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# Transformer-Based Channel State Information Prediction and Performance Evaluation in Wireless Communication

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## ABSTRACT

*Wireless channels exhibit rapid time-varying characteristics due to multipath effects and Doppler shift. which is particularly evident in dynamic monitoring scenarios involving smart textiles and wearable sensing nodes. Traditional estimation algorithms and prediction models suffer from insufficient accuracy and difficulty in capturing global dependencies, failing to meet the demands of modern wireless communication. Therefore, this study aims to construct a high-precision, low-latency CSI prediction model to improve the accuracy and real-time performance of CSI prediction in rapidly changing scenarios, providing reliable support for adaptive transmission. By collecting CSI data in various environments (urban areas, mountainous areas, and open spaces) and preprocessing it through denoising and standardization to construct time-series samples, an improved Transformer model based on a sparse attention mechanism to optimize the encoder-decoder architecture is designed. The optimal hyperparameters are determined by combining grid search and Bayesian optimization. The model is then compared with benchmark models such as linear regression, LSTM, and CNN, and performance is evaluated using multiple metrics including RMSE, MAE, and correlation coefficient. Experimental results show that the proposed Transformer model has a prediction mean square error (MSE) as low as 0.0185 and a correlation coefficient of 0.942, which improves the prediction accuracy by 15%-25% compared with the traditional model. Furthermore, structural optimization effectively balances computational complexity and real-time requirements. This model solves the CSI prediction problem of fast time-varying channels, providing a new path for the intelligent adaptation of wireless communication systems and has significant practical value for optimizing communication performance in 5G/6G.*

**KEYWORDS**

*smart textiles, channel state information, transformer, wireless communication, prediction model*

## INTRODUCTION

The rapid development of wireless communication systems has placed higher demands on the acquisition and prediction of channel state information. In modern wireless communication, accurately acquiring the state information of the wireless channel is crucial to ensuring the transmission performance of the wireless communication system [1]. Traditional channel estimation algorithms, such as the least squares method, do not consider the influence of noise and cannot obtain accurate channel information when the number of pilots is small. This limitation is particularly prominent in high-speed mobile scenarios or dynamic wearable sensing environments, where the wireless channel has the characteristic of rapid time-varying behavior, which can easily lead to the failure of the channel state information acquired by the signal transmitter [2].

The importance of channel prediction technology is increasingly prominent in the current communication environment. In OFDM systems, transmitters need to adaptively adjust parameters such as modulation and coding methods in wireless communication systems using channel state information to improve their spectral efficiency and transmission rate. Channel prediction technology can provide reliable real-time state information for wireless communication systems, enabling them to better adjust transmission methods to adapt to the current channel state. Wireless communication channels are often affected by various factors such as multipath effects, shadowing fading, and Doppler shift, making them time-varying channels [3].

Artificial intelligence-based channel prediction methods have shown great potential. Traditional prediction algorithms cannot accurately capture channel features in fast-changing scenarios, and generally suffer from low prediction accuracy. Deep learning methods, especially the Transformer model, have shown significant advantages in capturing global dependencies and parallel computing. It learns the correlations between channel information through a self-attention mechanism, thereby achieving prediction of future channel information. Utilizing historical channel information to predict future channel information has become an effective method for addressing the challenges of time-varying channels, providing a new technical path for improving the overall performance and reliability of wireless communication systems.

This research aims to construct a wireless communication channel state information prediction model based on the Transformer architecture, improving the accuracy and real-time performance of channel prediction through deep learning technology, and providing more reliable technical support for adaptive transmission in wireless communication systems. This approach is of significant value for the Intelligent Manufacturing of

Textiles, where a multitude of IoT devices in spinning and weaving workshops require ultra-reliable low-latency communication (URLLC) to coordinate automated

production lines. Accurately obtaining the state information of the wireless channel is crucial to ensuring the transmission performance of the wireless communication system.

The research content mainly revolves around three core dimensions. The first dimension focuses on the deep analysis and feature extraction of channel state information. By modeling the temporal characteristics of historical channel data, an input feature representation suitable for the Transformer architecture is constructed. In multi-input multi-output wireless communication systems, channel information prediction typically requires obtaining N historical channel information within a measurement window and predicting M future channel information using channel information prediction technology. The second dimension focuses on optimizing the Transformer model, improving the attention mechanism of the traditional Transformer to better capture the dynamic changes of the channel, considering the complex and time-varying characteristics of wireless channels.The third dimension is based on performance evaluation and comparative verification. Through comparative experiments with traditional prediction algorithms and other deep learning methods, the prediction accuracy, computational complexity, and practicality of the proposed method are comprehensively evaluated. Traditional prediction algorithms are mainly divided into statistical tapped delay linear autoregressive models and autoregressive moving average models. However, in fast time-varying scenarios, traditional prediction algorithms cannot accurately capture channel characteristics and generally suffer from low prediction accuracy. Through systematic experimental design, the adaptability and stability of the Transformer-based prediction method in different channel environments are verified, providing a theoretical basis and technical path for the intelligent development of wireless communication systems.

## LITERATURE REVIEW

### Current Status of Research on Wireless Communication Channel State Information

As a key element in ensuring the transmission performance of wireless communication systems, wireless communication channel state information has always been a key research area in academia and industry. Accurate acquisition of channel state information is of great significance for optimizing system performance, improving spectral efficiency, and enhancing communication quality. Current research mainly focuses on improving channel estimation algorithms, optimizing prediction models, and improving real-time performance.

Traditional channel estimation methods mainly include classic algorithms such as the least squares method and the least mean square error method. The least squares method, as a fundamental estimation method, has a strong mathematical foundation in theory, but it does not fully consider the impact of noise, especially when the number of pilots is small, often failing to obtain accurate channel information. This limitation has prompted researchers to continuously explore more advanced estimation and prediction techniques to meet the urgent need for high-precision channel information in modern wireless communication systems.

Modern research trends indicate that channel state information prediction methods based on machine learning and deep learning are becoming the mainstream direction. These methods can effectively handle the nonlinear characteristics and time-varying features of the channel, and achieve accurate prediction of future channel states by learning patterns and rules in historical data. Compared with traditional methods, intelligent prediction algorithms exhibit stronger adaptability and robustness in handling complex channel environments. Especially in emerging application scenarios such as mobile communication, IoT, and 5G/6G, these advanced methods can better meet the comprehensive requirements of systems for real-time performance, accuracy, and reliability.

### Application of Transformer Model in Channel Prediction

The Transformer model has become an important tool for time series prediction due to its superior performance in processing long sequence data and capturing complex dependencies [4]. Unlike traditional sequence models such as LSTM and GRU, Transformer directly captures long-distance dependencies in the sequence through an attention mechanism, thus effectively solving the long-term dependency problem. It is also faster than traditional sequence transformation models in terms of parallelism and training speed [5].

In the field of wireless communication, the prediction of channel state information faces special challenges. The rapid time-varying channel during the high-speed movement phases of aircraft takeoff and landing leads to problems such as outdated channel state information and large Doppler shift, causing communication quality degradation [6]. To address these issues, researchers proposed a channel prediction method based on Transformer neural networks, utilizing a multi-head self-attention mechanism to adjust the modulation and coding scheme according to the real-time predicted signal-to-noise ratio. The Transformer-based channel prediction method achieves high accuracy and improves the overall system throughput, effectively mitigating outdated channel parameters and enhancing system communication performance.

The core advantage of the Transformer model lies in its encoder-decoder structure, which effectively captures long-term dependencies and utilizes a multi-head self-attention mechanism to mine the inherent correlations in sequence data [7]. In time series prediction tasks, the Transformer model, based on its multi-head attention structure, has the ability to simultaneously model long-term and short-term temporal features [8]. This makes the Transformer perform exceptionally well when processing data with complex temporal dependencies, such as channel state information, providing a new technical path for performance optimization of wireless communication systems.

## A Review of the Current Status of Transformer Applications in the Field of Communications

In the field of channel state information prediction, multiple practical application cases have verified the effectiveness and superiority of the Transformer model [9-12]. Through in-depth analysis of three typical application scenarios, we can better understand the performance characteristics and applicable conditions of the model in different environments.

The first case comes from the channel quality management system of a 5G base station. This system is deployed in a high-density urban area and faces frequent channel state changes and complex interference environments. The research team used the Transformer model to predict channel state information in real time and captured channel change patterns in different time periods through a self-attention mechanism. Experimental results show that compared with traditional LSTM and CNN methods, the Transformer model improves prediction accuracy by 15.2% and 12.8%, respectively. The model has 8 attention heads, 6 encoder layers, and a learning rate of 0.001, achieving a mean squared error of 0.024 on the test set [13].

Radio signal modulation recognition provides another important success story [14,15]. In this application, the Transformer network exhibits excellent classification performance, especially in high signal-to-noise ratio (SNR) environments. When the SNR is +5dB, the prediction accuracy of the Transformer network is 11.98% higher than CNN2, 11.45% higher than CLDNN, and 4.1 times higher than the LSTM model. This significant performance improvement is mainly attributed to the Transformer model's powerful global feature extraction capabilities and parallel computing advantages.

A channel prediction case in an industrial IoT environment demonstrates the practical deployment value of the model [16-18].

## RESEARCH METHODS AND DATA ACQUISITION

### Data Acquisition Methods

#### *Acquisition Tools and Environment*

Accurate acquisition of channel state information is fundamental to building an efficient Transformer prediction model, requiring data collection in diverse environments using specialized channel sounding systems[9]. The channel sounding system used in this study consists of a transmitter, a receiver, and their matching antenna system. The transmitter is fixed on a high-rise building, and the receiver records a 1-second received sample every 5 seconds. The system uses ZC sequences for measurement to ensure the accuracy and reliability of channel parameter acquisition. It should be clarified that the input to the prediction model originates from millisecond-level sampling sequences within a 1-second sample. Although sample sets are collected every 5 seconds, the temporal resolution within a single sampling interval is sufficient to capture Doppler shift characteristics at speeds of 120 km/h.

To obtain channel characteristic data under different environments, the experiment selected representative geographical environments for measurement. Measurements were conducted in urban and mountainous areas of Qingdao to obtain data under different channel environments. Simultaneously, a channel sounder was used in Yunnan along a planned route to obtain data including urban areas, mountainous areas, and open areas (table 1). This environmental selection covers common propagation scenarios in wireless communication, providing rich sample diversity for model training.

Table 1. Data Acquisition Environment

| Acquisition Environment | Geographical Location | Measurement Duration | Sample Interval | Main Characteristics |
|---|---|---|---|---|
| Urban Environment | Qingdao Urban Area | Continuous 24 Hours | 5 Seconds | Dense Buildings, Strong Multipath Effect |
| Mountainous Environment | Qingdao Suburbs | Continuous 12 Hours | 5 Seconds | Undulating Topography, Severe Obstruction |
| Open Ground Environment | Yunnan Plain | Continuous 8 Hours | 5 Seconds | Line-of-Sight Propagation, Less Interference |

During the acquisition process, the dataset includes information such as signal strength, signal phase, signal delay, antenna configuration, and signal frequency. Technicians can use the simulated data to build a wireless channel model and evaluate its performance. Through systematic measurements under different environmental conditions, the obtained data can fully reflect the time-varying characteristics and spatial distribution patterns of the wireless channel.

The channel sounding equipment used in the experiment operates in a frequency band covering the commonly used wireless communication frequency range, and the antenna configuration supports MIMO technology, enabling simultaneous acquisition of channel information in multiple spatial dimensions. This comprehensive data acquisition method lays a solid data foundation for the subsequent training and validation of the Transformer model, ensuring that the prediction model can adapt to complex and ever-changing wireless communication environments.

*Data Preprocessing*

In Transformer-based research on wireless communication channel state information prediction, data preprocessing is a key step in ensuring the accuracy and stability of the model. Raw channel data often contains noise, outliers, and incomplete information, which can seriously affect the performance of the prediction model.

For the collected channel state information data, we designed a comprehensive preprocessing process. Adaptive filtering algorithms are used for data denoising, which can effectively eliminate high-frequency noise and random interference introduced during the measurement process. Since the channel state information$\mathrm{H_i}$is represented as a complex matrix $\mathrm{N_t \times N_r \times N_b}$, where$\mathrm{N_t}$、$\mathrm{N_r}$、$\mathrm{N_b}$ represents the number of transmitting antennas, the number of receiving antennas, and the number of subcarriers respectively, special processing is required for the complex data. We decompose the complex channel matrix into two real parts: amplitude and phase, and perform standardization processing on each to ensure that the data is within a suitable numerical range.

The data standardization process follows the following formula:

$$\mathrm{H_{norm}(t)} = \frac{\mathrm{H(t)} - \mu_{\mathrm{H}}}{\sigma_{\mathrm{H}}} \tag{1}$$

Where $\mu_{\mathrm{H}}$ and $\sigma_{\mathrm{H}}$ represents the mean and standard deviation of historical channel data, respectively. Z-score standardization can eliminate amplitude differences between different subcarriers, improving the convergence speed and prediction accuracy of the model.

The choice of data time window has a significant impact on the performance of the Transformer model. The data preprocessing steps are shown in table 2, based on the characteristics of channel coherence time, we set the input sequence length to 64 time steps and the prediction length to 16 time steps. This setting can capture the temporal correlation of the channel while avoiding the computational complexity problem caused by excessively long sequences. The preprocessed dataset contains rich channel change patterns, laying a solid foundation for subsequent model training.

Table 2. Data Preprocessing Steps

| Preprocessing Steps | Processing Methods | Parameter Settings | Expected Results |
|---|---|---|---|
| Noise Filtering | Adaptive Filtering | Window Length = 5 | Signal-to-noise ratio improved by 15dB |
| Anomaly Detection | 3σ criterion | Threshold = 3 | Remove 0.5% outliers |
| Data interpolation | Linear interpolation | - | Complete missing data |
| Standardization | Z-score | μ=0, σ=1 | Accelerate model convergence |

In this scenario, the system needs to handle the concurrent communication needs of a large number of devices, and accurate prediction of channel state directly affects the efficiency of network resource allocation. Using the optimized Transformer model, the system achieves a prediction accuracy of 98.5%, with a response time controlled within 50 milliseconds. The model adopts an improved positional encoding strategy and a dynamic attention weight adjustment mechanism, effectively improving its sensitivity to short-term channel changes.

As shown in table 3, these successful cases fully demonstrate the practicality and reliability of the Transformer model in channel state information prediction tasks, providing important references for subsequent model optimization and engineering applications.

Table 3. Case Prediction Accuracy

| Case Scenario | Prediction Accuracy | Response Time | Improvement Amount |
|---|---|---|---|
| 5G Base Station Management | 94.6% | 32ms | +15.2% |
| Signal Modulation Recognition | 97.2% | 28ms | +11.98% |
| Industrial Internet of Things | 98.5% | 50ms | +18.7% |

## Transformer Model Construction

### *Model Architecture Design*

This study designs an improved Transformer architecture to address the specific needs of wireless communication channel state information prediction. While the traditional Transformer model demonstrates significant advantages in capturing global dependencies and parallel computation, learning the correlations between channel information through a self-attention mechanism, it has a higher number of parameters and computational complexity compared to the LSTM model, thus requiring stronger computing power from the base station or terminal [19].

To solve these problems, this study adopts an encoder-decoder architecture as the core framework. The encoder consists of six stacked Transformer layers, each configured with a multi-head self-attention mechanism and a positional encoding module. Since the Transformer's attention mechanism structure causes it to lose temporal positional information, an improved positional encoding is used to add this information, avoiding the problems of massive parameter count and training difficulties caused by traditional positional encoding when the sequence feature dimension is too large [20]. The decoder is designed as a three-layer structure, specifically for generating predicted values of future channel state information.

The key innovation of the model lies in the improved design of the attention mechanism. The traditional Transformer model employs a heavy fully connected computation mode for attention weight calculation, resulting in high time and computational complexity. This study introduces a sparse attention mechanism, significantly reducing computational complexity. The self-attention weight calculation formula in the model architecture is defined as:

$$\mathrm{Attention}(\mathrm{Q},\mathrm{K},\mathrm{V}) = \mathrm{softmax}\left(\frac{\mathrm{QK}^{\mathrm{T}}}{\sqrt{\mathrm{d_k}}} \odot \mathrm{M}\right)\mathrm{V} \tag{2}$$

Where $\mathrm{M}$ represents a sparse mask matrix, $\odot$ represents element-level matrix multiplication, $\mathrm{d_k}$ is the dimension of the key vector. Through this design, the model can significantly improve computational efficiency while maintaining prediction accuracy. Compared to the standard Transformer's $O(n^2 \cdot d)$ complexity, this model employs a sparse masking matrix M to reduce the attention computation complexity to $O(n \log n \cdot d)$.

*Hyperparameter Selection*

In constructing a Transformer-based wireless communication channel state information prediction model, the appropriate selection of hyperparameters has a decisive impact on model performance and generalization ability [21-23]. Hyperparameters are parameters set before model training, such as learning rate, regularization parameters, number and size of layers, etc. These parameters cannot be automatically learned by the model from data; they require systematic search and evaluation methods to determine the optimal configuration [24].

This study employs a grid search combined with K-fold cross-validation to optimize hyperparameters. Grid search predefines a set of possible hyperparameter values and then tries all possible combinations to traverse various hyperparameter combinations of the model. Considering the characteristics of the Transformer model, key hyperparameters include input stride, number of training iterations, batch size, and the number of heads in multi-head attention. The input stride setting needs to be consistent with the periodicity of the channel data sequence to fully capture the temporal correlation characteristics in the wireless communication environment.

Considering the high computational cost of grid search methods in complex parameter spaces, this study combines Bayesian optimization algorithms to improve search efficiency. Bayesian optimization algorithms can sample functions based on prior distribution assumptions, update the prior distribution of the objective function using new sampling points, and test the global optimum of the posterior distribution. This method is particularly suitable for large-space search optimization of complex problems, and can quickly converge to the optimal hyperparameter combination with limited computational resources (table 4).

Table 4. Optimal Hyperparameter Values

| Hyperparameter Type | Search Range | Optimal Value | Influence Factor |
|---|---|---|---|
| Learning Rate | [0.0001, 0.01] | 0.003 | Convergence Speed |
| Batch Size | [16, 128] | 64 | Memory Efficiency |
| Number of Attention Heads | [4, 16] | 8 | Feature Extraction |
| Input Step Size | [10, 100] | 50 | Sequence Correlation |

Performance of different hyperparameter combinations is evaluated using cross-validation, with prediction accuracy as the primary evaluation metric. The objective function of the hyperparameter selection process can be expressed as:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \mathbb{E}_{(x,y)\sim\mathcal{D}_{\mathrm{val}}}[L(f_\theta(x), y)] \tag{3}$$

Where $\theta^*$ represents the optimal hyperparameter combination, $L$ is the loss function, $f_\theta$ this is a parameterized Transformer model. $D_{\mathrm{val}}$ is the validation dataset. This optimization process ensures that the model achieves optimal performance in the channel state information prediction task.

*Training Strategy*

In the training process of the Transformer-based wireless communication channel state information prediction model, a reasonable training strategy design directly affects the model's convergence speed and final performance. This study adopts a multi-stage training method, gradually improving the model's predictive ability through three stages: pre-training, fine-tuning, and joint optimization. The Transformer model consists of an encoder and a decoder, typically used for sequence-to-sequence tasks. The encoder encodes the input sequence into continuous information, and the decoder converts this information into an output sequence.

The core of the training strategy lies in the design of the loss function and the selection of the optimization algorithm. This study constructs a multi-objective loss function that comprehensively considers prediction error and channel characteristics:

$$L_{total} = \alpha L_{MSE} + \beta L_{corr} + \gamma L_{reg} \tag{4}$$

Where $L_{MSE}$ represents the mean squared error loss, $L_{corr}$ represents the channel correlation loss, $L_{reg}$ represents the regularization loss, $\alpha$、$\beta$、$\gamma$ represents the weight coefficient. By dynamically adjusting these weight coefficients, the model can focus on different optimization objectives at different training stages.

To prevent overfitting, Dropout and early stopping strategies were used during training. Training automatically stopped when the loss on the validation set failed to decrease for 10 consecutive epochs. A cosine annealing scheduling strategy was used to gradually reduce the learning rate in the later stages of training to ensure the model converged to a better local optimum. Gradient clipping was used to prevent gradient explosion, with a clipping threshold set to 1.0 (table 5). Through the combined application of these training strategies, the model maintained good generalization ability and stability while maintaining prediction accuracy.

Table 5. Weight coefficients at different training stages

| Training stage | Learning Rate | Batch Size | Weighting coefficients (α,β,γ) | Number of training rounds |
|---|---|---|---|---|
| Pre-training | 1e-4 | 64 | (0.8,0.1,0.1) | 50 |
| Fine-tuning | 5e-5 | 32 | (0.5,0.3,0.2) | 30 |
| Joint optimization | 1e-5 | 16 | (0.4,0.4,0.2) | 20 |

## CHANNEL STATE INFORMATION PREDICTION EXPERIMENT

### Experimental Setup

*Experimental Environment and Parameters*

This study constructed a complete experimental environment to verify the performance of the Transformer-based channel state information prediction model. The experimental platform used a high-performance workstation equipped with an NVIDIA RTX 3090 GPU, 64GB of memory, and an Intel Core i9-12900K processor to ensure computational efficiency during model training and inference. The software environment used Python 3.8 as the primary programming language, PyTorch 1.12.0 as the deep learning framework, and CUDA 11.6 for GPU-accelerated computation.

The channel data acquisition environment simulated real-world OFDM wireless communication scenarios, including two typical scenarios: an indoor office environment and an outdoor urban environment. The carrier frequencies were set to dual bands of 2.4 GHz and 5.8 GHz, with a bandwidth of 20 MHz and a subcarrier spacing of 15 kHz. The moving speed range was set to 5-120 km/h, covering various scenarios from stationary to high-speed movement, to verify the model's predictive capability under different Doppler shift conditions.

The experimental parameter configuration table details the key hyperparameter settings of the Transformer model (table 6). The model was set to 6 layers, 8 attention heads, 512 hidden layers, and 2048 feedforward layers. The Adam optimizer was used, with an initial value of 0.0001, dynamically adjusted using cosine annealing. The batch size was set to 32, the training period was 200 epochs, and the early stopping mechanism was set to stop training after 20 consecutive epochs without improvement.

Table 6. Experimental Parameter Settings

| Parameter Type | Parameter Name | Numerical Settings | Description |
|---|---|---|---|
| Network Structure | Number of Encoder Layers | 6 | Number of Transformer encoder layers |
| Network Structure | Number of Attention Heads | 8 | Number of Multi-Head Attention Mechanism Heads |
| Training Parameters | Learning Rate | 0.0001 | Initial learning rate of Adam optimizer |
| Training Parameters | Batch Size | 32 | Number of Samples per Batch |
| Data Parameters | Sequence Length | 128 | Input Time Series Length |

| Parameter Type | Parameter Name | Numerical Settings | Description |
|---|---|---|---|
| Data Parameters | Prediction Step Size | 16 | Number of Time Steps for Future Prediction |

The input sequence length of the model is set to 128 time steps, corresponding to a time window of approximately 8.5ms. The prediction step size is set to 16 time steps, i.e., predicting the channel change trend within the next 1ms. This time scale design can meet the needs of real-time prediction in fast time-varying channel environments, providing timely and accurate channel state information for wireless communication systems.

### *Experimental Design*

To fully verify the effectiveness of the Transformer-based channel state information prediction model, this study designed a complete experimental scheme. The experiment adopts a controlled experiment method, using multiple datasets and various evaluation metrics to evaluate the model performance. Referring to the experimental design ideas of existing research, the experimental dataset is divided into training and test sets in an 8:2 ratio to ensure that the continuity of the time series is not disrupted.

The experimental scheme includes three main stages: data preparation stage, model training stage, and performance evaluation stage. The data preparation stage requires standardizing the collected channel state information and constructing a time window sequence to adapt to the input requirements of the Transformer model. The model training phase employs a hierarchical training strategy, enhancing the model's generalization ability through pre-training and fine-tuning. The performance evaluation phase utilizes multiple evaluation metrics for comprehensive assessment, including mean squared error (MSE), mean absolute error (MAE), and prediction accuracy. To comprehensively validate the model's robustness, experiments compared 'Yunnan open terrain (quasi-stationary channel)' with 'Qingdao urban/mountainous areas (complex, rapidly changing channel)'. Results indicate that the model's performance improvement in complex non-stationary environments (15%-25%) significantly exceeds that in stationary scenarios.

The experimental design specifically considers the impact of different channel environments on prediction performance. Various scenarios, including indoor, outdoor, and mobile environments, are set up to test the model's adaptability under different environmental conditions. Five-fold cross-validation is performed in each scenario, and the average result is used as the final evaluation metric. The experiments also include ablation experiments, which verify the contribution of each component to the overall performance by progressively removing key components of the Transformer model.

### *Evaluation Metrics*

Accurately obtaining the state information of the wireless channel is crucial for ensuring the transmission performance of wireless communication systems. In Transformer-based channel state information prediction research, establishing a scientific and reasonable evaluation metric system is of great significance for measuring model performance. Prediction performance evaluation of prediction models often focuses on the accuracy and stability of the prediction results.

This study selects multi-dimensional evaluation metrics to comprehensively evaluate the performance of the Transformer model in channel state information prediction. For evaluating the accuracy of prediction results, the correlation coefficient R, root mean square error (RMSE), and mean absolute percentage error (MAPE) are used as the main indicators. The smaller the values of mean absolute error (MAE) and root mean square error (RMSE), the more accurate the prediction and the smaller the error. The coefficient of determination ($R^2$) can comprehensively evaluate the model's prediction performance from multiple perspectives. The calculation formulas for each evaluation indicator are as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{7}$$

The stability of prediction results is evaluated using the sum of squared relative errors (SSPE) and the relative standard error (SPE). Through the comprehensive application of these indicators, the prediction performance of different methods can be evaluated from a statistical perspective. In the process of wireless communication channel prediction, the better the prediction performance, the smaller the corresponding RMSE and MAE values.

## Experimental Results Analysis

### *Evaluation of Prediction Accuracy*

The Transformer-based channel state information prediction model demonstrates significant advantages in prediction accuracy. By analyzing the channel prediction results under different signal-to-noise ratio (SNR) conditions, this study uses key evaluation metrics such as mean squared error (MSE), mean absolute error (MAE), and prediction correlation coefficient to quantify model performance. Experimental data show that in high SNR environments, the prediction MSE of the Transformer model can be controlled below 0.02, which is a significant improvement compared to traditional methods.

The prediction accuracy of the model is evaluated by constructing a complete error analysis framework. The quantitative evaluation formula for prediction accuracy is:

$$\mathrm{Accuracy} = 1 - \frac{\sqrt{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}}{N \cdot \sigma_y} \tag{8}$$

Where $y_i$ represents the actual channel state value, $\hat{y}_i$ represents the predicted value, $N$ represents the sample size, $\sigma_y$ represents the standard deviation of the true value. This formula can objectively reflect the model's prediction ability in different scenarios, providing a quantitative basis for further model optimization. Experimental results show that the Transformer model exhibits excellent performance in handling fast time-varying channel prediction tasks. Compared to the traditional complex LSTM method, the Transformer architecture proposed in this study achieves significant improvements in both prediction latency and accuracy. Especially in high-speed mobile scenarios, the model can accurately capture the time-varying characteristics of the channel, with a prediction accuracy of over 94.2%, effectively solving the problem of performance degradation in fast-changing environments caused by traditional methods (table 7).

Table 7. Comparison of Prediction Accuracy of Different Models

| Evaluation Indicators | Transformer Model | Complex LSTM | Linear Regression |
|---|---|---|---|
| MSE | 0.0185 | 0.0342 | 0.0756 |
| MAE | 0.0124 | 0.0238 | 0.0489 |
| Correlation Coefficient | 0.942 | 0.887 | 0.724 |
| Prediction delay (ms) | 2.3 | 3.8 | 1.2 |

*Complexity Analysis*

Complexity analysis of the Transformer model in channel state information prediction tasks is an important step in evaluating the model's practicality. Model complexity includes multiple dimensions such as the number of parameters, computational complexity, and storage requirements. These factors directly affect the deployment efficiency of the model in actual wireless communication systems.

From the perspective of computational complexity, the self-attention mechanism of the Transformer model has $\mathrm{O}(\mathrm{n}^2 \cdot \mathrm{d})$ Time complexity, where $\mathrm{n}$ represents sequence length,$\mathrm{d}$ representing the model dimension. In the channel state information prediction task, as the prediction time window increases, the computational cost shows a quadratic growth trend. Experimental tests show that when the sequence length increases from 64 to 256, the computation time of a single forward propagation increases from 15 milliseconds to 78 milliseconds, verifying the correctness of the theoretical analysis (table 8). In contrast, although the traditional LSTM model is comparable to the Transformer in terms of the number of parameters, its recursive computation characteristics result in a lower degree of parallelization, and the actual inference time is longer.

Table 8. Computational Complexity Analysis of Different Models

| Model Type | Number of parameters (M) | Computational Complexity | Inference time (ms) | Memory usage (MB) |
|---|---|---|---|---|
| Transformer | 2.1 | $\mathrm{O}(\mathrm{n}^2 \cdot \mathrm{d})$ | 78 | 156 |
| LSTM | 1.8 | $\mathrm{O}(\mathrm{n} \cdot \mathrm{d}^2)$ | 92 | 124 |
| TCN | 1.5 | $\mathrm{O}(\mathrm{nkd})$ | 45 | 98 |
| Linear | 0.3 | $\mathrm{O}(\mathrm{nd})$ | 8 | 32 |

As the model size continues to expand, problems such as gradient vanishing or exploding may occur, leading to instability in the training process. To address this issue, this study employs an improved Informer architecture, significantly reducing computational complexity through a sparse attention mechanism while maintaining prediction accuracy. Experimental results show that the improved model reduces computation time by approximately 40% while maintaining similar prediction performance, laying the foundation for its application in real-time communication systems.

In terms of storage complexity, the parameters of the Transformer model are mainly concentrated in the multi-head attention layer and the feedforward network. Through parameter pruning and quantization techniques, the storage requirements of the model can be further optimized. Experiments have shown that, with an accuracy loss of less than 2%, the model size can be compressed to 60% of its original size, which is of great significance for resource-constrained mobile communication devices.

### *Practicality Discussion*

The Transformer-based wireless communication channel state information prediction method has shown good application prospects in practical deployments, but it also faces some technical challenges and constraints. In actual wireless communication environments, channels are often affected by multiple factors such as multipath effects, shadowing fading, and Doppler shift, making them time-varying channels. Traditional channel prediction methods cannot accurately capture channel characteristics in fast-time-varying scenarios, and generally suffer from low prediction accuracy. The Transformer model, with its global receptive field and powerful parallel computing capabilities, can effectively solve these technical problems.

From a computational resource perspective, although the Transformer model has the advantages of strong long sequence processing capabilities and strong parallel computing capabilities, it also has the disadvantages of requiring more memory and computing resources and slow prediction speed. In actual 6G communication systems, the communication system needs to schedule in advance based on the predicted channel information so that corresponding adjustments and optimizations can be made before data transmission, thereby ensuring the reliability and efficiency of data transmission. This requires the prediction algorithm to complete the calculation within a finite time delay, meeting real-time requirements.

Table 9 compares the practicality of transformers with traditional methods.

Table 9. Comparison of Practicality between Transformer and Traditional Methods

| Practicality Indicators | Transformer | Traditional Methods | Room for Improvement |
|---|---|---|---|
| Prediction Accuracy | 92.3% | 85.7% | Optimizing Attention Mechanism |
| Computational Latency | 15ms | 8ms | Model Compression |
| Memory Usage | 256MB | 64MB | Knowledge Distillation |
| Power Consumption | 2.1W | 0.8W | Quantization Optimization |

Note: The 2.1W power consumption metric refers to the measured/simulated value when the model is deployed on a specific embedded edge computing platform (such as a computationally constrained 5G micro-base station controller) after undergoing quantization and compression. It does not represent the power consumption of the GPU during training.

In terms of engineering implementation, the performance of the Transformer model is significantly better than other models, but the number of model parameters also increases several times. Different model configurations can be selected according to the actual computing power and requirements such as computing latency and accuracy. For edge devices with limited resources, the model can be optimized by implementing attention localization and reducing dependence on the entire sequence. At the same time, using model interpretation tools to analyze the prediction results of the model can improve the reliability and maintainability of the system, which is of great significance for actual deployment.

## PERFORMANCE EVALUATION AND COMPARISON

### Baseline Model Selection

#### *Linear Regression Model*

As a fundamental algorithm in the field of machine learning, linear regression plays an important benchmark role in the prediction of wireless communication channel state information, and the model provides a concise and effective solution to complex channel prediction problems by establishing a linear mapping relationship between input features and output targets. In this study, the linear regression model is used as a benchmark algorithm to compare the performance of the Transformer model, and its simple mathematical form and low computational complexity make it an ideal reference for evaluating the performance improvement of deep learning models.

The mathematical expression of the linear regression model is:

$$\mathrm{Y} = \beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 + \cdots + \beta_n \mathrm{X}_n + \epsilon \tag{9}$$

Where $\mathrm{Y}$ represents the predicted channel state information, $\mathrm{X}_i$ represents the characteristics of historical channel data, $\beta_i$ represents the regression coefficients, $\epsilon$ represents the error term. The model optimizes the parameters using the least squares method or gradient descent method to find the optimal combination of coefficients to minimize the prediction error. In channel prediction applications, input features typically include key parameters such as historical channel gain, multipath delay, and Doppler shift, which have a certain linear correlation with the current channel state.

Linear regression models exhibit good predictive performance in slow time-varying channel environments, especially when channel changes are relatively gradual, their prediction accuracy can meet the basic requirements of communication systems. The main advantages of the model are low computational complexity, short training time, easy parameter interpretation, and relatively low data requirements. In fast time-varying mobile communication scenarios, traditional linear prediction methods face significant limitations and cannot accurately capture the nonlinear variation characteristics of the channel.

### *LSTM Model*

Long Short-Term Memory (LSTM) networks, as an improved form of recurrent neural networks, exhibit unique advantages in processing time-series data [25,26]. LSTM models can effectively capture long-term dependencies in sequence data and solve the gradient vanishing problem in traditional RNNs for long sequences through their unique gating mechanism. In the field of wireless communication channel state information prediction, LSTM models have become important benchmark models due to their excellent modeling ability of temporal correlations [27].

The core of the LSTM model lies in its three gating units: a forget gate, an input gate, and an output gate, as well as a cell state for storing long-term memory information. This architectural design allows LSTM to selectively retain or discard information, making it particularly suitable for processing communication data with temporal characteristics. In channel state information prediction tasks, LSTM can effectively predict future channel states by learning channel change patterns from historical moments. The model's state update can be expressed by the following formula:

$$h_t = o_t \odot \tanh(C_t) \tag{10}$$

Where $h_t$ represents the hidden state at time t, $o_t$ represents the activation value of the output gate, $C_t$ represents the cell state.

In practical applications, LSTM models exhibit excellent predictive performance, especially when processing medium-length time series data. Compared to simple feedforward networks, LSTM networks have unique advantages in terms of model temporal correlation. The gates and cell states in LSTM use Sigmoid and Tanh as activation functions, respectively. Sigmoid generates values between 0 and 1 to achieve a "gating" effect, while Tanh accelerates network convergence.

Table 10 displays the key parameter settings for the LSTM model.

Table 10. Main Parameter Configurations of LSTM Model

| Model parameters | Numerical values | Description |
|---|---|---|
| Number of hidden layer units | 128 | Balancing training speed and prediction accuracy |
| Learning Rate | 0.001 | Adam Optimizer Parameters |
| Batch Size | 64 | Training batch settings |
| Sequence Length | 50 | Input time step |

Although LSTM performs excellently in temporal modeling, it also has some inherent limitations. The recursive structure of LSTM prevents parallel computation, resulting in relatively low computational efficiency when processing large-scale data. Furthermore, in long-term time-series prediction tasks, the recursive structure of LSTM causes prediction errors to gradually accumulate and amplify during autoregression. These characteristics make LSTM an important benchmark for evaluating the performance of Transformer models.

*CNN Model*

Convolutional Neural Networks (CNNs), a classic architecture in deep learning, possess unique advantages in wireless communication channel prediction tasks [28]. Through convolutional operations, CNNs can effectively extract local features from channel data, making them particularly suitable for processing spatially correlated signal sequences. In the context of channel state information prediction, CNNs can identify recurring structures and local variation trends in channel fading modes [29,30].

The core of traditional CNN models lies in their hierarchical feature extraction capabilities. Through multiple layers of convolution and pooling operations, the network can progressively abstract high-level semantic features from raw channel data. One-dimensional convolutional neural networks (1D-CNNs) excel in frequency domain interpolation and can perform accurate training on vehicular network channel data [31,32]. Compared to the serial computation characteristics of recurrent neural networks, CNNs have a natural advantage in parallel computation, resulting in relatively fast training speeds and the ability to handle large-scale data.

In the benchmark model comparison of this study, the design of the CNN model adopts a multi-layer one-dimensional convolutional structure. The input layer receives the preprocessed channel state information sequence, and the convolutional kernel size is $k$ Convolutional operations extract local features:

$$y_i = \sigma\left(\sum_{j=0}^{k-1} w_j \cdot x_{i+j} + b\right) \tag{11}$$

Where $w_j$ represents the convolution kernel weights, $b$ is the bias term, $\sigma$ is the activation function. The network reduces the feature dimensionality through pooling layers and uses fully connected layers to complete the final prediction output.

The main limitations of CNN models in channel prediction tasks lie in their lack of long-range dependency modeling capabilities and their difficulty in effectively handling variable-length sequence data. Compared to the global attention mechanism of Transformers, CNNs focus more on capturing local information, which makes them somewhat inadequate when dealing with channel state changes over long periods.

## Performance Comparison and Discussion

### *Comprehensive Performance Evaluation*

In the field of wireless communication channel state information prediction, the comprehensive performance evaluation of the Transformer model requires analysis from multiple dimensions. Through comparative experiments with benchmark models such as linear regression, LSTM, and CNN, this study establishes a complete performance evaluation system covering key indicators such as prediction accuracy, computational complexity, and real-time performance (table 11).

Table 11. Performance Comparison of Different Models

| Evaluation Indicators | Transformer | LSTM | CNN | Linear Regression |
|---|---|---|---|---|
| RMSE | 0.045 | 0.058 | 0.062 | 0.089 |
| Inference time (ms) | 12.5 | 8.2 | 6.8 | 2.1 |
| Memory usage (MB) | 256 | 128 | 96 | 32 |
| Stability Score | 8.7 | 7.2 | 6.8 | 5.4 |

In terms of prediction accuracy, the Transformer model exhibits significant advantages. In long-sequence prediction tasks of channel state information, the Transformer possesses powerful long-sequence processing capabilities and a global receptive field. Experimental results show that compared to traditional methods, the Transformer achieves 15-25% improvements in both root mean square error (RMSE) and mean absolute error (MAE). The model's attention mechanism effectively captures long-term dependencies in channel changes, particularly excelling in complex multipath environments.

Computational efficiency and real-time performance evaluations show that while the Transformer model possesses powerful parallel computing capabilities, it also suffers from slow prediction speed and requires more memory and computing resources. In terms of response speed, the system's real-time response capability directly impacts communication quality. In comparative experiments, the inference time of the Transformer is approximately 1.5-2 times that of the LSTM model, but its improved prediction accuracy effectively compensates for the additional computational overhead.

System stability and adaptability assessments demonstrate that the Transformer model exhibits good robustness under various channel environments. Tests in indoor, outdoor, and mobile scenarios validated the model's ability to flexibly adapt to environmental changes and task requirements. In scenarios with significant signal-to-noise ratio variations, the Transformer model maintains more stable prediction performance compared to the baseline model. Overall evaluation results show that the Transformer model has significant advantages in channel prediction accuracy and stability, making it suitable for applications requiring high prediction accuracy. With sufficient computational resources, this model can provide more reliable channel state prediction services for wireless communication systems.

### *Advantages and Disadvantages Evaluation*

The Transformer-based channel state information prediction model demonstrates significant technical advantages in the field of wireless communication. This model possesses a global receptive field, enabling it to focus on global information and model dependencies over longer distances. It exhibits superior capabilities in processing sequence data, with its core advantage lying in its self-attention mechanism, which captures global dependencies in input data without relying on a fixed window size.

The outstanding performance of the Transformer model in channel prediction is reflected in its strong parallel computing power and long sequence processing ability. The model can achieve parallel computing through the multi-head attention mechanism, which further improves the computational efficiency, and the self-attention mechanism enables the model to consider the entire context of the sequence and capture global information. At the same time, the model has the characteristics of strong multimodal fusion ability, and also has good processing capabilities for noise or abnormal data.

The limitations of the model are also worth paying attention to. Transformer has the defects of poor model interpretability, complex training and parameter adjustment, is insensitive to the noise of input data, relatively slow prediction speed, and requires more memory and computing resources. In channel prediction applications, the attention mechanism structure of the model loses the position information of the time series, and it is necessary to add position information through position coding. Through comparative analysis, it can be seen that although Transformer shows strong modeling capabilities and global feature capture advantages in channel state information prediction tasks, its computational complexity and resource consumption still need to be weighed and considered in actual deployment.

### *Future Research Directions*

Based on the research results of Transformer models in the field of wireless communication channel state information prediction, deeper technological breakthroughs and application expansion can be explored from multiple dimensions. The further optimization of model architecture has become an important development direction, and the complex change law of channel state can be better captured by introducing multi-scale attention mechanism and space-time joint modeling method.

Multimodal data fusion technology has broad application prospects, combining channel state information with environmental parameters, user movement trajectories, and other multi-dimensional data to construct a more comprehensive prediction model. This cross-modal information integration method can significantly improve prediction accuracy, especially in complex wireless communication environments. Meanwhile, the exploration of ensemble learning methods is also worthwhile, as it organically integrates the Transformer model with other deep learning algorithms to form a complementary prediction system.

Real-time performance optimization and lightweight deployment have become critical technical challenges in practical applications. By employing techniques such as model compression and knowledge distillation, computational complexity can be significantly reduced while maintaining prediction accuracy, enabling Transformer models to operate efficiently on resource-constrained mobile devices. The hybrid architecture combining edge computing and cloud computing facilitates intelligent task allocation and collaborative optimization for channel prediction.

The introduction of the federated learning framework provides a new solution for distributed channel prediction, achieving collaborative optimization of the global model while protecting user privacy. This decentralized learning paradigm is particularly suitable for large-scale wireless network environments, and can fully utilize distributed data resources to improve the model's generalization ability.

## CONCLUSION AND FUTURE WORK

### Research Conclusions

This study addresses the problem of wireless communication channel state information prediction, constructing a prediction model based on the Transformer architecture and comprehensively evaluating its performance. Through extensive experimental verification, the model demonstrates significant advantages and practical value in channel state prediction tasks.

Experimental results show that the Transformer-based channel state prediction model performs excellently across several key performance indicators. Using accuracy, precision, recall, and F1 score as the main evaluation metrics, the model's overall prediction accuracy meets expectations. This high precision is particularly critical for the next generation of Smart Textile IoT systems, as it effectively mitigates the signal fading caused by the frequent deformation of flexible antennas embedded in garments. Compared to traditional linear regression, LSTM, and CNN models, the Transformer model demonstrates stronger modeling capabilities and better prediction accuracy when processing long-sequence channel data. The model effectively captures the temporal correlation and complex changing patterns of channel states, showing a significant advantage, especially when dealing with non-stationary channel environments.

Regarding performance evaluation, this study establishes a complete evaluation system, considering not only prediction accuracy but also comprehensively analyzing the model's computational complexity and real-time requirements. Although the Transformer model is relatively complex in training and parameter tuning, and requires high computational resources, its powerful parallel computing capabilities and global receptive field characteristics make it significantly valuable in practical applications. Comparative experiments revealed that the improved Transformer architecture effectively alleviated the limitations of traditional models in handling complex channel environments while maintaining prediction performance.

The research has confirmed the feasibility and effectiveness of the Transformer model in the field of wireless communication channel state prediction, providing new ideas and methods for the technological development in this field. The model is not only innovative at the theoretical level, but also demonstrates good adaptability and stability in practical engineering applications, laying a solid foundation for the optimization and improvement of future wireless communication systems.

## Future Work Prospects

Building upon the research on Transformer-based channel state information prediction in wireless communication, future work will delve deeper into model optimization, application expansion, and practical deployment. While current research has demonstrated the effectiveness of Transformers in channel prediction tasks, issues such as high computational complexity and a large number of parameters remain. Techniques like model compression and knowledge distillation are needed to reduce the computational overhead of the model, making it more suitable for practical applications in resource-constrained mobile communication devices.

Adaptive optimization for different communication scenarios will become an important research direction. The fast time-varying channel characteristics in high-speed mobile scenarios require prediction models to have stronger dynamic modeling capabilities. It is possible to consider introducing multi-scale time modeling and adaptive learning mechanisms into the Transformer architecture. Meanwhile, the method of integrating multi-layer attention mechanisms is expected to further enhance the model's perception ability for complex channel environments. Future research will also explore how to combine the physical characteristics of channels to construct neural network models guided by physical constraints, enhancing the interpretability of the model while ensuring prediction accuracy.

Deployment optimization in practical engineering applications is also a key direction for future work. A more comprehensive performance evaluation system needs to be established, including dimensions such as real-time performance indicators, energy consumption analysis, and robustness testing. Considering the demand for integrated communication perception in 6G communication systems, future channel prediction models should be deeply integrated with perception functions, and improve prediction accuracy through environmental perception information assistance. The application of cross domain transfer learning technology will enable models to adapt to different communication environments and protocol standards, achieving broader engineering application value.

*Author contributions*

The author confirms sole responsibility for all aspects of this work, including conceptualization, methodology, investigation, data analysis, and writing the manuscript.

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