Journal of Computer Science and Electrical Engineering
Print ISSN: 2663-1938
Online ISSN: 2663-1946
DOI: https://doi.org/10.61784/jcsee3143

TIME-SERIES PREDICTION AND PERFORMANCE EVALUATION OF OPTICAL COMMUNICATION CHANNEL STATES BASED ON AN IMPROVED LSTM MODEL

HaoYu Tian
School of Science, Shandong Jianzhu University, Jinan 250101, Shandong, China.

Abstract: Optical communication channel states are highly dynamic and are easily affected by noise, nonlinear impairments, received power fluctuations, atmospheric turbulence, and link instability. Accurate time-series prediction of channel states is therefore important for link quality assessment, performance optimization, and intelligent communication control. To improve prediction accuracy and stability, this study proposes an improved CNN-BiLSTM-Attention model for time-series prediction and performance evaluation of optical communication channel states. In the proposed framework, convolutional neural networks extract local fluctuation features from multidimensional channel state sequences, bidirectional long short-term memory networks capture temporal dependencies, and an attention mechanism emphasizes critical time steps related to future channel degradation. Channel state indicators, including received optical power, OSNR, SNR, Q-factor, BER, and EVM, are constructed as model inputs or evaluation variables. Experimental results show that the proposed model outperforms ARIMA, SVR, GRU, LSTM, and BiLSTM in terms of MAE, RMSE, MAPE, and R2. In addition, the prediction-assisted evaluation results indicate that the proposed method can reduce BER and outage probability while improving Q-factor, demonstrating its potential for intelligent optical link monitoring and adaptive communication control.
Keywords: Optical communication; Channel state prediction; CNN-BiLSTM-Attention; Performance evaluation

1 INTRODUCTION

Optical communication has become a fundamental technology for modern high-speed networks, data center interconnection, free-space optical links, and next-generation intelligent communication systems because of its high capacity, high transmission rate, low attenuation, and strong immunity to electromagnetic interference. However, in practical transmission environments, optical communication channels are not always stable [1-3]. Their states can be jointly affected by fiber dispersion, nonlinear impairments, amplifier noise, received optical power fluctuations, atmospheric turbulence, and link misalignment. These factors may cause dynamic variations in optical signal-to-noise ratio, bit error rate, Q-factor, and channel gain, thereby affecting transmission quality and link reliability. Accurate time-series prediction of optical communication channel states is therefore significant for link performance evaluation, fault warning, adaptive modulation, and intelligent resource allocation [4-6].

In recent years, machine learning and deep learning methods have been increasingly applied to optical communication channel modeling, signal detection, link quality estimation, and nonlinear impairment compensation. Compared with conventional analytical models or pilot-assisted estimation methods, deep learning models can automatically learn complex nonlinear mappings from historical data and show stronger adaptability to dynamic channel conditions. Among these methods, long short-term memory networks are widely used for dynamic channel prediction and link state monitoring because they can capture temporal dependencies in sequential data. Nevertheless, standard LSTM models still have limitations when dealing with complex optical communication channels, including insufficient local feature extraction, limited identification of critical time steps, and accumulated errors in multi-step prediction [7-9].

To address these challenges, this study proposes an improved CNN-BiLSTM-Attention model for optical communication channel state prediction. In the proposed framework, convolutional neural networks are employed to extract local fluctuation features from channel state sequences, bidirectional LSTM networks are used to learn forward and backward temporal dependencies, and an attention mechanism is introduced to emphasize key time steps that contribute more significantly to future channel states. A multidimensional channel state indicator system and sliding-window samples are constructed, and the model is evaluated from the perspectives of prediction accuracy, communication performance, and model complexity. The effectiveness of the proposed method is verified by comparison with ARIMA, SVR, GRU, LSTM, and BiLSTM.

2 RELATED WORK

2.1 Optical Communication Channel State Monitoring

Optical communication channel state monitoring is essential for maintaining stable operation of high-speed optical communication systems. Its goal is to sense, estimate, and analyze link-quality-related parameters and determine whether the channel is in a normal, degraded, or potentially failed state. In optical fiber communication systems, typical

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indicators include OSNR, chromatic dispersion, nonlinear noise, BER, and Q-factor. These indicators reflect signal quality from different perspectives. OSNR measures the relationship between optical signal power and optical noise power, BER directly reflects the error level at the receiver, and Q-factor provides an indirect representation of transmission reliability [10].

For free-space optical and optical wireless communication systems, channel state monitoring must also consider atmospheric turbulence, rain and fog attenuation, occlusion, received optical intensity fluctuation, and pointing errors. Compared with fiber channels, these channels usually exhibit stronger non-stationarity and randomness. As a result, static channel models cannot always accurately describe the dynamic evolution of channel states. Continuous monitoring and advanced prediction are therefore important for improving system reliability and link availability.

2.2 Deep Learning-Based Channel Prediction

Deep learning has shown strong potential in optical communication tasks such as channel estimation, signal detection, nonlinear compensation, fault diagnosis, and link quality prediction. CNNs are suitable for extracting local patterns from signal sequences or feature matrices, such as short-term power fluctuations and local noise variations. RNNs, GRUs, and LSTMs are suitable for modeling temporal dependencies in channel state sequences. Hybrid models such as CNN-LSTM and LSTM-DNN combine different representation abilities and have been used in optical wireless communication, ultraviolet communication, and fiber-optic equalization.

Although existing deep learning methods have improved optical communication performance, several issues remain. Some studies focus on a single indicator, such as OSNR or BER, and do not fully model multidimensional channel states. Other studies emphasize prediction accuracy but provide limited analysis of communication performance indicators. In addition, complex neural networks may increase computational cost, which should be evaluated when considering practical deployment. Therefore, it remains valuable to develop a prediction method that balances accuracy, communication performance, and model complexity.

2.3 LSTM and Improved Time-Series Models

LSTM is an improved recurrent neural network designed to alleviate gradient vanishing and gradient exploding problems in long-sequence modeling. Through input, forget, and output gates, LSTM controls the retention and update of historical information and can capture long-term temporal dependencies. In optical communication systems, channel quality parameters are affected by historical transmission states, environmental disturbances, and system operating conditions, so LSTM is a suitable tool for channel state prediction.

However, standard LSTM mainly focuses on sequential dependency modeling and is less effective in extracting local abrupt changes or high-frequency disturbances. BiLSTM improves sequence representation by learning forward and backward dependencies. CNN-LSTM enhances local feature extraction, while Attention-LSTM highlights critical time steps. Based on these ideas, this study constructs a CNN-BiLSTM-Attention model that integrates local feature extraction, bidirectional temporal learning, and key-state weighting to improve optical communication channel state prediction.

3 METHODOLOGY

3.1 Channel State Indicators and Dataset Construction

To perform time-series prediction, the optical communication channel is described as a multivariate state sequence. The channel state vector at time t is defined as Xt = [Pr(t), OSNR(t), SNR(t), Q(t), BER(t), EVM(t)], where Pr denotes received optical power, OSNR denotes optical signal-to-noise ratio, SNR denotes signal-to-noise ratio, Q denotes optical link quality factor, BER denotes bit error rate, and EVM denotes error vector magnitude. These variables describe power stability, noise level, transmission reliability, and modulation quality. As shown in table 1.

Table 1 Main Channel State Indicators Used in this Study

Indicator	Symbol	Description	Function
Received optical power	Pr	Reflects link attenuation and power fluctuation	Input variable
Optical signal-to-noise ratio	OSNR	Measures optical signal quality under noise interference	Input or output variable
Signal-to-noise ratio	SNR	Reflects equivalent signal reliability	Input variable
Q-factor	Q	Indicates optical link transmission quality	Output or evaluation variable
Bit error rate	BER	Represents transmission error performance	Output or evaluation variable
Error vector magnitude	EVM	Measures modulation accuracy and signal distortion	Evaluation variable

Assuming that the original dataset contains N continuously collected time points, the complete dataset can be denoted as D = {X1, X2, ..., XN}. For one-step prediction, the model predicts the next channel state based on a historical input window. For multi-step prediction, the output is extended to several future time steps. This transformation converts the continuous sequence into supervised learning samples.

3.2 Data Preprocessing and Sliding Window Samples

Original channel state data may contain missing values, outliers, and scale differences. Missing data are filled using linear interpolation or local mean values. Outliers are detected using the boxplot method or the 3-sigma criterion and corrected by local interpolation. Since different variables have different numerical ranges, Min-Max normalization is used to map input variables into the interval [0,1]. As shown in table 2.

Table 2 Data Preprocessing and Sample Construction Procedure

Step	Operation	Purpose
Missing value processing	Linear interpolation or local mean filling	Preserve sequence continuity
Outlier detection	3-sigma rule or boxplot method	Reduce the effect of abnormal observations
Normalization	Min-Max scaling	Eliminate scale differences among variables
Sliding window construction	Historical sequence to future target	Convert time series into supervised samples
Dataset splitting	Chronological split	Avoid temporal information leakage

A sliding-window method is adopted to generate training samples. Given a window length L and a prediction horizon m, each input sample consists of L consecutive historical channel state vectors, and its label is the target channel state in the following m time steps. The dataset is divided into training, validation, and testing sets in chronological order, typically using a ratio of 70%, 15%, and 15%, which avoids temporal information leakage caused by random splitting.

3.3 Proposed CNN-BiLSTM-Attention Model

The proposed model consists of an input layer, a CNN feature extraction layer, a BiLSTM temporal modeling layer, an attention weighting layer, and a fully connected output layer. The CNN layer extracts local fluctuation patterns, such as short-term received power drops, OSNR variations, or sudden BER changes. The BiLSTM layer learns temporal dependencies from both forward and backward directions, thereby improving contextual sequence representation. The attention layer assigns larger weights to critical historical time steps that have stronger influence on future channel states. Finally, a fully connected layer maps the weighted representation to the prediction target. As shown in table 3.

Table 3 Structure of the Proposed CNN-BiLSTM-Attention Model

Module	Function	Output feature
Input layer	Receives sliding-window channel state sequences	Multidimensional temporal samples
CNN layer	Extracts local fluctuation patterns	Local feature maps
BiLSTM layer	Learns bidirectional temporal dependencies	Contextual temporal features
Attention layer	Assigns weights to critical time steps	Weighted feature representation
Fully connected layer	Maps features to prediction target	Predicted channel state

Compared with standard LSTM, the proposed model can not only learn long-term dependencies but also capture local fluctuation features and identify important time periods. This makes it more suitable for complex optical communication channels with nonlinear and non-stationary behavior.

3.4 Evaluation Metrics

To evaluate the model comprehensively, three types of metrics are used. Prediction accuracy is evaluated by MAE, RMSE, MAPE, and R2. Communication performance is evaluated by BER, Q-factor, OSNR estimation error, and outage probability. Model complexity is evaluated by the number of parameters, training time, and inference time. This evaluation system links numerical forecasting accuracy with practical optical link performance. As shown in table 4.

Table 4 Evaluation Metrics Used in this Study

Category	Metric	Description
Prediction accuracy	MAE	Average absolute prediction error
Prediction accuracy	RMSE	Sensitivity to large prediction errors
Prediction accuracy	MAPE	Relative prediction error
Prediction accuracy	R2	Goodness of fit
Communication performance	BER	Transmission reliability
Communication performance	Q-factor	Optical link quality
Communication performance	OSNR error	Accuracy of optical signal quality estimation
Communication performance	Outage probability	Risk of link interruption

Category	Metric	Description
Model complexity	Parameters and time	Deployment and real-time prediction capability

4 RESULTS AND DISCUSSION

4.1 Prediction Performance Comparison

To evaluate prediction capability, ARIMA, SVR, GRU, LSTM, and BiLSTM were selected as baseline models. ARIMA represents a traditional time-series method, SVR represents a conventional machine learning model, and GRU, LSTM, and BiLSTM represent recurrent neural network baselines. The prediction target in this section was OSNR, and the performance was evaluated using MAE, RMSE, MAPE, and R2.

Table 5 Prediction Performance Comparison of Different Models

Model	MAE	RMSE	MAPE/%	R2
ARIMA	0.184	0.237	6.82	0.861
SVR	0.153	0.205	5.74	0.889
GRU	0.126	0.171	4.58	0.918
LSTM	0.112	0.158	4.21	0.932
BiLSTM	0.098	0.141	3.76	0.947
Proposed CNN-BiLSTM-Attention	0.073	0.109	2.91	0.972

As shown in Table 5, the proposed CNN-BiLSTM-Attention model achieved the best prediction performance among all compared models. Compared with standard LSTM, the proposed model reduced MAE from 0.112 to 0.073 and RMSE from 0.158 to 0.109. The R2 value increased from 0.932 to 0.972, suggesting stronger fitting ability for nonlinear and time-varying optical channel characteristics. The traditional ARIMA model showed the weakest performance because it assumes relatively stable linear temporal relationships, while recurrent neural networks achieved better results by exploiting temporal memory.

4.2 Time-Series Forecasting Results

Figure 1 compares the predicted OSNR sequences of LSTM, BiLSTM, and the proposed model with the observed channel state sequence. During relatively stable periods, all three models can follow the general trend. However, when the channel state changes rapidly, standard LSTM shows prediction delay, while BiLSTM reduces the deviation by using bidirectional sequence information. The proposed model provides the closest curve to the observed OSNR, especially in rapid degradation and recovery periods.

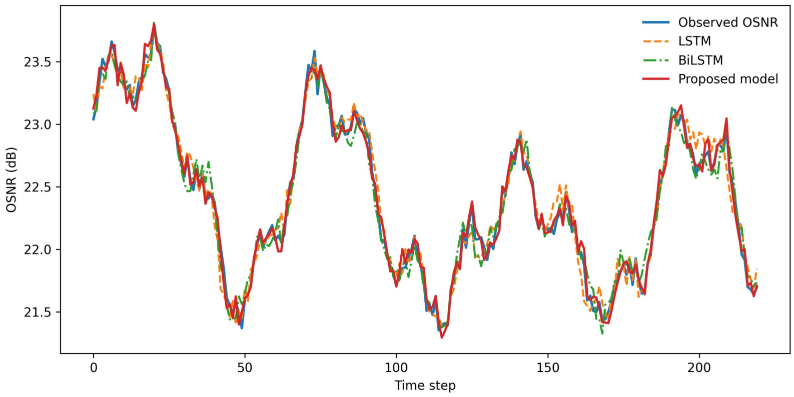

Figure 1 Time-series Prediction of Optical Channel State

The improved tracking ability is mainly attributed to CNN-based local fluctuation extraction and attention-based key time-step weighting. This result suggests that the proposed model can identify potential link degradation more effectively than standard recurrent structures.

4.3 Multi-Step Prediction Analysis

For practical optical communication systems, predicting only the next time step may not be sufficient for early warning and adaptive control. Therefore, multi-step forecasting was further evaluated using forecast horizons of 1, 3, 5, 10, and 15 time steps.

Table 6 Multi-step Forecasting Performance of Different Models

Forecast horizon	LSTM RMSE	BiLSTM RMSE	Proposed RMSE
1-step	0.158	0.141	0.109
3-step	0.181	0.163	0.126
5-step	0.214	0.190	0.146
10-step	0.279	0.251	0.184
15-step	0.342	0.307	0.229

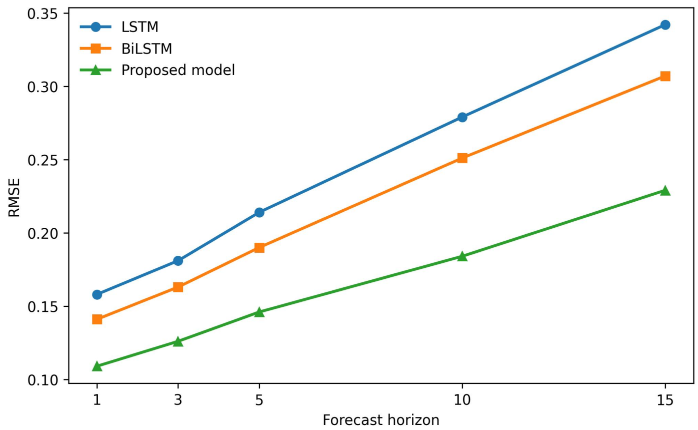

Figure 2 Multi-step Forecasting Error

Table 6 and Figure 2 show that the prediction error of all models increases as the forecast horizon becomes longer, which is expected because future channel uncertainty increases over time. Nevertheless, the proposed model consistently achieves the lowest RMSE under all horizons. For the 10-step prediction task, the RMSE of LSTM increases to 0.279, whereas that of the proposed model is only 0.184. This indicates better robustness in medium-term channel state forecasting.

4.4 Communication Performance Evaluation

Beyond numerical forecasting accuracy, the practical value of the model should be evaluated using communication performance indicators. Accurate channel state prediction can provide prior information for adaptive modulation, power adjustment, coding rate selection, and link maintenance. Therefore, BER, Q-factor, OSNR estimation error, and outage probability were compared under different prediction-assisted methods.

Table 7 Communication Performance under Different Prediction-assisted Methods

Method	BER	Q-factor/dB	OSNR error/dB	Outage probability/%
Without prediction	2.40E-3	7.82	-	6.15
LSTM-assisted	9.80E-4	8.64	0.42	3.87
BiLSTM-assisted	7.20E-4	8.91	0.35	3.14
Proposed-assisted	3.90E-4	9.47	0.21	1.86

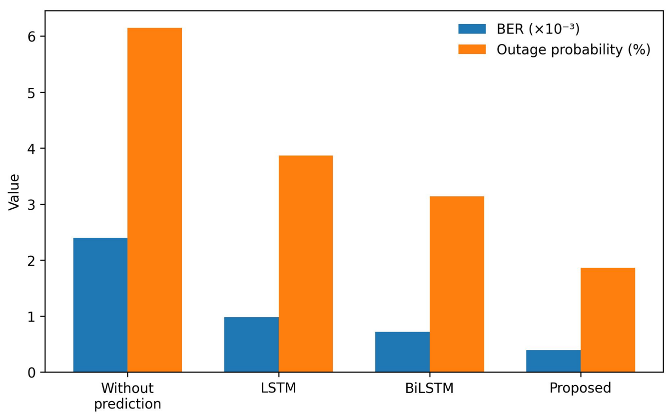

Figure 3 Communication Performance Comparison

As shown in Table 7 and Figure 3, prediction-assisted link evaluation significantly improves communication performance. The proposed method achieves the lowest BER, the highest Q-factor, and the lowest outage probability. This confirms that improved channel state prediction can be translated into better link reliability and provides practical support for intelligent optical communication control.

4.5 Ablation Study and Complexity Analysis

To verify the contribution of each component, an ablation study was conducted by gradually introducing CNN, BiLSTM, and Attention modules. The tested variants included LSTM, CNN-LSTM, BiLSTM, BiLSTM-Attention, and the complete CNN-BiLSTM-Attention model.

Table 8 Ablation Study of the Proposed Model

Model variant	MAE	RMSE	MAPE/%	R2
LSTM	0.112	0.158	4.21	0.932
CNN-LSTM	0.094	0.137	3.68	0.951
BiLSTM	0.098	0.141	3.76	0.947
BiLSTM-Attention	0.085	0.126	3.32	0.961
CNN-BiLSTM-Attention	0.073	0.109	2.91	0.972

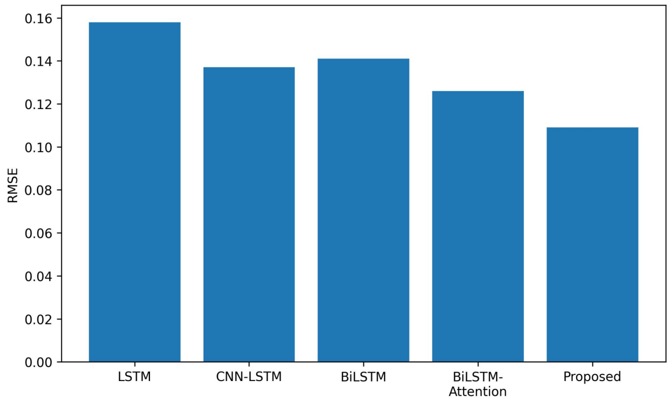

Figure 4 Ablation Results of Model Components

Table 8 and Figure 4 demonstrate that each module contributes to prediction improvement. CNN reduces errors by extracting local channel fluctuation patterns, BiLSTM improves temporal representation, and Attention enhances the identification of key degradation periods. The complete model achieves the best overall performance, confirming that the proposed hybrid structure is effective.

Table 9 Model Complexity Comparison

Model	Parameters	Training time/s	Inference time/ms
GRU	42000	38.5	1.6
LSTM	58000	46.2	2.1
BiLSTM	91000	63.7	3.4
Proposed CNN-BiLSTM-Attention	126000	78.9	4.8

As shown in table 9. The proposed model introduces additional parameters and training cost because it includes convolutional layers, bidirectional recurrent units, and attention weighting. However, its inference time remains within the millisecond level, indicating potential for real-time or near-real-time channel state prediction. Therefore, the model achieves a reasonable balance among prediction accuracy, communication performance, and deployment feasibility.

5 CONCLUSION

This study proposed an improved CNN-BiLSTM-Attention model for time-series prediction and performance evaluation of optical communication channel states. By integrating convolutional neural networks, bidirectional long short-term memory networks, and an attention mechanism, the proposed model was designed to capture local fluctuation characteristics, bidirectional temporal dependencies, and critical time-step information from multidimensional channel state sequences. Compared with traditional time-series models and standard recurrent neural networks, the proposed model showed stronger capability in describing the nonlinear, time-varying, and non-stationary characteristics of optical communication channels.

The experimental results demonstrated that the proposed CNN-BiLSTM-Attention model achieved better prediction performance than ARIMA, SVR, GRU, LSTM, and BiLSTM. In particular, the model obtained lower prediction errors and higher goodness of fit, indicating that the hybrid architecture can more accurately track dynamic variations of optical channel states. The time-series prediction results further showed that the proposed model performed well not only under relatively stable channel conditions but also during rapid channel degradation and local fluctuation periods. This suggests that the proposed method is effective in identifying potential link quality changes and improving channel state forecasting reliability.

In addition to prediction accuracy, this study evaluated the proposed method from the perspective of communication performance. The results indicated that more accurate channel state prediction can contribute to lower bit error rate, higher Q-factor, reduced OSNR estimation error, and lower outage probability. Therefore, the proposed model is not only useful for numerical time-series prediction but also has practical significance for optical link quality assessment, early warning of channel degradation, and adaptive communication control.

Although the proposed model achieved promising results, several aspects still require further investigation. Future studies can introduce online or incremental learning mechanisms so that the model can continuously update parameters according to newly collected channel data. Physical knowledge of optical transmission, such as fiber nonlinear effects, attenuation laws, and OSNR evolution mechanisms, can also be incorporated into the model to improve interpretability and generalization ability. Furthermore, channel state prediction can be connected with adaptive modulation, dynamic power allocation, coding rate adjustment, and intelligent link maintenance. By combining data-driven prediction, physical constraints, and real-time control strategies, optical communication systems may move toward more intelligent, reliable, and self-optimizing operation.

COMPETING INTERESTS

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

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