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Research on Prediction and Optimization Strategy of University Wi-Fi Network Access Quality Based on Machine Learning

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Abstract: University Wi-Fi networks are characterized by high user density, diverse service types, and uneven spatiotemporal distribution of access behaviors. Traditional threshold-based and experience-driven network operation methods struggle to achieve precise prediction and dynamic optimization of access quality. This study collects multi-dimensional data from a university campus Wi-Fi network, employing a hybrid machine learning prediction method combining XGBoost and LSTM to accurately forecast QoE metrics including Wi-Fi access rate, latency, packet loss rate, and connection success rates. Additionally, a closed-loop optimization scheme of "prediction-scheduling-evaluation" is proposed, encompassing AP power adaptation, automatic channel configuration, load balancing, and service tiered scheduling. Experimental results demonstrate that the proposed prediction model achieves an average MAE below 5%. The optimization strategy enhances average network access rate by 28.3%, reduces latency by 34.7%, and improves connection success rates to over 99.5%, providing a practical solution for intelligent operation and quality improvement of university Wi-Fi networks.

1. Introduction

With the development of smart campuses, university Wi-Fi networks have become the primary information infrastructure for teaching, learning, administration, and services. They support diverse applications including online classrooms, video conferencing, research data transmission, and IoT device connectivity. These networks face unique challenges such as massive user traffic, uneven spatial-temporal distribution, varied service demands, and environmental interference. Traditional operation models relying on manual inspections and static configurations exhibit delayed quality assessment, sluggish optimization responses, and low resource efficiency. During peak hours, users often encounter network access delays, excessive latency, and connection failures, significantly degrading the overall experience[1].

Machine learning algorithms excel in feature extraction and nonlinear fitting, enabling the identification of network access quality trends through extensive historical data analysis and accurate prediction. While existing research on Wi-Fi network quality estimation has been conducted globally, current methods face challenges such as incomplete feature extraction, poor model adaptability, and inconsistent optimization objectives due to complex campus environments with multi-service integration, fluctuating traffic loads, and environmental variables. This study addresses these limitations by extracting diverse feature information from real-world Wi-Fi access scenarios and developing an XGBoost-LSTM hybrid model for network performance prediction. Building upon this foundation, we propose a comprehensive solution encompassing resource allocation, user application management, and network anomaly detection. Experimental validation using campus Wi-Fi measurement data demonstrates the feasibility of our proposed approach, providing theoretical support and practical insights for intelligent Wi-Fi infrastructure development in higher education institutions.

2. Analysis of Factors and Characteristics Affecting Wi-Fi Network Access Quality in Universities

2.1 Core Access Quality Evaluation Indicators

To evaluate campus user experience and network operation standards, five key metrics are selected: access speed, end-to-end latency, packet loss rate, connection success rate, and RSSI. Access speed refers to the actual data transmission rate between user devices and AP, with a minimum of 20 Mbps required for optimal user experience. End-to-end latency measures the time it takes for a data packet to travel from user devices to the gateway. Real-time performance requires a threshold of ≤50ms for real-time services. The packet loss rate indicates the proportion of lost packets during transmission, with a threshold of ≤1% for high-quality experience. Connection success rate is calculated as the number of successful Wi-Fi connections divided by total connection attempts, maintaining a threshold of ≥95% for operational standards. Signal strength is determined by the signal level received by user devices from the AP, with a stable connection threshold of ≥-65dBm.

2.2 Key Factors Affecting Access Quality

AP performance characteristics are fundamental factors affecting access quality, including model type, transmission power, channel bandwidth, CPU utilization, memory usage, online user count, and concurrent connections. These directly determine the AP's carrying capacity and transmission efficiency. For instance, when the number of online users exceeds 80 per AP, CPU utilization may easily surpass 80%, leading to a significant drop in access speed. User behavior exhibits distinct spatiotemporal patterns: access peaks during morning hours (8:00-10:00) and evening hours (7:00-9:00), with high-density areas including academic buildings, libraries, and dormitory zones. Common activities range from web browsing and video streaming to online courses, file downloads, and IoT connectivity. Different devices' Wi-Fi protocol support also impacts access quality. Network interference factors include co-channel interference, adjacent-channel interference, wall attenuation, electromagnetic wave interference, and obstacle effects. Concrete walls typically cause 15-20dB signal loss, while laboratory equipment like elevators may further degrade signals. Network configuration parameters also play a critical role—excessive or insufficient AP density, improper channel planning, over/underpowered transmissions, misconfigured authentication mechanisms, and inappropriate QoS settings can lead to resource contention and frequency interference, ultimately reducing overall access performance.

In addition to the above factors, the physical environment where APs are deployed also has a non-negligible impact on access quality. For example, in open spaces such as stadiums or large lecture halls, the signal propagation range is relatively wide, but there may be issues of uneven signal coverage due to the lack of obstacles to reflect signals. Conversely, in complex indoor environments with multiple partitions and small rooms, such as office buildings with many separate offices, the signal may be blocked by walls and partitions, resulting in dead zones where access is difficult or the signal is extremely weak. The height and location of AP installation are also crucial. If an AP is installed too low, it may be easily blocked by furniture or people, affecting signal transmission; if installed too high, the signal may spread too widely, leading to overlapping coverage areas and increased interference between adjacent APs. Moreover, the surrounding environment of the AP, such as the presence of metal objects, can cause signal reflection and refraction, resulting in signal distortion and instability. For example, metal shelves in a warehouse or metal decorations in a lobby can significantly affect the propagation path of Wi-Fi signals, leading to fluctuations in access quality. Weather conditions can also impact access quality in outdoor deployment scenarios. Rain, fog, and thunderstorms can attenuate wireless signals to varying degrees. Heavy rain may cause a signal loss of 5-10dB per kilometer, making it difficult for users in outdoor areas to maintain stable connections. Temperature changes can also affect the performance of AP components, such as the stability of the antenna and the operation of internal circuits, indirectly influencing access quality. For instance, in extremely high-temperature environments, the AP may experience thermal throttling, reducing its processing speed and transmission efficiency[2].

2.3 Feature Engineering Construction

Based on the identified influencing factors, we designed 23 input features across four categories: AP performance, user behavior, environmental interference, and network configuration. After preprocessing the data to fill in missing values and remove outliers, we standardized the features using the Min-Max normalization method. Feature selection was performed by calculating mutual information between each feature and the target variable, along with XGB feature importance. The final model input variables consisted of 18 primary features, which reduced the impact of excessive information on the model and improved computational speed and result accuracy to some extent.

3. Construction of Wi-Fi Access Quality Prediction Model Based on Machine Learning

3.1 Model Selection Basis

University Wi-Fi access data exhibits nonlinear, time-series, and multi-feature coupling characteristics, which cannot be adequately addressed by a single model that simultaneously considers both static and temporal features. The XGBoost model effectively handles structural data and nonlinear characteristics, demonstrating strong predictive performance for static features such as AP performance, environmental interference, and network configurations. Meanwhile, LSTM excels at capturing long-range correlations in time series, making it ideal for modeling the temporal variations in user access behavior. To address these challenges, this study proposes a hybrid XGBoost-LSTM prediction model that integrates the strengths of both approaches, enabling unified modeling of static and time-series features to enhance predictive accuracy.

3.2 Architecture of Hybrid Forecasting Model

The model architecture consists of four core components: feature preprocessing, XGBoost static feature modeling, LSTM temporal feature modeling, and fusion output. The preprocessing module performs data cleaning, normalization, and feature selection, then categorizes processed features into static and temporal datasets, with the temporal dataset using a 15-minute time window. The XGBoost static feature modeling layer processes static features through an XGBoost-based nonlinear mapping function to predict static feature values. The LSTM temporal feature modeling layer learns user temporal variation patterns using gate mechanisms, generating predictive outputs. The fusion output layer combines predictions from both categories through weighted integration, with weights determined by the relative importance of static and temporal features for different quality metrics.

3.3 Model Training and Optimization

To build the database, we obtained Wi-Fi operation data from a university between September and December 2024, covering three campuses with 1,200 access points. With an average of over 50,000 students using Wi-Fi daily, we collected 1.8 million samples and proportionally divided them into a 7:2:1 dataset for training, validation, and testing. Using grid search combined with cross-validation, we fine-tuned XGBoost parameters including learning rate, decision tree depth, and maximum depth, as well as LSTM parameters such as hidden layer units, time windows, batch size, and iteration rounds. For regression tasks, we employed mean squared error as the loss function to update network weights and biases through backpropagation, ultimately reducing prediction errors.

3.4 Comparison Model and Evaluation Index

Random forest, support vector machine regression, and single-model XGBoost and LSTM were set as control methods. The prediction performance was comprehensively evaluated using mean absolute error, root mean square error, and coefficient of determination as evaluation criteria. Lower error values and a closer coefficient of determination to 1 indicate higher prediction accuracy and better fitting performance of the models.

4. Optimization Strategies for Wi-Fi Network Access Quality in Universities

4.1 Dynamic Power Adjustment Strategy for AP

To address coverage gaps or excessive interference caused by static AP power settings, a dynamic power adjustment scheme is implemented based on predicted access speeds and signal strength. When the RSSI average in an AP's coverage area drops below-65dBm with access speeds under 10Mbps, the AP's transmission power is increased by 2-3dBm to enhance signal coverage. Conversely, if the AP's co-channel interference exceeds-80dBm or the packet loss rate surpasses 2%, the transmission power is reduced by 1-2dBm to mitigate interference. A dynamic power adjustment range is maintained to prevent interference from excessive power or coverage voids from insufficient power, ensuring a power difference of less than 5dBm between adjacent APs for uniform coverage.

4.2 Channel Intelligent Allocation Strategy

To mitigate co-channel and adjacent-channel interference caused by suboptimal channel planning, this approach employs genetic algorithm-based channel allocation. The optimization objective minimizes network interference while maximizing channel utilization, with AP channel allocation schemes serving as chromosomes. Through iterative selection, crossover, and mutation, the system achieves optimal allocation. Key principles include maintaining at least a 3-channel interval between floors and implementing channel multiplexing within the same area. Non-overlapping channels are prioritized, such as 1, 6, and 11 in the 2.4GHz band, and 36,40,44, and 48 in the 5GHz band, to minimize interference between adjacent frequencies.

4.3 User Load Balancing Strategy

To address the degradation of access quality caused by excessive AP load during peak hours, a load balancing algorithm based on AP load thresholds was designed according to user density and online user prediction results. The load threshold for each AP is configured based on its model and performance settings. When the predicted online user count reaches 90% of the AP's load threshold, new users and low-priority service users are redirected to nearby, less busy APs. This scheduling mechanism ensures that the load disparity between APs remains below 20%, preventing frequent disconnections due to excessive reassignment. It also prioritizes real-time services such as online courses and video conferences to maintain uninterrupted access.

4.4 Business Priority Scheduling Policy

To address the varying QoS requirements of different services, a 802.11e-based priority scheduling strategy is developed based on service type predictions. University services are categorized into four priority levels: high priority for online courses, video conferences, and scientific data transmission; medium priority for file downloads and email communication; low priority for web browsing and social media; and the lowest priority for IoT device access and background updates. Using a weighted round-robin scheduling algorithm, different bandwidth weights are assigned to each priority level to ensure high-bandwidth and low-latency services. The weights are dynamically adjusted based on access quality predictions, with higher priority services receiving increased weight during network congestion.

4.5 Fault Early Warning and Active Operation & Maintenance Strategy

The system establishes a three-tier fault alert framework based on access quality prediction results to enable early detection and resolution of faults. The first-tier alert indicates minor faults, predicting access points with speeds below 15Mbps or latency exceeding 80ms, and sends AP performance check notifications. The second-tier alert signals moderate faults, forecasting connection success rates below 95% or packet loss rates above 3%, with channel/power adjustment recommendations. The third-tier alert triggers severe anomalies, automatically dispatching maintenance personnel and activating backup APs to ensure access continuity when APs are predicted to go offline or experience widespread access failures[3].

5. Experimental Verification and Result Analysis

5.1 Experimental Environment and Data

The experiment utilized 120 access points (APs) across three representative campus zones—teaching buildings, libraries, and dormitory areas—to collect real-world data from December 2024. The dataset covered both peak and off-peak hours, with testing devices including smartphones, laptops, and tablets. It also included common university activities like online courses, video streaming, and file downloads, ensuring the data's authenticity and representativeness.

5.2 Comparison of Prediction Model Performance

The performance comparison of various models on the test set demonstrates that the XGBoost-LSTM hybrid model outperforms other models in both average absolute error and root mean square error for access rate and latency prediction, with a coefficient of determination exceeding 0.94. Its prediction accuracy significantly surpasses that of single models. Further tests on packet loss rate and connection success rate prediction show the hybrid model achieving average absolute errors of 0.12% and 0.38%, respectively, with coefficient of determination values of 0.936 and 0.952. These results meet the precision requirements for predicting access quality in university Wi-Fi networks, validating the effectiveness of the hybrid model.

5.3 Validation of Optimization Strategy Effects

Table 1 Comparison of Network Performance Metrics Before and After AP Optimization in Test Areas

Metric	Before optimization	Postoptimality	Amplitude of variation
Average connection speed (unit: Mbps)	16.80	**21.60**	28.3%
Average end-to-end latency (in milliseconds)	72.30	**47.20**	-34.7%
average packet loss rate	**2.1%**	**0.8%**	**-61.9%**
Connection success rate	96.2%	**99.6%**	3.5%
Average AP load balancing rate	**78.5%**	**92.3%**	**17.6%**
User satisfaction score	7.20	**8.90**	23.6%

Table 2 Comparison of Optimization Effects in Different Regions

Region	Speed up	Delay reduction	Packet loss rate decreases	Connection success rate	Load balancing performance improved
teaching building	32.1%	38.5%	-	-	-
library	-	-	65.3%	99.8%	-
dormitory area	-	-	-	-	20.2%

After deploying the optimization strategy on APs in the test area, comparative analysis of network performance metrics before and after optimization revealed significant improvements across all metrics. As shown in Table 1, the average access speed increased from 16.8 Mbps to 21.6 Mbps, representing a 28.3% improvement; average end-to-end latency decreased from 72.3 ms to 47.2 ms, a 34.7% reduction; average packet loss rate dropped from 2.1% to 0.8%, a 61.9% decrease; connection success rate rose from 96.2% to 99.6%, a 3.5% increase; average AP load balancing ratio improved from 78.5% to 92.3%, a 17.6% rise; and user satisfaction score climbed from 7.2 to 8.9, a 23.6% enhancement.

The optimization results varied across different zones. As shown in Table 2, the teaching building, with the highest peak user density, achieved a 32.1% increase in access speed and a 38.5% reduction in latency. The library, hosting the most diverse service types, saw its packet loss rate drop by 65.3% and connection success rate rise to 99.8%. The dormitory area, the most densely populated zone, demonstrated a 20.2% improvement in load balancing, demonstrating the optimization plan's broad applicability and effectiveness across diverse scenarios.

5.4 Robustness Testing

To further validate the proposed model and strategy, simulations were conducted under three extreme scenarios: sudden high load, severe interference, and abrupt changes in terminal types. Under these conditions, the hybrid prediction model maintained an average absolute error below 6%. The optimization strategy ensured network access speeds exceeding 18Mbps and connection success rates above 98.5%, demonstrating the model's strong adaptability and effective handling of extreme situations. The approach also supports dynamic management of university Wi-Fi networks.

To assess the model's stability under continuous operational stress, a 72-hour uninterrupted load test was performed, simulating peak user access periods with concurrent connections reaching 5,000 terminals. Throughout the test, the system maintained stable latency below 30ms, packet loss rates consistently under 0.3%, and CPU/memory utilization remained within safe thresholds (≤75% and ≤80% respectively). Additionally, fault injection experiments were carried out by randomly disconnecting 10% of access points and introducing 20% packet corruption. The self-healing mechanism embedded in the optimization strategy enabled automatic rerouting within 2.3 seconds on average, with service recovery rates reaching 99.2% and no data transmission interruptions reported. These results confirm that the proposed solution not only performs well under extreme scenarios but also maintains long-term operational stability and fault tolerance, making it suitable for large-scale, high-dynamic network environments.

6. Conclusion

To support precise prediction and dynamic optimization of Wi-Fi access quality in universities, traditional operation and maintenance models can no longer meet the growing demands of campus users. This study proposes a closed-loop optimization method based on machine learning, establishing an XGBoost-LSTM hybrid model to accurately predict key Wi-Fi access quality metrics. Building upon this research, the method implements network resource optimization through AP power management, channel allocation, load balancing, service scheduling, and fault prediction.

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