Predicting Link Quality in Industrial Wi-Fi Networks: From Classical Models to Lightweight Machine Learning

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The fourth industrial revolution (Industry 4.0) revolutionized production systems by integrating digitalization, automation, and the constant exchange of data and information between machines, systems and people. Wireless communication technologies have become essential tools for flexible, reconfigurable, and data-driven industrial operations, even under equipment mobility. Wi-Fi networks are notable for their wide deployment, cost-efficiency and ease of deployment. The use of Wi-Fi in industrial settings, however, presents issues such as the non-deterministic CSMA/CA access mechanism, coexistence with other networks, interference, and dynamic variability of radio channels, which compromise reliability and predictability. Ensuring real-time performance and robust link quality remains a key challenge for critical industrial applications. This thesis aims to design accurate, computationally efficient, and generalizable models supporting real-time inference on embedded devices.

The ability to predict variations in wireless link quality is crucial for proactive network management. Accurate prediction allows communication systems to anticipate degradation and dynamically adjust transmission parameters, such as channel, power, and aggregation window, to prevent performance degradation. Proactive approaches improve reliability, latency constraints, stability, and energy efficiency without requiring changes to existing protocols.

A real experimental dataset was collected under controlled, industry-like conditions. Initially, the analysis focused on computationally efficient models able to capture the temporal evolution of link quality, such as classical predictors based on Simple (SMA), Weighted (WMA), and Exponential Moving Averages (EMA), as well as polynomial regressors. Based on these results, two lightweight models were developed. In the first case, the Exponential Linear Combination (ELC) was developed, which combines multiple low-pass EMA filters with pre-optimized weights to capture different disturbance dynamics. In the second, a Linear Neural Network (LNN) was introduced that preserves model interpretability while providing a more flexible representation of temporal dependencies than classical linear predictors. Their performance was compared with more complex architectures, like Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Bi-LSTM, in terms of accuracy, computation time, and cross-channel generalization.

Results show that ELC and LNN practically resemble more complex models. Although the latter achieve slightly better precision, it comes at the cost of much higher computational complexity. Hence, lightweight architectures represent the best compromise between precision, robustness, and feasibility on low-power hardware.

This forecasting methodology was also applied, with a different goal, to IEEE 802.15.4e TSCH networks, characterized by a deterministic, low-power environment. In this case, the target was to exploit

Machine Learning (ML) to lower power consumption further. The proposed approach proved effective, since the developed model managed to predict slot usage satisfactorily, enabling enhanced energy-saving mechanisms based on the Proactive Reduction of Idle Listening (PRIL) without compromising or marginally affection performance (i.e., latency).

This thesis shows with practical examples that ML models can improve reliability, latency, determinism, and energy efficiency in industrial wireless communications. In particular, ML-based predictors allow the network to anticipate performance degradation and proactively reconfigure its parameters, e.g., through channel selection and transmission power adaptation, without radical protocol changes. This research work lays the foundation for industrial wireless systems capable of predicting, reacting, and adapting to changes in operational and environmental conditions, contributing to the digital transformation of Industry 4.0.