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Machine Learning Methods in the Wireless Communication Physical Layer and Their Comparison with Traditional Algorithms

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Abstract. As wireless communication evolves towards 5G and 6G, the physical layer faces increasing demands for performance and robustness in complex channels, high-dimensional systems, and non-ideal hardware. Consequently, traditional model-driven methods depend on accurate assumptions about the channel and noise. Though they are theoretically optimal under ideal conditions, their performance easily degrades when channel mismatch occurs or statistical characteristics are unknown. Hence, machine learning methods are increasingly applied to physical-layer design and optimization. This paper reviews the research progress of machine learning methods in the wireless communication physical layer and conducts a comparative analysis with traditional model-driven algorithms. Focusing on multiple typical tasks, and mainly based on relevant literature indexed in databases such as IEEE and ACM as well as classical theoretical works in communication principles, representative research achievements from 2013 to 2025 are systematically summarized and analyzed. The role of data-driven methods is discussed in terms of modeling approaches, performance behavior, and complexity characteristics. The analysis indicates that machine learning demonstrates strong modeling capability in complex nonlinear channels and low signal-to-noise ratio environments, particularly achieving superior performance in modulation recognition and high-dimensional detection tasks. However, issues such as dependence on training data, generalization capability, and interpretability still need to be addressed.

Keywords: Wireless Communication, Machine Learning, Channel Estimation, Signal Detection, Data-Driven Methods

1. Introduction

As wireless communications evolve towards high-frequency operation, large antenna arrays, and smart networks, physical-layer design is shifting from well-modeled to hard-to-model systems. In particular, large-scale MIMO, millimeter-wave communications, and high-mobility scenarios lead to channels with complex and dynamic characteristics. As a result, traditional signal processing methods that rely on accurate statistical models are prone to performance degradation in complex electromagnetic environments, under hardware impairments, and in the presence of unknown interference. To overcome the limitations of model-driven approaches, machine learning techniques

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have gradually been introduced into physical-layer signal processing. Data-driven methods learn the mapping between received signals and task objectives, reducing, to some extent, the dependence on channel statistical information. In recent years, they have demonstrated promising performance in tasks such as channel estimation, signal detection, and modulation recognition. However, existing studies are fragmented, focusing on specific tasks or algorithm improvements, with limited analysis on computational complexity, generalization, and the comparison of model-driven and data-driven methods across different conditions and scales. This paper presents a unified physical-layer signal model to review and compare machine learning applications in the core tasks. It also examines the shift in modeling paradigms, the trade-off between performance and complexity, and the potential of hybrid frameworks that incorporate physical priors in terms of generalization ability and practical implementability. To this end, relevant literature from the IEEE and ACM databases published between 2013 and 2025 is reviewed. Combined with the theoretical foundations of communication principles, a comparison of model-driven and data-driven methods forms a unified framework and clarifies the relationships in existing research.

2. Fundamentals of machine learning for wireless physical layer

2.1. Problem formulation of physical layer tasks

Physical-layer tasks in wireless communications essentially involve processing the received signal under the effects of noise and channel distortion to achieve information recovery, symbol decision, or category classification. Typical tasks include signal estimation, signal detection, and modulation recognition. Under a unified framework, the received observation can be expressed as

$$y=Hx+n \tag{1}$$

where x denotes the transmitted signal, H is the channel matrix, n is the additive noise, and y is the received signal. Different physical-layer tasks can be viewed as inference problems of unknown variables, such as x, channel parameters, or signal classes, under this model. Traditional methods rely on accurate statistical models for decision rules, but modeling becomes challenging in complex or rapidly changing environments. In contrast, machine learning methods model the relationship between y and the target variables in a data-driven manner, providing a new solution paradigm for physical-layer tasks in complex scenarios [1,2].

2.2. Machine learning techniques used in physical layer

In wireless communication physical-layer tasks, machine learning methods have been widely used for tasks like channel estimation, signal detection, and modulation recognition. According to the availability of labeled information, common learning approaches can be categorized into supervised learning, unsupervised learning, and deep learning. Specifically, when supervisory information is available, supervised learning methods use labeled data to learn the mapping between inputs and outputs, and are commonly applied to tasks such as channel parameter estimation, symbol decision, and modulation type classification at the physical layer. Model training typically aims to minimize prediction error, with representative methods including support vector machines, decision trees, and k-nearest neighbor algorithms. In contrast, unsupervised learning methods do not rely on explicit label information but instead discover intrinsic structures in the data by analyzing the statistical properties or distribution of the received signals. In physical-layer tasks, unsupervised learning can be used to identify different signal patterns or characterize latent channel state variations, for

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example by clustering received signals into groups or modeling distributions to capture channel dynamics. In addition, deep learning methods realize automatic feature representation of signals through multi-layer nonlinear mappings and can serve as model architectures for both supervised and unsupervised tasks.

2.3. Comparison between model-driven and data-driven approaches

Signal processing methods in the wireless communication physical layer can be broadly categorized into model-driven and data-driven approaches, which differ in their modeling strategies and reliance on physical priors. Due to the limitations of single approaches in complex scenarios, system designs increasingly adopt hybrid strategies that integrate physical priors with data-driven learning.

Specifically, model-driven methods rely on communication theory and physical channel models to derive analytical optimal or approximate solutions through modeling of the channel, noise, and modulation processes. For example, maximum likelihood (ML) minimizes error probability by comparing probability density functions under different hypotheses, while minimum mean square error (MMSE) estimation uses second-order statistics of the channel and noise for an optimal linear estimate. When real-world channel conditions involve severe multipath, nonlinear interference, or unknown statistical characteristics, model mismatch can cause performance degradation. In contrast, data-driven methods leverage machine learning or deep learning to directly learn the mapping between received signals and task objectives from data, bypassing the need for explicit modeling. In scenarios with high channel uncertainty or strong system nonlinearity, data-driven approaches offer superior adaptability and robustness.

3. Typical physical-layer tasks in wireless communications based on machine learning

3.1. The machine learning-based channel estimation

In the wireless physical layer, channel estimation faces challenges from incomplete or dynamically changing statistical information. Traditional methods like least squares (LS) and linear minimum mean square error (LMMSE) perform well when statistical priors are known or the channel is stable, but they are prone to mismatch in high-mobility or complex multipath environments. While the LS method does not rely on statistical information, it fails to fully exploit channel correlations, limiting its mean square error (MSE) performance. The LMMSE method is optimal when the covariance is known with known covariance, but in practice, it's hard to model accurately, and performance degrades sharply under mismatch.

Unlike traditional methods, machine learning treats channel estimation as a mapping from observed signals to channel states, learning the channel's nonlinear characteristics and correlations in a data-driven way. Moreover, deep learning methods, including DNNs, CNNs, and RNNs, can capture spatiotemporal structures and nonlinear relationships, greatly reducing MSE in low SNR, multipath fading, or high-mobility scenarios. Incorporating physical constraints or using traditional estimation results (LS/LMMSE) as inputs can further enhance model stability and generalization. As shown in Figure 1, in a high-mobility MIMO-OFDM system, an autoencoder combined with channel attention weights LS features for extraction, reducing MSE while maintaining lower complexity than LMMSE [3]. However, the performance of deep learning methods depends on the consistency between training data and the actual environment, so integrating traditional models and physical priors can improve generalization capability.

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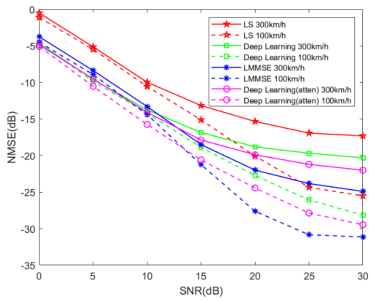


Figure 1. Comparison of NMSE performance of channel estimation algorithms under different user mobility speeds

3.2. The machine learning-based signal detection

Given the received vector y, signal detection identifies the most likely transmitted symbol vector from the finite set S. The optimal decision follows the Bayesian maximum a posteriori (MAP) criterion. In multi-antenna systems, maximum likelihood (ML) detection accurately captures the structure of multi-user interference, but the number of symbol combinations grows exponentially with the number of antennas and modulation order, making it impractical for large-scale systems. In contrast, zero-forcing (ZF) and minimum mean square error (MMSE) detection construct decision boundaries through linear transformations, effectively mitigating interference. In the presence of multi-user coupling or nonlinear distortions, linear decisions cannot accurately characterize the true decision boundaries, leading to significant performance degradation.

To address the challenge of high-dimensional nonlinear decision boundaries, machine learning approaches treat detection as a nonlinear mapping, learning the joint features of symbol modulation and index modulation from training data. In OFDM-IM systems, the FullTrans-IM model employs a Transformer architecture, using attention mechanisms to capture spatiotemporal correlations, hence reducing bit error rate and outperforming traditional methods under multipath fading channels [4]. The network architecture is shown in Figure 2.

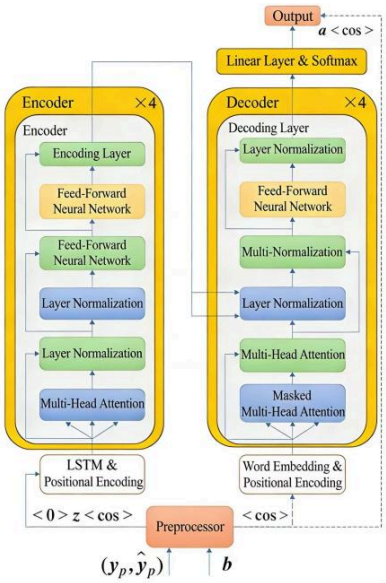


Figure 2. FullTrans-IM signal detection network architecture

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Related studies indicate that this model can maintain detection accuracy in high-dimensional coupled systems and effectively mitigate performance degradation caused by increasing complexity, as shown in Figure 3. However, due to the high training and inference costs, the network design and parameter scale must balance performance and resource consumption according to the application scenario. In low signal-to-noise ratio (SNR) or interference-uncertain environments, the robustness of the detector is reflected in the stability of the decision boundaries against statistical perturbations. Traditional linear methods are prone to errors with noise or interference shifts, while learning-based methods optimize decision boundaries through empirical risk minimization, adapting to diverse training samples and better handling interference variations. And this advantage arises from the reconstruction of complex feature spaces rather than altering the physical propagation mechanism. The generalization capability of the model remains limited by the consistency between training data and the actual environment. Thus, practical implementations must carefully balance performance, complexity, and feasibility.

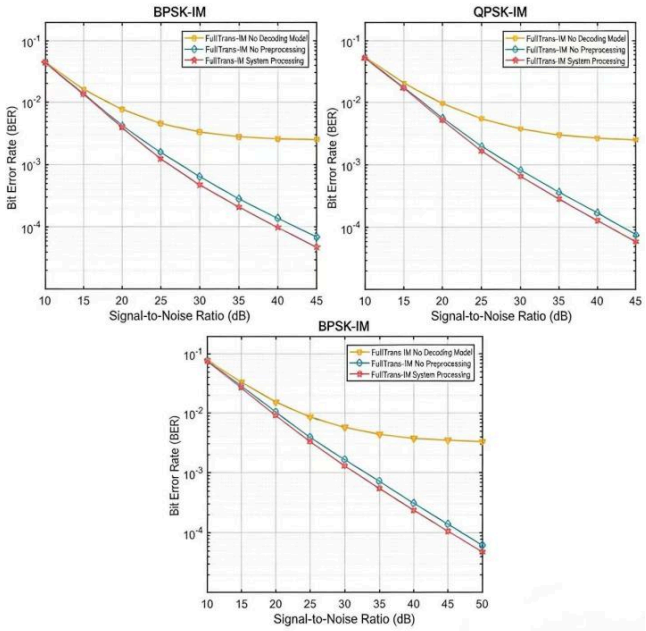


Figure 3. Ablation study comparison

3.3. The machine learning-based modulation recognition

Automatic modulation classification (AMC) aims to determine the modulation scheme of a received signal in unknown or partially known communication environments. This problem can be modeled as a multi-hypothesis testing task, where each modulation corresponds to a probabilistic model. Traditional maximum likelihood methods achieve optimal decisions under ideal conditions but rely heavily on prior knowledge of channel parameters, noise distribution, and synchronization. When these conditions change, decision accuracy drops significantly.

To reduce reliance on statistical models, handcrafted feature-based methods map signals into a low-dimensional feature space and perform recognition using thresholds or classifiers. Common features include higher-order statistics, cyclic spectra, and constellation patterns. In the presence of fading, frequency offsets, phase noise, or interference, fixed features have limited discriminative power, revealing the shortcomings of traditional methods in dynamic environments. Moreover, deep learning methods automatically map raw signals to modulation categories, significantly improving

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classification performance. Meng et al. proposed the CNN-AMC model, which uses long symbol sequences and estimated SNR as inputs, employing a multi-layer convolutional structure to extract multi-scale features and adaptively capture complex signal structures. This model achieves higher recognition accuracy across multiple modulation types and dynamic channels [5]. Compared with traditional methods, the end-to-end design unifies feature extraction and classification, reducing dependence on prior knowledge.

In practical environments, noise uncertainty, frequency offsets, phase jitter, and multipath fading can alter signal statistical characteristics, often causing traditional methods to fail. Deep learning, by leveraging diverse training samples, learns features in the representation space that are invariant to such perturbations, enabling adaptive adjustment. This robustness stems from the expressive power of complex feature spaces rather than explicit modeling of the physical propagation mechanism. Nevertheless, the generalization performance of the model depends on the consistency between training data and real-world conditions, so engineering applications must carefully consider the diversity of training data, model complexity, and implementability [5].

4. Performance comparison of machine learning-based physical layer methods

4.1. Differences among existing methods and comparison dimensions

In the wireless physical layer, traditional model-driven algorithms and ML-based methods differ in handling channel uncertainty and complex tasks. Traditional approaches depend on explicit signal models and statistical assumptions, with performance constrained by model accuracy. Although they can approach optimal solutions under known channel and noise conditions, their adaptability to nonlinear or time-varying channels is limited. In contrast, ML methods learn input-output mappings from data, reducing dependence on precise models and demonstrating stronger adaptability and performance advantages in nonlinear and dynamic environments. Compared to traditional methods, ML approaches, such as deep learning models, rely on network architecture, parameter optimization, and training data distribution, with fewer constraints from physical models. Traditional methods, including LS, LMMSE, maximum likelihood detection, and belief propagation decoding, offer predictable computational structures that facilitate hardware optimization and theoretical analysis. To provide a comprehensive comparison between these two categories, evaluation can be conducted along three dimensions: performance, computational complexity and scalability, and robustness. These dimensions respectively assess accuracy under different channel conditions, feasibility in large-scale or real-time systems, and stability under channel variations or statistical deviations.

4.2. Performance and complexity trade-offs for specific tasks

Traditional model-driven algorithms can achieve near-optimal performance when channel statistics are stable and prior information is accurate. However, in complex scenarios like multipath fading, hardware impairments, or multi-user interference, deviations from model assumptions can lead to performance degradation. In contrast, machine learning methods capture complex channel features through nonlinear mappings, compensating for model errors and improving accuracy. In terms of computation, traditional algorithms primarily rely on matrix operations. Though the computational cost can be high in large-scale MIMO or broadband systems, it can be mitigated through hardware optimization. Machine learning methods shift most of the computational burden to the training phase, resulting in fixed and parallelizable complexity during online inference.

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Furthermore, system evaluation should consider training cost, parameter storage, model updates, and retraining in dynamic environments to assess scalability and practical feasibility. Robustness is another key metric. Traditional algorithms are sensitive to statistical deviations, where even minor variations degrade performance. In contrast, machine learning methods, with their strong expressive capacity, maintain stability in nonlinear or dynamic channels. And hybrid approaches that combine outputs from traditional algorithms with model knowledge can balance performance, computational cost, and robustness in physical-layer tasks, achieving a more favorable trade-off.

4.3. Cross-task characteristics and method trade-offs

Across different physical-layer tasks, traditional methods and machine learning approaches exhibit similar trends. When statistical priors are reliable and the model is well-defined, traditional methods remain competitive, offering predictable performance, lower cost, and strong interpretability. These methods typically rely on explicit statistical models and mathematical formulations, effectively leveraging their strengths in standard scenarios such as channel estimation, signal detection, and modulation recognition. In particular, when channel conditions are known or relatively simple, the performance of traditional methods often approaches optimality. However, as channel complexity grows or signal structures become harder to model, machine learning approaches demonstrate their advantages. Through nonlinear mappings, these methods capture spatiotemporal correlations and signal features. Even in challenging environments like multipath propagation, low SNR, or dynamic conditions, these approaches maintain high performance. Also, hybrid architectures hat incorporate domain knowledge or traditional algorithm outputs balance accuracy, cost, and robustness, while enhancing adaptability across tasks.

5. Existing challenges and future research directions

5.1. Data dependency and generalization

The performance of machine learning methods in the wireless physical layer relies heavily on the quality, size, and diversity of training data. If the training data lacks coverage of diverse channel conditions, noise levels, and interference patterns, the model's performance may degrade greatly when faced with unseen channels or modulation schemes [6,7]. And this data dependence makes generalization a key challenge for physical-layer algorithms. In particular, under dynamic channels or cross-scenario deployments, model performance can deteriorate, affecting estimation accuracy and classification reliability. As such, approaches like few-shot learning, self-supervised learning, and cross-domain adaptation have been proposed, enhancing model adaptability and stability in changing environments.

5.2. Interpretability and reliability

Although deep learning methods demonstrate high performance in physical-layer tasks, their lack of interpretability can influence the reliability and controllability of communication systems [8]. In high-reliability applications, model outputs must be precise and offer clear rationale and verifiable reasoning. Specifically, deep neural networks typically operate as "black boxes," thus making their behavior difficult to predict under abnormal channel conditions, unseen interference patterns, or system mismatches, which may compromise system safety and stability. Thus, explainable artificial intelligence (XAI) approaches have been proposed. For example, Gizzini et al. introduced the XAI-CHEST framework, which analyzes the decision-making process to identify input features that

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critically influence the output, thereby enhancing model transparency and trustworthiness [9]. Such interpretability mechanisms can help engineers understand model behavior and provide essential confidence for deploying learning-based physical-layer algorithms in high-reliability scenarios.

5.3. Integration with next-generation wireless systems

With the evolution from 5G to 6G, future wireless systems operating under high data rates, low latency, and multi-service scenarios impose stricter demands on the adaptability and reliability of physical-layer algorithms, creating both challenges and opportunities for system-level integration of machine learning methods [8]. Under complex channel conditions and multi-dimensional resource allocations, traditional model-driven methods struggle to balance performance and robustness, whereas purely data-driven methods are limited in generalization and interpretability. Consequently, research has focused on integrating physical priors with data-driven learning to optimize both performance and system reliability. Specifically, explainable deep learning frameworks can adapt to dynamic channel environments while also offering decision analysis and reliability assessment to support the collaborative design of model-driven and data-driven methods. Existing studies show that, under complex conditions such as doubly selective channels, explainable learning approaches can reveal model behavior, laying a technical foundation for intelligent physical-layer algorithms in next-generation wireless systems, while boosting system robustness, trust, and long-term evolution.

6. Conclusion

This paper presents a systematic analysis of the development and theoretical boundaries of machine learning methods in the wireless physical layer from a unified signal model view. Focusing on three representative tasks, channel estimation, signal detection, and modulation recognition, the study compares and organizes model-driven and data-driven approaches in terms of modeling paradigms, performance, computational complexity, robustness, and generalization capability. The results show that traditional methods excel with accurate statistical assumptions and analytically tractable system structures. However, as uncertainty, nonlinearity, or model mismatch increase, machine learning methods can approximate the mapping from observations to decisions, showing greater adaptability. Besides, cross-task analysis shows that as uncertainty grows, the main determinants of performance gradually shift from model accuracy to representation capacity and data coverage. Despite the promising potential of machine learning approaches, their practical deployment remains constrained by dependence on training data, limited interpretability, and system implementation challenges. Future research can tackle these challenges with hybrid models that combine physical insights and data-driven learning, boosting adaptability, decision transparency, and framework consistency across scenarios. Such efforts will balance performance, robustness, and implementability, thereby providing guidance for the development of physical-layer algorithms in 6G and beyond.

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