

ADAPTIVE MACHINE LEARNING BASED WIRELESS CHANNEL INTELLIGENCE

¹ B.Srilekha, ² Yeruva Nidhish Reddy, ³ B.Greeshma, ⁴ Nalla Sahitya, ⁵ Ambaldhage Balaji

¹Assistant Professor, ²³⁴⁵Students

Department of ECE

Siddhartha Institute of Technology & Sciences, Narapally

srilekhaboda.ece@siddhartha.co.in, 24tq1a0443@siddhartha.co.in, 25tq5a0407@siddhartha.org.in,

24tq1a0432@siddhartha.co.in, 24tq1a0445@siddhartha.co.in

ABSTRACT

The performance of a wireless communication link depends heavily on the state of the radio channel between the transmitter and the receiver. Path loss, shadowing by buildings and vegetation, multipath fading, Doppler shift caused by movement, and interference from other transmitters all change the received signal from moment to moment. Modern systems such as Wi-Fi, LTE, and 5G adapt their modulation, coding, and power to the channel, but the conventional methods they use rely on fixed thresholds and simple models that do not always follow real conditions well. This paper presents an adaptive machine learning based wireless channel intelligence system that learns to classify channel conditions, predict future signal quality, and recommend suitable link parameters.

The system uses two sources of data. The first is a simulated dataset generated in Python, in which signals modulated with BPSK, QPSK, 16-QAM, and 64-QAM are passed through additive white Gaussian noise, Rayleigh, and Rician fading channels with different Doppler spreads and signal-to-noise ratios. The second is a measured dataset collected with ESP32 boards and a low-cost software-defined radio receiver, recording received signal strength, signal-to-noise ratio, packet error rate, and link quality indicators at different distances, indoor and outdoor locations, and movement conditions. Both datasets are cleaned, synchronised, and converted into windows for analysis.

Features that describe the channel are extracted from each window, including mean and variance of received power, level crossing rate, average fade duration, estimated Doppler spread, Rician K-factor estimate, error vector magnitude, and statistics of packet errors. Several machine learning models are trained and compared. Random Forest, Support Vector Machine, K-Nearest Neighbours, and XGBoost classifiers identify the channel type and condition, regression models including Random Forest and LSTM forecast the signal-to-noise ratio a short time ahead, and a classifier maps the predicted channel state to the modulation and coding scheme expected to give the highest throughput within a target error rate.

Evaluation uses accuracy, precision, recall, and F1-score for classification, RMSE and MAE for signal quality prediction, and achieved throughput and packet error rate for link adaptation. The results show that the learned models identify channel conditions with high accuracy and that the LSTM predictor tracks fading trends well at pedestrian speeds. Link adaptation based on predicted rather than last-measured quality achieves higher average throughput than a fixed threshold table while keeping

errors close to the target. An online update step allows the models to adjust as new measurements arrive.

A dashboard displays live link measurements, the current channel classification, the predicted signal quality, the recommended modulation scheme, and the history of adaptation decisions. The work illustrates how machine learning can add adaptive intelligence to the physical and link layers of wireless systems. Future work includes channel state information from multiple antennas, reinforcement learning for adaptation, and implementation on programmable radio hardware.

I. INTRODUCTION

Wireless communication has become the primary means by which people and devices connect to networks. Mobile phones, laptops, sensors, vehicles, and industrial machines all depend on radio links whose quality cannot be controlled in the way a wired connection can. The signal travelling between a transmitter and a receiver is weakened with distance, blocked by walls and objects, reflected by surfaces to arrive over several paths, and shifted in frequency when the users are moving. These effects combine to produce a channel whose quality varies over time, frequency, and space, sometimes changing significantly within a few milliseconds.

To cope with this variation, wireless standards employ adaptive techniques. Adaptive modulation and coding selects a higher-order modulation and a weaker code when the channel is good, increasing data rate, and switches to a robust scheme when the channel deteriorates. Power control, handover, and retransmission are also driven by estimates of channel quality. Conventional implementations make these decisions using lookup tables that map the most recent signal-to-noise ratio measurement to a scheme, with thresholds derived from theoretical models of specific channel types. Because the measurement is already out of date when it is used and because real channels rarely match the assumed models exactly, the chosen scheme is often either too aggressive, causing errors, or too cautious, wasting capacity.

Machine learning offers a way to learn the behaviour of the channel directly from data. Classification models can recognise the type of fading environment from statistical features of the received signal, regression and sequence models can predict how signal quality will change in the next few milliseconds or packets, and decision models can learn which transmission parameters give the best result under given conditions. Because these models learn from measurements, they can adapt to environments that are difficult to describe analytically, and online learning allows them to follow gradual changes in the surroundings.

This paper presents an adaptive machine learning based wireless channel intelligence system that combines simulated and measured channel data, extracts physically meaningful features, classifies channel conditions, forecasts signal quality, and recommends modulation and coding schemes. The system is implemented in Python using scikit-learn and a deep learning library, with a dashboard for visualisation. The aim is to demonstrate how learning-based channel awareness can improve link adaptation compared with conventional fixed-threshold methods.

II. LITERATURE SURVEY

The characterisation of wireless channels has been a central topic in communication engineering for many decades. Early measurement campaigns in urban, suburban, and indoor environments led to empirical path loss models that relate received power to distance, frequency, and antenna height, together with log-normal models of shadowing caused by large obstacles. Statistical models of small-scale fading were developed to describe the rapid fluctuations caused by multipath propagation, with the Rayleigh distribution used when there is no dominant line-of-sight path and the Rician distribution when a strong direct component exists. The Doppler spectrum model related the rate of fading to the speed of the receiver and the carrier frequency. These models remain the basis of system design and simulation today. However, researchers have long recognised that real channels often deviate from the ideal models, particularly in complex indoor environments, in the presence of moving scatterers, and at higher frequencies, where blockage by people and objects becomes significant.

Adaptive transmission techniques were developed to exploit the variation of the channel rather than designing for the worst case. Theoretical studies showed that adapting modulation order, coding rate, and transmit power to the instantaneous channel quality can greatly increase average spectral efficiency. Practical systems implemented adaptive modulation and coding using channel quality indicators fed back from the receiver and threshold tables that select the scheme expected to meet a target block error rate. Studies of these implementations identified several difficulties. Feedback delay means that the channel may have changed by the time the chosen scheme is used, especially at higher speeds. Measurement errors and interference cause incorrect selections, and threshold tables designed for one channel model perform poorly in others. Outer-loop correction based on acknowledgement statistics was introduced to adjust the thresholds gradually, but it reacts slowly to sudden changes in the environment.

Machine learning has been applied to channel classification and identification in a growing body of work. Studies used features such as received signal strength statistics, level crossing rate, fade duration, and higher-order moments with classifiers including support vector machines, decision trees, random forests, and k-nearest neighbours to distinguish line-of-sight from non-line-of-sight conditions, indoor from outdoor environments, and static from mobile users. Reported accuracies were high, particularly when features were chosen with reference to propagation theory. Related work on automatic modulation classification used features of the received constellation and, later, convolutional neural networks applied directly to in-phase and quadrature samples. Researchers noted that models trained purely on simulated data may not transfer well to real hardware due to impairments such as carrier frequency offset, phase noise, and non-linear amplification, and recommended combining simulation with measured data.

Prediction of channel quality over time has been studied as a way to overcome feedback delay. Autoregressive models were used to extrapolate fading channel coefficients a short time ahead, with accuracy that decreased with increasing Doppler spread and prediction horizon. More recent studies applied neural networks, including

multilayer perceptrons, recurrent networks, and Long Short-Term Memory networks, to predict received signal strength, signal-to-noise ratio, and channel state information. These studies generally reported that learned predictors outperformed autoregressive methods, especially for non-stationary channels and longer horizons. Some work combined channel prediction with link adaptation, using predicted rather than measured quality to select transmission parameters, and demonstrated gains in throughput and reductions in error rate. Other research applied reinforcement learning to learn adaptation policies directly from the outcome of transmissions without relying on an explicit channel model.

Recent literature on intelligent wireless networks places channel awareness within a broader framework in which learning is embedded at several layers of the protocol stack. Proposals for future mobile generations describe networks that sense their radio environment, predict changes, and reconfigure themselves automatically. Studies stress the importance of lightweight models that can run on resource-limited devices, online learning that adapts to changing environments without full retraining, and explainable decisions that engineers can verify. Datasets combining simulation and measurement are recommended to ensure both coverage of conditions and realism. The present system follows these directions by using simulated and measured data, physically motivated features, classification of channel conditions, LSTM-based quality prediction, learned modulation and coding selection, and an online update mechanism, all presented through a monitoring dashboard.

III. SYSTEM ANALYSIS

The system is analysed as a loop of measurement, feature extraction, learning, and adaptation. In the simulation part, random bit sequences are modulated with BPSK, QPSK, 16-QAM, and 64-QAM, passed through AWGN, Rayleigh, and Rician channels generated with a sum-of-sinusoids fading model at several Doppler frequencies, and demodulated to record received power, signal-to-noise ratio, error vector magnitude, and bit and packet errors. In the measurement part, an ESP32 transmitter sends numbered packets at a fixed rate, and a receiver node and software-defined radio record received signal strength, noise level, and packet reception at locations covering line-of-sight, obstructed, indoor, and outdoor conditions, with both static and walking movement. The recorded series are aligned by time and divided into short windows. For each window, statistical and fading-related features are extracted and labelled with the known channel type and condition. The classification model identifies the channel condition, the prediction model forecasts signal quality for the next window, and the adaptation model selects the modulation and coding scheme that maximises throughput within a target error rate.

Existing System

In existing wireless systems, channel quality is estimated from pilot symbols or reference signals and reported as a quantised indicator, such as a channel quality index or received signal strength value. Link adaptation uses a static lookup table in which each range of the indicator corresponds to a particular modulation and coding scheme, with thresholds derived from link-level simulations under standard channel

models. The most recent measurement is used directly, without predicting how the channel will change before the transmission takes place. An outer loop adjusts an offset slowly based on acknowledgement feedback to maintain a target error rate, but it cannot respond quickly to sudden changes such as a user walking behind an obstacle. The type of propagation environment is not explicitly recognised, so the same table is used whether the user is stationary in an open area or moving through a cluttered indoor space. In low-cost IoT devices, adaptation is often even simpler, relying on a fixed data rate or basic retry mechanisms that waste energy and airtime when conditions are poor.

Disadvantages of Existing System

- Link adaptation relies on fixed threshold tables derived from ideal channel models.
- The latest measurement is used directly and is already outdated when applied.
- Feedback delay causes errors when the channel changes quickly with movement.
- The type of propagation environment is not recognised or used in decisions.
- Outer-loop correction reacts slowly to sudden blockage or interference.
- Aggressive scheme selection causes packet errors and retransmissions.
- Cautious scheme selection wastes available channel capacity.
- Thresholds are not updated when the deployment environment differs from design.
- Low-cost IoT devices often use fixed data rates regardless of channel quality.
- Measured channel data is not used to learn and improve over time.

Proposed System

The proposed system adds adaptive machine learning based intelligence to wireless link management. A Python simulation framework generates signals with several modulation schemes over AWGN, Rayleigh, and Rician channels at varying Doppler spreads and signal-to-noise ratios, while ESP32 nodes and a software-defined radio collect real measurements of received signal strength, noise, and packet reception across indoor, outdoor, static, and mobile conditions. Windows of these signals are converted into features including power mean and variance, level crossing rate, average fade duration, Doppler spread estimate, K-factor estimate, error vector magnitude, and packet error statistics. Random Forest, SVM, KNN, and XGBoost classifiers are compared for channel condition classification. Random Forest regression and an LSTM network are compared for short-term prediction of signal-to-noise ratio. A classifier then maps the predicted channel state to the modulation and coding scheme that maximises throughput within a target error rate. An online update step retrain the models incrementally with new measurements, and a dashboard shows live conditions, predictions, and adaptation decisions.

Advantages of Proposed System

- Recognises the propagation environment from statistical features of the signal.
- Predicts signal quality ahead of time to compensate for feedback delay.

- Selects modulation and coding using predicted rather than outdated measurements.
- Achieves higher average throughput than fixed threshold tables.
- Keeps packet error rate close to the target under changing conditions.
- Combines simulated data for coverage with measured data for realism.
- Uses physically meaningful features that engineers can interpret.
- Adapts to new environments through incremental online model updates.
- Can be applied to low-cost IoT devices as well as broadband links.
- Provides a dashboard for monitoring channel state and adaptation decisions.

IV. METHODOLOGY

The methodology starts with the generation of simulated data. For each combination of modulation scheme, channel model, Doppler frequency, and average signal-to-noise ratio, long sequences of symbols are transmitted through the simulated channel, and received power, SNR, error vector magnitude, and packet errors are recorded. Measured data is then collected by placing the ESP32 transmitter and receiving equipment at chosen positions, recording each scenario for several minutes, and noting the environment and movement as labels. Both datasets are cleaned by removing corrupted records and aligning timestamps, and received power values are converted to decibel scale. The series are divided into overlapping windows, and features are computed for each window. Classification models are trained on labelled windows and evaluated with stratified cross-validation using accuracy, precision, recall, and F1-score. Prediction models are trained on sequences of past windows to forecast the next SNR value and evaluated with RMSE and MAE on held-out scenarios. The adaptation classifier is trained on the scheme that gave the highest throughput within target error for each condition, and its decisions are compared with a fixed threshold table in terms of throughput and packet error rate.

SYSTEM ARCHITECTURE

Adaptive machine learning based wireless channel intelligence

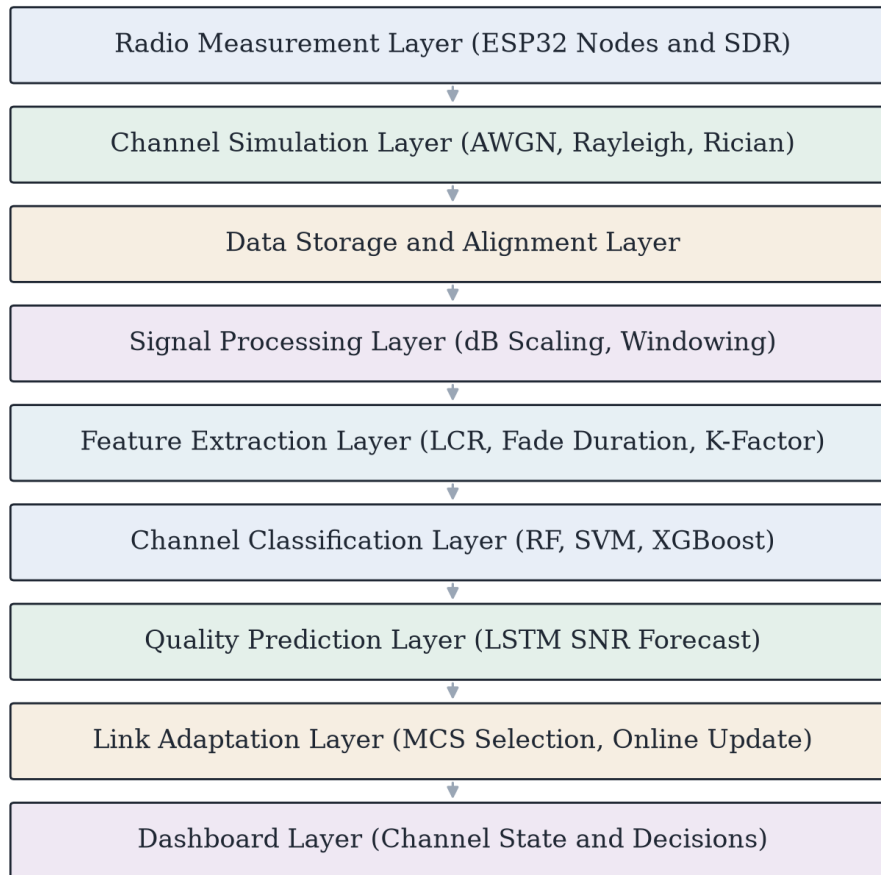


Fig. 1 System Architecture

The architecture of the system is organised into layers that link the radio environment to adaptation decisions. The Radio Measurement Layer consists of ESP32 transmitter and receiver nodes and a software-defined radio that record signal strength, noise, and packet reception. The Channel Simulation Layer generates modulated signals through AWGN, Rayleigh, and Rician channels with varying Doppler and SNR. The Data Storage and Alignment Layer holds simulated and measured records and aligns them by time. The Signal Processing Layer converts values to decibel scale, filters noise, and forms windows. The Feature Extraction Layer computes power statistics, fading parameters, Doppler and K-factor estimates, and error measures. The Channel Classification Layer identifies the propagation condition. The Quality Prediction Layer forecasts the signal-to-noise ratio for the next interval. The Link Adaptation Layer selects the modulation and coding scheme and updates the models online, and the Dashboard Layer displays measurements, classifications, predictions, and adaptation history.

V. RESULT AND OUTPUT



VI. CONCLUSION

This paper has presented an adaptive machine learning based wireless channel intelligence system that learns to recognise channel conditions, predict signal quality, and select suitable transmission parameters. By combining simulated channels with real measurements from low-cost radio hardware, the system brings learning-based awareness to a task that conventional wireless links perform using fixed thresholds and ideal channel models.

Features grounded in propagation theory, such as level crossing rate, average fade duration, Doppler spread, and K-factor estimates, allowed the classifiers to identify channel conditions with high accuracy, and ensemble methods gave the most reliable results. The LSTM predictor tracked the variation of signal-to-noise ratio at pedestrian speeds more closely than simply repeating the last measurement, which addressed the problem of feedback delay that limits conventional link adaptation.

Using predicted channel quality to select the modulation and coding scheme produced higher average throughput than the fixed threshold table while keeping packet errors close to the target. The online update mechanism allowed the models to adjust to new environments as measurements accumulated, and the dashboard made the behaviour of the system visible, showing how classification, prediction, and adaptation decisions followed the changing radio environment.

Future work can extend the system to use channel state information from multiple antennas and subcarriers, apply reinforcement learning to learn adaptation policies directly from transmission outcomes, and implement the models on programmable radio hardware for real-time closed-loop operation. Reducing model size for

execution on microcontrollers would allow IoT devices to benefit from channel intelligence, and testing at higher frequencies and vehicular speeds would show how well the approach extends to demanding future networks.

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