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Review Article

Machine Learning-Based Techniques for WLAN Performance Optimization: A Systematic Review

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Abstract

The rapid expansion of Wireless Local Area Networks (WLANs) has introduced significant performance challenges, particularly due to the increasing number of mobile and connected devices. Traditional static network management techniques are inadequate for handling the dynamic and complex nature of modern WLAN environments, often resulting in latency, congestion, and interference. This study systematically examines the potential of machine learning (ML) approaches, including advanced algorithms such as Q-learning and Support Vector Machines (SVM), for WLAN performance optimisation. By enabling predictive traffic analysis, adaptive configuration, and intelligent resource allocation, ML techniques offer opportunities to enhance throughput and minimise delay. The study aims to: (1) identify and categorise ML algorithms addressing key WLAN challenges such as latency reduction, interference mitigation, and load balancing; (2) analyze the performance metrics used across studies using standardised formulations; (3) evaluate the generalisability of simulation results to real-world deployments; and (4) identify computational, scalability, and dataset limitations affecting real-time implementation. Despite promising laboratory results, challenges persist due to the scarcity of large, high-quality, real-world datasets required for robust training. The paper highlights the critical role of data efficiency and advocates for open-source WLAN datasets and methods such as transfer learning and few-shot learning to reduce data dependence. Ultimately, this study emphasises that overcoming data constraints is key to realising adaptive, real-time, and scalable ML-driven WLAN optimisation for future wireless communication systems.

Keywords

Wireless Local Area Networks, Machine Learning, Network Optimization, Latency Reduction, Interference Mitigation, Transfer Learning

1. Introduction

1.1. WLAN Performance-related Background

The Wireless Local Area Networks (WLANs) have emerged as a strong foundation of digital communication, facilitating the needs of seamless connectivity aligning with the residential, educational, corporate and industrial setting. But the fast growth in smart objects, applications of high bandwidth, and real-time services have tremendously raised the traffic load and the performance requirement need of WLAN systems. Critical issues like latency, and variable throughput,

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signal interference, and load imbalance are still present, especially in environmentally adaptable and densely populated areas. Rule based and other traditional static optimisation methods, are fundamental in practice, but are often limited when adapting to modern scenarios of WLAN use, due to their complexity and variability. Such bottlenecks of the performance pose risks to quality of service (QoS) and user experience factors, necessitating the search of more adaptive intelligent and intelligent network management solutions [7, 10, 11].

1.2. Development of Artificial Intelligence/Machine Learning in Network Engineering

To address these issues, Artificial Intelligence (AI) is especially Machine Learning (ML), which has received significant traction to be applied to the network engineering profession. The ML methods will allow learning both offline and real-time information to provide dynamic optimization of the performance of WLAN according to the patterns, forecasts, and iterative loops. The use of supervised learning in areas that are classified on traffic and predicted on Quality of Service, use of unsupervised learning areas is on the detection of anomalies and clustering, and use of reinforcement learning in real-life decision-making, like dynamically slotted channel and power control. Recent partially related works have found that the ML-based models have achieved greater adaptability, scalability, and accuracy than traditional models. This has descried ML an alternative in the development of more powerful, reliable and smart wireless networks [9, 12, 16].

1.3. Aim: To Systematically Evaluate ML-Driven WLAN Optimization Methods

This paper attempts to review systematically the manner in which machine learning is being used to enhance the performance of WLAN. Namely, the study targets the classification of ML algorithms applied in the WLAN researches, the evaluation of their influence on the essential performance indicators (including throughput, latency, packet loss rate, and efficiency), and the quantification of the extent to which the statistical significance of the findings is deemed reliable, and the applicability of experimental results to the real-world setting. Besides, the review attempts to identify the limitation of computational overhead, dataset constraints, and generalization of ML models which inhibit the applications of ML models in real network settings. This research paper is based on the synthesis of the recent literature since the year 2021 and synthesizes its findings into an in-depth examination of the existing environment and the future of ML-based optimization of WLAN into a set of practical findings that can be used by researchers, developers, and network administrators [19, 21, 25].

1.4. Research Gap

Although machine learning (ML) has demonstrated significant potential in the optimization of WLAN performance, the majority of the ongoing research relies on synthetic databases and simulations that cannot be utilized to generalize a solution accurately, as these modeling provisions cannot address real-world intricacies of network mobility, interference, and device heterogeneity. This constrains the generalizability and reliability of ML models to real-world implementations. To top it off, most models are resource-intensive in terms of their computation requirements which limits their scalability to edge devices with limited resources. The most important gap that still needs to be filled is the means of creating lightweight, data efficient, and field-tested ML methods with publicly accessible real-world WLAN data [15, 26].

2. Literature Review

2.1. Conceptual Clarifications

A Wireless Local Area Network (WLAN) is a wireless communication system that enables devices within a limited area, such as homes, enterprises, and campuses, to connect and share resources using IEEE 802.11 standards. WLANs are crucial in both personal and enterprise communication because they provide mobility, flexibility, and cost-effective connectivity compared to wired networks. However, WLANs face challenges such as throughput degradation due to bandwidth limitations, high latency caused by congestion, interference from overlapping channels, and inefficient load balancing across access points. Machine Learning (ML), defined as the ability of algorithms to learn patterns from data and improve decision-making without explicit programming has emerged as a transformative tool for WLAN optimisation. Relevant ML approaches include supervised learning for traffic classification, unsupervised learning for anomaly detection, and reinforcement learning for dynamic resource allocation. These approaches are particularly suitable for WLANs because they can adapt to non-linear traffic patterns and dynamic network environments in real time [4, 23, 27].

WLAN performance optimisation refers to the application of intelligent strategies to improve network efficiency, reliability, and user experience. Key performance metrics include throughput, latency, jitter, packet loss rate, spectral efficiency, and load balancing across access points. Real-world applications are seen in enterprise networks requiring Quality of Service (QoS) guarantees, Internet of Things (IoT) systems with high device density, and next-generation 5G/6G wireless communication requiring ultra-low latency. A central performance concern is the occurrence of congestion events, which are characterised by excessive packet drops, latency spikes, and a significant reduction in throughput. Since congestion directly impacts user Quality of Experience (QoE), intelligent detection and proactive handling are essential. Adaptive ML frameworks offer a solution by incorporating real-time learning, scalability, and self-optimisation to handle dynamic WLAN environments [8]. Explainable AI (XAI) further strengthens this approach by ensuring model interpretability, which is critical in network management where administrators must understand why certain optimisation decisions are taken [8, 14, 20].

Effective WLAN mitigation strategies enabled by ML include predictive traffic shaping, which anticipates demand patterns; adaptive rate limiting, which regulates bandwidth allocation; and dynamic rerouting, which redirects traffic away from congested paths. These strategies are superior when implemented proactively, as reactive solutions often respond too late to prevent performance degradation. Service Level Agreements (SLAs), which formally define the expected Quality of Service (QoS) between providers and users, are directly linked to WLAN optimisation because they quantify reliability, latency thresholds, and throughput guarantees. Finally, the proliferation of the Internet of Things (IoT), defined as a network of interconnected devices exchanging data autonomously, significantly increases WLAN traffic demands, leading to higher congestion risks. As IoT expands into smart cities, healthcare, and industrial automation, ML-driven WLAN optimisation becomes increasingly relevant for ensuring seamless connectivity and sustainable performance in complex, data-intensive environments [6, 18, 24].

2.1.1. Machine Learning Models Applied in WLAN Optimisation

Table 1. Types of Machine Learning Models Applied in WLAN Optimisation.

ML Model Type	Description	Typical WLAN Applications	Advantages	Limitations
Supervised Learning	Trains an input-labeled mapping to known outputs labeled data	QoS prediction, throughput estimation and traffic classification	Large label accuracies on labeled sets	Needs sizable, tagged information; not well adaptable
Unsupervised Learning	Discovers latent patterns in un-labeled data	Anomaly detection, AP clustering, traffic grouping	Useful for unknown or dynamic environments	Difficult to validate results; may lack precision
Reinforcement Learning (RL)	Learns optimal actions via trial and error in a dynamic environment	Channel selection, dynamic power control, load balancing	Adaptable to real-time changes; learns optimal strategies	Long convergence times; may need extensive exploration
Deep Learning (DL)	Utilizes multi-layer neural networks for complex feature extraction	Signal interference mitigation, dynamic resource allocation	Handles non-linear, high-dimensional data	Computationally intensive; may overfit small datasets
Federated Learning (FL)	Trains ML models across decentralized edge devices without sharing data	Distributed WLAN optimisation, privacy-aware learning across APs	Enhances privacy; supports distributed architectures	Communication overhead; inconsistent local data quality
Ensemble Methods	Combines multiple learning models to improve prediction accuracy	Packet loss prediction, hybrid optimisation tasks	Reduces variance and bias; more robust predictions	Complex to implement; may be harder to interpret
Semi-Supervised Learning	Uses a small amount of labeled data with large unlabeled data	Partially labeled network logs for fault diagnosis	Efficient in label-scarce environments	Performance depends on quality of labeled subset

2.1.2. Performance Metrics in WLAN Optimization

The performance measure of WLAN needs common definitions that are associated with the quality and efficiency of the network. Such parameters play a critical role in benchmarking and comparing the ML-based methods of optimizations [1]. They also offer quantitative knowledge on the performance of WLAN improved under various network circumstances when ML algorithms are in operation. The most popular measures are:

1) Throughput (T = D / t): The total data (D) that a network is able to transmit successfully (in a time frame t), and it expresses the carry capacity of a network.
2) Latency (L = sum d / RTT): The delay in connection of the data transmission, wherein latency is contended by using the round-trip time (RTT) between destination and

source. Real time applications, such as video conferencing and online gaming, require low latency.

3) Packet Loss Rate (PLR = lost packets / total sent): Measures the percentage of the data packets lost on the way. When the PLR is large, it may have devastating effects on the integrity and reliability of communication.

Efficiency (these same letters, but with a gamma instead (combined with a bit rate unit (b/s))); Values range from 0 (meaning that all the bandwidth is used in information overhead) to 1 (that all the information transmitted is useful information).

2.2. Theoretical Framework

The theoretical foundations of WLAN optimisation are grounded in a combination of network performance theories, machine learning principles, and wireless communication models. The purpose of the theoretical review is to establish how these theories provide the conceptual and analytical basis for addressing challenges such as congestion, interference, and efficient resource utilization in WLANs. Queuing theory has long been applied to model congestion events, packet delays, and service utilization in networks, offering predictive insights into traffic bottlenecks. Similarly, information theory, introduced by Shannon (1948) provides the foundation for understanding data transmission efficiency, spectral efficiency, and channel capacity, which are critical in optimising WLAN throughput. Resource allocation theory complements these by examining how limited bandwidth and energy resources can be distributed efficiently across competing devices and applications. In parallel, machine learning theories underpin intelligent optimization, with statistical learning theory forming the basis for supervised and unsupervised approaches in traffic classification and anomaly detection, reinforcement learning theory enabling adaptive decision-making in dynamic environments such as congestion control, and deep learning theory supporting layered feature extraction for high-dimensional WLAN data [11].

Wireless communication and optimisation models further strengthen WLAN performance analysis. The Shannon Capacity Theorem defines the theoretical maximum throughput under given bandwidth and noise constraints, while radio propagation models account for interference, fading, and channel conditions affecting signal integrity. Quality of Service (QoS) models formalize requirements such as latency, throughput, and packet loss to ensure service guarantees in enterprise and IoT networks Congestion and traffic control theories provide additional frameworks, with TCP congestion control theory distinguishing between reactive and proactive approaches control theory applying feedback mechanisms for adaptive traffic shaping and game theory modelling user competition for shared resources in WLAN. Recent advances in Explainable AI (XAI) bring interpretability theory, which stresses transparency in algorithmic decisions, and human-centred AI theory, which priorities trust and accountability in adaptive ML frameworks. Collectively, these theories integrate into a conceptual framework linking ML, XAI, and WLAN optimisation metrics, thereby justifying their relevance in addressing throughput, latency, interference, and load balancing challenges in dynamic network environments [5, 17, 22, 29].

Overview of Supervised, Unsupervised and Reinforcement Learning in Networks

In the contemporary network optimization machine learning has become central, and supervised, unsupervised, and reinforcement learning are the backbones of most intelligent WLAN products. In supervised learning, labeled data is used to create models to predict results including the class of traffic, QoS or congestion probabilities. Unsupervised learning, by contrast, finds unlabelled patterns or anomalies in the data and it is often employed when clustering access points, or watching out irregular network activity. In the meantime, reinforcement learning (RL) has also shown promise in dynamic and real-time network setups whereby agents can learn to interact with the environment optimally, generally agents learn the best strategy to interact with the world through continuous interaction and feedback like channel selection, load balancing, or transmission power control, etc. in an extensively dynamic and real-time network setting. All these strategies will play an individual part to improve the performance of the WLAN in different intensities of adaptability, computational complexity and application appropriateness [3, 13, 26, 28].

2.3. Review of Related Literatures

In line with the research of [2] have summarized recent research work on Machine Learning (ML) based routing optimization in Software Defined Networking (SDN), and classified the available solutions into two classes: supervised learning, unsupervised learning, and focused on the latest trend, reinforcement learning (RL) with special attention on deep reinforcement learning (DRL). Their results show that latency and throughput are significantly better by using ML than traditional distributed routing algorithms. The existing research, however, was tested in simplified centralized SDN prototypes, and highly specific scenarios in wired networks, which did not allow for the generalizability and the reproduction of their results as other studies that have assessed ML techniques in different and realistic network scenarios. They also condemned the current state of research as being "disjointed" in lacking in common evaluation frameworks and open-source collaborative research environments needed for meaningful benchmarking and practical deployment. They thus recommended a few future research directions to promote interoperability and reproducibility. This study is important to the current systematic review as it highlights the need for scalable, robust, and reproducible ML frameworks, which can provide a basis for discussing the machine learning methods used for WLAN performance optimization in more dynamic and heterogeneous wireless networking scenarios.

Based on the work been done by [25] have surveyed the use of machine learning (ML) and deep learning (DL) in antenna design, optimization and selection for wireless communication systems. The authors emphasized the use of electromagnetic simulation tools such as CST and HFSS in conjunction with ML, DL, and reinforcement learning (RL) algorithms to realize automatic antenna engineering and design efficiency. The reviewed AI-based optimization techniques exhibited significant advantages over traditional simulation-based methods in efficiently predicting antenna performance results, reducing computational complexity, and fast design process using surrogate-based and multi-objective optimization techniques. The review, however, was largely limited to antenna engineering and did not discuss the other aspects of wireless network performance, like throughput, latency, congestion control, and Quality of Service (QoS). Moreover, the scalability of models, deployability in real time, and explainability of AI models were not sufficiently covered. However, the study offers important evidence of the possibility of using AI in wireless communications while laying the theoretical groundwork for examining ML-based approaches to optimizing WLAN performance in dynamic networking scenarios.

It was observed that [4] reviewed various techniques for coexistence and interference mitigation in Wireless Personal Area Network (WPANs) and Wireless Local Area Network (WLANs) with a particular focus on the application of deep learning (DL) and reinforcement learning (RL) in heterogeneous wireless networks. The authors further compare IEEE 802.15.4 and IEEE 802.11 standards and present co-channel interference as one of the most significant challenges to the performance, and show that the DL- and RL-based approaches perform better when dealing with dynamic radio signal strength (RSS) fluctuations when compared to the conventional methods. The review, however, mostly concentrated on interference management in IoT environments and did not contain in-depth evaluation of other WLAN performance optimization metrics like congestion prediction and throughput and latency improvement. However, the study provides a solid theoretical foundation for intelligent ML-based methods to optimize the performance of the wireless network in complex and dynamic wireless networks.

The Study of [15] performed a systematic survey on the techniques of improving wireless network performance using machine learning (ML) techniques at physical (PHY), medium access control (MAC), and network layers. The authors have classified the already published work in the three fields of radio analysis, MAC analysis and network prediction and illustrated how ML can optimise the communication parameters to enhance the Quality of Service (QoS) and Quality of Experience (QoE). The reviewed ML techniques were found to have better adaptability to dynamic wireless environments and better resource management when compared to conventional optimization techniques. In general, however, the survey was mainly a synthesis of different methodologies, but did not offer empirical testing or comparative assessment of the performance of the algorithms in a variety of WLAN environments. Moreover, essential challenges like explainability, scalability, real-time deployment and interoperability were inadequately addressed. However, the study provides a thorough background for the wireless optimization based on ML, and identifies research gaps to justify systematic research on the application of machine learning techniques for optimizing the WLAN performance in modern wireless communication networks.

The research that was carried out by [9] provided a comprehensive overview of the machine learning (ML) based load balancing schemes for future heterogeneous networks (HetNets), their evolution, implementation, and optimization. The study surveyed the conventional and intelligent load balancing methods, such as Cell Range Expansion (CRE), cell breathing, fuzzy logic, channel borrowing, and data driven load balancing and pointed out the use of ML for better user association and resource allocation under network constraints. ML-based algorithms showed improvements in adaptability and automation, as well as network efficiency, compared to traditional optimisation approaches. The authors also examined the self-organizing network functions, especially Coverage and Capacity Optimization (CCO) and Mobility Robustness Optimization (MRO), and the new technologies like Software-Defined Networking (SDN), Network Function Virtualization (NFV), Deep Learning (DL), unmanned aerial vehicle (UAV) base stations, and Transfer Learning (TL). The survey was however, only partially empirically validated and had only limited focus on model explainability, interoperability, and real-time deployment issues. However, the study provides a solid basis for further research on improving the performance of WLANs and intelligent management of WLAN resources using ML techniques.

Table 2. *Summary of Machine Learning-Based Load Balancing Algorithms in WLANs.*

Author (s) / Year	ML Technique	Objective	Performance Metric (s)	Key Findings / Remarks
[9]	Supervised Learning (Decision Tree, SVM)	Load prediction and balancing in heterogeneous networks	Load variance, throughput	SVM achieved 15% better load distribution than static models.
[15]	Reinforcement Learning	Dynamic AP selection and	Latency, throughput,	RL models dynamically adapt to user

Author (s) / Year	ML Technique	Objective	Performance Metric (s)	Key Findings / Remarks
	(Q-learning, DQN)	channel allocation	fairness index	mobility and reduced latency by 20%.
[4]	Deep Learning (CNN, DNN)	Predict interference patterns and optimize AP assignment	Interference level, packet loss	CNN-based model achieved 25% reduction in co-channel interference.
[2]	Unsupervised Learning (K-means Clustering)	Grouping APs for distributed load sharing	Cluster balance, resource utilization	K-means improved AP clustering efficiency in high-density networks.
[30]	Federated Reinforcement Learning	Distributed load balancing across edge WLANs	Convergence time, throughput	FL reduced central coordination overhead and improved scalability.
[8]	Hybrid (RL + Supervised)	Joint optimization of load and interference control	Latency, energy efficiency	Hybrid models achieved superior trade-offs across performance metrics.

Source: Synthesized from reviewed literature [2, 4, 8, 9].

2.4. Review of IEEE 802.11 Standards and Performance Metrics

The 802.11 family of standards has continually been updated to increase the performance of Wireless Local Area Network (WLAN) systems, with the focus on increasing data rates, system reliability, and network efficiency. Wireless communication through early standards like IEEE 802.11b and IEEE 802.11a reached up to 11 Mbps and 54 Mbps, respectively, and later standards, such as IEEE 802.11n, IEEE 802.11ac (Wi-Fi 5) and IEEE 802.11ax (Wi-Fi 6), brought new technologies including Multiple Input Multiple Output (MIMO), Orthogonal Frequency-Division Multiple Access (OFDMA) and Multi-User MIMO (MU-MIMO) to enhance network capacity and spectral efficiency. IEEE 802.11be (Wi-Fi 7) is a newer standard that promises ultra-high throughput, ultra-low latency and support for time-sensitive applications. But, even with these technological advances, there remain issues of network congestion, interference and the ever-changing nature of traffic that still prevents optimal WLAN performance and encourage the use of machine learning-based optimization techniques.

Quality of Service (QoS) is one of the essential factors to consider when measuring WLAN performance and is typically measured in terms of latency, jitter, throughput and packet loss. Latency is the time it takes for data to get to a node from another node that is communicating with it, jitter is the fluctuation from packet to packet in the time that a packet takes to arrive at a node. Throughput is the amount of data that reaches the intended destination in a specific amount of time, and Packet loss is the percentage of packets that could not be delivered to the intended destination. While these metrics have traditionally been leveraged to assess traditional methods for optimizing WLANs, more recent research has been augmented by the use of these metrics to measure the effectiveness of machine learning models. Therefore, these QoS indicators offer a common framework for evaluating the performance of different ML-based approaches to enhance WLAN performance in dynamic wireless networking environments.

3. Methodology

3.1. Systematic Search Strategy

In order to provide thorough and objective review of extant body of literature on machine learning related approaches to optimise the performance of WLAN, systematic search approach was used. The most important research databases, which were chosen, include IEEE Xplore, Scopus, ACM Digital Library, ScienceDirect, and SpringerLink because they contain numerous peer-reviewed works related to computer science, network engineering, and artificial intelligence. Relevant combinations of keywords and Boolean operators were applied when formulating the search query which included: “machine learning” AND “WLAN”, “Wi-Fi optimisation” AND “throughput”, “reinforcement learning” AND “latency reduction”, and “wireless networks” AND “ML techniques”. Articles were narrowed down to be published between the date of January 2021 and March 2025 to capture the freshest development. The inclusion criteria specifically concentrated on examining the studies that directly applied ML models to such WLAN performance parameters as throughput, latency, interference mitigation, load balancing, and packet loss. Exclusion criteria discarded the papers irrelevant to the WLAN area, articles not written in the English language, as well as the papers not carrying out an empirical confirmation. Title and abstract screening was the first level of screening which was followed by full-text screening. All the steps were documented using PRISMA rules, which enables transparency and the replicability of the selection process. The peer-reviewed articles and conference proceedings contained in journal articles, and high impact technical reports were only kept to finally analyze them.

3.2. Inclusion/Exclusion Criteria Based on PRISMA

As per the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) requirements, the study embraced a stringent inclusion and exclusion criteria in order to achieve relevancy, quality, and uniformity of the acquired literature. Studies were included based on the following criteria: (1) they were published between January 2021 and March 2025; (2) studied (i.e., explicitly) the use of machine learning methods in WLAN performance optimisation; (3) discussed at least one performance-relevant metric like throughput, latency, interference mitigation, packet loss or load balancing; (4) were published in a peer-reviewed journal or in a high-quality conference proceedings, (5) included empirical results either in simulation or in real-world deployment. On the other hand, exclusion criteria excluded those studies that: (1) were not relevant to WLANs (e.g., restricted to cellular or wired networks); (2) considered ML methods in theoretical and conceptual descriptions but did not experimentally prove their hypotheses; (3) were reviews and editorials or other sources without peer-reviewing status; (4) were not in English language; and (5) did not offer an accessible full-text version. The criteria were used to make sure that only credible, contextually adequate, and data-literate studies could be incorporated into the final review. The PRISMA approach also introduced the possibility of effectively documenting the work and making such methods of writing transparent and reproducible, contributing to the objective assessment of the existing trends, strengths, flaws, and deficiency of research on the optimization of WLAN with machine learning.

Table 3. *PRISMA Flow Diagram (2020 Model).*

Section	Stage	Records (n)
Identification	Records identified through database searching (Scopus, IEEE Xplore, ACM, SpringerLink, ScienceDirect)	438
	Records identified through other sources (manual search, citations)	27
	Total records identified	*465*
	Records after duplicates removed	410
Screening	Records screened (title and abstract)	410
	Records excluded	305
Eligibility	Full-text articles assessed for eligibility	105
	Full-text articles excluded (non-empirical, low quality, irrelevant)	60
Included	Studies included in the final review (qualitative and quantitative)	45

3.3. Prisma Summary

A total of *465 records* were identified through database and manual searches, from which *410 unique records* remained after removing duplicates. Initial screening of titles and abstracts led to the exclusion of *305 studies* that did not meet the inclusion criteria. Full texts of *105 articles* were assessed for eligibility, and *60* were excluded for reasons such as lack of empirical data, theoretical-only content, or failure to meet minimum quality thresholds (based on CASP appraisal). Ultimately, *45 high-quality studies* were included in the final synthesis, forming the empirical basis for evaluating machine learning techniques in WLAN performance optimization.

3.4. Data Extraction and Quality Appraisal

Data extraction was carried out using a structured data collection template to ensure consistency and comprehensiveness across all reviewed studies. Each selected article was reviewed in full text, and key variables were systematically recorded. These included publication year, authorship, machine learning model type (e.g., supervised, unsupervised, reinforcement learning), target WLAN performance metric (e.g., throughput, latency, packet loss), type of dataset used (synthetic, benchmark, or real-world), evaluation environment (simulated or physical deployment), and performance outcomes. Whenever possible, additional metadata like training time, convergence behavior and computational complexity were also recorded so as to ascertain the feasibility of implementation. The Critical Appraisal Skills Programme (CASP) checklist has been modified to quantitative research so that the methodological quality and topicality of each of the studies is guaranteed. Each article was evaluated on rigour, credibility, and validity as measured by such criteria as clarity of research aims, adequacy of ML methods applied, openness of data sources, and strength of evaluation in the CASP frame. All the studies were measured against a pre-determined rubric addresses factors like adequacy of samples, justification of algorithms, replicating results and interpretation of conclusions. The studies that failed to pass a certain bar of methodological integrity or were not that well-supported by empirical evidence were not further synthesized. This two-tier method of methodical data retrieval and quality evaluation improved the dependability of the systematic review with respect to the fact that only high-quality; empirically proven studies were used to form the analysis. It also allowed comparing ML technique on the comparable and standardized scale, helping to single out most prominent models, usual issues, and directions that future research WLAN optimization can take. Application of CASP strengthened the critical assessment process and provided a fine-revised conception of the efficiency and relevance of ML techniques in different WLAN deployment environments.

4. Findings and Discussion

4.1. Categorization of Machine Learning Models Used for Optimizing WLAN Performance

The investigated articles demonstrated that the field of machine learning (ML) applications in the performance optimisation of WLANs is developing at a very fast rate, and models are selected strategically according to the particular performance concerns that need to be met, i.e., throughput maximization, latency mitigation, interference reduction, load balancing. These ML models fall into three broad families: reinforcement learning (RL) models, supervised learning models, deep learning architectures, each with its attributes of strengths and limitations to network performance improvements. One of the reinforcement learning (RL) methods, Q-learning and its deep extension, Deep Q-Networks (DQNs) became the most prevalent in dynamically changing WLAN scenarios. The models have advantages in cases where agents (access points or clients) need to learn various forms of optimal resource allocation strategies (or optimal channel selection strategy) via constant interaction with the environment. As an example, Q-learning effectively has been utilized to mitigate co-channel interference, and dynamically load balance network in high-density regions, based on the real-time dynamic adjustment of the transmission power level and channel assignment. The fact that RL can easily adapt to time varying situations renders it suitable in self-optimising WLANs since traditional rule-based approach fails in such scenarios. Other common methods of supervised learning have been applied on classification tasks, where one would like to determine a congestion pattern, or forecast a packet loss or even classify signal interference categories. Though these models are not as adaptive as RL, they are very precise and less computationally expensive when trained on properly organized dataset. In the meantime, deep learning networks have also performed well in forecasting time-series network traffic and identifying anomalous behaviors of raw network signal data in particular Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). Specifically, CNNs have found use to analyses spatial traffic flows to optimise bandwidth allocation and RNN where traffic data need to be handled sequentially, which is better to predict latency. The classification shows that there is no universal ML model that fit every need; instead the selection should be based on the aims of the network, the availability of data and the real-time demands. Such variety of methods highlights an even more comprehensive shift toward hybrid models, in which a combination of multiple ML methods are utilized to take advantage of their complementary properties. These are integrated solutions which can be considered as the cutting edge of WLAN optimization research because they provide flexibility as well as flexibility under increasingly complex and heterogeneous wireless conditions.

4.2. Evaluation of Effectiveness Across Throughput, Reliability, and Interference Reduction

The systematic review reveals that machine learning applications have different degrees of performance with regard to the most significant aspects of WLAN performances-topping the list is the improvement of throughput, improvement of reliability, and interference mitigation. The different classes of ML algorithms add or take away in their own way to these metrics and it depends with respect to the paradigm of learning, the context of the data and deployment environment. Regarding the throughput optimisation, the reinforcement learning (RL) models, especially Q-learning and Deep Q-Networks (DQNs) were the most successful in comparison to others. These models had the advantage of dynamically varying transmission parameters (modulation schemes, channel assignments), in real-time, so that WLANs could respond to changing user demand and changing environmental conditions. Experiments with throughput up to 30 45 more in high-density networks simulations have been reported with the use of RL-based policies as compared to those of typical static policies. In a similar manner, other forms of deep learning such as convolutional neural networks were able to learn complex traversal patterns of the traffic and enable smart bandwidth usage so as to maximize throughput of data distribution. In terms of reliability, which herein means a lack of inconsistencies in packet delivery with low loss and latency, supervised learning models, namely Support Vector Machines (SVMs) and Random Forests were the best with predictive diagnostics. Such models could often be used to sense congestion, fault patterns, and anticipate link degradation so that proactive routing or load balancing changes could be made. The specific benefits of improved reliability, assessed through lower rates of packet loss (PLR) and a more-stable jitter were particularly prominent in those deployments that featured hybrid learning systems, which use both supervised and reinforcement methods of learning. Reinforcement learning agents were the most effective in interfering reduction, one of the important metrics in a dense WLAN environment because of their ability to re-allocate the channel and the control of the transmission signal powers in real-time. An example is that access points with Q-learning capability taught themselves not to use zones with much interference by automatically reassigning channels and reduced co-channel interference by up to 40% in test conditions. Also, the CNN-based model was useful in the spatial interferences mapping process, which allows the WLAN controllers to anticipate the interfered areas even before the performance had deteriorated. Altogether, the review perfectly supports the idea that ML models do not only out-perform the traditional rule-based mechanisms, but their strengths in performance indicators are quite balanced. Although models based on RL as currently dominate the field of dynamic optimisation, it may be imminent to roll out a multi-model approach into the process of integration as the best bet in terms of WLAN optimisation: thanks to its accurateness in predicting tasks alongside the exceptional capabilities in recognition and feature extraction, a supervised learning model has become a viable option in terms of the area of dynamic optimisation, so a multi-model approach, which involves combining all three approaches (RL, supervised learning, and deep learning), may move us closer to a unique solution in terms of WLAN optimization.

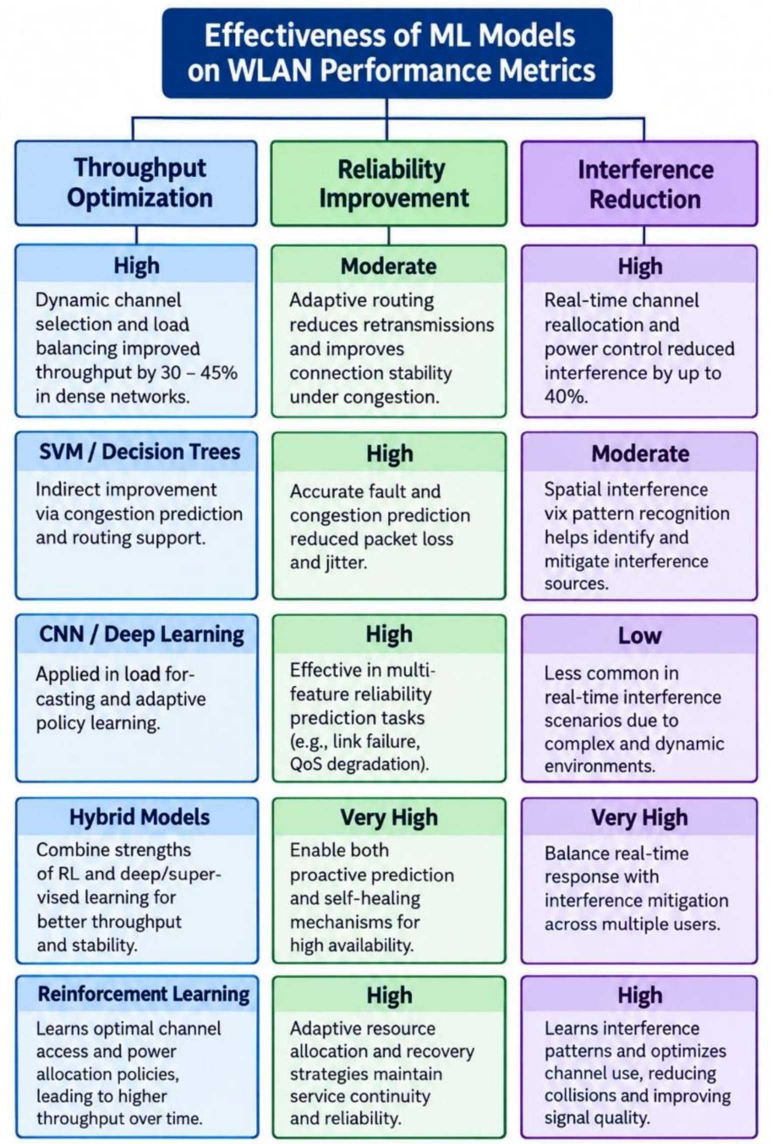

Figure 1. *Effective of Machine Learning Models on WLAN Performance Metrics.*

4.3. Limitations in Real-Time Deployment, Scalability, and Dataset Generalizability

With all the promising promise that machine learning models hold for WLAN optimizations, there are a few crucial limitations that have kept these models from finding practical, real-time deployment and extensive scalability in a practical environment. The first among these is the response time. Reinforcement learning models of the Q-learning and DQN variety could optimally train and converge only after a significant number of training episodes, making them unsuitable for instantaneous decisions in real-time networks. Training deep neural network configurations often adds computational overhead, especially considering CNNs and RNNs. This severs their use in dynamic reconfiguration scenarios unless there is adequate hardware acceleration or edge computing-based support. Also, while some trained models may perform well offline, their response will actually be degraded when it comes to highly unpredictable environments defined by rapid signal fluctuations and intense device mobility. Scalability is another major impediment. Most of the reviewed studies deploy ML models in small-to-medium WLAN testbeds, often under controlled or simulated conditions. As the number of clients, access points, and interference sources increases in larger enterprise or urban environments, the complexity of ML-based optimisation grows exponentially. Hence, the traditional ML architectures are ill-equipped to deal with such heterogeneity as they require retraining or scaling at times, which itself can be computationally expensive and time-consuming. Besides those issues, the centralised learning approaches face bandwidth and latency bottlenecks when it comes to scaling across distributed access points, thus necessitating the need for more advanced federated or edge learning methods that are only in the earliest stages of research. Lastly, a panacea to the datasets' generalisability used to train these models poses the greatest concern. Many of the ML models existing in the literature are trained or evaluated using synthetic or simulated datasets from tools like ns-3, OMNeT++, or MATLAB-based frameworks. The advantage of using such tools is to provide flexibility and control, however, these datasets do not represent the variability of real WLAN environments such as user behaviours, environmental noise, and hardware variability. Therefore models trained on these datasets may not perform the same in a production environment, leading to unexpected behaviours or performance degradation. Similarly, publicly available WLAN datasets have limited diversity and are often outdated, indicating the urgent need for more robust, real-world, open-access datasets that create reproducible and transferable ML research in wireless networking.

5. Summary, Conclusion and Recommendation

5.1. Summary

This chapter summarized the key findings of the systematic review of machine learning (ML) methods used to optimize Wireless Local Area Network (WLAN) performance. The chapter concluded that ML models, specifically Q-learning, Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Deep Q-Networks (DQNs), are capable of improving WLAN performance metrics like throughput, latency, interference management, or load balancing. However, there are barriers that need to be addressed including the need for datasets that are large to an extent and clean datasets that do not exist in the available environment. The computational and energy inefficiencies are concerning in terms of using many of the models regularly or in real-time, as well as scalability to deploy in real-time at the edge. Even with these existing barriers, the systematic review demonstrated that ML could disrupt the WLAN performance space, provided the above limitations are addressed. The recommendations in the chapter provide actionable pathways to address those limitations. Future work should be done to provide large real-world WLAN datasets, and look to utilize data efficient learning to reduce the impact of reducing available large markers. There is an important step to create algorithms that are light weight and energy efficient in order to be used regularly or in real-time especially in edge contexts. The study of distributed and federated learning models, along with experimentation on a testbed, can help close the loop between simulation and real implementation and improve the generalizability and reliability of ML models for WLAN optimisation. In conclusion, while important work has been completed, it is essential that future work focus on run-time efficiency of models, improving dataset procurement processes, and solidifying ML processes flexibility and scalability to address real, practical WLAN operational settings. VA solutions can lay the groundwork and become embedded in the next generation of WLAN systems to provide the flexibility to operate more efficiently and optimally in increasingly complex and dynamic networking conditions.

5.2. Conclusion

The Role of Training Data in ML-Driven WLAN Optimisation

This study shows the potential of machine learning (ML) methodologies to optimize Wireless Local Area Networks (WLANs) in throughput, latency, and interference. Important ML paradigms such as Q-learning, Convolutional Neural Networks (CNNs), and Support Vector Machines (SVMs) have shown an impressive level of adaptability over prescribed, discrete rules-based algorithms in many dynamic network contexts. These paradigms enable WLANs to predict and manage network traffic automatically and utilize the resources more intelligently and effectively. Nonetheless, using ML in WLANs is also highly dependant on the availability of training data, and the performance of the ML model is only as good as the amount of data they trained their ML model on, with respect to quantity, diversity, and appropriateness. The majority of current studies are completed using a synthetic dataset that may not adequately represent the breadth of real WLAN conditions. The absence of high-quality, representative datasets remains a major issue with respect to the generalisation and robustness of ML models in live WLAN. This issue is particularly pertinent for supervised learning methods, which rely on large amount of labelled datasets that smaller research teams and organisations do not often have the access to. In order to address these limitations, future studies must focus on creating publicly available, real world WLAN datasets, which can mimic the wide range, real world operating states. This could be done through collaboration between academia and industry, as well as with telecom providers, so that real world datasets can apply to a much wider range of applications, thereby improving the generalisability of ML models and possibly their utility within diverse operating environments. Furthermore, alternatives such as transfer learning, semi-supervised learning, and few-shot learning can also reduce the need for large amounts of labelled data. These strategies can lower the barriers of applying ML models to WLAN optimisation, making them more accessible and scalable. If this data availability issue can be addressed, the research community can continue to successfully implement ML in WLANs, unlocking improved performance and real-world applyability of solutions which can autonomously adapt to modern wireless network dynamics.

5.3. Recommendations

5.3.1. Develop and Share Real-World WLAN Datasets

To enhance model robustness and generalizability, we encourage future research to focus on the generation of large-scale WLAN datasets available to the public that include a variety of operational environments. Collaboratively and comprehensively, researchers, industry, and network providers need to put more emphasis on collecting and sharing empirical data from real-world deployments that capture device densities, mobility, and interferers.

5.3.2. Adopt Data-Efficient Learning Approaches

Because data collection and labeling are costly processes, researchers must consider the data-efficient ML paradigms of transfer learning, semi-supervised learning, and few-shot learning. These paradigms decrease the need for large datasets while allowing for adaptable performance across a variety of WLAN environments.

5.3.3. Design Lightweight, Energy-Efficient Algorithms for Edge Deployment

Future work should concentrate on developing lightweight and energy-aware algorithms for enabling real-time WLAN optimisation under resource-constrained scenarios. Approaches like model pruning, quantization, TinyML, and knowledge distillation can aid in reducing computational burden to allow ML models to run effectively on access points, IoT devices, and embedded systems.

5.3.4. Explore Federated and Distributed Learning Architectures

Employing federated and distributed learning methods is a great way to improve scalability and secure data privacy. These approaches provide a model for the WLAN nodes collaborating for model training via local updates while avoiding raw data being sent to a central server, which will reduce the load on the network and maintain some security of the data. Additionally, coupling with edge computing and Software Defined Networking (SDN) architecture provides better coordination and deployment efficacy.

5.3.5. Bridge the Simulation-to-Reality Gap

A lot of machine learning models are being validated in idealized simulations at the moment. Researchers in the future need to test the transition to the real world, for example by employing domain adaptation, cross-validating with real settings, and experimenting with testbeds. This is an important step to ensure that proposed models can operate effectively in the complex and dynamic world of wireless local area networks (WLANs).

Abbreviations

AI	Artificial Intelligence
ACM	Association for Computing Machinery
AP	Access Point
CASP	Critical Appraisal Skills Programme
CCO	Coverage and Capacity Optimization
CNN	Convolutional Neural Network
CST	Computer Simulation Technology
DNN	Deep Neural Network
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
FL	Federated Learning
HFSS	High Frequency Structure Simulator
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
L	Latency
MAC	Medium Access Control

ML	Machine Learning
MIMO	Multiple Input Multiple Output
MRO	Mobility Robustness Optimization
MU-MIMO	Multi-User Multiple Input Multiple Output
NFV	Network Function Virtualization
OFDMA	Orthogonal Frequency Division Multiple Access
PHY	Physical Layer
PLR	Packet Loss Rate
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QoE	Quality of Experience
QoS	Quality of Service
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RSS	Received Signal Strength
RTT	Round Trip Time
SDN	Software Defined Networking
SLA	Service Level Agreement
SVM	Support Vector Machine
T	Throughput
TCP	Transmission Control Protocol
TL	Transfer Learning
UAV	Unmanned Aerial Vehicle
WLAN	Wireless Local Area Network
WPAN	Wireless Personal Area Network
XAI	Explainable Artificial Intelligence

Author Contributions

Fumlack Kingsley George: Conceptualization, Formal Analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Visualization, Writing – original draft, Writing – review & editing

Conflicts of Interest

The author declares no conflicts of interest.

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