 7275 (2022)
16. Ma, Z., Dong, Y., Liu, H., Shao, X., Wang, C.: Forecast of non-equal interval track irregularity based on improved grey model and PSO-SVM. IEEE Access 6, 34812-34818 (2018)
17. Falamarzi, A., Moridpour, S., Nazem, M.: Development of a tram track deterioration prediction model based on the acceleration data. Structural Infrastructure Engineering 15, 1308-1318 (2019)

18. Wang, X., Liu, X., Euston, T.L.: Relationship between track geometry defect occurrence and substructure condition: a case study on one passenger railroad in the United States. Construction and Building Materials 365, 130066 (2023)
19. Wang, X., Dai, J., Liu, X.: A spatial-temporal neural network based on ResNet-Transformer for predicting railroad broken rails. Advanced Engineering Informatics 65, 103126 (2025)
20. Faghih-Roohi, S., Hajizadeh, S., Nunez, A., Babuska, R., De Schutter, B.: Deep convolutional neural networks for detection of rail surface defects. In: Proceedings of the 2016 International Joint Conference on Neural Networks (IJCNN), pp. 2584-2589 (2016)
21. Jahan, K., Niemeijer, J., Kornfeld, N., Roth, M.: Deep neural networks for railway switch detection and classification using onboard camera images. In: 2021 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1-8 (2021)
22. Liu, J., Du, D., He, J., Zhang, C.: Prediction of remaining useful life of railway tracks based on DMGDCC-GRU hybrid model and transfer learning. IEEE Transactions on Vehicular Technology 73(6), 7561-7575 (2024)
23. Zhang, Y., Yang, X., Ivy, J., Chi, M.: ATTAIN: attention-based time-aware LSTM networks for disease progression modeling. In: Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence (IJCAI-19), pp. 4369-4375. International Joint Conferences on Artificial Intelligence Organization, Macao (2019)
24. Liu, X., Du, H., Yu, J.: A forecasting method for non-equal interval time series based on recurrent neural network. Neurocomputing 556, 126648 (2023)
25. Chen, L., Tian, Z., Zhou, S., Gong, Q., Di, H.: Attitude deviation prediction of shield tunneling machine using time-aware LSTM networks. Transportation Geotechnics 45, 101195 (2024)
26. Song, B., Liu, Y., Fang, J., Liu, W., Zhong, M., Liu, X.: An optimized CNN-BiLSTM network for bearing fault diagnosis under multiple working conditions with limited training samples. Neurocomputing 574, 127284 (2024)
27. Tang, C., Zhang, Y., Wu, F., Tang, Z.: An improved CNN-BILSTM model for power load prediction in uncertain power systems. Energies 17(10), 2312 (2024)
28. Wu, M.-P., Wu, F.: Predicting residential electricity consumption using CNN-BiLSTM-SA neural networks. IEEE Access 12, 71555-71565 (2024)
29. Li, X., Zhou, S., Wang, F., Fu, L.: An improved sparrow search algorithm and CNN-BiLSTM neural network for predicting sea level height. Scientific Reports 14(1), 5266 (2024)