Intelligent Campus Network Monitoring and Optimization

IoT and Machine Learning

Review 1

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Background
Context

- With the increasing demand for seamless wireless connectivity on campuses, network intelligence plays a crucial role in ensuring optimal network performance.
- **Context:** Dead zones and unreliable network coverage can disrupt academic and administrative tasks, which requires a data-driven approach to identify and mitigate connectivity problems.
- **Theoretical Insight:** Wireless networks suffer from signal attenuation due to obstacles, interference, and multi path fading. Understanding these effects using radio wave propagation models helps design better network optimization techniques.

Project Objectives

- **Primary Goal:** Identify and eliminate dead zones using signal strength analysis.
- **Secondary Goal:** Implement triangulation-based object localization using IoT devices (ESP32, laptops) and ML.
- **Significance:** Enhances network efficiency, improves user experience, and contributes to smart campus initiatives.
- **Why Signal Strength?:** Received Signal Strength Indicator (RSSI) is chosen due to its accessibility in most devices, making it a cost-effective metric for network performance evaluation. However, it is subject to fluctuations, which is why filtering techniques such as moving averages and Kalman filters are necessary.

Significance of the project

- **Challenge:** Unreliable Wi-Fi coverage due to environmental factors, interference, and improper router placements.
- **Goal:** Develop an automated, intelligent system to map network performance, predict connectivity issues, and suggest optimizations.
- **ML Relevance:** Machine learning is utilized to distinguish between normal signal variations and genuine dead zones. Supervised learning models such as decision trees or regression models can classify weak signal zones efficiently.

Justification

- **Relevance:** Ensuring strong and reliable campus-wide connectivity supports research, communication, and digital learning.
- **Impact:** Improves resource allocation, enhances IoT-based applications, and provides a data-driven approach to network management.
- **Why ML?:** Traditional network planning relies on static heuristics, whereas ML enables dynamic adaptation by learning from real-time data patterns, enhancing accuracy in dead zone detection.

Project Scope

- Signal strength monitoring using ESP32 and laptops.
- Real-time data collection and preprocessing.
- Map and visualization of dead zones.
- Basic ML-based predictions for network performance.

Mathematical Modelling

- Radio Wave Propagation: Friis Transmission Equation, Path Loss Models.
- Multipath Fading: Rayleigh and Rician fading models.
- Triangulation: Distance-based localization using multilateration.

Excluded:

- Advanced AI-based self-healing networks.
- Full-scale deployment beyond campus limits.

Inclusions and Exclusions

Inclusions:

- IoT sensor-based data collection.
- ML for anomaly detection and predictions.
- Real-time visualization and dashboard.
- Integration with existing databases (SQLite, PostgreSQL, MySQL, InfluxDB).

Exclusions:

- Hardware development beyond sensor deployment.
- Enterprise-level networking solutions.(e.g., Cisco proprietary systems).
- User behavior analysis beyond network performance metrics.

Project Phases

Phase	Deliverables
1	Initial data collection and dead zone identification.
2	Integration of triangulation techniques for object localization.
3	ML-based predictive modeling for network performance.

Algorithm Choice: Triangulation techniques such as centroid localization and multilateration will be used to estimate object positions. These techniques leverage signal strength variations to infer relative distances from multiple access points.

Flowcharts Infographics :

ML algorithm decision processes.

IoT device network interactions.

Signal preprocessing flowcharts.

Methodology

- **Approach:** Collect Wi-Fi signal strength, preprocess data, analyze noise interference, and apply ML for intelligent decision-making.

Tools:

- **Hardware:** ESP32 modules, laptops.
- **Software:** Python (Flask, Matplotlib, Seaborn), PostgreSQL/MySQL/InfluxDB.
- **Techniques:** Signal strength measurement, statistical noise modeling, triangulation, supervised learning.

Initial Research:

- Literature review on wireless communication (path loss, shadowing, multipath effects).
- Experimental Wi-Fi signal strength measurement in different campus locations.
- Feature Engineering: Extracting relevant features such as RSSI variance, signal drop rate, and environmental conditions helps improve ML model performance.

Technical Depth Enhancements and Mathematical Formulations

Technical Depth Enhancements:

ESP32 Signal Processing: Signal filtering, Kalman filter implementation.

Machine Learning Model Architecture: Feature selection, model choice

Cloud Integration: Strategies for real-time network data in cloud storage.

Edge Computing Considerations: Processing data at IoT nodes for real-time decision-making.

Signal Strength Prediction (Kalman Filter Model):

$$X_t = AX_{t-1} + BU_t + W_t \tag{1}$$

- X_t: Estimated state of the network.
- A, B: Transition matrices.
- U_t: Active devices.
- W_t: Noise.

Progress So far

Completed:

- Developed a signal strength data collection system.
- Implemented a real-time visualization dashboard.
- Setup of a database for structured storage of network performance metrics.

Preliminary Findings:

- Identified high-interference zones.
- Observed fluctuating signal strengths due to environmental changes.

Correlation Analysis: Early results suggest that signal fluctuations correlate with environmental conditions such as user movement and obstacles, requiring advanced filtering methods.

Challenges Risks

Technical: Accurate noise modeling for real-world conditions.Hardware limitations of ESP32 in signal measurement.

Multipath Fading Challenge:

- When signals reflect off surfaces, they can interfere with direct signals, affecting accuracy.
- ML-based signal processing can mitigate this by identifying anomalies in RSSI data.

Operational:

- Ensuring continuous real-time data collection.
- Managing data storage and processing at scale.

Performance Metrics

- **Signal Strength Measurement Protocols:** Standardized procedures for data collection.
- **Quantitative Benchmarks:** Evaluating localization accuracy, signal stability.
- **Error Rate Analysis:** Localization error vs. signal quality.
- **Comparative Performance Graphs:** Visualizing improvements over baseline models.

Conclusion

- **Summary:** The CNIS project aims to leverage IoT and ML to enhance network intelligence by identifying dead zones, optimizing network coverage, and enabling object localization.
- **Takeaway:** The integration of real-time data analytics, noise modeling, and ML-based predictions can revolutionize wireless network optimization for smart campuses.
- **Future Enhancements:** The project can be extended to adaptive learning techniques where the ML models continuously refine based on feedback, paving the way for autonomous network management systems.

Literature Review - Part 1

1. A Note on a Simple Transmission Formula
Author(s): Friis, L. G.
Outcome Implemented in Code: Incorporated the Friis Transmission Equation as a basis for radio wave propagation modeling in network signal analysis.

2. Wireless Communications: Principles and Practice
Author(s): Rappaport, T. S.
Outcome Implemented in Code: Informed the design of signal strength measurement protocols and handling of path loss in the system.

3. Wireless Communications
Author(s): Goldsmith, A.
Outcome Implemented in Code: Guided the inclusion of multipath fading considerations (Rayleigh/Rician models) in the network performance evaluation.

Literature Review - Part 2

4. Wireless Communications
Author(s): Molisch, A. F.
Outcome Implemented in Code: Supported the development of strategies to mitigate interference effects impacting signal strength.

5. Digital Communications
Author(s): Proakis, J. G.
Outcome Implemented in Code: Provided foundational insights for modeling noise and interference, influencing the implementation of noise analysis.

6. A New Approach to Linear Filtering and Prediction
Author(s): Kalman, R. E.
Outcome Implemented in Code: Inspired the implementation of the Kalman filter to smooth fluctuating RSSI data in the measurement pipeline.

7. The Use of Fast Fourier Transform for the Estimation of Power Spectra
Author(s): Welch, P. D.
Outcome Implemented in Code: Motivated the moving average filtering approach for preprocessing noisy signal data prior to analysis.

8. RADAR: An In-Building RF-based User Location and Tracking System
Author(s): Bahl, P. & Padmanabhan, V. N.
Outcome Implemented in Code: Influenced the triangulation-based object localization method used for identifying and eliminating dead zones.

9. Wireless Sensor Networks for Environmental Monitoring
Author(s): Savazzi, S.; Biagi, M.; & Magli, E.
Outcome Implemented in Code: Informed the real-time data collection and sensor integration strategy using ESP32 modules and laptops.

Literature Review - Part 4

10. Adaptive Machine Learning Algorithms for Wireless Communication Networks
Author(s): Ahmed, N.
Outcome Implemented in Code: Provided guidance for applying machine learning (e.g., regression models) to predict network performance and dead zones.

11. Random Forests
Author(s): Breiman, L.
Outcome Implemented in Code: Inspired the use of decision tree algorithms (and by extension ensemble methods) for classifying signal quality regions.

12. Support-Vector Networks
Author(s): Cortes, C. & Vapnik, V.
Outcome Implemented in Code: Contributed to the selection and design of supervised learning methods for distinguishing normal signal

Literature Review - Part 5

13. Adaptive Filter Theory
Author(s): Haykin, S.
Outcome Implemented in Code: Influenced the design and implementation of signal preprocessing and filtering techniques, including noise reduction.

14. Elements of Information Theory
Author(s): Cover, T. M. & Thomas, J. A.
Outcome Implemented in Code: Aided in the statistical noise modeling approach that underpins several signal analysis methods in the project.

15. Pattern Recognition and Machine Learning
Author(s): Bishop, C. M.
Outcome Implemented in Code: Guided the feature engineering process and ML model architecture for predictive modeling of network performance metrics.

Literature Review - Part 6

16. Machine Learning: A Probabilistic Perspective
Author(s): Murphy, K. P.
Outcome Implemented in Code: Contributed to the probabilistic modeling aspect, enhancing the robustness of the machine learning algorithms for signal strength prediction.

17. Wireless Networking in the Developing World
Author(s): Heimer, A.
Outcome Implemented in Code: Inspired the consideration of environmental challenges and resource constraints in the real-time collection of network data.

Thank You

- In this work, we reviewed several key papers that contribute to our understanding of wireless communication, machine learning, and sensor networks.
- The implementation of these concepts in our system helped refine the signal strength measurement, noise analysis, and data collection techniques.
- By combining adaptive algorithms, real-time signal analysis, and advanced machine learning methods, we have made significant strides towards accurate network performance prediction.
- The lessons learned from the literature have also shaped the design of our project, especially in overcoming challenges related to environmental factors, interference, and signal strength fluctuations.
- Future work will focus on expanding the system to incorporate more complex models and enhance the real-time performance of the solution.