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TRANSMISSION DELAY PREDICTION METHOD FOR OPTOELECTRONIC COMMUNICATION SYSTEMS BASED ON TEMPORAL FEATURE ENHANCEMENT

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Abstract: Transmission delay prediction is essential for low-latency service assurance and intelligent operation in optoelectronic communication systems. In practical transmission environments, delay is not only determined by physical propagation distance, but is also affected by traffic load, bandwidth utilization, queue status, bit error rate, and optical link quality. To improve prediction accuracy under dynamic system conditions, this paper proposes a transmission delay prediction method based on temporal feature enhancement. The proposed method first analyzes the main factors influencing transmission delay and constructs a prediction variable set including historical delay, traffic load, bandwidth utilization, queue length, bit error rate, and received optical power. Then, lag features, sliding-window statistical features, and difference features are introduced to enhance the temporal representation of the original monitoring data. Based on the enhanced feature sequence, an LSTM-based prediction model is developed to learn the nonlinear temporal relationship between system states and future transmission delay. Experimental results show that the proposed method achieves lower prediction errors than ARIMA, SVR, XGBoost, and standard LSTM models. The ablation analysis further confirms that temporal feature enhancement can effectively improve the model's ability to capture historical dependence, short-term fluctuation, and dynamic variation trends.
Keywords: Optoelectronic communication systems; Transmission delay prediction; Temporal feature enhancement; LSTM

1 INTRODUCTION

With the rapid development of high-speed data transmission, intelligent sensing, industrial Internet, edge computing, and data center interconnection, optoelectronic communication systems have become an essential component of modern information infrastructure [1-3]. Compared with conventional electrical communication systems, optoelectronic communication systems offer significant advantages, including high transmission rate, large bandwidth capacity, strong resistance to electromagnetic interference, and low transmission loss. However, in practical operating environments, transmission delay is not determined solely by the propagation distance of optical signals. It is also affected by traffic fluctuation, bandwidth utilization, node buffer status, optoelectronic conversion, bit error rate, and channel quality variation. Under burst traffic or unstable link conditions, delay may exhibit nonlinear fluctuations, which can degrade quality of service and communication reliability [4-6].

Existing studies have made progress in communication system performance prediction. Traditional methods usually estimate network delay based on queuing theory, statistical analysis, or empirical models, but they are limited in describing complex nonlinear relationships and dynamic temporal variations. In recent years, machine learning and deep learning methods have been increasingly introduced into optical network performance prediction, including QoT estimation, dynamic bandwidth allocation, traffic prediction, and neural network-based signal processing. Nevertheless, most existing studies mainly focus on traffic prediction, link quality assessment, or fault detection, while dedicated prediction of transmission delay in optoelectronic communication systems remains insufficient. In addition, many models directly use raw delay sequences or single state variables as inputs, without fully exploiting lag characteristics, local fluctuation patterns, and trend information embedded in historical data [7-9].

To address these issues, this paper proposes a transmission delay prediction method for optoelectronic communication systems based on temporal feature enhancement. The major factors affecting transmission delay are first analyzed, and a prediction variable set is constructed by incorporating historical delay, traffic load, bandwidth utilization, queue status, and link quality indicators. Lag features, sliding-window statistical features, and difference-based variation features are then introduced to enhance the original time-series data. Finally, an LSTM-based model is developed to learn the nonlinear temporal relationship between enhanced system states and future transmission delay. The effectiveness of the proposed method is verified through comparison with ARIMA, SVR, XGBoost, and standard LSTM models.

2 TRANSMISSION DELAY CHARACTERISTICS AND DATA DESCRIPTION

2.1 Transmission Delay Characteristics

In optoelectronic communication systems, transmission delay is a comprehensive performance indicator affected by both physical transmission mechanisms and dynamic network operating states. Although optical links usually provide high bandwidth and low propagation loss, the actual end-to-end delay observed in practical systems may fluctuate due to traffic variation, node processing, buffer accumulation, optoelectronic conversion, and link quality degradation. Therefore, transmission delay should be regarded as a dynamic variable jointly influenced by multiple system factors [10].

Generally, the transmission delay can be divided into propagation delay, processing delay, queuing delay, scheduling delay, and channel-related delay. Propagation delay is mainly determined by the transmission distance and the propagation speed of optical signals in the medium. Processing delay is introduced by modulation, demodulation, optoelectronic conversion, packet processing, and forwarding. Queuing delay is caused by temporary traffic accumulation in buffers. Scheduling delay is related to bandwidth allocation, wavelength assignment, and resource management. In addition, when optical link quality deteriorates, the increase in bit error rate or retransmission may indirectly increase effective transmission delay. As shown in table 1.

Table 1 Main Components of Transmission Delay in Optoelectronic Communication Systems

Delay component	Main cause	Dynamic characteristic
Propagation delay	Optical signal propagation along the transmission link	Relatively stable
Processing delay	Optoelectronic conversion, modulation, demodulation, and node processing	Moderately variable
Queuing delay	Buffer accumulation caused by traffic load variation	Highly dynamic
Scheduling delay	Bandwidth allocation and transmission resource scheduling	Related to network control strategy
Channel-related delay	Bit errors, signal degradation, and possible retransmission	Affected by link quality

Among these delay components, propagation delay is usually predictable under a fixed physical link structure, while queuing delay, scheduling delay, and channel-related delay are more difficult to estimate due to their dependence on real-time system states. From the perspective of time-series modeling, transmission delay usually exhibits temporal dependence, short-term fluctuation, and trend variation. These characteristics provide the basis for introducing temporal feature enhancement in the proposed prediction method.

2.2 Data Description and Prediction Variables

To predict transmission delay effectively, this study considers a set of variables that reflect both network operating conditions and optical link status. The input data are assumed to be collected from the monitoring system of an optoelectronic communication network at fixed sampling intervals. Each sample contains the measured transmission delay and several related state variables, such as traffic load, bandwidth utilization, queue length, bit error rate, received optical power, and time index. As shown in table 2.

Table 2 Prediction Variables Used in This Study

Variable	Description	Role in delay prediction
Historical delay	Transmission delay measured at previous time steps	Captures temporal dependence
Traffic load	Amount of transmitted data or packet arrival rate	Reflects service pressure
Bandwidth utilization	Ratio of occupied bandwidth to available bandwidth	Indicates resource usage
Queue length	Number of packets or data units waiting in buffer	Reflects congestion level
Bit error rate	Error rate of the optical transmission link	Describes link reliability
Received optical power	Optical power received at the terminal	Represents signal quality
Time index	Sampling time, hour, or period indicator	Captures periodic variation

Let D_t denote the measured transmission delay at time t, and let X_t represent the system state vector composed of delay-related, traffic-related, and link-quality-related variables. Based on a historical observation sequence within a time window of length L, the objective is to estimate the delay at the next time step. Compared with prediction based only on raw delay values, incorporating multiple system variables provides more comprehensive information about the causes of delay changes. Before model training, missing values are filled, abnormal samples are corrected or removed, and all variables are normalized. The time-series data are then transformed into supervised learning samples through a sliding-window strategy.

3 PROPOSED PREDICTION METHOD

3.1 Overall Framework

To improve prediction accuracy, this study proposes a temporal feature-enhanced LSTM prediction method. The main idea is to extract useful temporal information from original monitoring data and then use an LSTM-based model to learn the nonlinear relationship between system states and future transmission delay. Compared with directly using raw delay sequences, the proposed method introduces additional temporal features to describe historical dependence, short-term fluctuation, and dynamic variation trends.

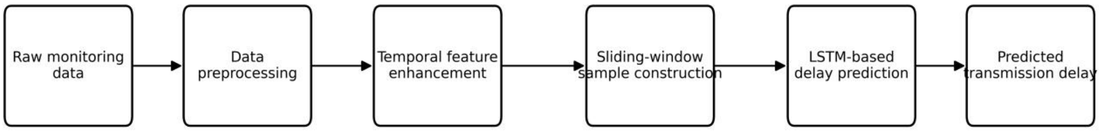

Figure 1 Framework of the Proposed Temporal Feature-enhanced Transmission Delay Prediction Method

As shown in Figure 1, the proposed framework consists of data preprocessing, temporal feature enhancement, sliding-window sample construction, and LSTM-based delay prediction. Temporal feature enhancement transforms the original variables into a richer representation, allowing the prediction model to better capture delay evolution patterns.

3.2 Temporal Feature Enhancement

Transmission delay usually changes continuously over time and is affected by recent historical states. Therefore, only using the current value of each variable may not be sufficient to describe the delay variation process. This study expands the input information from three aspects: lag characteristics, local statistical characteristics, and difference characteristics. Lag features represent the influence of previous system states on future delay. Sliding-window statistical features describe local fluctuation, including mean, maximum, minimum, and standard deviation. Difference features capture variation trends, such as whether delay or traffic load is increasing or decreasing. As shown in table 3.

Table 3 Temporal Feature Enhancement Strategy

Feature type	Example	Function
Lag feature	D(t-1), D(t-2), F(t-1), Q(t-1)	Captures historical dependence
Statistical feature	Mean, maximum, minimum, standard deviation	Describes short-term fluctuation
Difference feature	D(t)-D(t-1), F(t)-F(t-1)	Reflects variation trend
Load-related feature	Traffic load, bandwidth utilization, queue length	Represents network operating state
Link-quality feature	Bit error rate, received optical power	Reflects optical link condition

After feature enhancement, the input vector contains the original system state variables together with lag, statistical, and difference features. This enhanced representation explicitly describes historical continuity, local instability, and trend variation, providing a stronger data basis for subsequent delay prediction.

3.3 LSTM-Based Delay Prediction Model

After temporal feature enhancement, an LSTM-based model is constructed to learn the mapping relationship between historical system states and future transmission delay. LSTM is suitable for time-series prediction because it can selectively retain useful historical information and reduce the influence of irrelevant or noisy information. The enhanced feature sequence within a sliding window is used as the model input, and the output is the predicted transmission delay at the next time step. During training, the LSTM layer learns temporal relationships among enhanced feature vectors, and the fully connected output layer maps the learned representation to the final prediction value. The model is optimized by minimizing the mean squared prediction error between measured and predicted delay values. As shown in table 4.

Table 4 Main Steps of the Proposed Prediction Method

Step	Operation	Purpose
Step 1	Data cleaning and normalization	Improve data quality and consistency
Step 2	Temporal feature enhancement	Extract historical dependence and fluctuation information
Step 3	Sliding-window construction	Transform time-series data into supervised samples
Step 4	LSTM model training	Learn nonlinear temporal mapping
Step 5	Delay prediction	Output future transmission delay

4 RESULTS AND DISCUSSION

4.1 Experimental Settings

To evaluate the effectiveness of the proposed method, comparative experiments were conducted using transmission monitoring data from an optoelectronic communication system. The dataset contains historical delay, traffic load, bandwidth utilization, queue length, bit error rate, received optical power, and time index. Missing values were filled by interpolation, abnormal samples were removed according to statistical thresholds, and all variables were normalized. Four representative baseline models were selected for comparison, including ARIMA, SVR, XGBoost, and standard LSTM. As shown in table 5.

Table 5 Experimental Settings

Item	Setting
Prediction task	One-step-ahead transmission delay prediction
Input variables	Delay, traffic load, bandwidth utilization, queue length, BER, received optical power, time index
Data split	70% training, 15% validation, 15% testing
Sample construction	Sliding-window strategy
Baseline models	ARIMA, SVR, XGBoost, LSTM
Proposed model	Temporal feature-enhanced LSTM
Evaluation metrics	MAE, RMSE, MAPE, R^2

4.2 Prediction Performance Comparison

The prediction performance of different models is shown in Table 6. Overall, the proposed method achieves the best performance among all compared models. Compared with ARIMA, SVR, and XGBoost, the proposed method significantly reduces prediction errors, indicating that deep temporal modeling is more suitable for capturing nonlinear delay variation in optoelectronic communication systems. Compared with the standard LSTM model, the proposed method further decreases MAE from 1.74 to 1.31 and RMSE from 2.36 to 1.88, demonstrating the effectiveness of temporal feature enhancement.

Table 6 Prediction Performance Comparison of Different Models

Model	MAE	RMSE	MAPE	R^2
ARIMA	2.84	3.67	8.92%	0.781
SVR	2.31	3.05	7.46%	0.826
XGBoost	1.92	2.58	6.18%	0.871
LSTM	1.74	2.36	5.62%	0.895
Proposed method	1.31	1.88	4.21%	0.932

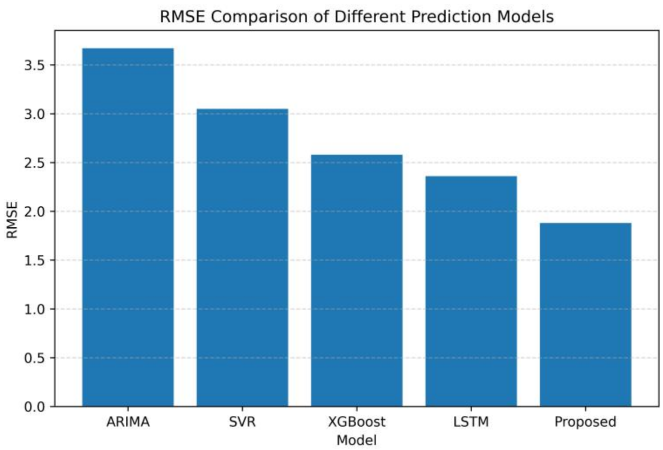

Figure 2 RMSE Comparison of Different Prediction Models

As shown in Figure 2, the RMSE decreases gradually from ARIMA to the proposed method. The proposed method reduces RMSE by approximately 48.8% compared with ARIMA and by approximately 20.3% compared with standard LSTM. This improvement shows that the enhanced temporal features provide additional useful information for delay prediction, especially when the delay sequence contains short-term fluctuation and nonlinear variation.

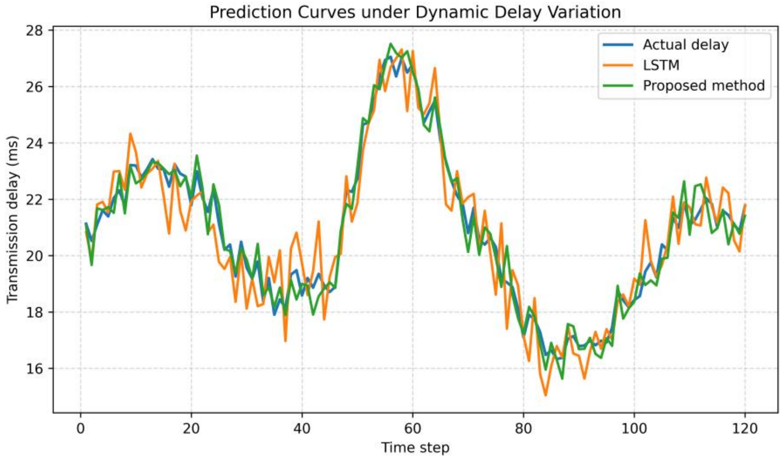

Figure 3 Prediction Curves under Dynamic Delay Variation

Figure 3 compares the prediction curves of the standard LSTM model and the proposed method. The standard LSTM can generally follow the overall trend, but it produces larger deviations during rapid delay variation. In contrast, the proposed method is closer to the actual delay curve in both stable and fluctuating periods. This indicates that lag features and statistical fluctuation features help the model recognize recent delay evolution more accurately, while difference features improve its sensitivity to increasing or decreasing delay trends.

4.3 Ablation Analysis

To further verify the contribution of temporal feature enhancement, an ablation experiment was conducted by gradually adding different types of enhanced features to the LSTM model. As shown in Table 7, the original LSTM model only uses raw time-series variables. After adding lag features, RMSE decreases from 2.36 to 2.18, indicating that historical dependence is important. When sliding-window statistical features are further introduced, RMSE decreases to 2.02, showing that local fluctuation information is also useful. The full proposed method achieves the lowest RMSE of 1.88 and the highest R^2 of 0.932.

Table 7 Ablation Results of Temporal Feature Enhancement

Model variant	Lag features	Statistical features	Difference features	RMSE	R^2
LSTM	×	×	×	2.36	0.895
LSTM + lag features	√	×	×	2.18	0.907
LSTM + lag + statistical features	√	√	×	2.02	0.918
Proposed method	√	√	√	1.88	0.932

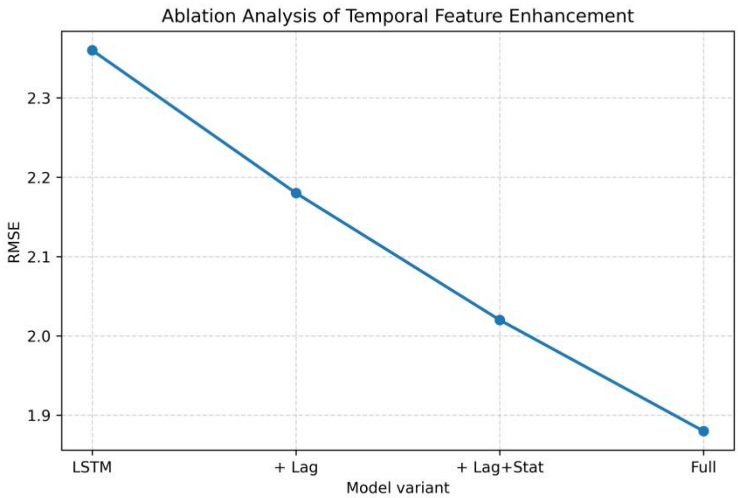

Figure 4 Ablation Analysis of Temporal Feature Enhancement

Figure 4 visually confirms the gradual decrease in RMSE as more temporal enhancement information is included. The improvement from the original LSTM to the full model suggests that temporal feature enhancement does not simply increase feature dimension, but provides meaningful representations of delay evolution. Lag features describe historical continuity, statistical features describe local instability, and difference features capture dynamic variation trends.

4.4 Discussion

The experimental results demonstrate that the proposed temporal feature-enhanced LSTM model is more effective than traditional statistical models, conventional machine learning models, and standard LSTM. The main reason is that transmission delay is affected by multiple time-varying factors. When only raw variables are used as model inputs, important temporal patterns may remain implicit and difficult to learn. By explicitly constructing lag, statistical, and difference features, the proposed method provides clearer information about historical dependence, short-term fluctuation, and trend variation.

From an engineering perspective, accurate delay prediction can support intelligent operation and low-latency service assurance. The system can identify potential congestion or performance degradation in advance and then support dynamic bandwidth allocation, routing adjustment, resource scheduling, and link state monitoring. The temporal feature enhancement strategy is also flexible and can be extended to different communication scenarios by incorporating other available monitoring variables, such as node temperature, packet loss rate, modulation format, or signal-to-noise ratio.

5 CONCLUSION

This study proposed a transmission delay prediction method for optoelectronic communication systems based on temporal feature enhancement. Considering that transmission delay is affected not only by physical propagation but also by traffic load, bandwidth utilization, queue status, and optical link quality, the proposed method introduced lag features, sliding-window statistical features, and difference features to strengthen the temporal representation of system monitoring data. On this basis, an LSTM-based prediction model was constructed to learn the nonlinear relationship between enhanced temporal features and future transmission delay.

The experimental results showed that the proposed method achieved better prediction performance than traditional statistical models, conventional machine learning models, and the standard LSTM model. The ablation analysis further confirmed that lag features, statistical features, and difference features all contributed to the improvement of prediction accuracy. These results indicate that the proposed method is suitable for transmission delay prediction in dynamic optoelectronic communication environments and can support low-latency service assurance, congestion warning, dynamic bandwidth allocation, routing optimization, and intelligent network operation.

Future research can be extended in several directions. Real-time monitoring data from practical optoelectronic communication platforms can be introduced to verify robustness and generalization ability. Graph neural networks may be combined with temporal models to describe multi-node and multi-link topology characteristics. In addition, online learning and lightweight model deployment can be explored to support real-time delay prediction in edge devices and large-scale optical communication networks.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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