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Machine Learning-Based Noise Reduction Techniques for Enhanced Wireless Communication Performance and Reliability: A Review

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ABSTRACT

The rapid expansion of wireless communication systems has resulted in an increased need for high-speed, reliable, and low-latency data transmission. However, challenges such as noise and interference significantly degrade signal quality, affecting system performance across applications like IoT, autonomous vehicles, and smart cities. Traditional noise reduction methods, including adaptive signal processing, are insufficient in modern dynamic environments. Machine Learning (ML)-based noise reduction techniques have emerged as promising solutions, offering intelligent, real-time adaptation to enhance system performance. AI-driven approaches have shown improvements in throughput, latency, and reliability, enabling advanced solutions for next-generation wireless networks, including 5G and 6G.

Keywords: *Machine Learning, Wireless Communication, Noise Reduction, Signal Processing.*

I. INTRODUCTION

The rapid expansion of wireless communication systems has led to an unprecedented demand for high-speed, reliable, and low-latency data transmission across diverse applications such as the Internet of Things (IoT), autonomous vehicles, smart cities, industrial automation, and immersive multimedia services. However, one of the most critical challenges affecting wireless communication performance is the presence of noise and interference, which significantly degrades signal quality, increases bit error rates, and reduces overall system efficiency. Traditional noise reduction techniques, including linear filtering and adaptive signal processing methods, often struggle to cope with the dynamic and highly complex nature of modern wireless environments. As a result, Machine Learning (ML)-based noise reduction techniques have emerged as a promising solution for enhancing the robustness and adaptability of wireless communication systems. Recent advancements in Artificial Intelligence (AI) and ML have significantly transformed communication technologies by enabling intelligent, data-driven decision-making processes. Tran (2026) emphasized that AI and ML have been increasingly integrated into wireless communication systems to address challenges such as spectrum allocation, traffic management, security vulnerabilities, and adaptive network design. The study highlighted that ML-based approaches improve system performance metrics including throughput, latency, and reliability by enabling intelligent signal processing and real-time adaptation. However, the study also noted challenges such as high computational complexity and data dependency, which limit large-scale real-time deployment. Similarly, Owais and Shongwe (2026) explained that next-generation 5G and 6G wireless networks require advanced ML techniques to handle massive data traffic generated by IoT devices, autonomous systems, and cloud-based applications. They noted that supervised, unsupervised, and reinforcement learning models are increasingly being used for adaptive signal processing, interference mitigation, and dynamic resource allocation. These ML techniques are particularly important in reducing noise and improving signal quality in highly congested network environments. In optical and wireless hybrid communication systems, Chowdhury et al. (2025) demonstrated that Machine Learning and Deep Learning (DL) techniques significantly enhance noise reduction in Visible Light Communication (VLC) systems. They reported that ML-based models improve channel estimation, modulation classification, and symbol detection, thereby reducing the effects of environmental noise, signal blockage, and interference. Similarly, Sliti et al. (2024) found that DL algorithms improve VLC system reliability by addressing challenges such as non-linearity, mobility, and resource management.

Noise-related challenges are also prevalent in Powerline Communication (PLC) systems. Kavvinguru et al. (2025) identified impulsive noise, cyclostationary noise, and narrowband interference as major factors affecting signal quality in PLC networks. Their study highlighted that ML-based classification and mitigation techniques significantly reduce bit error rates and enhance communication reliability by adapting to different noise environments. At the physical layer of wireless communication, Lv and Luo (2023) emphasized that deep learning-based channel estimation plays a crucial role in improving signal reconstruction accuracy under noisy conditions. In addition, Sejan et al. (2022) discussed the use of Intelligent Reflecting Surfaces (IRS) combined with ML techniques to control electromagnetic wave propagation and reduce interference in 6G wireless networks. These advancements demonstrate the growing role of ML in enabling adaptive and noise-resilient communication systems. Furthermore, Mao et al. (2018) and Dai et al. (2020) highlighted that deep learning enables wireless networks to automatically extract meaningful features from high-dimensional data, such as noise patterns, interference levels, and traffic congestion. These capabilities allow for intelligent optimization of modulation schemes, routing protocols, and spectrum allocation strategies, thereby reducing the impact of noise in complex wireless environments. Earlier foundational studies also support the integration of ML in communication systems. Burghal et al. (2020) showed that ML-based localization systems improve accuracy and robustness in noisy RF environments, while Basu and Bhattacharyya (2018) emphasized that big data analytics and ML algorithms enhance network optimization and indirectly contribute to noise reduction by improving system efficiency.

II. RESEARCH BACKGROUND

Tran (2026) was cited for highlighting that the ongoing advancements in Artificial Intelligence (AI) and Machine Learning (ML) had significantly transformed communication technologies. The study emphasized that these innovations offered effective solutions to challenges including spectrum allocation, security vulnerabilities, traffic management, and adaptive network design. It was reported that AI and ML had been increasingly integrated into wireless communication environments, with applications in intelligent traffic forecasting, deep learning-based signal processing, anomaly detection for security enhancement, and reinforcement learning for dynamic resource allocation. Through a combination of mathematical modelling, empirical analysis, and real-world implementations, the study demonstrated that AI-driven approaches improved performance metrics such as throughput, latency, and reliability. Additionally, it was noted that deploying AI/ML in real-time networks faced challenges related to data demands, computational complexity, and security risks. The research further indicated that emerging technologies, including 6G, quantum-AI hybrids, and continual learning, were expected to enable more self-optimizing and adaptive communication systems.

Owais and Shongwe (2026) highlighted that fifth-generation (5G) and sixth-generation (6G) wireless communications were designed to achieve markedly higher data speeds, minimal latency, and notable improvements in base station efficiency. They emphasized that the rapid growth in broadband data usage, driven by Internet of Things (IoT) devices, smart home systems, autonomous vehicles, and virtual reality applications, necessitated the advancement of 5G and 6G networks to overcome the limitations of previous telecommunication technologies. The authors argued that these networks were expected to serve as critical infrastructure for emerging services, introducing new requirements and challenges that complicated the attainment of performance objectives. They reviewed the role of machine learning (ML) in 5G and 6G systems, covering supervised, unsupervised, and reinforcement learning techniques, and suggested that ML would assume a central role in enhancing network performance. Furthermore, they examined various challenges within these wireless networks and identified research opportunities for leveraging ML to address them effectively.

Chowdhury et al. (2025) investigated the emerging field of visible light communication (VLC) as a high-speed wireless communication technology leveraging light-emitting diodes. They highlighted that while VLC offered benefits such as high bandwidth, energy efficiency, and improved security, it also faced significant challenges, including environmental interference, noise, signal blockage, and the necessity of a direct line of sight. To address these issues, they examined the application of machine learning (ML) and deep learning (DL) techniques in VLC systems, focusing on areas like channel estimation, noise mitigation, modulation classification, and symbol detection. The authors reviewed the contributions of DL in advanced VLC configurations, including intelligent reflecting surface-assisted MIMO and non-orthogonal multiple access systems, as well as hybrid VLC/RF networks emphasizing resource management and dynamic network selection. They also discussed DL-based indoor localization and image sensor-based VLC implementations for vehicular environments. Using four major databases—Google Scholar, ScienceDirect, Web of Science, and IEEE Xplore—they identified studies evaluating model architectures, channel models, modulation strategies, performance metrics, and applications, concluding with directions for ML/DL integration in security, intelligent networking, and real-time adaptive VLC control.

Kavvinguru et al. (2025) conducted a comprehensive review on Powerline Communication (PLC), highlighting its role in transmitting both data and power over a single channel, with applications in smart grids, home automation, and IoT devices. They noted that the rising data rates in PLC systems had been increasingly affected by various noise types, including Impulsive Noise (IN), Cyclostationary Noise (CN), and Narrowband Interference Noise (NIN), which were reported to elevate the Bit Error Rate (BER) and weaken signal strength. The study traced the evolution of PLC over the years, detailing the characteristics and sources of different noises and explaining their underlying causes. Furthermore, the authors summarized noise mitigation techniques, emphasizing approaches tailored to specific noise types rather than general reduction methods. They compared these techniques based on performance and applicability, and proposed a novel noise-based selection framework to enhance PLC efficiency. Their findings were presented as a guide for understanding PLC development and advancements in targeted noise-mitigation strategies.

Sliti et al. (2024) investigated the application of Machine Learning (ML) algorithms within Visible Light Communication (VLC) technology, which was recognized as a promising approach for high-speed data transmission due to its dual capability of illumination and data transport. The study examined how ML algorithms could address several critical challenges inherent in VLC systems, including mitigation of non-linearity, accurate channel estimation, detection of modulation formats, localization, security enhancement, mobility optimization, and resource management. It was reported that the integration of ML techniques could significantly improve the efficiency and reliability of VLC networks, ensuring more stable and uninterrupted data flow. Furthermore, the research highlighted the practical difficulties associated with implementing ML in VLC, emphasizing algorithmic complexity, computational requirements, and system adaptability. The authors also outlined potential directions for future research, suggesting avenues for optimizing ML-driven VLC performance and expanding its applicability in next-generation optical wireless communication systems.

Lv and Luo (2023) investigated the rapid development of wireless communication technology and highlighted that intelligent communication had become a key research focus following the fifth generation (5G). They noted that deep learning emerged as a prominent artificial intelligence technique extensively applied in the physical layer of wireless communication to enable intelligent receiving processing. Channel estimation was identified as a critical component of physical layer communication, necessary for accurate information recovery. The authors reviewed prior research on the application of deep learning methods in channel estimation, beginning with a discussion of conventional channel estimation techniques and their respective advantages and limitations. They further described several common neural network architectures and analyzed the use of deep learning in channel estimation through both data-driven and model-driven approaches. Additionally, they extended the review to emerging scenarios, including reconfigurable intelligent surface (RIS)-aided communication systems, and discussed the challenges and prospective research directions needed to advance next-generation wireless communication.

Sejan et al. (2022) examined intelligent reflecting surfaces (IRS) as programmable devices capable of controlling electromagnetic wave propagation through the modification of surface electric and magnetic properties, positioning IRS as a key smart technology for sixth-generation (6G) communication networks. They highlighted that, alongside the growing computational power of devices, machine learning (ML) techniques had been increasingly adopted in wireless communications. The study provided a comprehensive overview of the state-of-the-art in ML, with particular emphasis on deep learning (DL)-based IRS-enhanced communication, focusing on operating principles, channel estimation (CE), and applications of ML within IRS-assisted networks. Additionally, they systematically reviewed existing IRS-enhanced wireless network designs and identified critical challenges and research opportunities associated with integrating IRS with emerging technologies. Their findings underscored the potential of IRS to improve next-generation wireless communication performance while also emphasizing the need for further investigation into practical implementation, optimization, and the convergence of ML and IRS technologies.

Helal (2022) examined the recent advancements in terahertz (THz) signal generation and radiation methods, highlighting the emerging proposals for joint THz communications and sensing (CAS) applications in future wireless systems. The study suggested that THz spectroscopy could be performed on user equipment devices to identify relevant material and gaseous components, and emphasized that THz-specific signal processing techniques were crucial for the efficient utilization of the THz band. The article provided an overview of preprocessing methods such as standard normal variate (SNV) normalization, minimum–maximum normalization, and Savitzky–Golay (SG) filtering, along with feature extraction approaches including principal component analysis (PCA), partial least squares (PLS), t-distributed stochastic neighbour embedding (t-SNE), and nonnegative matrix factorization (NMF). Classification techniques, particularly support vector machines (SVMs), k-nearest neighbour (kNN), discriminant analysis (DA), and naive Bayes (NB), were evaluated, while the potential of deep learning for sensing and localization at the THz band was also explored. The study further analysed performance–complexity trade-offs and proposed future research directions in joint CAS applications.

Dahrouj (2021) highlighted that despite the increasing interest in the integration of machine learning and optimization, existing studies remained fragmented across the research landscape, and a comprehensive overview of their reciprocity was still lacking. The study examined a particular direction of interplay between learning-driven solutions and optimization, providing a structured background and summarizing relevant theory. It was noted that machine learning, along with its variants, had gained prominence due to its capabilities in automating analytical modelling. The review described how learning-based techniques, including supervised, unsupervised, and reinforcement learning, had evolved to complement various optimization problems in both testing and training contexts. Specific attention was given to the use of deep neural networks, echo-state networks, reinforcement learning, and federated learning for solving analytically intractable and complex optimization problems. The paper discussed applications in communications and signal processing, such as wireless scheduling, resource management, power control, aerial base station placement, virtual reality, and vehicular networks, and suggested future directions involving THz sensing, 6G networks, underwater optical networks, and distributed optimization.

Burghal et al. (2020) highlighted the increasing interest in location-based services over the last few decades, noting that localization systems utilizing Radio Frequency (RF) signals had demonstrated effectiveness for both indoor and outdoor applications. They observed, however, that these systems continued to face challenges regarding complexity and accuracy. The authors indicated that Machine Learning (ML), particularly deep learning, had emerged as a promising approach to mitigate such issues, offering practical data-driven tools for integration into localization frameworks. Their study provided a comprehensive survey of ML-based RF localization solutions, covering system architectures, input features, ML methodologies, and dataset usage. They emphasized the interaction between domain knowledge derived from localization physics and ML techniques, discussing how features, wireless standards, and preprocessing influenced outcomes. Additionally, they reviewed applied ML methods, dataset acquisition strategies, and publicly available datasets, summarizing insights from nearly 400 papers and identifying open research problems while offering a concise overview of relevant ML and wireless propagation concepts.

Dai et al. (2020) examined the transformative potential of wireless communications, emphasizing emerging applications such as virtual reality and the Internet of Things. They highlighted that these developments introduced significant challenges, including unknown channel models and stringent low-latency requirements in large-scale, super-dense networks. The authors noted that the remarkable success of deep learning (DL) across various fields, particularly in computer science, had prompted growing interest in applying DL techniques to overcome these challenges. In their review, they investigated two dominant methodologies: DL-based architecture design, which diverged from traditional model-based block design approaches in wireless communications, and DL-based algorithm design, demonstrated through examples of techniques relevant to 5G and beyond. They discussed the underlying principles, key characteristics, and performance improvements associated with these methodologies. Furthermore, they identified open problems and future research directions, emphasizing the synergistic relationship between DL and wireless communications and suggesting that their review could inspire innovative contributions to the field.

Amirabadi (2019) highlighted that Machine Learning (ML) for Optical Communication (OC) had recently emerged as a rapidly growing research area and was expected to continue attracting significant interest in the following years. The novelty of this field was attributed primarily to the uniqueness of its application domain rather than to methodological innovations, as state-of-the-art ML algorithms were predominantly employed. The literature review indicated that numerous ML algorithms had not yet been applied in OC, and many OC applications remained unexplored, reflecting the nascent nature of the research. Consequently, tutorial investigations were considered necessary to familiarize researchers with the latest developments and gaps in the field. While some tutorials had addressed the topic from an OC perspective, they largely overlooked the ML viewpoint. Amirabadi’s work, for the first time, reviewed ML for OC from the perspective of ML, providing a comprehensive overview intended to assist OC experts—who were not necessarily ML specialists—in understanding applicable ML methodologies, thereby offering broader generality and deeper insight compared with previous surveys.

Mao et al. (2018) highlighted that deep learning (DL) had emerged as a promising machine learning tool for accurate pattern recognition in complex raw data and was increasingly applied to enhance intelligence in wireless networks characterized by large-scale topology and dynamic radio conditions. They indicated that DL, by employing multiple neural network layers, enabled acute feature extraction from high-dimensional data and could identify network dynamics such as hotspots, interference distribution, congestion points, traffic bottlenecks, and spectrum availability through analysis of parameters including delay, loss rate, and link signal-to-noise ratio. The study surveyed the applications of DL across various network layers, encompassing physical layer modulation and coding, data link layer access control and resource allocation, as well as routing layer path search and traffic balancing. Additionally, they noted its use in augmenting network functions such as security and sensing data compression, while emphasizing unresolved research challenges that could guide future investigations in DL-based wireless network design.

Basu and Bhattacharyya (2018) observed that communication technology had been undergoing a paradigm shift, as enterprises increasingly redirected their focus toward smart communication networks to utilize network traffic data more effectively. They noted that modern communication systems, especially mobile networks, had been generating an enormous volume of information at both the system framework and end-user levels. This data was considered a valuable source of insights related to user location, mobility patterns, and calling preferences. The authors highlighted that network operators had envisioned using this vast traffic data for internal administrative purposes, particularly for network management and optimization. They further emphasized that achieving this vision had required the development and implementation of advanced machine learning algorithms for big data analytics in communication networks. Such algorithms were expected to extract meaningful information from network activity while accounting for limited communication resources and to leverage this knowledge for both internal operations and external service applications.

Syed et al. (2017) had presented telehealth monitoring as an innovative approach that synergised the advantages of Information and Communication Technologies (ICT) and the Internet of Things (IoT) for delivering healthcare services to remote, distant, and underserved regions. The study had aimed to extend healthcare delivery beyond conventional clinical settings by technologically connecting patients with healthcare providers. It had been reported that telehealth technologies had become increasingly advanced and more fully integrated into healthcare service delivery. Particular emphasis had been placed on tele mammography as an important telehealth application for the early diagnosis of breast cancer in rural and remote areas. The authors had also proposed a novel tele mammography system using wavelet-based image processing for pre-processing, tumor detection, and image enhancement. A comparative evaluation of Multi-Layer Perceptron, J48, Random Forest, and K-Nearest Neighbour classifiers had been conducted using MIAS data. The findings had indicated that the neural network classifier had achieved the best performance in classifying benign, malignant, and normal mammographic images.

III. KEY FINDINGS FROM STUDY

Author (Year)	Study Focus	Methodology	Key Findings	Relevance to Noise Reduction in Wireless Systems
Tran (2026)	AI/ML in wireless communication systems	Mathematical modeling and empirical analysis	AI/ML improves throughput, latency, and reliability in communication networks	ML enables adaptive signal enhancement and noise-aware optimization

Owais & Shongwe (2026)	ML in 5G and 6G networks	Review of ML-based network models	ML enhances resource allocation, traffic management, and network efficiency	Supports interference mitigation and adaptive noise handling
Chowdhury et al. (2025)	Visible Light Communication (VLC) systems	Comprehensive survey of DL methods	DL improves modulation, channel estimation, and signal detection	Reduces optical noise, interference, and signal blockage
Kavvinguru et al. (2025)	Powerline Communication (PLC) noise mitigation	Survey-based comparative analysis	Identified impulsive, cyclostationary, and narrowband noise effects	ML-based filtering reduces BER and improves signal clarity
Sliti et al. (2024)	ML applications in VLC systems	Systematic literature review	ML enhances reliability, mobility, and resource management	Improves robustness against environmental noise
Lv & Luo (2023)	Deep learning for channel estimation	DL-based physical layer modeling	Improved accuracy in channel estimation and signal recovery	Enhances noise-resilient signal reconstruction
Sejan et al. (2022)	IRS-assisted wireless communication	ML-enhanced system design review	IRS improves signal control and propagation in 6G networks	Reduces interference and enhances signal quality
Helal (2022)	THz communication and sensing	Signal processing + ML techniques	Improved sensing, classification, and signal analysis	ML reduces atmospheric and channel noise in THz systems
Dai et al. (2020)	Deep learning in wireless networks	Architecture and algorithm review	DL improves feature extraction and network intelligence	Enhances adaptive noise prediction and mitigation
Mao et al. (2018)	Intelligent wireless networks	Comprehensive DL survey	DL improves modulation, routing, and resource allocation	Enables noise-aware network optimization
Burghal et al. (2020)	ML-based RF localization	Survey of ~400 studies	ML improves localization accuracy in noisy RF environments	Enhances robustness against signal distortion and noise
Basu & Bhattacharyya (2018)	ML in wireless communication analytics	Big data and ML integration study	ML improves network management and optimization	Indirectly reduces noise through system efficiency
Amirabadi (2019)	ML in optical communication	ML-focused review	Identified gaps in ML application in OC systems	Highlights ML potential in optical noise mitigation
Syed et al. (2017)	Telecommunication & ML-based imaging	ML classification (NN, RF, KNN)	Neural networks achieved highest classification accuracy	Demonstrates ML effectiveness in signal interpretation under noise

IV. CONCLUSION

Machine Learning (ML)-based noise reduction techniques have emerged as a highly effective and transformative approach for improving the performance of modern wireless communication systems. With the rapid expansion of data-intensive applications such as IoT, autonomous vehicles, 5G/6G networks, and real-time multimedia services, wireless channels are increasingly affected by various types of noise, including thermal noise, impulsive noise, interference, fading effects, and environmental distortions. Traditional signal processing methods, although widely used, often fail to adapt efficiently to dynamic and heterogeneous communication environments. The reviewed literature clearly demonstrates that ML and Deep Learning (DL) techniques significantly enhance noise mitigation capabilities by enabling intelligent, data-driven decision-making processes. Tran (2026) highlighted that AI/ML integration improves key network performance parameters such as throughput, latency, and reliability by enabling adaptive signal processing and intelligent network optimization. Similarly, Owais and Shongwe (2026) emphasized that ML plays a central role in next-generation 5G and 6G networks by supporting dynamic resource allocation and interference management in highly complex environments. In specialized communication domains such as Visible Light Communication (VLC), Powerline Communication (PLC), and Terahertz (THz) systems, ML-based techniques have proven particularly effective in addressing noise-related challenges. Chowdhury et al. (2025) and Sliti et al. (2024) demonstrated that deep learning models improve channel estimation, modulation detection, and signal reconstruction in VLC systems, thereby reducing the impact of environmental and optical noise. Likewise, Kavvinguru et al. (2025) identified that ML-based noise classification significantly improves signal reliability in PLC systems by reducing impulsive and narrowband interference. At the physical layer, Lv and Luo (2023) confirmed that deep learning-based channel estimation enhances signal recovery in noisy wireless environments, while Sejan et al. (2022) showed that Intelligent Reflecting Surfaces (IRS) combined with ML techniques can dynamically control signal propagation and reduce interference in advanced 6G systems. Furthermore, foundational studies by Mao et al. (2018) and Dai et al. (2020) established that deep learning enables intelligent feature extraction from complex wireless data, allowing networks to automatically identify and mitigate noise patterns. Overall, ML-based noise reduction techniques provide adaptive, scalable, and efficient solutions that significantly outperform conventional signal processing methods. They enable wireless systems to become more intelligent, self-optimizing, and resilient in the presence of unpredictable noise and interference.

V. FUTURE SCOPE

Despite significant progress, ML-based noise reduction in wireless communication systems still presents several open research challenges and opportunities for future exploration. One of the primary challenges is the high computational complexity associated with deep learning models, which limits their real-time deployment in resource-constrained devices such as IoT sensors and edge nodes. Future research is expected to focus on the development of lightweight, energy-efficient ML models that can operate effectively in real-time communication environments. Another important direction involves the integration of Federated Learning (FL) and Edge AI to address data privacy concerns and reduce communication overhead. By enabling decentralized learning across distributed devices, FL can enhance noise reduction capabilities without requiring centralized data storage, making it highly suitable for 6G and large-scale IoT networks. The convergence of ML with emerging communication technologies such as Reconfigurable Intelligent Surfaces (RIS), Terahertz communication, and quantum communication systems also presents promising opportunities. These technologies can significantly enhance signal control, propagation efficiency, and noise suppression capabilities in complex wireless environments. In addition, future research may explore hybrid AI models that combine reinforcement learning, unsupervised learning, and deep learning to achieve more robust and adaptive noise mitigation strategies. Self-learning and self-healing communication networks are expected to become a key focus area, enabling systems to automatically detect, predict, and eliminate noise without human intervention. Finally, explainable AI (XAI) is expected to play a critical role in improving the transparency and interpretability of ML-based communication systems. This will be essential for ensuring reliability, security, and trust in mission-critical applications such as healthcare, autonomous transportation, and industrial automation. In conclusion, ML-based noise reduction techniques represent a foundational pillar for the future of intelligent wireless communication systems. Continued research and innovation in this field will lead to more efficient, adaptive, and resilient communication networks capable of meeting the growing demands of next-generation technologies.

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