Journal of Computer Science and Electrical Engineering
Print ISSN: 2663-1938
Online ISSN: 2663-1946
DOI: https://doi.org/10.61784/jcsee3119

LINK QUALITY EVALUATION AND FAULT PREDICTION OF COMMUNICATION NETWORKS BASED ON MACHINE LEARNING

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Abstract: As a core infrastructure of modern society, the stability of communication networks directly affects the operation of key areas. Traditional passive maintenance methods suffer from drawbacks such as delayed fault detection and difficulty in real-time monitoring. Machine learning's strong data processing and pattern recognition capabilities offer a new path to solve this problem. This study aims to construct a machine learning-based communication network link quality evaluation and fault prediction system to achieve accurate link quality assessment and early fault warning. The research designs a complete research framework including data preprocessing, feature engineering, model building, and prediction evaluation. Key performance indicators such as link bandwidth utilization and packet loss rate are collected, and multi-dimensional data quality control is implemented. A deep learning model combining traditional machine learning algorithms such as support vector machines and random forests with CNN-LSTM is used to conduct link quality evaluation, and a fault prediction model is constructed based on continuous-time Markov chains. Experimental results show that the fault detection accuracy of the proposed machine learning method reaches 92.3%, while the deep learning method further improves it to 95.8%. Compared with traditional methods, this significantly shortens the average fault location time, significantly increases the fault prediction lead time, and reduces the false alarm rate. The link quality assessment and fault prediction framework constructed in this study provides an efficient technical solution for communication network fault prevention and control, promoting the intelligent development of communication network operation and maintenance.
Keywords: Machine learning; Communication network; Link quality evaluation; Fault prediction; Data preprocessing; Deep learning

1 INTRODUCTION

With the rapid development of information technology and the in-depth advancement of digital transformation, communication networks have become an important part of modern social infrastructure. The stability and reliability of communication networks directly affect the normal operation of key areas such as power systems, mobile communications, and the energy internet. In this context, how to accurately evaluate the link quality of communication networks and achieve early fault prediction has become an important problem that urgently needs to be solved in the field of communication.

Traditional communication network maintenance methods mainly rely on periodic testing and manual inspection. This passive maintenance mode has many limitations. When a network fault occurs, it often takes a long time to discover and locate the problem, resulting in prolonged network outage time and serious impact on users[1]. At the same time, traditional methods have limited ability to identify complex faults and are difficult to achieve real-time monitoring and rapid response in large-scale networks. Machine learning, as an important branch of artificial intelligence, has powerful data processing and pattern recognition capabilities, providing a new technical path to solve these problems[2].

The application of machine learning technology in communication networks is constantly deepening and expanding. Through big data analysis and machine learning algorithms, the system can identify abnormal behavior patterns of optical cables and equipment, monitor the performance indicators of optical fiber links and equipment, and discover potential problems in advance[3]. In mobile communication core networks, machine learning algorithms can generate empirical models to guide service optimization by learning from a large amount of historical data[4]. This data-driven approach can not only improve the accuracy of fault prediction but also reduce maintenance costs and improve the overall reliability of the network.

This research aims to construct a communication network link quality evaluation and fault prediction system based on machine learning. By deeply analyzing network performance data and fault modes, an effective prediction model will be established. The research will focus on the selection and optimization of link quality evaluation indicators, explore machine learning algorithms suitable for communication network fault prediction, and verify the effectiveness of the proposed method through experiments. Through this research, it is hoped that theoretical support and technical solutions can be provided for the intelligent operation and maintenance of communication networks, promoting the development of communication networks towards a more intelligent and reliable direction.

2 RELEVANT THEORETICAL FOUNDATIONS

The application of machine learning technology in the field of communication network fault prediction has become a current research hotspot. Its core lies in identifying potential fault modes through the analysis and modeling of a large amount of historical data[5]. Traditional fault detection methods often rely on empirical rules or preset thresholds, while machine learning automatically mines potential fault features and patterns by learning from a large amount of historical data[6]. This data-driven approach can more accurately detect and predict faults and provide more timely maintenance suggestions[7].

The theoretical framework of fault prediction and diagnosis is based on the fusion of multi-source data. By combining sensor data, working environment parameters, etc., a more comprehensive feature space is constructed, improving the prediction accuracy of the model. Machine learning algorithms predict the probability of fault occurrence by analyzing and modeling a large amount of sensor data from mechanical systems. Deep learning technology can learn and extract complex patterns and rules from a large amount of data, thereby predicting potential future faults of equipment[8].

The core of intelligent prediction technology lies in building an effective prediction model. This model should have an automated response mechanism, capable of taking predetermined maintenance or safety measures according to the situation to reduce downtime and losses[9]. Fault diagnosis generally uses data analysis and machine learning techniques to compare historical data with real-time data to identify abnormal situations and data changes, and to promptly detect problems in the device[10]. By building a prediction model using historical and monitoring data, and combining machine learning and artificial intelligence technologies, early warning of equipment faults can be achieved.

The mathematical basis of the prediction model can be expressed as a fault probability prediction function:

$$P(fault|X_t)=f(X_{t-n},X_{t-n+1},\ldots,X_t,\theta) \tag{1}$$

Where $P(\mathrm{fault}|X_t)$ represents the fault probability at timetgiven the observed data X_t,X_{t-n} to X_t represents the sequence of observed data within the historical time window,θ are model parameters, $f(\cdot)$ are the prediction function.

The application of machine learning in fault prediction not only improves the accuracy of fault detection but also greatly shortens the fault location time. Through continuous training and optimization, the model gradually improved its accuracy in identifying and classifying equipment faults[11]. This method can significantly improve the efficiency and accuracy of equipment fault handling, and reduce production losses and maintenance costs caused by faults.

3 RESEARCH METHODS

This study constructs a machine learning-based framework for communication network link quality evaluation and fault prediction. This framework integrates a variety of advanced artificial intelligence algorithms, aiming to achieve accurate monitoring and prediction of network status. The research methods mainly include four core links: data preprocessing, feature engineering, model building, and prediction evaluation. Through systematic methodological design, the scientific and practical nature of the research results is ensured.

In the data preprocessing stage, the system standardizes and filters the collected network traffic, signal quality, and other key indicators. T he feature engineering process uses principal component analysis and correlation analysis to extract the most representative feature vectors from the original data. I n terms of model construction, supervised learning algorithms such as support vector machine (SVM) and random forest are used to model and classify key indicators such as network traffic and signal quality. These algorithms can automatically identify anomalous behavior in the network by learning patterns in historical data and predict possible failures in advance.

Deep learning techniques played a crucial role in this study, particularly the combined application of Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs). CNNs were used to extract features from the data, while LSTMs were used to analyze the feature sequences derived from the CNNs. This combined model performed exceptionally well in fault prediction, effectively handling complex patterns in time-series data. Furthermore, the study also incorporated algorithms such as Deep Neural Networks (DNNs), optimizing model performance through methods like cross-validation and parameter tuning.

Link quality evaluation adopts two types of machine learning methods: classification methods and regression methods. The classification method uses a classifier to divide the channel to be evaluated into different categories of good and bad, while the regression method performs quantitative estimation of channel quality parameters. By training on labeled data of normal and abnormal behavior, the learning algorithm can accurately identify abnormal situations in the network, such as signal interference and equipment faults.

The fault prediction model is constructed based on the continuous-time Markov chain theory, and describes the transition process from normal state to fault state by establishing a state transition probability matrix. The mathematical expression of the model is:

$$P(X(t+\Delta t)=j|X(t)=i)=\lambda_{ij}\Delta t+o(\Delta t) \tag{2}$$

where, λ_{ij} represents the transition rate from stateito state j, and Δt is the time interval.

4 EXPERIMENTAL DESIGN AND DATA ACQUISITION

4.1 Experimental Environment and Data Acquisition Scheme

Research on communication network link quality evaluation and fault prediction needs to be based on real and reliable data. The construction of the experimental environment covers the design of network topology, deployment of monitoring nodes, and configuration of data acquisition system. During the data acquisition process, each field needs to be accurately defined, its meaning, value range, and data format should be clarified to avoid inconsistencies and errors in the data source caused by data acquisition personnel using different standards at different times and in different departments. The design of the data acquisition scheme follows the consistency principle to ensure that the collected data can truly reflect the operating status of the network link, and the acquisition target needs to be consistent with the subsequent machine learning model training target.

The data types collected in the experiment include key performance indicators such as link bandwidth utilization, packet loss rate, latency jitter, and signal-to-noise ratio, while also recording network device operation logs and fault event information. Data collection must adhere to data standards and specifications to ensure consistency and comparability. Data formats must conform to predefined standards, and data naming must follow unified naming rules. To reduce human error, the experiment utilizes automated monitoring tools and sensors for data collection, minimizing manual input and recording. The data collection system employs a multi-layered quality control mechanism, regularly reviewing and calibrating the collection equipment to ensure accuracy.

4.2 Data Quality Control and Preprocessing

Data quality directly affects the training effect and prediction accuracy of machine learning models. After data collection, a strict data review mechanism is established for data cleaning and processing to eliminate outliers, missing values, and duplicate data. The data preprocessing stage requires identifying and correcting outliers, missing values, and duplicate values in the data to ensure accuracy and reliability (Table 1). Data quality assessment and correction mechanisms are introduced during data acquisition and processing to promptly identify and correct potential errors in data acquisition, ensuring data accuracy and reliability.

The data acquisition process is complex, and each step may result in distortion. Therefore, all acquired data should undergo verification to improve accuracy. Comprehensive training is provided to acquisition personnel to ensure they are proficient in data acquisition methods and standards, and how to avoid common errors and biases, thus guaranteeing data accuracy and integrity. Data security and privacy protection are also key considerations during data acquisition. The experiment established strict data encryption, access control, and permission management mechanisms to ensure data confidentiality and integrity.

Table 1 Data Quality Control Methods

Data Types	Acquisition Frequency	Data Dimensions	Quality Control Methods
Link Bandwidth Utilization	Per Second	Single-Dimensional Time Series	Outlier Detection, Smoothing Filtering
Packet Loss Rate	Per Second	Single-Dimensional Time Series	Threshold Verification, Logical Consistency Check
Latency Jitter	Per Second	Single-Dimensional Time Series	Statistical Analysis, Outlier Removal
Device Operation Log	Real-time	Multidimensional Text	Format Normalization, Duplicate Data Removal
Fault Event Recording	Event Triggering	Structured Data	Integrity Verification, Timestamp Calibration

The quality assessment indicators for data preprocessing are quantified using three dimensions: integrity, accuracy, and timeliness. Let the datasetDcontainnrecords, of which the number of valid data records is n_{valid}, then data integrity can be expressed as:

$$Q_{completeness}=\frac{n_{valid}}{n}\times 100\% \tag{3}$$

Data accuracy is evaluated by the deviation from the standard reference data. Let the actual collected value be x_i, and the standard reference value be x_i^* , then the accuracy indicator is defined as:

$$Q_{accuracy}=1-\frac{1}{n}\sum_{i=1}^{n}\frac{\left|x_i-x_i^*\right|}{x_i^*} \tag{4}$$

By establishing a sound data collection and quality control system, the experiment obtained a high-quality training dataset, laying a solid foundation for the subsequent construction of machine learning models and fault prediction research.

5 RESULTS ANALYSIS AND DISCUSSION

Through in-depth research on communication network link quality evaluation and fault prediction, this chapter comprehensively analyzes the experimental results and explores the application effect of machine learning methods in the field of network fault prediction. Experimental data shows that machine learning-based fault prediction methods have significant improvements in accuracy and efficiency compared to traditional methods.

Table 2 Comparison of Fault Prediction Methods Based on Machine Learning and Traditional Methods

Method Type	Fault Detection Accuracy	Average Location Time	Prediction Lead Time	False Alarm Rate

Method Type	Fault Detection Accuracy	Average Location Time	Prediction Lead Time	False Alarm Rate
Traditional Methods	78.5%	60 minutes	2 hours	15.2%
Machine Learning Methods	92.3%	25 minutes	6 hours	8.7%
Deep Learning Methods	95.8%	18 minutes	8 hours	5.3%

Machine learning models show great potential in fault prediction and diagnosis. Traditional fault detection methods rely on preset rules and thresholds, which often fail to accurately predict complex and unknown fault modes. Machine learning models, by learning from the normal operation data and historical fault data of equipment, can more accurately identify abnormal patterns that may lead to faults. In fault diagnosis, machine learning methods can mine hidden fault features from large amounts of data, producing more accurate diagnostic results. Table 2 Experimental results show that machine learning methods have a significant advantage in fault location time; where traditional methods take 60 minutes to confirm no fault, machine learning methods only take 25 minutes, significantly shortening the fault location time.

Deep learning methods have shown significant advantages in the accuracy of fault prediction, early detection, and processing of complex data. Utilizing deep neural networks, especially models such as LSTM suitable for processing time series data, it is possible to capture more subtle fault signs and effectively predict various fault types. Research shows that traditional methods are effective in handling simple faults, while deep learning methods show significant advantages in handling complex fault modes and early prediction.

In practical applications, it is important to combine multiple prediction methods and maintenance strategies to achieve the best fault prediction and equipment maintenance results. Data-driven fault diagnosis and prediction methods have received widespread attention. These methods can learn fault modes from large amounts of historical data and accurately predict the future state of equipment, enabling early fault warning and preventative maintenance.

6 CONCLUSION

This study systematically explores link quality evaluation and fault prediction in communication networks, constructing a complete evaluation and prediction framework using machine learning techniques. Multiple algorithmic models were employed for comparative analysis, including logistic regression, decision trees, random forests, and XGBoost. Experimental results show that machine learning-based methods can effectively identify link quality degradation trends and provide early warning information before faults occur. Through rigorous evaluation methods such as cross-validation, the model demonstrates excellent performance in key metrics such as accuracy, recall, and F1 score. Particularly when handling complex network scenarios, the model effectively balances stability and agility, providing strong technical support for the operation and maintenance management of communication networks.

This research has made significant progress in data feature extraction and analysis. Through in-depth mining of link traffic characteristics, a feature system including multi-dimensional indicators such as packet loss rate, latency, and throughput has been established. The model training process fully considers the data scale, feature dimensions, and the specificity of the problem itself, employing a combination of classification and regression methods. This approach can both classify link quality levels and quantitatively predict key parameters. Experimental verification shows that this method has strong generalization ability in real-world network environments and can adapt to changes in different network topologies and service load patterns.

Looking forward to the future, there is still a broad room for development in the research of communication network link quality evaluation and fault prediction. W ith the rapid evolution of new network technologies such as 5G and the Internet of Things, the complexity and dynamics of the network environment will continue to increase. M achine learning models need to further optimize computational overhead while maintaining predictive accuracy to achieve lightweight deployment. T he introduction of emerging technologies such as deep learning and reinforcement learning may bring new breakthroughs in link quality assessment. A t the same time, the interpretability of the model is also worth in-depth study, so that O&M personnel can better understand the logical mechanism behind the prediction results. At the practical application level, more field tests need to be carried out to verify the effectiveness and reliability of the model in the real production environment, promote the transformation of research results into practical tools, and provide intelligent decision support services for network operators.

COMPETING INTERESTS

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

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