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Railway Communication Network Signal Enhancement System Based on Machine Learning

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Abstract In railway environments, communication signals may become very weak due to geographical conditions, building structures, or other factors, leading to a decrease in communication quality. The Bidirectional Long Short-term Memory (Bi-LSTM) model was adopted to accurately predict the signal strength of future time steps. By establishing a railway communication network (RCN) signal enhancement system, the performance of the RCN was improved. A large amount of historical data on RCNs was collected and preprocessed. Features related to RCN signals were extracted, and the entire time series data was divided into datasets. By using bidirectional LSTM layers, patterns and features in the sequence were learned, and future signal strength was predicted and analyzed for targeted signal enhancement. The experimental results showed that the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of Bi-LSTM for signal strength prediction were 0.04 and 0.08, respectively. The average delay improvement rate of Bi-LSTM was 58.6%, and the interference suppression rates of Bi-LSTM model for electromagnetic interference, radio frequency interference, natural environment interference, multipath propagation interference, and mechanical vibration interference were 78.6 dB, 56.2 dB, 67.8 dB, 79.2 dB, and 71.2 dB, respectively. The application of Bi-LSTM model can effectively predict signal strength and provide a new method for signal enhancement in RCNs.

Index Terms Railway Transportation, Communication Networks, Signal Enhancement, Bidirectional Long Short-term Memory, Signal Strength Prediction

I. Introduction

The significance of RCN in guaranteeing safe train operation and information transfer is growing as railway transportation systems continue to expand [1], [2]. Among the many issues with traditional railway communication systems are their vulnerability to interference and uneven signal transmission [3], [4]. This may result in a decline in the quality of communication, which then has an impact on the dependability of data transfer and the security of train operations. Even though these systems may not function well in complicated train environments, classical signal processing and transmission technologies continue to be a major component of train communication networks. Railway lines pass through a range of environments and terrains, such as cities, suburbs, and hilly areas. As a result, signals on these lines may be susceptible to different types of interferences and attenuations, including weather variations and electromagnetic interference. Machine learning techniques can be used for signal augmentation and prediction to address these problems. Machine learning algorithms can detect patterns of signal attenuation in a range of environments and forecast potential attenuation trends in the future by evaluating previous data [5], [6].

In railway transportation, timely and reliable communication is crucial for the safe operation of trains, collaborative work between trains, and effective communication with train attendants. By enhancing RCN signals, real-time information transmission between trains and control centers is ensured, thereby reducing the probability of accidents. In railway communication engineering, wireless access technology is used to enhance communication signals and adapt to the variability of the railway environment through wireless access technology [7], [8]. Ai Bo adopted the fifth generation communication technology for RCN transmission, ensuring high reliability and throughput of communication [9]. In order to improve the mobile communication performance in high-speed trains, Kanno Atsushi proposed and demonstrated a fiber optic wireless system based on linear cells, where the 90 GHz millimeter wave radio access between the ground and train carriages operates in a centralized manner [10]. The fifth generation mobile communication technology provides greater bandwidth for railway communication, supporting high-definition video, high-capacity data transmission and other needs, thereby improving communication quality. Moreover, the low latency characteristics of 5G make real-time information transmission between trains and control centers faster, which helps to improve the safety of train operation [11], [12]. Improving

communication technology can solve most RCN problems, but there are certain limitations when dealing with the complex and dynamic communication environment of railways. The above research has not fully considered the comprehensive modeling of signal strength, delay, and interference, as well as accurate prediction of future communication conditions.

Machine learning can learn from a large amount of data, and many people have used machine learning to enhance communication network signals. Machine learning models can automatically recognize features and patterns in different environments by learning from a large amount of scene data, and can process large-scale and complex data, providing intelligent solutions [13]. The LSTM model can effectively capture long-term dependencies in temporal data and has good adaptability in communication network signal prediction. It can effectively capture the temporal characteristics of signals and improve prediction accuracy [14], [15]. In order to accurately model and predict changes in wireless channel quality, Kulkarni Adita proposed an encoder-decoder sequence to sequence model that can predict future wireless signal strength changes based on past signal strength data [16]. LSTM, through its specially designed long short-term memory units, can effectively capture long-term dependencies in time series data and consider distant historical information in prediction, which has stronger modeling ability for time series containing long-term trends and patterns [17], [18]. Machine learning algorithms can identify and resist various forms of interference, including electromagnetic interference, random noise, etc. By training models to identify interference sources and dynamically adjusting communication parameters, the system can improve anti-interference ability and ensure communication stability [19], [20]. The application of machine learning models can intelligently analyze communication network signals, but there is a lack of applying machine learning to RCN signal enhancement systems.

In order to improve the signal strength of RCN, a bidirectional LSTM model was introduced to capture the complex relationship of signal timing data to predict the signal strength of future time steps, and a RCN signal enhancement system was constructed. The RCN related data was collected, cleaned and standardized. The entire time series data was sorted from morning to evening according to timestamps, and time series data was divided. By learning patterns and correlation relationships in historical data through bidirectional LSTM, prediction of future signal strength was carried out. Targeted signal enhancement strategies were implemented, and bidirectional LSTM was compared with LSTM, Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). The results indicated that the application of Bi-LSTM could effectively reduce the error of signal strength prediction and maintain stability during continuous operation. Through the RCN signal enhancement system, the operational level of the entire railway transportation system was improved, which had a profound impact on improving the efficiency and safety, and providing better service quality of railway transportation.

II. Methods for Enhancing Communication Network Signals

II. A. Collecting Historical Data of RCNs

With the continuous development of railway transportation and the increasing demand for modernization, communication signals have become crucial in train operation, safety management, and passenger services [21], [22]. However, due to the diversity of geographical conditions, building structures, and other environmental factors along the railway line, communication signals are often severely affected, manifested as decreased signal strength, increased communication delay, and various interferences. This unstable communication situation directly affects the efficiency and safety of railway operations.

The enhancement of RCN signals can improve the reliability and stability of the RCN, ensure the stability of train operation and communication interaction, and thus improve the security of the entire railway system [23], [24]. By optimizing communication signals, the efficiency of information transmission between trains, between trains and signal equipment, and with other parts of the railway system can be improved, thereby enhancing the overall efficiency of railway transportation.

The RCN is shown in Figure 1.

RCN is a specific communication infrastructure established specifically to support the information transmission and communication needs of railway transportation systems. In modern railway systems, this network plays a crucial role in connecting key facilities such as trains, signal systems, stations, and dispatch centers to ensure safe, efficient, and collaborative train operations. This communication network relies on various network devices, including routers, switches, communication cables, etc., which together constitute a complete communication infrastructure. The RCN is an indispensable part of modern railway transportation systems, and its effective operation directly affects the safety and efficiency of trains, as well as the overall coordination of the transportation system.

The RCN signal is affected by various factors, and historical data of the RCN is collected, including signal strength, time delay, environmental factors, etc. Through professional radio measurement instruments, signal

strength data is collected and the collected time and other information are recorded. Through time delay measurement instruments, time delay data is collected, and the surrounding environmental data is obtained through various environmental sensors.

The collected data is shown in Table 1.

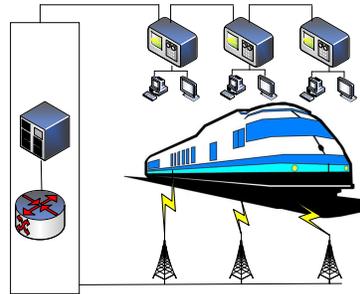


Figure 1: RCN

Table 1: Part of RCN data collected

Time	Signal strength (dBm)	Delay (ms)	Temperature (° C)	Humidity (%)
2021-02-01 08:00:00	-75	10	20	50
2021-02-01 08:15:00	-80	15	20	52
2021-02-01 08:30:00	-78	12	21	51
2021-02-01 08:45:00	-82	18	21	52
2021-02-01 09:00:00	-76	11	21	52
2021-02-01 09:15:00	-79	14	21	52
2021-02-01 09:30:00	-77	13	21	52
2021-02-01 09:45:00	-81	17	21	52
2021-02-01 10:00:00	-75	10	21	52
2021-02-01 10:15:00	-83	20	21	52

Table 1 shows the relevant data of RCN, including signal strength, time delay, temperature and humidity information, with time labels for each data point. The collection of signal strength helps to evaluate communication quality and ensure reliable information transmission between trains, between trains and dispatch centers, and between stations.

II. B. Data Preprocessing and Feature Extraction

Signal data frequently contains noise and outliers, which can be brought on by factors such as malfunctioning hardware, external interference, and other. To achieve more accurate and dependable analysis and modeling outputs, these noises and outliers are found and eliminated during the data preparation process [25], [26]. Data cleansing and temporal data normalization are key components of data preparation.

The average value of the data is used to replace outliers and fill in any missing numbers in order to assure the quality of the data. The results before and after outlier handling are shown in Figure 2.



(A): Data before handling outliers

(B): Data after handling outliers

Figure 2: Results before and after handling outliers

Signal strength is expressed in dBm and is an indicator used to measure the strength of a signal during transmission. The signal strength usually ranges from -30dBm to -100dBm. A signal strength close to -30dBm is considered very strong, while a signal strength close to -100dBm is weaker. In Figure 2 (A), the data before data preprocessing is shown. It can be observed that there are 6 data points with abnormal data, far exceeding the normal data range. Figure 2 (B) averages the outlier data through outlier handling, achieving a normal numerical range.

The collected temporal data contains multiple data features, and different data features have different dimensions and units. This dimensional difference may lead to certain features having a significant impact on the model, affecting its performance. Through standardization, the values of all features can be scaled to similar ranges, eliminating this difference [27], [28].

The z-score standardization method is adopted. For each time series data point x_i , the normalized value z_i is represented as:

$$z_i = \frac{x_i - \mu}{\sigma} \quad (1)$$

In Formula 1, μ is the mean of the data and σ is the standard deviation of the data.

The characteristics related to RCN signals are extracted, including signal strength, time delay, etc. The average signal strength is expressed as:

$$\bar{s} = \frac{1}{N} \sum_{i=1}^N s_i \quad (2)$$

The transmission delay is the time required for data to be transmitted from the sending end to the communication link. The formula for sending delay is:

$$TD = \frac{B}{V} \quad (3)$$

In Formula 3, B and V represent the size and transmission rate of the transmitted data, respectively.

The propagation delay is the time required for a data signal to propagate in the transmission medium, expressed as:

$$PD = \frac{L}{V} \quad (4)$$

In Formula 4, L represents the transmission distance.

Processing latency refers to the time required to process data at a communication node. The queuing delay is the time required for data to enter the input queue of a network node and wait for processing. The formula for queuing delay is:

$$QD = \frac{M}{W} \quad (5)$$

In Formula 5, M and W represent the amount of data in the queue and the processing rate, respectively.

The entire time series data is sorted by timestamp from morning to evening. The first half of the temporal data is used as the training dataset, and the second half of the temporal data is used as the testing dataset.

II. C. Establishing Bidirectional LSTM Model

LSTM is a variant of recurrent neural networks designed specifically for processing and learning long-term dependencies in temporal data [29], [30]. LSTM effectively solves the problems of gradient vanishing and exploding in long sequence training by introducing gating mechanisms [31], [32]. However, traditional LSTM models are unidirectional, and predictions at each time step only rely on past information, which cannot fully utilize future information. Moreover, the computation of unidirectional LSTM is sequential, and the computation of each time step depends on the previous time step, making it difficult to fully utilize the advantages of parallel computing, thereby increasing the demand for computing resources.

By taking into account both past and future data, bidirectional LSTM enables the model to simultaneously transmit information forward and backward at each time step, offering a more thorough comprehension of the complete sequence [33], [34]. In Figure 3, the bidirectional LSTM model is displayed.

The bidirectional LSTM layer collects patterns and features from the input sequence after the bidirectional LSTM model uses an embedding layer to first embed the sequence. Considering both forward and backward directions of information, the output of this model is concatenated from the outputs of forward and backward LSTM.

The bidirectional LSTM model uses mean square error as the loss function to determine how well it predicts signal strength. The following is the formula for mean square error:

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (6)$$

The model parameters are optimized by the formula:

$$C_{new} = C_{old} - r \times T \tag{7}$$

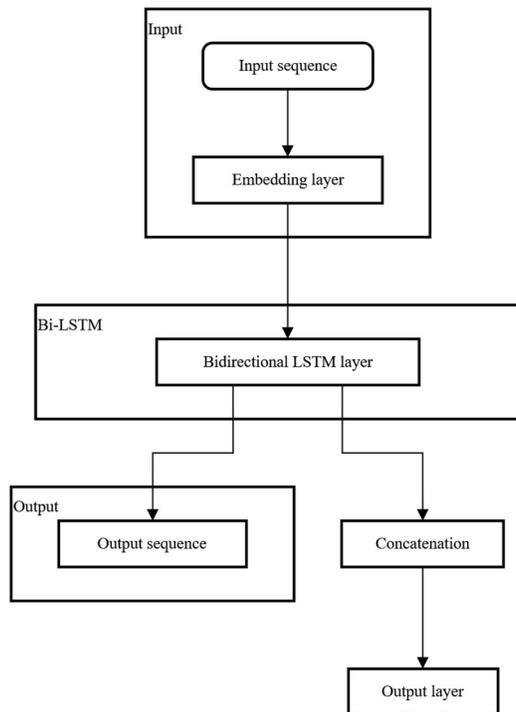


Figure 3: Bidirectional LSTM model

The interface of the RCN signal enhancement system is shown in Figure 4.



Figure 4: Interface of RCN signal enhancement system

The RCN signal enhancement system includes functions such as delay optimization, logging, channel management, and signal monitoring to handle the various challenges faced by the railway industry. This guarantees reliable, steady, and efficient communication links even under difficult conditions such as train operating, signal interference, and uneven terrain.

III. Evaluation of Communication Network Signal Enhancement

In RCNs, signal augmentation aids in delivering higher-quality communication. Geographic conditions, building structures, tunnels, and other environmental factors along railroad lines may cause communications signals to be interfered with, attenuated, or obscured, making them weak. The bidirectional LSTM model can lessen distortion and communication disruptions, anticipate and adjust to signal intensity attenuation, and enhance communication quality.

The bidirectional LSTM model's communication network signal enhancement is assessed by contrasting it with LSTM, SVM, RF, and KNN models; RMSE and MAE are used to assess the signal strength prediction error.

The RMSE formula can be written as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

The formula for MAE is:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

When establishing railroad communication networks, various forms of interference might arise, such as electromagnetic, radio frequency, multipath propagation, natural environment, and mechanical vibration interference. The interference suppression rate (ISR) is expressed as:

$$ISR = 10 \cdot \log_{10} \left(\frac{E_1}{E_2} \right) \quad (10)$$

In Formula 10, E_1 and E_2 represent the energy of the signal when there is no interference and the energy after introducing interference, respectively. The purpose of taking the logarithm is to quantify the multiple of the inhibitory effect. The larger the ISR, the better the suppression effect of the model on interference.

The latency improvement rate is an indicator that measures the effectiveness of system optimization in reducing latency, expressed as:

$$H = \frac{H_1 - H_2}{H_1} \quad (11)$$

In Formula 11, H_1 and H_2 represent the communication delay before optimization and the communication delay after optimization, respectively.

In order to analyze the stability of the continuous operation of the bidirectional LSTM model, tests are conducted every month for a period of 12 months to obtain the error of signal strength prediction.

IV. Results

IV. A. Signal Strength Prediction Error

The results of signal strength prediction using different models are shown in Figure 5.

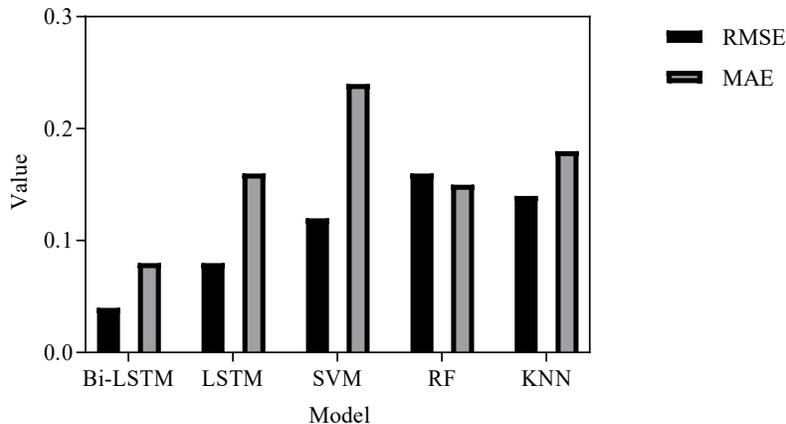


Figure 5: Signal strength prediction error

Signal strength is a key indicator for measuring communication quality. By accurately predicting signal strength, communication systems can better adjust parameters, allocate resources, optimize communication quality, and improve the stability and reliability of data transmission. The prediction error results of five models, Bi-LSTM, LSTM, SVM, RF, and KNN, were compared. Bi-LSTM significantly had lower signal strength prediction errors, mainly due to its ability to simultaneously consider both forward and reverse sequence information, thereby more comprehensively capturing contextual relationships in input data and more accurately understanding the dynamic changes and patterns in signal strength sequences. The RMSE and MAE for signal strength prediction using Bi-LSTM were 0.04 and 0.08, respectively.

IV. B. Optimization Results of Communication Delay

After predicting the signal strength of the RCN, the communication delay was optimized by dynamically adjusting the transmission power. The results of communication delay optimization are shown in Figure 6.

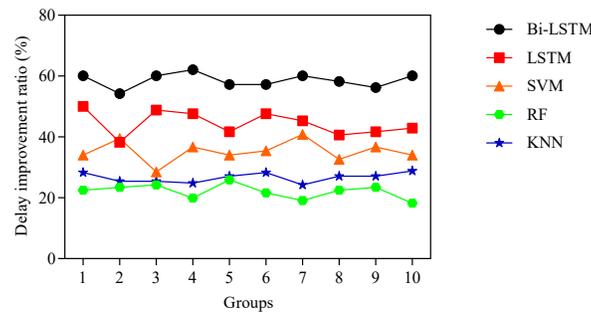


Figure 6: Results of communication delay optimization

Through Formula 11, it can be found that if the delay improvement rate was positive, it indicated that the optimized communication delay was smaller than the pre optimized communication delay, indicating a reduction in delay. On the contrary, if the delay improvement rate was negative, it indicated that the optimized communication delay was greater than the pre optimized communication delay, which introduced additional delay.

In Figure 6, the horizontal axis indicated that the test data was divided into 10 groups. The latency improvement rate of Bi-LSTM was relatively the highest. Bi-LSTM can better capture long-term dependencies in time-series data by considering both past and future sequence information, thus enabling targeted communication delay optimization. The average latency improvement rates of Bi-LSTM, LSTM, SVM, RF, and KNN were 58.6%, 44.4%, 35.2%, 22.1%, and 26.7%, respectively.

IV. C. Interference Suppression Effect

Interference suppression helps to improve the stability of railway communication systems and reduce the impact of signal fluctuations and sudden interference on communication. The interference suppression rates under different interference conditions are shown in Figure 7.

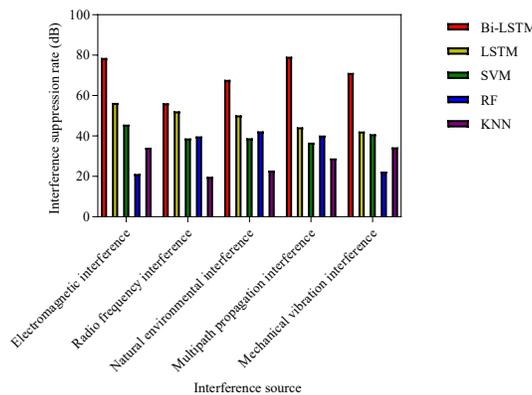


Figure 7: Interference suppression rate

In Figure 7, the horizontal axis represents 5 types of interference sources, and the vertical axis represents the interference suppression rate, measured in dB. The larger the value of interference suppression rate, the better the interference suppression effect. The interference suppression effect of the RCN signal enhancement system constructed using Bi LSTM was the best, which can effectively suppress multiple interference sources. The interference suppression rates of Bi-LSTM model for electromagnetic interference, radio frequency interference, natural environment interference, multipath propagation interference, and mechanical vibration interference were 78.6 dB, 56.2 dB, 67.8 dB, 79.2 dB, and 71.2 dB, respectively. Bi-LSTM adopts a bidirectional structure that takes into account both past and future sequence information, enabling it to comprehensively perceive the contextual relationships of signal strength. Bi-LSTM is expected to more effectively distinguish and suppress various interference sources that may exist in RCNs through comprehensive contextual information.

IV. D. Stability of Continuous Operation

Stable signal prediction means more accurate and reliable communication information, which helps to reduce communication interruptions and data transmission errors, improve communication stability, and ensure normal communication between trains and between trains and control centers. The stability of signal strength prediction over a period of 12 months is shown in Figure 8.

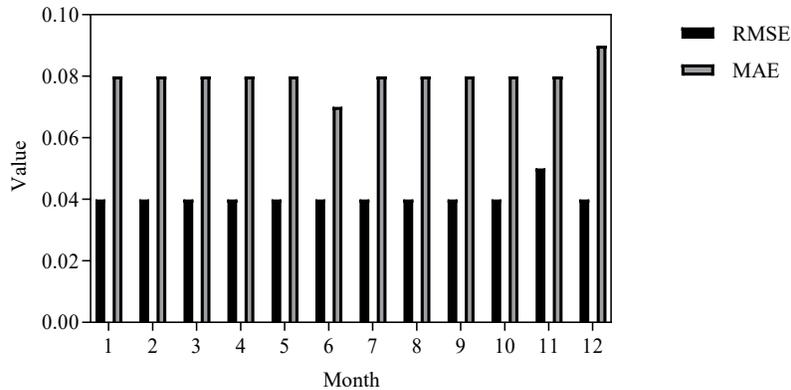


Figure 8: Stability of continuous operation

In Figure 8, the horizontal axis represents the duration of continuous operation, and the vertical axis represents the value of signal strength prediction error. The RMSE of the Bi-LSTM model for signal strength prediction was only 0.05 in November, and the values for the rest of the time were 0.04. During the 12 month continuous running time, the RMSE change of the Bi-LSTM model for signal strength prediction was only 0.01. Similarly, the variation in MAE values was also very small, reaching a minimum of 0.07 in June and a maximum of 0.09 in December. During the 12 month continuous operation period, the MAE change predicted by the Bi-LSTM model for signal strength was 0.02. Therefore, the Bi-LSTM model had high stability in predicting RCN signals.

V. Conclusions

Railway communication systems often face special environmental conditions, such as high-speed vehicle operation, complex terrain, and the need for signals to penetrate obstacles, which may lead to a decrease in signal quality. A large amount of RCN data was collected, preprocessed, and used to predict signal strength using a bidirectional LSTM model. Based on the predicted signal strength, targeted communication delay optimization was carried out to construct a RCN signal enhancement system. The experimental results showed that the Bi-LSTM model can effectively reduce the error of signal strength prediction and effectively suppress various interference sources. Railway communication is the foundation for ensuring the safe operation of trains. Through signal enhancement systems, the stability and reliability of communication can be improved, ensuring timely transmission of critical information, helping to prevent accidents, and enhancing the safety of the entire railway transportation system. However, the interference source environment analyzed in this article is not comprehensive enough. In the future, more comprehensive interference environments can be expanded for experimental analysis.

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