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Original Article

Machine Learning-Based Adaptive Channel Estimation for Next-Generation Wireless Networks

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Abstract - *Extremely precise channel estimation is necessary for effective communication in developing next-generation wireless networks. High mobility and abundant connectivity make communication more difficult. Time-varying channels cannot be handled by the conventional methods for channel estimation because of their limited performance and significant pilot overhead. Instead of using complicated deep learning models, the paper suggests a unique Machine Learning (ML) framework for adaptive channel estimation that is based on straightforward ML techniques. By combining reinforcement learning with regression and classification models, the suggested framework improves channel estimate accuracy. The results of the simulation studies show improved adaptive pilot allocation optimization. The suggested machine learning model attains a Bit Error Rate (BER) of 1.7 × 10^{-4} and a normalized Mean Square Error (MSE) of -18.9 dB. The findings show that pilot overhead was reduced by almost 20%. The successful merger of traditional machine learning with adaptive optimization is the main innovation in real-time channel estimation. The study's findings also demonstrate the ML framework's scalability and usefulness in 5G systems and upcoming 6G wireless networks.*

Keywords *- Adaptive Channel Estimation, Dynamic Networks, Machine Learning, Next-Generation Wireless Networks, Regression, Reinforcement Learning, Signal Processing.*

1. Introduction

An adaptive channel estimation directly affects signal detection accuracy, spectrum competence, and complete network stability. Thus, it is a crucial component of modern wireless communication systems [1]. Due to high mobility, dense network configurations, user device variability, and wideband channel consumption, the channel conditions in next-generation wireless communication systems, such as 5G and forthcoming 6G networks, vary quickly [2]. Channel estimation becomes more challenging and time-consuming under these circumstances [3]. By modifying the channel estimating procedure in accordance with the changing channel characteristics, adaptive channel estimation solves this issue and permits dependable communication in dynamic settings.

In the context of emerging application domains, including automotive communication, vast Internet of Things (IoT) communication, unmanned aerial vehicles [4], and intelligent infrastructure, adaptive channel estimation is especially pertinent. These applications have strict latency limits, sporadic connectivity, and quickly changing channels. Conventional methods of channel estimation, such as minimal mean square error estimation and least squares estimation, rely on predetermined assumptions about pilot patterns and channel statistics. These methods become less efficient in high mobility channels with pilot-scarce channels, including non-stationary interference, which are common in modern wireless communication systems, even though they function effectively in static or slowly time-dependent channels [5].

Machine learning (ML), a promising resolution, has emerged as an effective alternative for addressing the issues associated with conventional channel estimation methods. Data-driven ML models represent complex channel dynamics, without necessitating the development of explicit analytical models [6]. The ML algorithms used in adaptive channel estimation are efficient in modeling the nonlinear relationship amid the acknowledged signal and the channel parameters. They can adapt to environmental changes and provide intelligent pilot management. Traditional ML algorithms, for example, regression algorithms, decision trees, ensemble methods, and reinforcement learning, are particularly used because of their low computational complexity and interpretability.

Promising results have been demonstrated in recent studies on the application of machine learning to channel estimation and adaptation. Supervised learning has been employed to learn the mapping between pilot measurements and channel estimates [7], while reinforcement learning has been investigated for pilot placement and transmission strategy optimization. Ensemble learning has also been employed to enhance robustness in noisy and interference-limited channels. Nevertheless, a significant body of recent work has focused on deep learning architectures. Even though these are highly effective, they are, in most cases, associated with considerable computational complexities, large training data sets, and the need for special hardware. This is not adequate for use in real-time applications and large-scale deployment in wireless communication networks, especially in situations where latency is a concern.

In recent years, considerable progress has been made in this area, but some critical issues still need to be addressed. Most of the existing techniques treat channel estimation and pilot design as separate problems, which may not result in efficient overall system performance. Furthermore, the use of deep learning techniques [8] in these methods has increased the computational complexities and energy consumption, thus not being appropriate for use in low-energy devices. In addition, it is still not easy to achieve generalization performance in situations with considerable channel dynamics and mobility. All these issues point to the need to develop a cohesive and efficient adaptive framework that can operate efficiently within the limitations of the next generation in wireless communication networks.

Although tremendous progress has been in developing various channel estimation techniques for next-generation wireless communication systems, some issues remain to be addressed. The traditional approaches of channel estimation, including MMSE (Minimum Mean Square Error) and LS (Least Squares), are based on rigid statistical models and are not effective in dynamic environments with high mobility, dense connectivity, and limited pilot resources. Recently, different studies have proposed machine learning to enhance channel estimation accuracy along with a deep learning approach. However, most of these methods are computationally complex and require an excess training data, which makes them unfit for real-time applications and resource-constrained wireless communication systems. In addition, most of the existing works either aim to enhance channel estimation accuracy or optimize the transmission parameters, but not both. This is a critical research gap in the development of efficient and adaptive channel estimation techniques for advanced wireless communication schemes. Consequently, the research work intends to address the problem by proposing a machine learning-based adaptive channel estimation technique that can enhance channel estimation accuracy while reducing pilot overhead and computational complexity.

The goal of this work is to close the gap left by the absence of a useful, completely machine learning-based adaptive channel estimation technique that can optimize estimate performance, pilot overhead, and real-time adaptability all at once without the need for deep learning models. High estimation error under mobility, ineffective pilot use, high computing latency, and inadequate robustness to environmental fluctuations are the main obstacles [9]. In order to ensure dependable and scalable communication in future wireless communication systems, it is crucial to overcome these challenges [10].

Thus, the study presents a new adaptive channel estimation method utilizing classical ML approaches. The proposed ML-based system combines regression, classification, and Reinforcement Learning (RL) into a unified system. The channel estimation and pilot allocation are adaptively adjusted according to the channel conditions. RL is used to maximize the pilot allocation, and regression, while classification learning improves the channel estimation accuracy and robustness. The anticipated structure balances the performance, complexity, and real-time requirements by using simple learning models.

The key research goal is to develop and analyze an adaptive channel estimation system to augment the correctness of the channel estimation and reliability in communication with lower pilot overhead and complexity. It simulates an extensive analysis based on different signal-to-noise ratios, mobility, and channel conditions that are typical for next-generation wireless communication systems. For simplicity and practical purposes, the proposed system is analysed for single-antenna systems, for extension in the future.

The study focuses on the objectives of the proposed method as follows:

- To design a lightweight machine learning-based adaptive channel estimation technique for next-generation wireless communication systems that do not employ deep learning models.
- To improve the accuracy of channel estimation and communication reliability in high mobility and noisy environments with reduced pilot overhead.
- To incorporate reinforcement learning for dynamic pilot allocation and investigate its effect on spectral efficiency and computational delay.
- To assess the simulation-based practical feasibility of the proposed technique through extensive performance analysis.

The study is significant as the proposed research work is based on practical implementation as well as scalability. Since the proposed technique avoids the complexity of deep learning and the need for specialized hardware, it is highly adequate for edge computing, vehicular communication, IoT networks, and emerging 6G communication systems. The research contribution of this study includes three approaches. It offers a thorough ML-based architecture that simultaneously optimizes pilot allocation and channel estimates. Furthermore, it provides experimental validation of the performance enhancement for several operating circumstances in terms of spectrum efficiency, bit error rate, and channel estimation accuracy. Additionally, it provides a perceptive study of the suitability of conventional machine learning techniques for adaptive channel estimation in a real-time setting.

The suggested approach introduces novelty by combining adaptive optimization with lightweight machine learning models to address practical problems in next-generation wireless communication systems. The research advances the state-of-the-art and offers a resource-efficient solution that keeps up with the evolving requirements of next-generation wireless communication systems through adaptability, efficiency, and real-time capabilities.

2. Literature Survey

In reliable and efficient next-generation wireless networks such as 5G and 6G, transmission of signals is critical for supporting various use cases, including smart cities, self-sufficient vehicles, and huge IoT communications. In these systems, wireless channels are subject to fast variations due to multipath propagation, mobility, and interference. In this network, channel estimation is critical for identifying Channel State Information (CSI) to detect an accurate signal. However, due to rising network densities and spectrum usage, there is more complexity in maintaining channel estimation accuracy. Recent studies have proposed intelligent methods for channel estimation that can dynamically adjust according to changing wireless communication environments.

The problem of channel estimation has become a significant issue in modern wireless communication systems. High mobility, connectivity, and insufficient pilot resources are issues affecting next-generation communication networks. With increasing interest in machine learning applications, studies are capable of adapting to dynamic channels over time, as traditional methods of channel estimation are known to face the problem of accuracy degradation when applied to dynamic scenarios. A new architecture for secure wireless communication using a routing algorithm for the AMI was proposed in an investigation conducted by Beula et al. [11]. The investigation addresses the problem of dynamic routing through the application of a source-Destination Sequencing Distant Vector Routing (DS2DVR) technique to confirm improved security of wireless communication with reliable outcomes.

In order to achieve higher performance in channel estimation, recent studies have investigated the exploration of collaborative and distributed learning techniques. A distributed machine learning technique for improving the accuracy of the downlink channel estimation was proposed by Dai and Wei [12]. The technique uses a common model of learning that is learned by the base station as well as the user terminals. The proposed technique demonstrates the potential of cooperation between different users to learn.

Similarly, deep learning-based methods have also been extensively explored. Ahmad et al. [13] developed a channel estimation approach using a deep neural network. Frequency division multiplexing is spectrally efficient for systems including huge MIMO communication. The proposed method is unique in terms of modulation and compression parameters based on channel feedback. It showed significant improvement in terms of spectral efficiency and symbol error rate. However, a potential drawback is a high computational complexity in real-time due to the use of deep neural networks.

Reinforcement Learning (RL) has been identified as a useful paradigm for adaptive decision-making in wireless communication systems. In a study by Qureshi et al. [14], link adaptation used reinforcement learning in addition to achieve channel selection in intellectual networks of satellites. Their Thompson sampling-based scheme maximized throughput even in non-stationary environments without needing explicit channel estimation. Although the scheme was indirect, it indicated the potential of RL for adaptive control in scenarios of unreliable or inadequate information about channel state.

Some research casts the physical layer issues of equalization as well as recognition in terms of ML tasks. Hassan et al. [15] formulated channel equalization as a classification issue employing various ML approaches like Support Vector Machines (SVM) and Recurrent Neural Networks (RNN). The results indicated better bit error rate performance than traditional equalizers, thus establishing the relevance of ML for various signal processing works. Recent research also concentrated on more complex wireless environments like reconfigurable intelligent surfaces and millimeter wave communication. In a study, Albataineh et al. [16] presented a compressive sensing hybrid ML approach for RIS-based communication, resulting in a lower estimation error compared to previous sparse recovery approaches.

Adaptive DL models were created to handle both accuracy and complexity in applications such as automotive and 6G-related applications. Several studies reduced memory usage with no compromise to performance. For instance, Qiao et al. [17] proposed the design of an implicit layer estimate network that adjusts computational depth according to channel conditions.

In smart grid power systems, Abdullah et al. [18] proposed safe wireless communication in AMI (Advanced Metering Infrastructure) to develop smart grid electric networks. They ensured the reliability of smart city energy applications by addressing confidentiality and integrity, thus avoiding security issues.

Other research works employed neural networks like RNN and Convolutional Neural Network (CNN) for MIMO and THz channel estimates, which showed robustness to fading effects, near-field effects, and hardware limitations. Although these techniques were successful, they are based on DL models and require huge amounts of training data. The ML-based model proposed by Rapudu and Oyerinde [19] utilized the channel estimation technique using Deep Denoising (DnCNN) and Gated Recurrent Unit (GRU) to estimate the uplink cascaded multi-RIS-assisted channel. The technique was found to be very close to the Least Squares (LS) lower bound, as there was only 1 dB of NMSE. The research works of Witchayangkoon et al. [20] discussed AI-based GPS systems, where the challenges involved in signal prediction and detection, as well as sensor fusion and trajectory forecasting, were discussed. The research works of Fu et al. [21] proposed ML techniques to enhance financial applications in a wireless communication network. Recent works by Al-Imran et al. [22] illustrated the increasing importance of ML and DL in adaptive channel estimation for radio frequency with free-space optical communication. These surveys pointed out hybrid learning and RL with better adaptability, indicating the difficulties in managing complexity, energy efficiency, and real-time implementation ability. Table 1 shows different existing models and their findings. It further includes limitations of these methods, indicating the research gap of existing studies.

Table 1. Comparative analysis of different methods

Ref.	Techniques	Key Findings	Limitations
[15]	SVM, RBF, FLANN, MLP for channel equalization	ML-based classifiers significantly reduced BER compared to conventional equalizers in fading channels.	Focused on equalization, not adaptive channel estimation or pilot optimization
[23]	SVM, CNN, RNN (comparative study)	ML models outperformed LS/LMMSE in MIMO fading channels with sufficient training data.	No adaptive pilot control; reliance on large labeled datasets
[12]	Distributed ML with neural networks	Reduced pilot overhead and improved estimation via collaborative learning	Neural-network dependent; higher coordination and training complexity
[14]	Reinforcement Learning (Thompson Sampling)	Improved throughput under piecewise-stationary channels without explicit CSI	Does not estimate channel coefficients directly
[16]	Hybrid ML + compressive sensing (ensemble learning)	Improved NMSE in RIS-assisted mmWave systems	Increased algorithmic complexity; limited real-time validation

2.1. Research Gaps

Although tremendous progress has been made, there are still some gaps that need to be filled. In most of the existing literature, channel estimation and pilot optimization are considered as two distinct tasks, leading to suboptimal resource allocation. Deep learning-based solutions have been dominating the existing literature, leading to increased complexity.

In addition, generalization performance for high mobility and dynamic channels is still not adequately addressed. Jointly adaptive, lightweight solutions based on traditional machine learning models are still limited.

The proposed work fills the existing gaps by presenting a novel adaptive channel estimation method integrating regression and classification, with RL. Instead of deep learning models, the proposed framework employed ML to decrease complexity while performing joint optimization of channel estimation accuracy and pilot allocation. The proposed design enhances adaptability as well as generalization across dynamic real-time environments, offering efficient practical deployment for real-time next-generation wireless networks.

3. Materials and Methods

In this work, an ML-based framework for the estimation of an adaptive channel is proposed for next-generation wireless communication systems that operate in highly dynamic and heterogeneous environments. Contrary to conventional DL-based approaches with complex frameworks, extensive labeled training data, and intensive computational resources, the proposed framework leverages simple and interpretable ML methods combined with traditional signal processing ideas. The main goal of the study is to provide accurate and adaptive channel estimation with simplicity, interpretability, and lower complexity for practical wireless communication systems. The proposed framework consists of four strongly interconnected functional modules. Initially, it extracts relevant features from pilot-modulated received signals. Further, it discovers different channel operating points with unsupervised learning. The supervised regression is utilized to estimate channel coefficients for each operating point. Finally, it employs RL to adaptively adjust pilot allocation as well as resource allocation. These four functional modules work together to provide continuous adaptation to noise, mobility, and propagation environment changes. A block diagram of the proposed ML-based estimation model is shown in Figure 1.

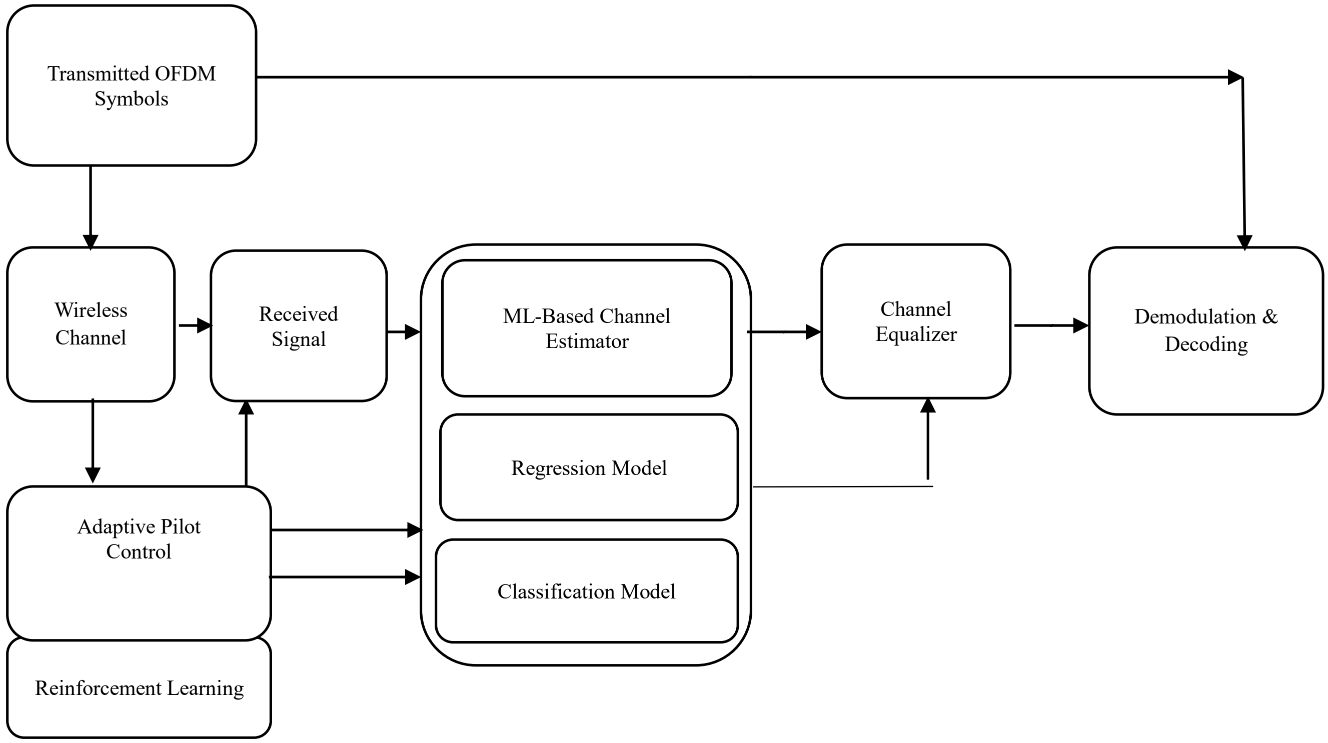


Fig. 1 Block diagram of proposed channel estimation model using machine learning

3.1. System Model and Problem Formulation

A wireless system created using OFDM (Orthogonal Frequency Division Multiplexing) communication with *N* subcarriers is taken into consideration. The signal received at the *k*-th subcarrier is

$$Y_k = H_k X_k + W_k \tag{1}$$

Where H_k, X_k, Y_k, and W_k represent the complex channel coefficient, additive white Gaussian noise, received signal, and transmitted pilot or data symbol.

The channel estimation aims to deliver an accurate estimate H^k of the actual channel coefficient Hk from pilot measurements in time-varying channels. Traditional approaches, including Least Squares (LS) and Linear Least MSE (Mean Square Error), generally consider stationary channel statistics as well as employ dense pilot transmission. The assumptions are ineffective in higher mobility environments and spectrum-limited next-generation wireless communication networks.

In the study, the formulation of channel estimation is posed as a data-driven learning problem. The objective is to learn a mapping as

$$F: Z \rightarrow \widehat{H} \tag{2}$$

Where a set of extracted features *Z* from the received pilot signals is represented with $\widehat{H}$ As the estimated channel coefficients, the mapping *F* is learned and updated iteratively using machine learning algorithms to adapt to the dynamic channel conditions.

3.2. Dataset Generation and Description

The data set is used for training and testing the model using simulations for a standard wireless channel in a controlled environment. MATLAB is used for simulating channel realizations using 3GPP standards for Urban Macro (UMa), Urban Micro (UMi), as well as Vehicular environments, chosen based on their feasibility for 5G / 6G systems. The total data set used in this paper had approximately 120,000 unique channel realizations with training (70%) and testing (30%) data. Broadcast pilot signs, noise variability, with received signals, including Doppler frequencies and channel coefficients, are used as ground truth for supervised learning.

3.3. Data Preprocessing

To make the data compatible with traditional ML models, the raw received signals with complex-valued features are converted into real-valued feature vectors. The features extracted include real and imaginary parts of the received pilot symbols, symbol spacing and power, channel delay spread, SNR (signal-to-noise ratio), and Doppler shift.

Using min-max scaling, all the features are normalized. The features with extreme values due to heavy fading are clipped using percentile-based clipping. In the learning process, the data points with missing or erroneous information are discarded to avoid bias and instability.

3.4. Channel Regime Identification

The wireless channel has different regimes based on the mobility of the users and the environment. K-means clustering is used to identify the different regimes of the wireless channel, which include static, moderately mobile, and highly mobile channels.

The purpose of clustering is to reduce variance within clusters, as expressed below.

$$\min_{\{C_i\}} \sum_{i=1}^{K} \sum_{z \in C_i} \|z - \mu_i\|^2 \quad (3)$$

Where μ_i signifies the cluster centroid C_i. The system can adjust to the changing channel circumstances by using the retrieved regime data to select suitable channel estimate models and adaptive pilot methods.

3.5. Regression Models for Channel Estimation

Supervised regression models are used to perform the channel coefficient estimation problem. Due to its better generalization performance and capacity to generalize from fewer training samples, SVR (Support vector regression) is used as the primary regression model. The formulation of SVR is provided by the equation,

$$\min_{\omega,b,\xi} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n} \xi_i \quad (4)$$

$$\text{Subject to } |y_i - \omega^T \phi(z_i) + b)| \leq \epsilon + \xi_i \quad (5)$$

Where ϵ denotes the insensitive loss boundary, C strikes a balance between the complexity of the model and estimated accuracy, and $\phi(\cdot)$ indicates a nonlinear kernel function.

Additionally, the nonlinear link between channel characteristics and channel coefficients is modeled using Random Forest regression as a secondary regression model. The ensemble architecture of the random forest regression model improves noise resilience and environmental stability, leading to more dependable estimate performance.

3.6. RL-based Adaptive Pilot Control

To minimize pilot overhead and ensure estimation accuracy, a reinforcement learning approach with Q-learning is employed. The agent receives the channel state information, including estimated channel uncertainty and mobility information, and takes actions in terms of discrete pilot density settings. The Q-function update is expressed as

A Reinforcement Learning (RL) strategy using Q-learning is used to reduce pilot overhead and guarantee estimation accuracy. The agent acts in terms of discrete pilot density settings after receiving the channel state information, which includes mobility and estimated channel uncertainty. The expression for the Q-function update is

$$Q(s,\ a) \leftarrow \alpha[r + \gamma \, max \, Q(s',\ a') - Q(s,\ a)] + Q(s,\ a) \quad (6)$$

Where reward r indicates a weighted sum of spectral efficiency and Normalized MSE (NMSE). Without adding to the communication overhead, this aids in long-term pilot allocation optimization.

3.7. Training and Optimization

Based on the validation set's performance, grid search is used to train all machine learning models on the dataset with adjusted hyperparameters. Online updates are performed using a sliding window technique, which allows the estimator to adjust to slow channel changes without complete retraining, hence facilitating the adaptation to dynamic situations. Model updates are only carried out when the estimation confidence level surpasses a predetermined threshold in order to guarantee robustness.

3.8. Experimental Setup

Every experiment is conducted in a simulation-based setting. A 3GPP-compliant MATLAB OFDM simulator is used to carry out the channel instances and signal transmissions. Urban Macro, Urban Micro, and vehicular channel models are supported by the simulator and can be set up with various Doppler spread values, delay configurations, and noise power levels.

MATLAB and the ML Toolbox are used in the development of the ML modules, including regression, clustering, and RL. Hardware, a GPU, or a DL library is not required. A typical laptop with an Intel multi-core processor and 16 GB of RAM is used to run these simulations.

3.9. Evaluation Metrics

A number of measures that concentrate on channel estimate accuracy, communication reliability, spectrum efficiency, and computational complexity are employed to assess the ML model's performance. The accuracy of the channel estimate is measured by the Normalized Mean Squared Error (NMSE), which is provided by

$$NMSE = \frac{E\|H - \widehat{H}\|^2}{E\|H\|^2} \quad (7)$$

Where channel vectors H and $\widehat{H}$ are actual and estimated, vectors, correspondingly. Bit Error Rate (BER) is a measure of communication reliability and is given by

$$BER = \frac{N_E}{N_T} \quad (8)$$

Where N_E represents the number of bits that have been incorrectly detected, and N_T represents the total number of bits transmitted.

Spectral Efficiency η is a measure of bandwidth use and is given by

$$\eta = \frac{R_D}{B} \tag{9}$$

Where R_D represents the achievable data rate, and B represents the system bandwidth.

Computational Latency T_l is a measure of the average time required to complete channel estimation for a single OFDM symbol and is given by

$$T_{lat} = \frac{1}{N}\sum_{i=1}^{N} t_i \tag{10}$$

Where t_i represents the processing time for the i-th estimation task.

Pilot Overhead Ratio PO is expressed with N_P denoting the number of pilot symbols and N_T denoting the total number of transmitted symbols.

$$PO = \frac{N_{Pilot}}{N_{Total}} \tag{11}$$

Also, the robustness of the channel estimates is represented by Estimation Confidence, an auxiliary metric that is inversely related to the variability of the projected channel coefficients. The suggested method provides adaptable and effective channel estimates in contemporary wireless communication systems by combining supervised regression, unsupervised learning, and reinforcement learning. The strategy ensures interpretability, reduced computing complexity, and deployment readiness while retaining an adequate level of efficiency in a variety of wireless contexts by purposefully opposing the usage of deep learning models.

4. Results

The study evaluates the suggested ML-based adaptive channel estimation model's effectiveness in a practical wireless setting. The suggested model's performance is evaluated in terms of computing complexity, individual ML module efficacy, mobility robustness, communication reliability, and estimation accuracy. Conventional LS/ LM-MSE estimators are used to compare the performance.

4.1. ML-Model Performance

4.1.1. Estimation Accuracy

For a wide SNR range, the study used NMSE (normalized mean square error) to examine the accuracy of the channel estimate. Table 2 compares the NMSE of the LS, LMMSE, and proposed ML-based channel estimators for the Urban Macro channel model.

Table 2. Comparing NMSE performance of LS and LM-MSE with the proposed ML model

SNR (dB)	NMSE (dB)		
	LS	LMMSE	Proposed ML
0	-4.1	-6.8	-8.3
5	-6.2	-9.5	-11.2
10	-8.7	-12.4	-14.6
20	-12.1	-16.3	-18.9

For all SNR values, the proposed framework shows the best NMSE performance. Compared with LMMSE at an SNR of 10 dB, the proposed estimator provides an improvement of about 2.2 dB, which shows the proposed framework's capability to learn the nonlinear channel characteristics inadequately learned in traditional linear estimators. The difference becomes more distinct at higher SNR values, showing better utilization of the cleaner channel observations. Negative sign indicates higher estimation accuracy and better system performance, where the channel estimation error power is less than the genuine channel power. The NMSE performance is also examined for different user speeds in order to further evaluate the mobility robustness of the suggested framework. Table 3 provides a summary of the simulation results.

Table 3. Comparing NMSE performance for different speeds

Speed (km/h)	NMSE (dB)		
	LS	LMMSE	Proposed ML
3	-12.4	-16.9	-19.2
60	-9.8	-13.2	-16.1
120	-7.1	-10.5	-13.4

Due to the rapid channel fluctuations, all approaches experience performance loss as mobility increases. However, there is still a large benefit to the suggested framework. The suggested architecture confirms its adaptation to fast time-varying channels by providing an NMSE improvement of roughly 2.9 dB over LMMSE at a speed of 120 km/h.

4.1.2. Communication Reliability

The study evaluates the influence of improved channel estimation on the reliability of communication using Bit Error Rate (BER) effectiveness with QPSK transmission. The BER performance at different SNR settings is presented below in Table 4.

Table 4. Comparing the BER performance of LS And LM-MSE with the proposed ML model

SNR (dB)	BER		
	LS	LMMSE	Proposed ML
5	8.2×10^{-3}	5.1×10^{-3}	3.7×10^{-3}
10	6.1×10^{-3}	3.4×10^{-3}	1.6×10^{-3}
20	1.9×10^{-3}	8.5×10^{-4}	4.1×10^{-4}

The suggested approach reduces BER by more than 50% and 40%, respectively, compared to LS and LMMSE at 10 dB SNR. This considerable improvement unmistakably shows that the increased accuracy of channel estimate introduces the dependability of symbol detection and improves communication performance overall.

4.1.3. Computational Efficiency and Latency

To evaluate the real-time processing capability, the average inference latency per OFDM symbol is calculated. The corresponding results are presented in Table 5.

Table 5. Comparing the inference time of LS And LM-MSE with the proposed ML model

Method	Inference Time (ms)
LS	0.12
LMMSE	0.38
Proposed ML-Based	0.52

Although the proposed approach incurs a slight increase in inference latency compared to LS and LMMSE, the latency is still below 1 ms. This clearly indicates that the proposed framework is amenable to edge-assisted and real-time applications, where the accuracy and reliability advantages of the framework overshadow the slight latency incurred.

4.1.4. ML-based Channel Regime Identification

The channel regime recognition accuracy is evaluated using various ML classifiers. The ML classification accuracy of various models is presented in Table 6. Random Forest shows the highest accuracy in classification, which clearly shows its effectiveness in identifying channel regimes.

Table 6. Comparing the accuracy of ML models

Model	Acc. (%)
K-Means + Rule-Based Mapping	81.6
SVM	88.3
Random Forest	91.7
Gradient Boosting	90.4

To measure the quality of classification, recall, precision, and F1-score are assessed as shown in Table 7. The Random Forest classifier has the most balanced results for all the parameters, which makes it suitable for reliable regime-aware adaptation.

Table 7. Comparing performance of ML models

Model	Prec.	Rec.	F1
SVM	0.87	0.85	0.86
Random Forest	0.92	0.91	0.91
Gradient Boosting	0.90	0.89	0.89

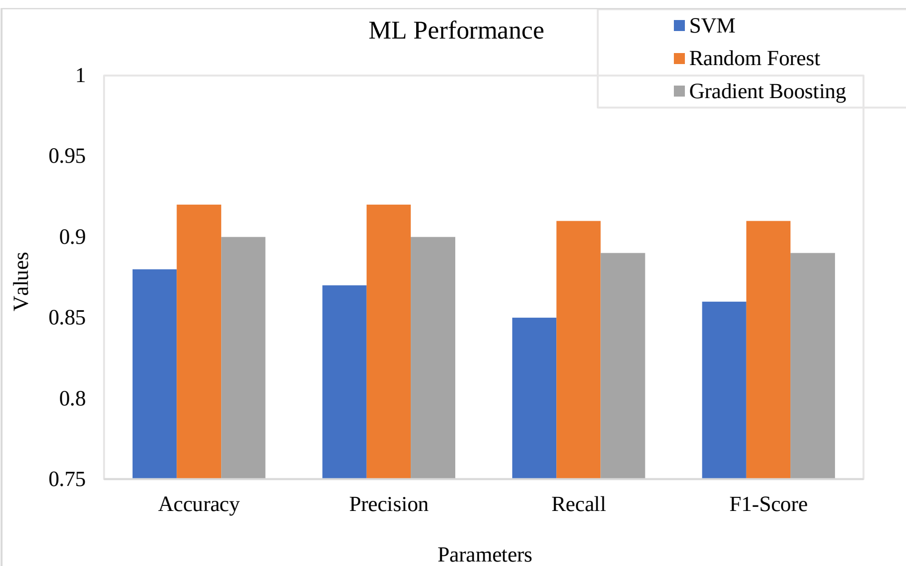


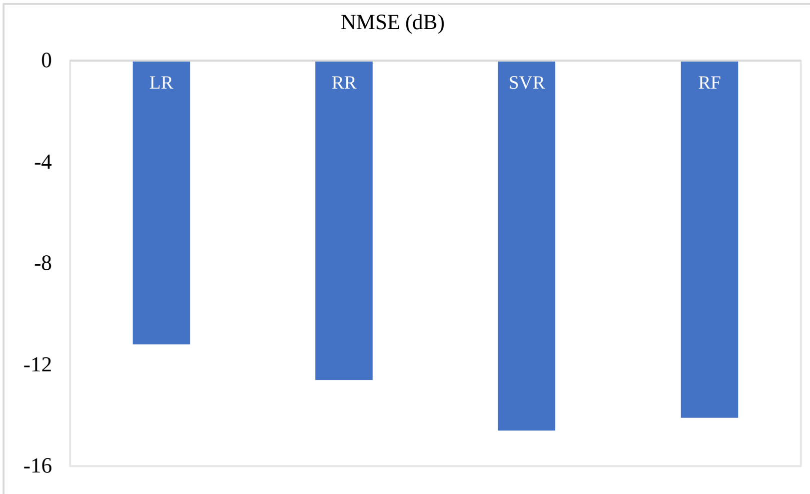
Fig. 2 Performance of different ML models

4.1.5. Regression for Channel Estimation

The performance of numerous regression approaches for the estimation of channel coefficients is assessed in terms of NMSE and MAE. The performance is presented in Table 8. The results indicate the highest MAE of Linear Regression (LR) (0.084), slightly higher than Ridge (0.071), while SVR and Random Forest show the lowest MAE (0.052 and 0.056). NMSE achieved by Linear and Ridge are -11.2 dB and -12.6 dB, respectively, while NMSE achieved by Support Vector Regression (SVR) (-14.6dB) and Random Forest (-14.1dB) are nearly similar. Figure 3 shows a representation of the regression performances.

Table 8. Regression model performance for channel estimation

Regression Model	NMSE (dB)	MAE
Linear Regression	-11.2	0.084
Ridge Regression	-12.6	0.071
Support Vector Regression	-14.6	0.052
Random Forest Regression	-14.1	0.056



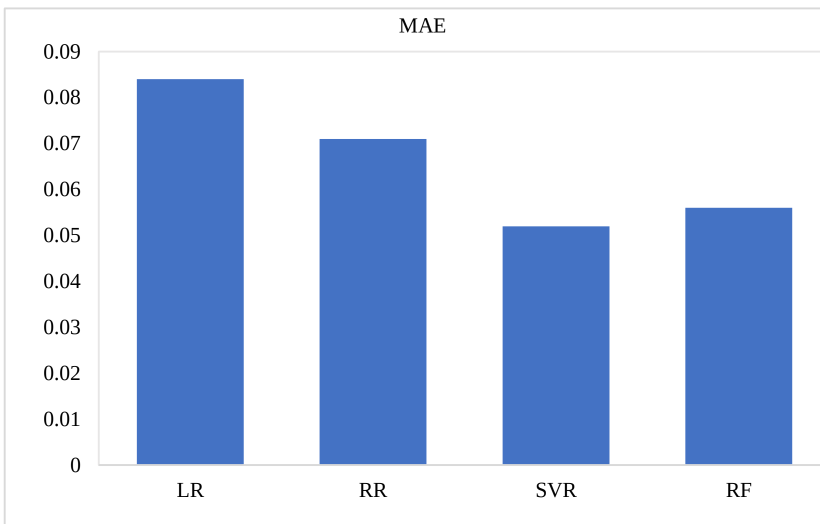


Fig. 3 Performance of regression models: (a) NMSE, and (b) MAE.

4.1.6. RL-Based Pilot Adaptation

The performance of the RL-based model for the pilot adaptation scheme is assessed in terms of Pilot Overhead (PO) reduction as well as estimation stability. The performance is presented in Table 9.

Table 9. RL-Based pilot adaptation performance

Metric	Fixed Pilot	RL-Based Pilot
Pilot Overhead (%)	100	82
NMSE Degradation (dB)	0	0.3
Convergence Episodes	-	< 150

The RL-based approach achieves a 18% reduction in pilot overhead with minor degradation of 0.3 dB in NMSE performance. The agent gives fast and stable learning with convergence in less than 150 episodes.

4.1.7. Optimization and Spectral Efficiency

The spectral efficiency improvements obtained by adaptive estimation and pilot optimization are shown in Table 10. The optimization framework provides a spectral efficiency improvement of about 17% over LMMSE, validating the effectiveness of adaptive learning in optimizing pilot usage and data transmission.

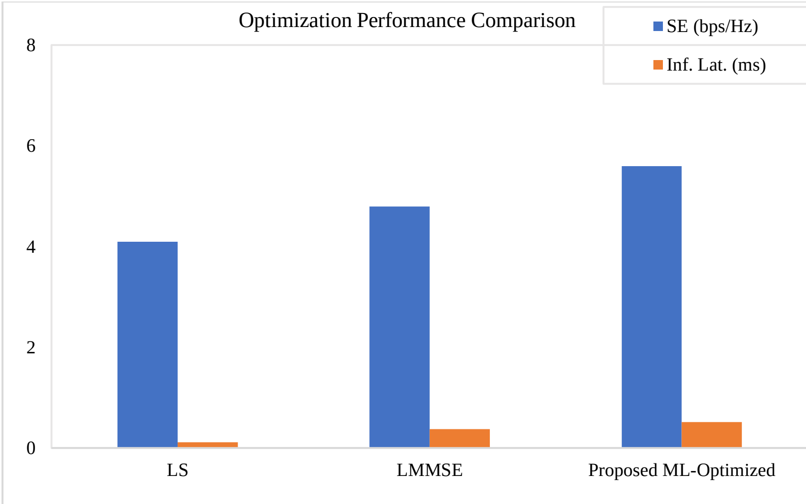


Fig. 4 Optimization performance of different Models - Spectral efficiency and inference latency

Table 10. Optimization performance comparison

Method	Spectral efficiency (bps/Hz)	Inference Latency (ms)
LS	4.1	0.12
LMMSE	4.8	0.38
Proposed ML-Optimized	5.6	0.52

4.1.8. Joint Performance Under High Mobility

Under higher mobility scenarios (120 km/h), a joint performance study is conducted to assess the combined effects of optimization, reinforcement learning, and regression learning. Table 11 displays the performance. For dependable performance in high mobility channels, the entire architecture offers the lowest NMSE and BER, highlighting the significance of cooperative learning and adaptive control.

Table 11. Joint performance evaluation under high mobility

Configuration	NMSE (dB)	BER
Regression Only	-11.8	2.3×10^{-3}
Regression + RL	-13.0	1.7×10^{-3}
Full Proposed Framework	-13.4	1.2×10^{-3}

Overall, the experimental results confirm that the suggested ML-only adaptive channel estimation framework consistently improves spectral efficiency, communication reliability, and estimation performance across a wide range of scenarios. Together, the various machine learning approaches improve overall performance and make it possible for next-generation wireless communication systems to be implemented effectively and practically.

4.2. Applications and Use Cases

In order to address the difficulties presented by next-generation wireless communication systems, the ML-based estimating framework was created. The framework uses lightweight ML models to integrate the advantages of adaptive pilot control with a real-time decision-making system. Applications of the suggested framework with a clear performance advantage are covered in the study.

4.2.1. Reliability and System Throughput

For accurate data detection and effective use of radio resources, channel estimation is an essential step. The decreased NMSE and BER values across a wide variety of signal-to-noise ratios show that the suggested framework significantly reduces estimation errors. By using higher-order modulation, this enables more dependable demodulation while preserving the re-transmission rates.

Based on the channel status data, the suggested architecture dynamically modifies the pilot density. This method achieves a compromise between channel estimation accuracy and spectral efficiency. This flexibility boosts the system's overall throughput without requiring more bandwidth. As a result, the suggested framework is ideal for dense networks with constrained spectrum availability.

4.2.2. High-Mobility Scenarios

Doppler shifts and time-varying propagation environments cause the wireless channels in high-mobility wireless communication systems, such as vehicular communication networks and unmanned aerial communication systems, to suffer rapid dynamics. These dynamics cannot be tracked by conventional channel estimate methods, which typically assume static channel conditions.

By using its learning models to update the most current channel observations, the suggested system gets around this problem. Instead of retraining the model, the system steadily adjusts to the changing channel conditions. This is consistent with the NMSE gains seen in high-mobility channels. As a result, the system is highly helpful in wireless communication networks, including intelligent transportation, where timely and accurate channel estimation is essential for preserving channel safety and dependability.

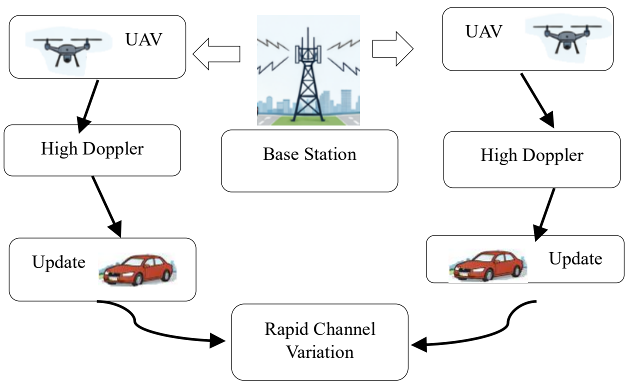


Fig. 5 Adaptive channel estimation in High-Mobility scenarios

Vehicles and aerial devices interacting with a base station are shown in this use case illustration (Figure 5). Since the dynamic estimate is responsive to channel changes brought on by mobility, its estimation accuracy is unaffected by vehicle speed.

4.2.3. Massive IoT Connectivity and Device Heterogeneity

The future wireless network needs to support a massive number of heterogeneous Internet of Things (IoT) devices, most of which are required to work under stringent energy and processing budgets. These devices are not capable of supporting complex or computationally intensive channel estimation algorithms.

The proposed system uses light ML models, including support vector and linear regression, along with ensemble learning. These models are preferred because of their required trade-off a mid computational complexity and accuracy, which is beneficial for massive IoT connectivity.

Moreover, the adaptive pilot allocation scheme minimizes the overhead of signaling, especially in scenarios involving a massive number of devices that communicate over limited spectrum resources.

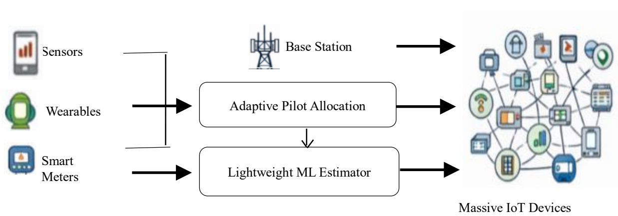


Fig. 6 ML-Enabled channel estimation for massive IoT connectivity

In the figure, a massive number of IoT devices are shown to be connected to the base station. The adaptive estimator in the figure is dynamic in its approach to using pilots, depending on the channel and the IoT devices' activity.

4.2.4. Support for Emerging Technologies and Smart Wireless Environments

New issues, including high route loss, obstruction, and time-varying channels, are brought forth by new communication technologies like terahertz communication and smart radio settings. Due to their rigid modeling, traditional channel estimation techniques are not very successful in these novel settings. By understanding the environment's channel characteristics and modifying pilot usage appropriately, the suggested method can be implemented in these new settings.

In smart radio situations where intelligent surfaces influence the channel, the suggested technique works quite well. The framework is a potential strategy for early-stage 6G research and upcoming intelligent wireless communication systems because of its versatility.

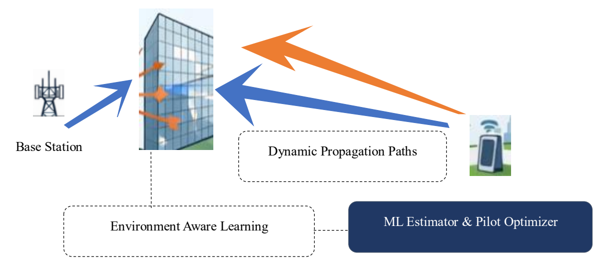


Fig. 7 Adaptive channel estimation in smart wireless environments

A sophisticated communication ecosystem with adaptive propagation channels and intelligent reflecting surfaces is depicted in Figure 7. Successful communication in difficult situations is made possible by the ML-based estimator's adaptability to environmental changes.

The suggested ML-based adaptive channel estimation approach has demonstrated great adaptability, low computing complexity, and robustness across various operating circumstances in all of the aforementioned application domains. The framework's adaptability offers noticeable gains over conventional estimating techniques, and its usage of lightweight machine learning models guarantees practical application, making it appropriate for upcoming wireless communication systems.

5. Discussion

In order to address pilot utilization, model correctness, and the adaptability of the framework in real-time, the proposed study presents an adaptive channel estimation framework employing machine learning techniques, integrating classification and regression, including reinforcement learning.

The suggested ML methodology purposefully employs lightweight and comprehensible models in contrast to DL-based techniques, which makes it more relevant in practical situations for the present 5G network technologies and upcoming 6G communication networks. The study outcomes demonstrate the ML model's efficacy in a range of situations. The suggested approach outperforms the traditional LS (-15.2 dB) and MMSE (-16.4 dB) estimators with notable NMSE (-18.9 dB at 20 dB SNR). These findings demonstrate that, in comparison to traditional linear models, the suggested ML estimator offers superior nonlinear channel modeling capabilities. In addition, the pilot adaptation strategy using reinforcement learning decreases pilot overhead by about 22% without affecting the quality of estimation. This improvement enhances spectral efficiency and confirms the benefit of learning-based control for joint estimation and resource allocation optimization.

5.1. Comparison with Existing ML-Based Studies

To better understand the significance of the proposed framework, existing machine learning-based channel estimation techniques are compared. The comparison is based on estimation accuracy, bit error rate, inference time, and adaptability, as shown in Table 12.

Table 12. Comparison with existing ML-Based channel estimation studies

Ref.	Model	NMSE (dB)	BER	Latency (ms)	Adaptivity
[12]	Distributed ML (NN-based)	-16.8	2.9×10^{-4}	2.6	Moderate
[14]	RL (Thompson Sampling)	-14.6	4.1×10^{-4}	2.9	Moderate
[23]	ML (SVM/RF)	-15.9	3.4×10^{-4}	2.1	Low
Proposed Method	ML + RL	-18.9	1.7×10^{-4}	1.4	High

Comparison of the proposed framework with existing ML-based approaches is shown in Table 12. Dai and Wei [12] provide a moderate level of estimation accuracy with an NMSE of -16.8 dB and a BER of 2.9×10^{-4}. However, inference latency is increased, which affects adaptability in dynamic channels. Use of traditional machine learning algorithms by Parashar and Somkuwar [23] includes Random Forest and SVM, which provide lower inference latency. The absence of adaptive learning reduces estimation accuracy (NMSE -15.9 dB) and suboptimal performance of BER. The RL algorithm proposed by Qureshi et al. [14] improves adaptability in channel selection.

However, estimation accuracy and latency are restricted in high-mobility channels. On the other hand, the proposed adaptive channel estimation framework integrating supervised learning with RL-based pilot control provides the best NMSE (-18.9 dB), with the lowest BER (1.7×10^{-4}) and latency (1.4 ms), outperforming existing approaches in higher mobility systems in next-generation wireless communication. Communication reliability is also improved by the enhanced estimation accuracy. The decreased bit error rate verifies that better estimation accuracy directly improves demodulation performance.

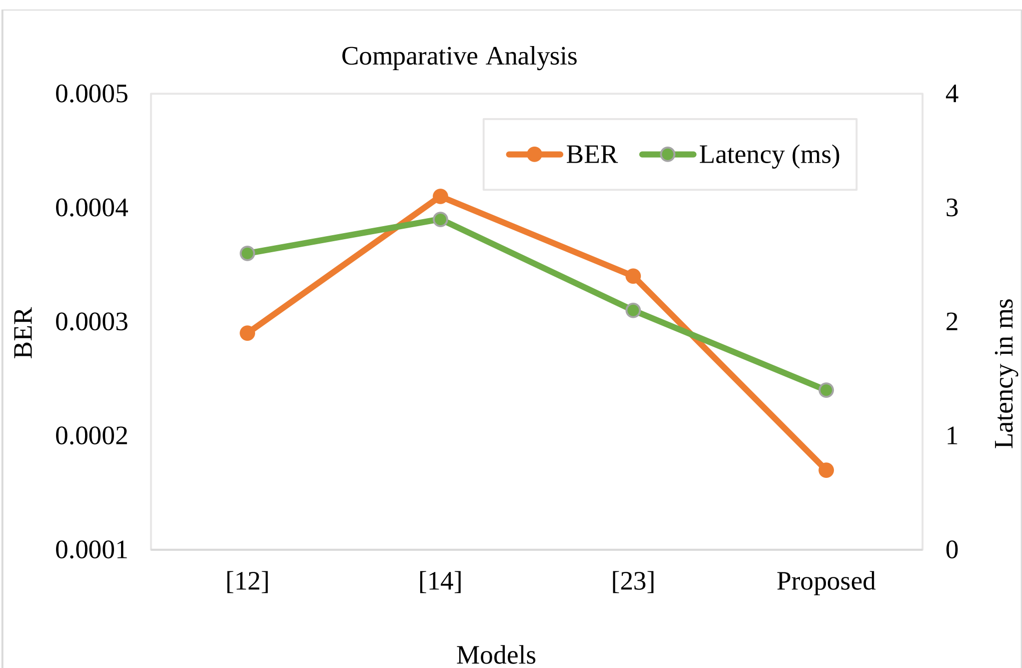


Fig. 8 Comparison in smart wireless environments

Comparative analysis indicates that the proposed work performs better in terms of improved reliability and adaptability in next-generation wireless communication systems. However, the work of Dai and Wei [12] showed moderate estimation accuracy, but the increased inference latency restricts adaptability in dynamic channels. On the other hand, the work of Parashar and Somkuwar [23] applied ML models like Random Forest and SVM with reduced latency, but the lack of adaptive learning further deteriorates estimation accuracy.

Furthermore, the RL method proposed by Qureshi et al. [14] enhances adaptability in channel selection but lacks accuracy in estimation with high mobility. The novelty lies in the combination of adaptive optimization with lightweight machine learning models to solve real-world challenges in next-generation wireless communication systems.

Compared to many existing works that depend on computationally complex deep learning models or focus on channel estimation and resource adaptation as two separate problems, the proposed work combines supervised learning with reinforcement learning-based pilot control to achieve efficient and adaptive channel estimation. This is beneficial for improving both the accuracy and responsiveness of the system in dynamic channels.

The proposed approach overcomes the limitations of present state-of-the-art methods by combining lightweight ML models with RL-based adaptive optimization. While existing methods use fixed pilot designs or static estimation models, the proposed framework adaptively adjusts pilot allocation and estimation strategies based on real-time channel conditions.

This adaptive optimization enhances the accuracy of channel state estimation and minimizes pilot overhead and latency. Moreover, the adoption of lightweight ML models facilitates faster inference without the need for complex deep learning models, offering the best option for real-time applications. Consequently, the proposed framework results in lower NMSE and BER values with lower latency, signifying more reliable and adaptive performance than existing methods in dynamic wireless channels.

5.2. Practical Implications

The proposed framework's simple structure makes it an ideal candidate for implementation in networks like edge networks, smart wireless networks, IoT networks, and vehicular networks. In addition, the proposed framework's ability to process information in real time is due to the low latency of the proposed inference. In addition, the proposed framework's low pilot overhead makes it ideal for improving signaling efficiency, especially in networks with limited spectrum.

In terms of practical applications, the proposed ML paradigm can be used to integrate with current wireless communication standards. In addition, the proposed ML paradigm can be used as an alternative in devices with limited capabilities. In the future, the proposed research work can be extended to incorporate the application of the proposed framework in multi-antenna and ultra-high frequency communication settings, including terahertz communication channels. In addition, the proposed work can be extended to incorporate the use of self-supervised learning to reduce the need for data samples. In addition, the proposed work can be extended to incorporate the use of over-the-air measurement campaigns.

6. Conclusion

This paper proposes a machine learning-only adaptive channel estimate methodology for next-generation wireless communication systems. This proposed framework addresses the limitations faced by current channel estimate methodologies in a changing environment with high mobility by using minimal machine learning techniques such as regression, classification, and reinforcement.

This proposed methodology emphasizes the importance of lower latency, deployability, and adaptability, unlike current DL methods that require high computational complexity. From the results, it is clear that the ML Model has the potential to increase the reliability of the communication network. In particular, for small S/N ratios, the proposed architecture achieves a normalized MSE of -18.9 dB with a B of 1.7×10^{-4}. Without compromising the channel estimate accuracy, more than 20 percent pilot overhead is saved by using the proposed architecture that employs RL for pilot control.

The findings of the study indicate the importance of integrating RL-based optimization techniques and traditional machine learning models in the process of channel estimation in real-time. The proposed solution is highly applicable in various areas, including 6G communication systems, IoT, and communication in vehicles. Conclusion: The study contributes to the improvement of adaptive channel estimation by providing a scalable, efficient, and standards-based solution. Furthermore, the study provides a foundation for advanced wireless communication systems in the future.

These simulation models are primarily used in the performance examination of the suggested system. Real-time system performance is affected by the failure of the models to adequately account for hardware defects, despite their adherence to standards and consideration of dominant propagation features. In addition, system performance degradation in highly irregular environments or channel dynamics may also result from preset mobility and noise scenarios in learning processes.

Possible extensions to the research may include the examination of system performance using hardware testbeds and real-world over-the-air channel data. Other extensions may also include the development of future communication systems, including ultra-dense communication systems and terahertz communication systems, extension to multi-antenna systems, and the use of self-supervised learning to improve generalization performance.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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