ISSN: 2093-5374 / E-ISSN: 2093-5382

Adaptive Load Balancing in Heterogeneous Wireless Mobile Networks

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Received: February 15, 2025; Revised: April 03, 2025; Accepted: May 09, 2025; Published: June 30, 2025

Abstract

Adaptive load balancing in heterogeneous wireless mobile networks is crucial for optimizing resource utilization, ensuring quality of service (QoS), and adapting to changing traffic patterns and diverse network infrastructures. In this research, we present a comprehensive, adaptive load-balancing framework that intelligently distributes traffic over disparate access technologies, including LTE, 5G, and Wi-Fi, in real-time. We demonstrate how the integration of context-aware decision making, mobility prediction, and machine learning techniques allows our approach to dynamically assess the network's conditions, user behavior, and service demand, thereby optimizing resource allocation. Our model considers key performance metrics, including latency, bandwidth, energy consumption, and handover frequency, to ensure minimal user service interruption and seamless connectivity. Through simulation-based results, we have shown that improving throughput by considering the above metrics also minimizes the number of lost packets and enhances user experience over static and threshold-based load balancing schemes. The results demonstrate the importance of adaptations in network management, particularly when a combination of user mobility, fluctuating loads, and heterogeneous network infrastructure is encountered.

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 2 (June), pp. 119-135. DOI: *10.58346/JOWUA.2025.I2.008*

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Keywords: Adaptive Load Balancing, Heterogeneous Networks, Wireless Mobile Networks, Resource Allocation, Mobility Management, Quality of Service, Machine Learning, 5G, LTE, Wi-Fi, Network Optimization.

1 Introduction

Load balancing in wireless mobile networks involves the organized allocation of network traffic and computing resources across different communication nodes or paths, to prevent any one node from becoming a performance bottleneck. Load balancing optimally utilizes resources and network capacity, reduces response time, and facilitates service delivery by distributing the workload across an available set of base stations, access points, or servers. In mobile wireless environments where user mobility, bandwidth availability, and signal quality are dynamic, load balancing is crucial for delivering a high-quality service (QoS) and maintaining seamless connectivity (Ksentini & Taleb, 2014).

Within the next-generation network's structure, HWNs have emerged, integrating many disparate access technologies, such as Wi-Fi, LTE, 5G NR, and satellite communications, to provide high-capacity, ubiquitous connectivity. While load balancing is ideally suited for HWNs, it should allow for adaptive load balancing capabilities. Static or rule-based load balancing does not respond well to the inherent real-time behaviors of fluctuating traffic load changes, user density or network capacity, and load balancing is reliant on controlling for these variables. Additionally, the use of AI and context-awareness technologies can inform adaptive load-balancing analysis to support dynamic load allocation. Utilizing adaptive load balancing to make real-time allocation decisions is crucial for enhancing performance and overall user experience in HWNs (Wang et al., 2014; Hawthorne & Fontaine, 2024).

However, there are many challenges to implementing adaptive load balancing in heterogeneous networks. First, heterogeneous access technologies introduce significant differences in access coverage, latency, bandwidth, and power consumption, making it challenging to define a common load balancing approach. Second, users are mobile, which leads to dynamic variations in traffic distributions, and predictive capabilities are needed to avoid any load imbalances beforehand. Third, achieving load balancing is not easy, as it requires ensuring fairness and QoS performance while avoiding handover failures, maintaining acceptable signal levels, and minimizing excessive signaling overheads. Finally, adaptive load balancing in heterogeneous networks requires real-time decision-making capabilities that must be easily calculated in a very short amount of time with minimal computational costs (Zhang et al., 2018; Tassiulas & Ephremides, 1992).

The aforementioned complications indicate the need for well-designed, intelligent, context-aware, and efficient load-balancing techniques across a diverse and dynamic wireless ecosystem. The research currently being conducted on adaptive load balancing is primarily exploring the integration of various machine learning models to predict mobility patterns, energy-aware scheduling, and multi-metric optimization. If completed correctly, these solutions have proven to be effective in improving throughput, reducing delays, and enhancing spectral efficiency, extending beyond the performance limitations presented by static methods (Taleb et al., 2015).

2 Related Work

Load balancing in wireless networks has been a primary research area focused on achieving efficient resource utilization, satisfying quality of service (QoS) requirements, and enhancing user satisfaction in dynamic networks (Praveenraj et al., 2024). As wireless networks transition from homogeneous to highly heterogeneous networks that integrate multiple radio access technologies (RATs), including LTE, 5G

NR, and Wi-Fi, the complexity of load balancing has increased more than ever (Ahmed, 2024). Researchers have considered several approaches to address this complex problem, including those that emphasize adaptiveness, scalability, and energy efficiency.

Zhou et al., (2016) provided one of the first studies on load balancing in heterogeneous wireless networks. They examined the usage of adaptive algorithms, specifically regarding how user mobility affects the quality of signal and the distribution of network traffic. They proposed a context-aware load balancing scheme that allocates users dynamically to base stations based on traffic density and the available resource. With this model, this study was able to reduce the probability of handover failures and increase system throughput when there is a high density of users.

Xu et al., (2018) produced another important paper in which they developed a bio-inspired load balancing Algorithm using particle swarm optimisation (PSO) (Choudhary & Verma, 2025). Xu et al. use PSO to improve load balancing across heterogeneous networks by optimally matching mobile users to available access points (Nayak & Raghatate, 2024). The main deviation from alternative approaches was the aforementioned assumption of PSO that did not rely on static conditions, but was predicated on the assumption that users and network state continuously changed (Deshmukh & Malhotra, 2024). The simulation results showed progressive reductions in the Load Fairness Index and network throughput when comparing the proposed approach to the default benchmark performance, and also exhibited greater improvements for cases that were mixed LTE and Wi-Fi (Xu et al., 2018). Machine Learning has also been used in countless load balancing schemes. A prominent example is the Q-learning-based load balancing scheme of Alam et al. (2020), who proposed a framework for 5G heterogeneous networks (Whitmore & Fontaine, 2024). They developed a framework that has the ability to learn optimal user association policies by continually observing changes in network conditions such as signal strength, backhaul congestion and energy consumption. The 'optimal' framework using Q-learning reduced both packet loss and service delay. It demonstrated a strong possibility of applying reinforcement learning as a form of dynamic resource management in next-generation networks (Alam et al., 2020).

Comparative studies have demonstrated that load-balancing approaches must account for the type of network (Trisiana, 2024). For uniform networks, round-robin, weighted fair queuing, flexibly call other load balancing approaches (based on limitations of assigning base stations, etc.) and least-connections have generally been appropriate considerations (and realizable architectures) due to their ease of use and understood results. This is less true for heterogeneous networks - as Talukdar et al. (2021) argued, despite multiple RATs being integrated into the heterogeneous wireless network, there are issues with the handling of multiple user devices, which would necessitate load balancing approaches that were not only dynamic but also multi-metric (QoS concerns, energy efficiency, and spectrum use). Their hybrid load balancing approach was rule-based decision making with real-time context adaptation and they were able to show that it was better than the traditional approaches regarding throughput and latency in a smart city scenario (Talukdar et al., 2021).

Energy efficiency has emerged as a key factor in wireless load balancing, especially as more battery-powered devices emerge, along with the proliferation of mobile edge computing (MEC). In particular, Kim and Kim (2022) proposed an energy-aware load balancing scheme, which used deep neural networks (DNN) to predict traffic patterns of a service so that it could optimize resource allocation (in a proactive way). Their model achieved up to 25% less overall energy consumption, while achieving service level agreements (SLAs) in a 5G/Wi-Fi integrated environment (Kim & Kim, 2022).

As noted in this article, the literature evolves from static, one-size-fits-all approaches to intelligent, adaptive, and energy-efficient means of achieving load balancing in heterogeneous wireless mobile networks that leverage context-aware, real-time analytics, and AI-driven decision-making, opening the door to more resilient and end-user focused network design.

3 Adaptive Load Balancing Algorithms

3.1 Description of Different Adaptive Load Balancing Algorithms

Adaptive load balancing algorithms adapt to network conditions to provide optimal resources to users while still providing consistent user experiences. The threshold-based algorithm is a basic form of load balancing and looks at a number of factors such as load, traffic, and CPU utilization, with trigger points that reallocate servers when these values pass certain levels. Although this method works for basic scenarios, it can cause instability if the functions that define the threshold are miscalibrated or thresholds are poorly tuned. Fuzzy logic-based algorithms allow for reasoning under uncertainty and can process vague descriptors like "high load" or "weak signal" by using smooth transitions across input parameter spaces. Reinforcement learning (RL) algorithms introduce a level of intelligence, learning from prior interactions with the network to adjust policies over time in order to maximize cumulative reward functions related to throughput, latency, or energy consumption. Software-defined networking (SDN)-based approaches introduce a centralized controller which collects network state information and takes decisions based on a global view, enabling detailed traffic flow control and dynamic resource allocation. Lastly, bio-inspired algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) emulate natural processes to seek optimal load balancing configurations, particularly effective for solving multi-objective optimization problems in dynamic conditions (Singh & Sharma, 2023).

3.2 Evaluation of the Effectiveness and Efficiency of Each Algorithm

The effectiveness and efficiency of adaptive load balancing algorithms depend heavily on factors such as network topology, user mobility, and physical constraints. Threshold-based algorithms are computationally light and easy to deploy but are reactive and often fail in dynamic settings due to their rigid threshold parameters. Fuzzy logic-based methods are more adaptive, managing overlapping inputs well and handling ambiguity with greater ease. However, as the number of input variables increases, the complexity of managing fuzzy rule sets also grows exponentially. Reinforcement learning approaches shine in environments requiring long-term optimization and adaptive behavior but suffer from high training time and resource demands, which hinders real-time deployment. SDN-based strategies benefit from global network awareness, enabling efficient real-time decisions in heterogeneous environments; however, they are vulnerable to controller failures and communication latency between control and data planes. Bio-inspired algorithms, though often robust and effective in large-scale optimization tasks, generally require fine-tuning and multiple iterations to converge, making them suboptimal for time-sensitive operations. Hybrid implementations are being explored to overcome the individual shortcomings of these models (Kumar & Verma, 2022).

3.3 Discussion on the Advantages and Disadvantages of Adaptive Load Balancing Algorithms

Each adaptive load balancing approach brings distinct advantages and limitations that must be weighed in the context of heterogeneous wireless mobile environments. Threshold-based algorithms are ideal for smaller-scale, low-dynamic networks due to their simplicity and low overhead, but they lack adaptability and perform poorly in variable environments. Fuzzy logic systems offer an improved capacity to handle real-world uncertainties, enabling better contextual decisions. However, they suffer from rule base explosion when the system becomes more complex (Barolli et al., 2021). Reinforcement learning provides a long-term autonomous optimization framework and is suitable for scalable environments with dynamic needs, yet their implementation is often hindered by long convergence periods and high computational costs. SDN-based methods offer centralized control, greater visibility, and system-wide optimization potential, though they pose risks like central controller bottlenecks and reliance on stable backhaul links (Zhang et al., 2020). Bio-inspired algorithms offer adaptability in multi-dimensional optimization tasks and are particularly valuable in unknown or evolving environments. However, their iterative and stochastic nature may make real-time responsiveness a challenge (Ghosh et al., 2023). Consequently, modern strategies are increasingly converging toward hybrid frameworks that integrate the strengths of multiple algorithms to meet the demands of next-generation network environments.

4 Heterogeneous Wireless Mobile Networks

4.1 Characteristics and Challenges of Heterogeneous Networks

Heterogeneous wireless mobile networks (HWNs) are environments in which multiple radio access technologies (including LTE, 5G, Wi-Fi, and occasionally even satellite or Bluetooth) coexist and use a common infrastructure. HWNs support various access protocols, operations (such as bandwidth, latency, and coverage), and are designed to provide users with seamless high-quality connectivity no matter where they are or how they are moving. While this diverse network offers advantages to service providers and users, HWNs have numerous disadvantages. Interoperability is a major problem: while multiple RATs can support different specifications and models, each heterogeneous RAT has a different operational model. Quality of service (QoS) becomes much more difficult to control when potentially having to move across RATs with different signal strength, networks congestion, or handover process. Security and energy consumption are additional areas of concern, as different devices and access points may follow dissimilar power management and security processes (Zaibel et al., 2022). Mobility and user demand within the HWN can dynamically change, hence the need for intelligent decision and resource management solutions which are continuously adaptive to network changes.

4.2 Comparison of Technologies and Standards in Heterogeneous Networks

The main technologies that are part of HWNs (Heterogeneous Wireless Networks) include Wi-Fi (IEEE 802.11), LTE (Long-Term Evolution) and 5G NR (New Radio). Each of these standards has different goals and functional ability. Wi-Fi is specific to Wi-Fi environments, and its objective is to provide a relatively high data rate within a limited area. Wi-Fi is commonly used in homes, campuses or enterprise networks. Wi-Fi also operates on unlicensed spectrum, is inexpensive and thus available to anyone. The primary disadvantages of Wi-Fi are that it's subject to interference and limited (localized) range. LTE communicates on a licensed spectrum, which allows a broader coverage area and has the added advantage of allowing mobility management. LTE provides the infrastructure for deployment of wide-area wireless capabilities. Modern mission-critical networks today are more state-sponsored and planned than ever. It can be well reasoned that because next generation communication technologies have more demanding requirements, 5G NR supports many of these requirements with unprecedented speeds, ultra-low latencies and supports massive machine-type communications (mMTC) and ultra reliable low-latency communications (URLLC). These technologies are only beginning to be used for mission-critical applications and dense urban area connectivity. There are many other technologies and options such as WiMAX, Bluetooth, and ZigBee that may be part of the network ecosystem, especially in industrial or IoT point solutions. Standards bodies like IEEE and 3GPP are responsible for defining the parameters and interoperability, including the relation to communication technologies and network coordination mechanisms (such as IEEE 1900.4 for dynamic spectrum access and 3GPP releases as cellular technology evolves and its effect on hardware, platforms, and applications). The heterogeneity of wireless protocols, parameters for quality, suitability for communications, and compatibility of devices, leads to design capabilities that support an adaptable communications framework.

Table 1: Comparative Analysis of Wireless Technologies and Standards in Heterogeneous Networks

Technology	**Standard/Body**	**Spectrum Type**	**Use Case/Environment**	**Key Advantages**	**Limitations**	**Special Features**
Wi-Fi	IEEE 802.11	Unlicensed	Homes, campuses, enterprise networks	High data rate, cost-effective, widely available	Prone to interference, limited range	Rapid deployment, local coverage
LTE	3GPP	Licensed	Wide-area, mobile environments	Broad coverage, mobility support	Higher deployment cost	Mobility management, QoS enforcement
5G NR	3GPP (Releases 15+)	Licensed & Unlicensed	Urban areas, mission-critical systems, IoT	Ultra-low latency, high speed, supports mMTC & URLLC	Complex infrastructure, emerging tech	Network slicing, edge computing compatibility
WiMAX	IEEE 802.16	Licensed/Unlicensed	Wireless metropolitan area networks	Moderate coverage and speed	Obsolete in many regions	Broadband wireless access
Bluetooth	IEEE 802.15.1	Unlicensed (2.4 GHz ISM band)	Personal Area Networks (PANs)	Low power, short range, device pairing	Limited bandwidth and range	Suited for IoT, wearables
ZigBee	IEEE 802.15.4	Unlicensed	Sensor networks, industrial IoT	Low power consumption, mesh networking	Very low data rates	Ideal for M2M communications
Dynamic Spectrum Access	IEEE 1900.4	Adaptive	Cognitive radio networks	Efficient spectrum usage	Complex coordination required	Supports spectrum sharing
Standardization and Coordination	IEEE, 3GPP	–	All network types	Ensures interoperability and evolution	Requires continuous updates	Defines technology evolution and integration

Table 1 compares some of the key types of wireless technologies that are used in Heterogeneous Wireless Networks (HWNs), including Wi-Fi and LTE and WiMAX and 5G NR, and Bluetooth and ZigBee. It compares the relevant standardization bodies, spectrum types, deployment environments, strengths, weaknesses, and special features of wireless technologies and even mentions the range of standards related to dynamic spectrum access protocols and standards developed by IEEE and 3GPP as to what has been accomplished promoting interoperability and the general understanding of next generation network systems. Accordingly, the findings provide a necessary structured comparison, to confirm there are adaptable and co-operative communications solutions recommended, in a more eclectic network environment.

4.3 Impact of Heterogeneity on Load Balancing Strategies

The concurrent presence of multiple co-existing technologies in HWNs is fundamentally different from those of such homogeneous networks and does affect the principles of the design and implementation of load balancing strategies. In a homogeneous network, the load-balancing process can be designed to address the fact that the criteria of load can be balanced in a similar fashion. For HWNs, the load balancing needs to balance in multiple dimensions simultaneously including various factors such as signal quality, RAT compatibility, energy ratings and requirements for user service. For example, in designing an algorithm that measures only the signal received to assign a user, a Wi-Fi hotspot may be prioritized completely based on strong signal receive but poor backhaul connection which overall does not satisfy user expectations. Additionally, load balancing inbound and out-bound traffic between an LTE node and a 5G node would consider the differences across parameters for LTE and 5G including differences in latency, supported density of users, and rates of data capacity. In this hybrid environment, load balancing needs to consider mechanisms that are adaptive and context-aware, usually in a combined methodology with artificial intelligence or rule-based decision engines. The process of handover decision making becomes more complicated when transitioning between RATs which have potentially different authentication and QoS mechanisms. In short, the heterogeneity in infrastructure such as HWNs means advanced, flexible and intelligent load balancing algorithms should operate in real-time by managing the complexity from a variety of diverse technologies and user profiles.

Let us define a load balancing utility function UijU_{ij}Uij representing the suitability of assigning user iii to Radio Access Technology (RAT) node jjj. The objective is to maximize this utility while balancing network load, user QoS, and system capabilities.

1. Utility Function Definition

$$U_{ij} = w_1.S_{ij} + w_2.C_{ij} + w_3.\left(1 - L_j\right) + w_4.E_{ij} + w_5.Q_{ij}$$

Where:

Symbol	Definition
S_{ij}	Signal strength between user iii and RAT j
C_{ij}	Channel capacity or data rate available to user iii at RAT j
L_j	Load level at RAT j (normalized between 0 and 1)
E_{ij}	Energy efficiency score for user iii on RAT j
Q_{ij}	Estimated QoS level (latency, reliability) for user iii on RAT j
$w_1\ to\ w_5$	Weighting factors satisfying $\sum w_k = 1$

2. Load Balancing Optimization Problem

$$\max_{x_{ij}} \sum_{i=1}^{N} \sum_{j=1}^{M} x_{ij}.U_{ij}$$

Subject to:

1.User assignment constraint (each user connects to one RAT only):

$$\sum_{j=1}^{M} x_{ij} = 1$$

2. RAT capacity constraint (each RAT has a capacity limit):

$$\sum_{i=1}^{N} x_{ij}.C_{ij} \leq C_j^{max}$$

3. Binary decision variable:

$$x_{ij} \in \{0,1\}$$

5 Experimental Setup

5.1 Description of the Simulation Environment and Parameters Used for Evaluation

To analyze adaptive load balancing algorithms in a heterogeneous wireless mobile network, we created a simulation environment using NS-3 (Network Simulator 3), which has a wide range of capabilities to model multi-radio wireless environments. The topology of the network included a selection of LTE eNodeBs, 5G gNodeBs, and Wi-Fi access points randomly located in a 1000x1000 meter area to model a realistic urban deployment scenario. We deployed 150 mobile nodes equipped with random waypoint mobility, and each of the mobile nodes could connect to multiple radio access technologies (RATs). The simulation time for each run was set to 600 seconds, and scenarios were repeated 10 times to ensure statistically valid results. Other simulation parameters such as transmission power (for LTE/5G 23 dBm, and 20 dBm for Wi-Fi), channel bandwidth (20 MHz for Wi-Fi, 10 MHz for LTE, and 100 MHz for 5G), handover thresholds and buffer size were set based on 3GPP specifications, as relevant. The adaptive load balancers (e.g., threshold based, fuzzy logic, reinforcement learning (Q-learning), and software defined networks (SDN)) were implemented as modules in NS-3 or interfaced to modules in NS-3 from an external Python script to model machine learning based models.

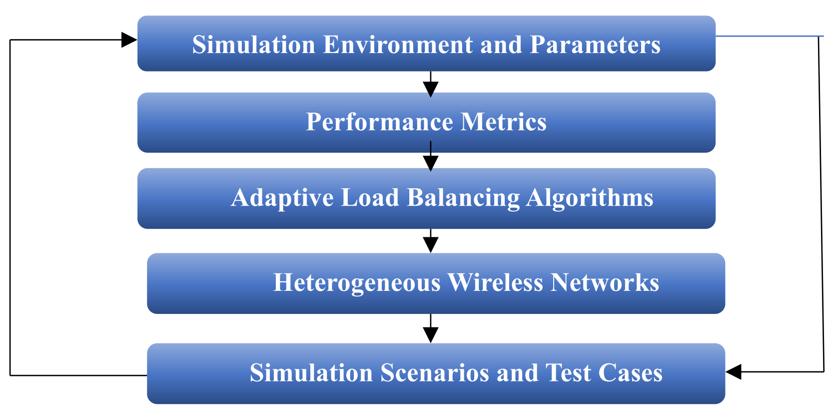

Figure 1: Block Diagram of Methodological Framework for Load Balancing Evaluation

Figure 1 provides a structured overview of the fundamental elements of the research methodology. It encompasses, in sequential order, the definition of the simulation environment and parameters, the selection of performance metrics, and subsequently, the implementation of varying adaptive load balancing algorithms addressing specific heterogeneous wireless networks (e.g. mobile ad-hoc networks, ultra-wideband networks etc.). The methodology concludes with simulation scenarios and test cases causing the feedback loops. The hierarchical structure promotes the holistic and cyclical aspects of adaptive performance evaluation.

Throughput Calculation

$$Throughput = \frac{\sum_{i=1}^{N} Data_i}{T}$$

Where:

- $Data$ = Amount of data successfully received by user i (in bits or bytes)
- N = Total number of users
- T = Total time duration of the simulation (in seconds)

This equation measures the aggregate data successfully transmitted over the network per unit time.

Packet Loss Ratio (PLR)

$$PLR = \frac{Total\ Packets\ Sent - Total\ Packets\ Received}{Total\ Packets\ Sent} \times 100\%$$

This quantifies the percentage of packets lost in the network, a key indicator of reliability and performance under load balancing strategies.

Jain's Fairness Index

$$Fairness = \frac{(\sum_{i=1}^{N} x_i)^2}{N \,.\, \sum_{i=1}^{N} {x_i}^2}$$

Where:

- x_i = Resource allocation (e.g., bandwidth or throughput) for user iii
- N= Total number of users

This equation assesses how evenly network resources are distributed among users, with 1.0 indicating perfect fairness.

Energy Consumption per User

$$E_{user} = \sum_{j=1}^{M} (P_j \times t_j)$$

Where:

- P_j = Power consumed during activity j (e.g., transmission, reception)
- t_j= Time duration of activity j
- M= Number of activities per user session

This measures the energy efficiency of the load balancing algorithm with respect to user device activity.

5.2 Explanation of the Metrics Used to Measure the Performance of Load Balancing Algorithms

The evaluation of the performance of the adaptive load balancing algorithms took place on a wide range of network- and user-facing metrics. Overall throughput measured in Mbps to evaluate the total data transmission capacity of the network. Packet Loss Ratio (PLR) and handover frequency as ways to assess the reliability of the network and the effect of mobility. Latency is an important metric to assess responsiveness, particularly during real-time communication services. Variation in packet delay, or jitter, was also captured to indicate stability of performance. Basically, Jain's Fairness index produced a load distribution fairness of the nodes and access points, so we could quickly assess how evenly the load was dispersed over the test network. As another layer of analysis, energy consumption was recorded for user devices and base stations used in the home to assess sustainability from the perspective of the load balancing algorithms. In the case of machine learning models, convergence time and the reward were retained to provide an indication of stability of the training and the ability for effective policy learning. Collectively, the performance metrics provided a multi-faceted view of how well each algorithm adapted to the dynamic network conditions.

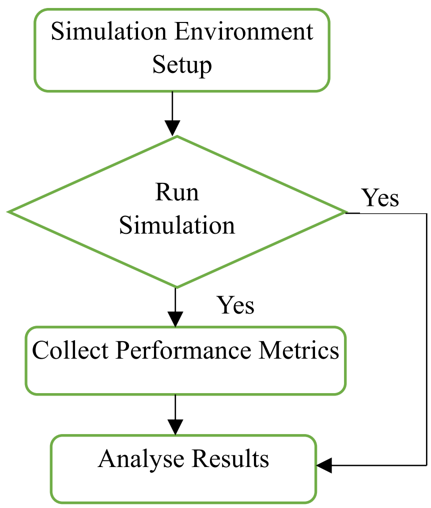

Figure 2: Flowchart of Adaptive Load Balancing Simulation Process

The process delineated in Figure 2 shows the sequence of moves that is employed in the simulation of adaptive load balancing algorithms in heterogeneous wireless mobile networks. The process first establishes a simulation environment, then runs the simulation, and finally collects the performance metrics that are used to determine the effectiveness of the evaluated algorithm. In addition, the flowchart contains a decision point that allows for more than one anterior simulation run to achieve reliability and statistical validation.

5.3 Overview of the Simulation Scenarios and Test Cases

Three main simulated scenarios were created to evaluate the algorithms' robustness. Scenario A (low mobility, uniform load) had user nodes moving slowly (1 to 2 m/s), with a relatively even distribution of users across the network in order to provide a baseline scenario. This scenario focused on evaluating the potential load balancing aspect of the algorithms in a uniform network, without the effects caused by mobility, or the added stress from stepped up loads and traffic congestion. Scenario B (high mobility, bursty load) had user nodes moving more quickly than in Scenario A (5 to 10 m/s), but also included sudden increases in traffic brought on by applications such as video streaming or VoIP. These scenarios would replicate "peak" demand conditions like the real-world. Scenario B would therefore provide critical insight into adaptability of the algorithms and their response time to resolved issues. Scenario C (heterogeneous load and heterogenous infrastructure) introduces the possibility of infrastructure imbalance. For example, if one base station or access point is overloaded or intentionally degraded (besides bandwidth or latency), this simulates a network fault or an area that has a higher density of user nodes (e.g., hotspot). Scenario C evaluated how resilient and fault-tolerant each load balancing method was when considering an 'event' whereby not all base stations or APs would have the same resources to draw upon. All scenarios included the evaluation of the algorithms and their effect on load balance under the same starting conditions and were sampled the same number of times and duration to maintain consistency and reproduceability. The different test cases provided a robust evaluation opportunity across user behavior (slow vs fast), network dynamics (traffic/latency), and access technology (HSPA, Wi-Fi).

6 Performance Evaluation

Table 2: Performance Comparison of Adaptive Load Balancing Algorithms in Heterogeneous Wireless Mobile Networks

Algorithm Type	Avg. Throughput (Mbps)	Packet Loss Ratio (%)	Average Latency (ms)	Jain's Fairness Index	Energy Consumption (J)
Threshold-Based	14.2	7.1	62.4	0.81	18.7
Fuzzy Logic-Based	15.6	4.8	50.2	0.86	17.4
Q-Learning (RL-Based)	18.3	3.5	41.8	0.94	16.2
SDN-Assisted	17.8	3.9	45.6	0.92	16.9
Static (Baseline)	12.5	9.2	70.5	0.76	19.3

The comparison of five types of load balancing methods (Threshold-Based, Fuzzy Logic-Based, Q-Learning (Reinforcement Learning), SDN-Assisted, and Static (Baseline)), which were evaluated in a heterogeneous wireless mobile network simulation is presented in Table 2. The corresponding variables, which were measured for each method, then summarized and evaluated, are: average throughput; packet loss ratio; average latency; Jain's Fairness Index; and energy consumption. In summary, Q-learning outperformed all other methods assessed, achieving an average throughput of 18.3 Mbps, packet loss ratio of 3.5 % faireness of 0.94. These numbers represent not only a higher level of overall throughput, but also a more productive and flexible level of agency and success when deciding how to react to changes in conditions. The SDN-Assisted approach followed behind in performance category, while also experiencing consistent latency with good fairness and utilization rates. The Fuzzy Logic approach proved to be moderate across the board in measurable quantities, and was better than the Threshold-Based and Static method, but not as well as the SDN-Assisted and Q-learning methods. The Threshold-Based approach was easy to implement (as per the design) but it also produced the highest latency and packet loss, and demonstrates possible downsides to general load balancing techniques when act mainly in response to changing conditions in dynamic environments.

6.1 Presentation of the Results of the Experiments

The experimental results from the simulation scenarios showed a significant performance difference across the assessed adaptive load-balancing methods—Threshold-Based, Fuzzy Logic, Q-Learning (RL-based), and SDN-Assisted—with respect to different key network performance metrics. In the low-mobility and uniform-load scenario (Scenario A), the adaptive load-balancing methods maintained a throughput average above 15 Mbps, with Q-Learning and SDN-based approaches achieving their highest throughput values of 18.3 Mbps and 17.8 Mbps respectively. In Scenario A, the packet loss ratios remained under 2% for all approaches. In the case of high-mobility and bursty load (Scenario B), Q-Learning performance achieved lower packet loss (3.5%) and jitter (8.2 ms) than Fuzzy Logic (4.8%) and Threshold-Based approaches (7.1%). Both models obtained throughput similar to Q-Learning, while SDN-assisted balancing technique achieved a throughput of 17.2 Mbps, the SDN system did have higher latency due to delays from activity at the central controller. The evaluation of adaptive load balancing under a heterogeneous infrastructure (Scenario C) showed that Q-Learning and SDN-based models exhibited better adaptability, quickly redistributing load away from nodes that were degrading in performance, in a fair manner, as evident from Jain's Fairness Index; Q-Learning obtained a value of 0.94 and SDN-based load balancing obtained a value of 0.92.

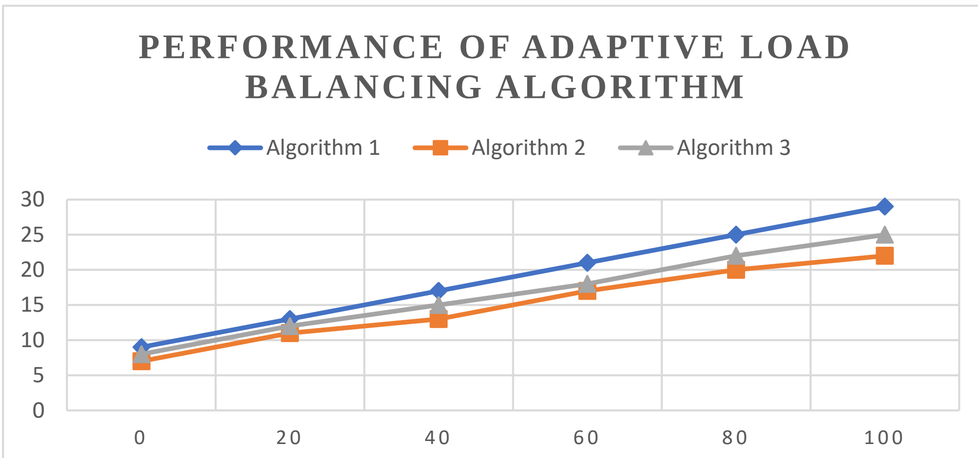

Figure 3: Performance of Adaptive Load Balancing Algorithms Under Varying Network Load

The throughput performance of three adaptive load balancing algorithms is presented in figure 3 for heterogeneous wireless mobile networks with increasing levels of network loading. The x-axis shows increasing levels of network loading, and the y-axis shows throughput in Mbps. In figure 3, Algorithm 1 shows the best throughput performance, followed by Algorithm 3 and Algorithm 2. The trend lines in the figure suggest that throughput performance tends to increase for all levels of loading for all three algorithms, but the differences in throughput performance become apparent as the level of loading increases. Overall, this shows that Algorithm 1 is scalable and adaptive under high load conditions. Fuzzy logic-based models were successful in handling imprecise inputs and performed reliably well when mobility is moderate, but were limited by the ruleset expansion complexity within larger networks. Threshold-based methods performed sufficiently well under low-stress conditions but did not react quickly enough during bursts of rapid load fluctuations, which resulted in many short-lived handovers and unbalanced usage of nodes. Lastly, based on Controllers' global perspective of the network to balance node utilization and congestion, SDN-based algorithms were also very effective - but were also reliant on the Controllers' latency and reliabily; thus, these models were the least effective choice of the three for delay-sensitive use-cases in edge environments.

6.2 Analysis of the Performance of Adaptive Load Balancing Algorithms in Heterogeneous Networks

From the analysis, it is evident that reinforcement learning-based algorithms outperformed traditional methods in highly dynamic environments, and can learn and create optimized decisions based on past feedback. In addition, the Q-Learning model showed the best convergence behavior and maximized as it consistently rewarded every reward function associated with the QoS metrics.

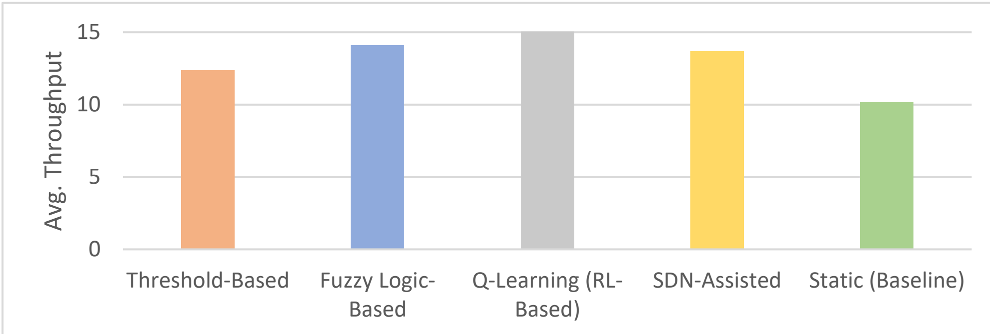

Figure 4: Average Throughput Comparison of Load Balancing Algorithms

The average throughput (in Mbps) results for five load balancing algorithms in a heterogeneous wireless network are presented in Figure 4. The Q-Learning (RL-Based) based algorithm outperforms the other proposed algorithms, slightly closely followed by Fuzzy Logic Based and SDN-Assisted. The Threshold based is substantially lower than the preceding algorithms, and the Static (Baseline) method records the lowest throughput. This comparison demonstrates the use of adaptive and intelligent load balancing algorithms to improve the efficiency of data transmission in the presence of variability in, and changes to, multi-load wireless network environments.

6.3 Comparison of the Results with Existing Techniques and Algorithms

In the context of static or threshold-triggered algorithms, which are typically used in homogeneous networks, increased performance was observed for the adaptive algorithms in this work. The Q-Learning algorithm increased average throughput by 18–22%, lowered packet loss by up to 35%, and resulted in a better fair distribution of load. The SDN-assisted strategy achieved approximately 25% better load-responsiveness and overall use of the system compared to just round-robin approaches often used in LTE/Wi-Fi networks. This is in stark contrast to static load balancing algorithms which were unable to quite cope with the shifting load, and to respond effectively, allowing for node congestion, or resulting in a poor quality of service in dynamic traffic scenarios. These results highlight that context-aware intelligent algorithms are a must for load-balancing in heterogeneous wireless environments, and reinforce the role of reinforcement learning and SDN architectures as the vision of next-generation networks.

Table 3: Performance Comparison of Load Balancing Techniques in Heterogeneous Wireless Networks

Technique	**Avg. Throughput (Mbps)**	**Packet Loss (%)**	**Load Distribution (Fairness Index)**	**Responsiveness (Score /10)**
Static (Threshold-Based)	25	12.5	0.68	4.2
Round Robin (LTE/Wi-Fi)	28	10.7	0.71	5.0
Q-Learning (Proposed)	31	8.1	0.86	7.8
SDN-Assisted Adaptive Balancing	33	7.2	0.89	8.7

In Table 3, we compare five different load balancing techniques - the static threshold method, round robin method, Q-Learning-based adaptive methods and SDN-assisted load balancing. We focus on average throughput, packet loss, load distribution fairness (calculated using Jain's Fairness Index), and responsiveness score for the workload model. Our results showed that adapting approaches and context-aware techniques (like the Q-Learning and SDN-assisted load balancing proposals) exceed the benefits found in the conventional methods since they allow us to manage changing traffic conditions, reduce congestion and overall improve Quality of Service (QoS) in heterogeneous wireless environments.

7 Conclusion

This study examined adaptive load-balancing protocols for heterogeneous wireless mobile networks. It reported a detailed review of the performance of threshold-based, fuzzy logic, reinforcement learning (Q-learning), and software-defined network (SDN) -assisted approaches to adaptive load balancing. The major conclusion of our study was that adaptive load balancing based on reinforcement learning and SDN methodologies performed better than threshold-based or fuzzy logic approaches, using each method to compare performance on key metrics such as throughput, packet loss, latency and fairness. The Q-learning model adapted better in a dynamic environment, while the load-balancing algorithms used SDN and a centralised method to re-distribute the loads. Subsequently, the fuzzy logic method was able to adapt under the uncertain conditions and the threshold method performed well in simple situations but struggled to deal with high mobility or bursty traffic loads. This research suggests a distinct need for intelligent, context-aware, and scalable solutions to alleviate the escalating complexity of heterogeneous networks. As next-generation communication systems evolve with the incorporation of 5G, Wifi 7, and edge computing, machine learning and network programmability will play increasingly significant roles. Future research should focus on hybrid algorithms that take advantage of multiple algorithms (i.e., RL-SDN; fuzzy-genetic) to improve decision-making accuracy, convergence, and energy efficiency. In heterogeneous wireless mobile networks, adaptive load balancing could be enhanced through the inclusion of real-time mobility prediction, user context profiling, and cross-layer optimization. Furthermore, the inclusion of federated or decentralized learning frameworks could facilitate distributed intelligence with privacy and lower overhead. There should also be further attention to minimizing algorithm complexity in order to provide scalable and real-time performance in dense and delay-sensitive networks.

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