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A Survey of Machine Learning Approach in Fractional Frequency Reuse in 5G Network

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ABSTRACT

Fractional Frequency Reuse (FFR) has emerged as a key interference mitigation technique for improving throughput and spectral efficiency in fifth-generation (5G) heterogeneous networks (HetNet), particularly in dense femtocell deployments. However, conventional FFR schemes rely on static or heuristic-based configurations that struggle to adapt to dynamic traffic patterns and complex interference conditions. Recently, machine learning (ML) techniques have been increasingly explored to enhance the adaptability and intelligence of FFR mechanisms. This paper presents a comprehensive survey of machine learning based approaches applied to FFR in 5G networks, with a focus on interference mitigation, throughput enhancement, and Quality of Service (QoS) improvement for cell-edge and indoor users. The study systematically reviews existing ML-driven FFR frameworks, categorizing them based on learning paradigms, network architectures, performance metrics, and deployment scenarios. Key findings reveal that reinforcement learning and deep learning methods are the most widely adopted due to their ability to operate under uncertain and time-varying network conditions. Furthermore, this survey identifies critical research gaps, including scalability challenges, limited real-time implementations, and insufficient consideration of heterogeneous traffic demands. By highlighting recent advances and open research directions, this work provides valuable insights for the development of intelligent, adaptive frequency reuse strategies for future 5G and beyond wireless networks.

Keywords: Fractional Frequency Reuse (FFR), Heterogeneous Networks (HetNet), interference mitigation, 5G networks, Machine Learning (ML)

1. INTRODUCTION

The growing reliance on gadgets such as smartphones, tablets, and other smart devices, which consume significant amounts of data, has significantly boosted the need for high-speed mobile data traffic (Musa et al., 2022). By 2025, it is anticipated that more than 60% of the global population will predominantly rely on mobile internet. With the increasing preference for video content on mobile devices, individual mobile data usage is projected to be five times higher by 2024. (Iago and Vicente, 2021). Between 2018 and 2025, the traffic demand will drive the number of IoT devices connected to mobile networks to approximately 25 billion.(Iago and Vicente, 2021). The amount of data is anticipated to increase exponentially in the presence of scarce spectrum and limited coverage. These developments have resulted in a significant need for greater capacity, improved throughput, and better signal-to-interference and noise ratio (SINR). Additionally, there are challenges with

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inadequate indoor coverage, the necessity for numerous base station installations, lower Quality of Service (QoS) for edge users, and a strong demand for higher data rates. (Salihu et al., 2017).

2. FIFTH GENERATION (5G) NETWORK

A 5G network is capable of efficiently supporting a large number of connections, offering very low latency and significantly increased network capacity. It has diverse applications, including e-health services, smart agriculture, and intelligent education systems. (Alozie et al., 2023). 5G technology is anticipated to cater to three broad categories of services: ultra-reliable low-latency communications (URLLC), enhanced Mobile Broadband (eMBB), and Massive Machine-Type Communications (mMTC), each having distinct Quality of Service (QoS) requirements. Massive Machine-Type Communications (mMTC) offers scalable connectivity for a vast array of devices, utilizing Multi-access Edge Computing (MEC) as a technological solution. (Kaaviya & Deepa, 2021). The advent of 5G technology introduces numerous challenges that must be tackled. Key issues include managing the vast data volumes resulting from the ultra-dense deployment of small cells (UDSC), selecting the appropriate Radio Access Technology (RAT), addressing the complexities of massive MIMO, mitigating interference, separating control and data planes, implementing intelligent authentication, optimizing beam selection, and reducing latency. (Kaaviya & Deepa, 2021).

Therefore, it is crucial to implement efficient strategies that can manage the substantial data volumes and other network resources effectively. Innovative wireless technology architectures and topologies are being proposed to address these needs. Notable among these are HetNets, Low Power Nodes (LPNs), Heterogeneous Cloud Radio Access Networks (H-CRANs), spatial interference coordination, coordinated multi-point (CoMP) transmission and reception, and techniques for self-configuration, self-optimization, and self-healing. (Nzenwata & Oludele, 2019).

3. HETEROGENEOUS NETWORK (HetNet)

One highly effective approach for tackling 5G network challenges is the Heterogeneous Network (HetNet). HetNet enhances existing cellular networks by integrating a variety of smaller base stations (BS) with different communication protocols, transmission capacities, coverage areas, carrier frequencies, and backhaul connections. For example, in densely populated areas, femtocells, picocells, microcells, and relay nodes are often deployed alongside macrocells. This setup allows HetNets to provide high-quality service (QoS) to a diverse range of users. (Agarwal et al., 2022).

The primary goal of HetNets is to increase network capacity through cell densification, bringing base stations (BSs) closer to user equipment (UEs). This involves deploying small cells within traditional macro-cellular networks, providing multiple connection options for UEs to enhance Quality of Service (QoS). HetNets offer numerous benefits, including improved coverage quality and high throughput, enhanced performance for cell edge users, increased spectral and energy efficiency, and reduced operational and capital expenses for 5G networks. (Agarwal et al., 2022).

4. FEMTOCELL.

A fundamental issue with HetNets is the interference between various cells and the inadequate coverage for indoor and edge users. Deploying numerous outdoor base stations (BSs) does not significantly benefit cellular operators. To address the need for increased network capacity, it has become essential to implement indoor coverage solutions. These solutions are typically installed within large buildings to serve as hotspots for user equipment (UEs) (Onu et al., 2018). To improve indoor coverage and capacity, deploying indoor femtocells is a promising solution. Femtocell technology is installed by users to support higher data rates and meet QoS requirements within a short coverage range. The femtocell technology is cost-effective and operates on low power and utilizes a licensed spectrum, and connects to the cellular network via broadband backhaul links, such as optical fiber or Digital Subscriber Line (DSL). Both the users and operators benefit from the femtocells. Users enjoy high-quality connections because of the proximity between the transmitter and receiver. Meanwhile, operators allowing users to self-deploy femtocells and offloading traffic can cut down Operational Expenditure (OPEX) and Capital Expenditure (CAPEX) (Agarwal et al., 2022). Despite their advantages, femtocell deployments face numerous technical challenges, including interference between femtocells, known as co-tier interference, and interference between femtocells and macrocells called cross-tier interference. These interference issues can significantly affect network performance, making it essential to select an appropriate access strategy.(Hafez et al., 2020). In femtocell networks, an interference avoidance strategy, where users avoid mutual interference instead of suppressing it, tends to be more effective. This survey addresses this gap by systematically reviewing machine learning approaches applied to FFR in 5G networks, classifying existing works, comparing their performance metrics, and identifying unresolved challenges and future research directions.

5. FREQUENCY REUSE

Inter-cell interference (ICI) is a crucial factor in cellular communication systems that impacts data transfer in the cell-edge zone by reducing the spectral efficiency of base stations. In mobile systems, frequency allocation has two main methods. The first method is Frequency Reuse Factor 1 (FRF 1), where base stations use different frequencies to transmit data, sharing 25% of the bandwidth to each sector, and the Fractional Frequency Reuse Factor 3 (FRF 3). Although this approach greatly reduces spectrum efficiency, it also decreases co-channel interference between adjacent cells (Musa et al., 2022). The FRF 1 is the simplest frequency reuse scheme. In RF1, the full spectrum is utilized in each cell without limitations on frequency resources or power distribution, as illustrated in Figure 1. This approach allows for high and peak data rates in system capacity. However, it also increases ICI, particularly at the edges of the cell, significantly limiting the performance of users in those areas and degrading overall spectral efficiency. (Onu et al., 2024).

In the FRF 3 scheme, the total bandwidth is divided into three distinct, non-overlapping sub-bands, which are then allocated to cells so that adjacent cells always use different frequencies, as shown in Figure 2. This approach reduces ICI, but results in each cell utilizing only a Using only one-third of the total available bandwidth results in a considerable reduction in capacity.

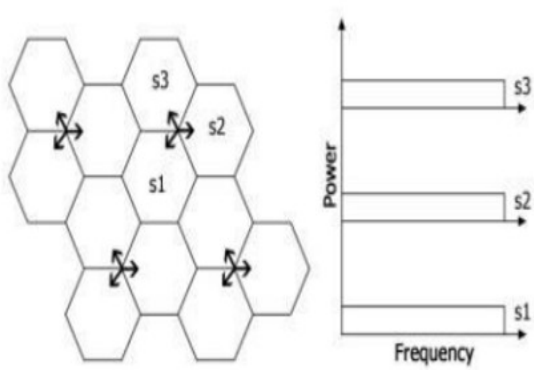

Figure 1: Frequency Planning for FRF 1 (Salihu et al.,2017).

Fractional Frequency Reuse (FFR): The FFR scheme was developed to overcome the shortcomings of conventional FRF methods. In FFR, a cell's coverage area is segmented into various zones, each assigned a specific frequency reuse pattern. The key objective of FFR is to manage interference, especially at the cell edges, where it is more prevalent. This technique allocates different portions of frequency bands to various parts of a cell, enhancing the SINR and reducing interference in wireless communication systems (Onu et al., 2024).

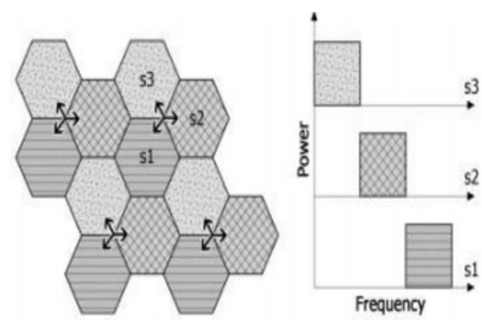

Figure 2: Frequency Planning for FRF 3.(Salihu et al., 2017)

Partial Frequency Reuse (PFR): Using the FRF throughout the entire cell is not bandwidth-efficient. To enhance the SINR for users at the cell edges while preserving high spectral efficiency, a higher reuse factor can be applied to the edge cell regions, while FRF 1 is used for the cell center regions (Salihu et al., 2017). The fundamental concept of PFR involves setting restrictions on certain resources so that specific classes of users do not utilize them. The PFR scheme is shown in Figure 3.

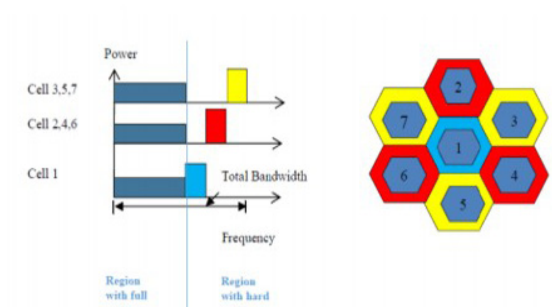

Figure 3: PFR scheme (Salihu et al., 2017)

The available bandwidth is partitioned into four distinct sub-bands. The UEs at the center of the cell are assigned a frequency band of FRF 1, while edge users of the cell are allocated a frequency band of FRF 3. This approach, known as FFR-FI (Fractional Frequency Reuse with Full Isolation), completely isolates users at the edge of the cell. However, since PFR does not make use of the full bandwidth available, this results in lower cell throughput compared to the RF1 scheme and inefficient use of available frequency resources. (Salihu et al., 2017).

Soft Frequency Reuse (SFR): The SFR strategy seeks to alleviate the significantly high ICI associated with the FRF 1 configuration while contributing more flexibility than the PFR scheme. As shown in Figure 4, in each sector, users at the edge cell are allocated a portion of the bandwidth with the highest power level, while users at the center of the cell are assigned the remaining frequency band at a lower power level. This method uses FRF 1 in the cell's central area, while a reuse factor above one is implemented in the cell's edge regions.

An Enhancement of the SFR scheme: This scheme is also called Soft FFR. These approaches may lead to lower overall cell throughput compared to the FRF1 scheme. Since PFR does not make use of the entire bandwidth available within the cell, the cell throughput will be reduced when compared to the FRF1 scheme. (Salihu et al., 2017).

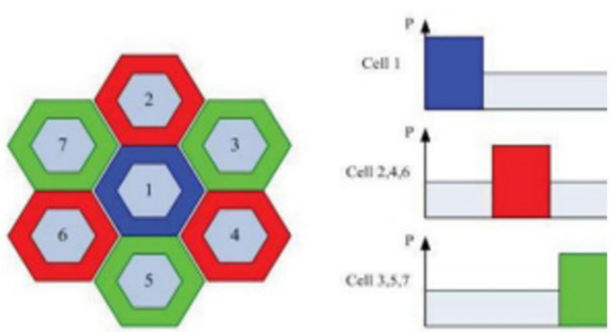

Figure 4. SFR scheme (Salihu et al., 2017)

An Enhancement of the SFR scheme: This scheme is also called Soft FFR. These approaches may lead to lower overall cell throughput compared to the FRF1 scheme. Since PFR does not make use of the entire bandwidth available within the cell, the cell throughput will be reduced when compared to the FRF1 scheme. (Salihu et al., 2017). SFR can enhance overall system capacity relative to PFR by making full use of the available bandwidth. However, it might still lead to a lower overall system capacity compared to the RF1 scheme. The SFFR scheme was introduced to enhance overall cell throughput. In soft fractional frequency reuse (SFFR), resources assigned to users at the edges of one cell can also be utilized by users in the inner regions of neighboring cells, subject to certain power limitations, as shown in Figure 5.(Salihu et al., 2017).

6. Machine Learning (ML)

Machine learning algorithms can be utilized to optimize frequency reuse effectively, which can offer intelligent decision-making capabilities. These algorithms are able to forecast interference events, learn from past data, and dynamically modify frequency reuse patterns in order to improve performance under various network conditions (Onu et al., 2024). Machine Learning (ML) has emerged as a highly promising solution for tackling challenges in 5G networks. It allows applications and systems to learn, predict, and make decisions automatically, without human intervention, thereby making machines more intelligent. Machine Learning can learn from available data sets or through interactions with the environment. Based on the learning methods, Machine learning methods are typically divided into three main categories: reinforcement learning, supervised learning, and unsupervised learning (Fourati & Alouini, 2021).

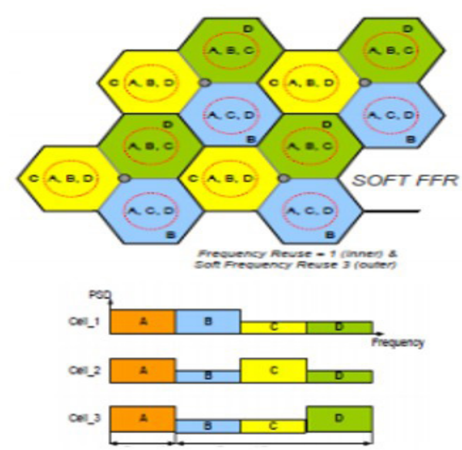

Figure 5: SFFR scheme (Salihu et al., 2017).

In supervised learning, a supervisor trains the system using historical data by tagging specific features, which helps predict outcomes. Algorithms in supervised learning use a training data set to learn and apply this knowledge to label new outputs. Examples of supervised learning techniques include linear regression, Support Vector Machines (SVM), Neural Networks (NN), and Bayes' theorem (Kaaviya & Deepa, 2021).

In unsupervised learning, there is no supervisor or tagged data to guide predictions. Since the expected outcomes are unknown, the system must learn independently. This method does not rely on a training data set. Instead, it divides unlabeled, heterogeneous data into smaller, homogeneous subsets that are easier to understand and manage. Unsupervised learning combines both unlabeled data and labeled data for training. E.g., game theory, K-Means clustering, load balancing, cell interruption management, and genetic algorithms. (Kaaviya & Deepa, 2021).

Reinforcement learning (RL) algorithms function similarly to unsupervised ones but include a reward mechanism that penalizes or rewards the system based on the quality of its decisions. In RL, the machine interacts with its environment to learn and aims to maximize its rewards. This mechanism allows the RL system to continuously update and improve. Examples of RL algorithms are Q-Learning, heuristic methods, and Genetic Algorithms (GA) (Trejo Narváez & Miramá Pérez, 2018) and (Kaaviya & Deepa, 2021).

The Machine learning techniques have been applied to FFR optimization with distinct objectives depending on the learning paradigm. Supervised learning methods are primarily used for interference prediction and SINR classification based on historical datasets. Unsupervised learning techniques, such as clustering, are employed for user grouping and traffic-aware resource partitioning. Reinforcement learning (RL), including Q-learning and deep reinforcement learning (DRL), is predominantly adopted for dynamic spectrum allocation and adaptive frequency reuse due to its ability to learn optimal policies through interaction with the network environment.

7. PREVIOUS STUDIES

Interference management in macro-femtocell environments has been thoroughly investigated in LTE and LTE-A networks. As technology evolved from First generation to 5th Generation and UE became more advanced, the demand for voice calls and data has increased, leading to interference issues that impacted the poor quality of service. To address this, many researchers have explored using Machine Learning to analyze SINR performance and identify effective interference mitigation strategies.

The Authors in (Bartoli et al., 2017) noted that HetNet deployment represents a revolutionary shift in networking paradigms that relies on increasing the number of access points and employing a multi-layered architecture to boost capacity and coverage of 5G networks. However, the widespread deployment of access points results in a significant increase in backhaul demand. To address this, the authors proposed a novel cross-layer approach that integrates resource allocation in both access and backhaul networks using an artificial intelligence (AI)-based technique. This approach incorporates two interconnected decision-making cores that share information: one is dedicated to physical layer elements, while the other oversees network resource management. These iterative processes collaborate to optimize traffic distribution within the backhaul network and enhance user cell association. This optimization aims to minimize unmet user data rate demands and reduce energy consumption by limiting the number of active cells.

The authors in (Trejo Narváez & Miramá Pérez, 2018) highlight automatic optimization as a crucial strategy for addressing issues like inter-cell interference. It discusses various machine-learning algorithms designed to tackle this problem of automatic optimization. These machine learning techniques enable self-organization, allowing cellular networks to adjust their parameters and adapt to environmental changes. The research aims for cellular systems to achieve self-optimization, an essential aspect of self-organizing networks, where the primary goal is for networks to autonomously respond to the specific demands of dynamic network traffic scenarios.

In (Nzenwata & Oludele, 2019). Frequency Reuse Systems in Cellular Networks. The authors describe the network generations with their characteristics and associated problems, and present a survey of frequency reuse techniques and how to calculate the total number of cells with replacement. In addition, it demonstrates the technique for identifying co-channel cells within a cellular network. The author's discussion focused on how deploying heterogeneous networks with micro, Pico, and femtocells can improve spectrum and energy efficiencies. Challenges were identified, and it was suggested to use an analytical model based on the spatial Poisson point process to evaluate Strict-FFR and SFR for optimizing frequency reuse. Strict FFR should be observed, allocating specific frequency bands to users in each tier who have the lowest average usage, to maximize coverage and rate gains. Meanwhile, SFR enables more effective spectrum sharing across different tiers, significantly reducing interference.

In (Alquhali et al., 2020) . The authors introduced the EFFR approach to address interference in femtocell networks, leveraging the deployment of small cell networks. These networks are anticipated to be widely used in wireless communications because they enhance signal quality and optimize spectrum efficiency. However, interference remains a significant issue, particularly in densely populated femtocell networks, where it degrades performance. To combat this, the proposed EFFR approach mitigates interference by dividing the frequency and cell area into three separate regions, each with a distinct frequency set. Femtocells are then strategically placed and assigned frequencies based on their respective regions. This method effectively reduces interference, improves overall throughput, and enhances the SINR.

In (Dahrouj et al., 2021), the authors focused on the interaction between optimization and learning-driven solutions, providing a comprehensive background and theory. Machine learning and its derivatives have gained popularity for their enhanced abilities in automating analytical models. Learning-based techniques, like reinforcement learning, have become essential in addressing many optimization problems during testing and training. The paper examines the use of methods like reinforcement learning, deep neural networks, federated learning, and echo state networks can tackle complex and analytically challenging optimization issues.

The author in (Mukherjee et al., 2021) examines three critical challenges in 5G mobile networks: communication during computing, frequency allocation, and power efficiency. This paper introduces a power-efficient network architecture that integrates micro-femtolet and macro-femtolet cells, leveraging SFFR. Macrocell and microcell base stations are deployed within the network to deliver robust offloading capabilities and signal strength to indoor users and edge users by incorporating femtocells. The proposed heterogeneous network (HetNet) aims to optimize power transmission, and analytical evaluations indicate that SFFR can reduce power transmission by approximately 10.87%. Additionally, the SINR is enhanced through this strategy. Experimental evaluations were conducted using a vector signal analyzer (VSA) and vector signal generator (VSG), while simulations using the Qualnet network simulator revealed that femtolets reduce energy consumption by approximately 2-34% compared to cloud-based offloading solutions.

In this paper (Kaaviya & Deepa, 2021). "Machine Learning Approaches for 5G Network Challenges," a thorough analysis is conducted to assess the efficiency of machine learning methods in tackling various 5G network challenges, including data rate optimization, beam selection, latency reduction, and energy efficiency. The paper begins with an introduction to 5G networks and an overview of machine learning approaches. It then provides a detailed survey of machine learning techniques and their applications in overcoming 5G network challenges. Machine learning is shown to be a powerful tool for enhancing 5G network performance by reducing congestion, increasing data rates, lowering latency, and improving energy efficiency and beam selection. Looking forward, the future of networks, termed "5G and beyond," will rely heavily on automatic, intelligent systems. Techniques such as situation-aware adaptive learning and collaborative learning are suggested as Methods to enhance the effectiveness of machine learning in upcoming networks that are being explored.

In this paper (Musa et al., 2022), the authors studied the performance Evaluation of SFFR and FRE-3 in 5G Networks based on cell spectral efficiency and throughput against the theoretical peak values outlined in NR 3GPP specifications. Simulation results indicate that FFR significantly outperforms FRF-3. However, despite this improvement, FFR still falls short of achieving the peak throughput and spectral efficiency values.

In (Alotaibi, 2023), the authors introduced a dynamic FFR approach aimed at optimizing the potential of small cell and femtocell networks. This approach aims to boost the network's capacity and improve system throughput by efficiently distributing radio resources to femtocells and small cells using a predefined cost function as a guideline. This cost function, evaluated for each sub-region, directs the dynamic FFR to allocate additional resources to femtocells and small cells that are lacking sufficient resources. Sub-regions with higher cost function values are allocated more radio resources, whereas those with lower values receive fewer resources. Throughput is used as the key metric to evaluate the proposed approach, and MATLAB simulations demonstrate that this dynamic FFR technique significantly outperforms the traditional fixed FFR approach.

In this paper, (Onu et al., 2024). Survey paper on frequency reuse schemes for enhanced 5G spectrum management. The author proposed a primary goal to identify and evaluate alternative frequency reuse approaches to optimize spectrum utilization, decrease interference, and improve overall network performance. Subsequently, the survey delves into recent advancements and emerging frequency reuse schemes that address the limitations of traditional methods. These include adaptive frequency reuse, cognitive radio-based approaches, among others. Each scheme is examined in terms of its key principles, benefits, and potential drawbacks. The evaluation encompasses key performance metrics such as throughput, spectral efficiency, interference mitigation, and overall system capacity. Furthermore, the paper discusses open research areas and the challenges in the field of frequency reuse and spectrum management. Promising directions for future research are identified, considering the evolving landscape of wireless communication technologies and emerging applications.

In this paper (Zhi et al., 2022). To ensure stringent Quality of Service (QoS) requirements while mitigating interference in heterogeneous cellular networks (HCNs), the authors investigated a joint optimization framework that integrates mode selection and channel allocation in device-to-device (D2D)–enabled networks operating over both millimeter-wave and conventional cellular bands. The problem was formulated as a system sum-rate maximization subject to QoS constraints for both cellular and D2D users. To address this challenge, a distributed multi-agent deep Q-learning architecture was developed, in which the reward function was carefully designed to align with the optimization objective. Moreover, to limit signaling overhead and enhance scalability, a partial information-sharing strategy was adopted, allowing D2D agents to learn optimal transmission modes and channel selections without requiring global network knowledge. Simulation results demonstrated that the proposed learning-based approach converges efficiently and delivers superior performance compared with existing benchmark schemes.

The authors in (Azimi et al., 2024), investigated joint power and radio resource allocation for both rate-based and resource-based users in 5G radio access network (RAN) slicing environments. To this end, they proposed an energy-efficient deep reinforcement learning–assisted resource allocation framework (EE-DRL-RA) that leverages a collaborative learning architecture combining deep learning (DL) and deep reinforcement learning (DRL). In the proposed scheme, DL is employed to guide long-term resource allocation decisions, while DRL is used to adapt resource allocation on a short-term timescale in response to dynamic network conditions. The asynchronous advantage actor–critic (A3C) algorithm and a stacked bidirectional long short-term memory (SBiLSTM) network are adopted as the DRL and supervised DL components, respectively. In addition, optimal power and resource block allocation for rate-based users is achieved by formulating an energy-efficient power allocation problem as a non-convex optimization task and solving it through an efficient iterative approach. A key strength of the proposed framework lies in its ability to jointly allocate transmit power and resource blocks while maintaining slice isolation with low computational overhead. Simulation results demonstrate that the EE-DRL-RA scheme outperforms state-of-the-art methods in terms of convergence speed, energy efficiency, computational complexity, user admission rate, and inter-slice isolation.

The Authors in (Konstantoulas et al., 2025), proposed a data-driven framework for joint user traffic forecasting and base station association in 5G networks using advanced neural network models. The framework adopts a hybrid learning strategy in which Long Short-Term Memory (LSTM) networks or Transformer architectures are employed to predict user traffic at base stations, while a Convolutional Neural Network (CNN) is utilized to perform user-to-base-station assignment under realistic deployment conditions. By jointly exploiting temporal traffic patterns and spatial user distribution, the proposed approach effectively captures long-term dependencies in 5G network data. Experimental results demonstrate high prediction accuracy, exceeding 99% in traffic forecasting tasks, thereby highlighting the framework's potential for enabling intelligent, data-driven resource allocation and proactive network management in next-generation cellular systems.

This study (Rayyis et al., 2025), the authors proposed an advanced deep learning–based framework for resource allocation prediction in 5G networks, combining convolutional layers with squeeze-and-excitation blocks, bidirectional long short-term memory (BiLSTM), and a self-attention mechanism. This hybrid architecture effectively captures both spatial dependencies and long-term temporal dynamics inherent in 5G traffic data. To address data imbalance, a customized weighted loss function was adopted, while Bayesian optimization was employed for optimal hyperparameter tuning. Simulation results demonstrate that the proposed model achieves state-of-the-art predictive performance, recording a Mean Absolute Error (MAE) of 0.0087, Mean Squared Error (MSE) of 0.0003, Root Mean Squared Error (RMSE) of 0.0161, Mean Squared Log Error (MSLE) of 0.0001, and Mean Absolute Percentage Error (MAPE) of 0.0194. In addition, the framework attained a high coefficient of determination with an R^2 score of 0.9964 and an Explained Variance Score (EVS) of 0.9966, confirming its strong capability to learn complex patterns within the dataset. Compared to conventional machine learning models and related studies, the proposed approach consistently outperforms existing methods, highlighting the effectiveness of deep learning for adaptive and accurate resource allocation in 5G wireless networks. Furthermore, the framework shows practical relevance for smart university environments, enabling efficient bandwidth distribution and reliable real-time connectivity for both educational and administrative services.

This work in (Umamaheswaran et al., 2025), The authors introduced a hybrid machine learning framework for dynamic resource management in 5G networks that integrates deep learning with reinforcement learning to adapt resource allocation to real-time network conditions and user demands. In this approach, a Deep

Neural Network (DNN) functions as a feature extractor, learning multi-dimensional representations of network performance metrics, user behavior, and environmental characteristics that govern 5G network dynamics. These learned features are subsequently utilized by a Reinforcement Learning (RL) agent, which acts as the decision-making component and interacts directly with the network environment to optimize resource allocation policies. The RL agent iteratively refines its decisions by maximizing a reward function derived from key performance indicators, including latency, throughput, and energy efficiency. Through continuous learning and adaptation, the model progressively enhances overall network efficiency under dynamic operating conditions. A major strength of the framework lies in the DNN's ability to capture complex nonlinear relationships within high-dimensional network data, coupled with the RL agent's capability to operate in real time and respond to network variations. Analytical evaluations and experimental results confirm the effectiveness of the proposed framework in achieving intelligent and efficient resource management, demonstrating its potential as a viable solution for next-generation 5G network optimization.

In this paper (Poltronieri et al., 2022), The study presented *MECForge*, an advanced multi-access edge computing (MEC) framework that leverages deep reinforcement learning to enable intelligent and autonomous resource management in 5G networks. Unlike conventional resource allocation strategies that rely on isolated performance metrics, MECForge formulates resource management as a unified optimization problem aimed at maximizing the total value of information delivered to end users. The proposed framework employs a Deep Q-Network (DQN) to learn optimal policies for allocating service components across edge resources in response to dynamic network conditions and user demands. Extensive experimental evaluations conducted in a simulated yet realistic MEC-enabled environment demonstrate that the proposed DQN-based algorithm converges efficiently and adapts effectively to variations in traffic patterns and service requirements. The results confirm that MECForge consistently outperforms baseline approaches by improving service utility and overall user experience. These findings highlight the potential of deep reinforcement learning to support autonomous, value-driven resource management in edge-assisted 5G architectures, particularly in scenarios characterized by heterogeneous services and stringent latency requirements.

Table 1: Comprehensive Comparison of Machine Learning and Reinforcement Learning Approaches for 5G Resource Allocation, Traffic Prediction, and Heterogeneous Network Optimization

Ref.	Focus Area	Methodology / Technique	Network Scenario	Key Contributions	Limitations / Gaps
Bartoli et al., 2017	Interference & resource management	AI-based cross-layer optimization	5G HetNet (access + backhaul)	Joint optimization of access and backhaul resources; reduced energy use and unmet data demand	Increased backhaul complexity
Narváez & Miramá., 2018	Self-optimization	ML-based automatic optimization	Cellular networks	Enables self-organizing networks for dynamic interference control	Limited real-time validation
Nzenwata and Oludele., 2019	Frequency reuse analysis	Analytical modeling (PPP-based)	Multi-tier HetNet	Comparison of Strict-FFR and SFR; interference reduction and SE improvement	Static assumptions
Alquhali et al., 2020	Enhanced FFR (EFFR)	Region-based frequency partitioning	Dense femtocell networks	Improved SINR and throughput via three-region reuse	Fixed region allocation
Dahrouj et al., 2021	Learning-based optimization	RL, DNN, federated learning	5G optimization problems	Demonstrates ML suitability for complex optimization tasks	High training overhead
Mukherjee et al., 2021	Power efficiency	SFFR-based HetNet	Macro–micro–Femto	Reduced power transmission (~10.87%); improved SINR	Specialized architecture

Musa et al., 2022	Performance e valuation	SFFR vs FRF-3	5G NR	FFR outperforms FRF-3 in throughput and SE	Below theoretical peak limits
Alotaibi, 2023	Dynamic FFR	Cost-function–based optimization	Small cell / femtocell	Significant throughput gain over fixed FFR	Cost metric sensitivity
Zhi et al., 2022	D2D resource optimization	Multi-agent DQN	mmWave + cellular HCN	Improved sum-rate and convergence under QoS constraints	Signaling complexity
Azimi et al., 2024	RAN slicing	DRL + DL (A3C, LSTM)	5G RAN	Joint power and RB allocation; improved EE and isolation	Algorithmic complexity
Konstantoulas et al., 2025	Traffic prediction & allocation	LSTM / Transformer + CNN	5G BS networks	>99% prediction accuracy; effective user association	High data dependency
Rayyis et al., 2025	Resource prediction	CNN + BiLSTM + attention	5G systems	State-of-the-art prediction accuracy; low error metrics	Prediction-focused only
Umamaheswaran et al., 2025	Dynamic resource management	DNN + RL hybrid	5G network	Real-time adaptive allocation; improved throughput and EE	Training complexity
Poltronieri et al., 2022	Edge computing	DRL-based MECForge	MEC-enabled 5G	Maximized value-of-information via autonomous control	MEC-centric scope

From the reviewed liter ature, reinforcement learning and deep learning emerge as the most frequently employed ML techniques for FFR optimization due to their adaptability to dynamic and uncertain environments. Throughput, SINR, and spectral efficiency are the most commonly reported performance metrics, while latency and fairness are less frequently addressed. Notably, most studies rely on simulation-based evaluations, with limited real-time or large-scale implementations. Key research gaps include scalability in ultra-dense deployments, integration with real-time traffic prediction, and the application of federated and collaborative learning frameworks for privacy-aware optimization.

8.0 Conclusion and Future Direction

This survey makes several important contributions to the study of machine learning-based Fractional Frequency Reuse (FFR) in 5G networks. First, it provides a comprehensive review of existing machine learning approaches applied to FFR, covering supervised learning, unsupervised learning, reinforcement learning, and deep learning techniques within heterogeneous 5G network environments. Second, the paper presents a structured classification of the reviewed studies based on learning paradigms, network architecture, optimization objectives, and performance metrics, thereby enabling a clear comparative analysis of different design approaches. Third, the survey critically examines the effectiveness of ML-driven FFR schemes in enhancing throughput, spectral efficiency, interference mitigation, and fairness compared to traditional static FFR methods. Finally, this work highlights current research trends and provides guidance for future system design and optimization in next-generation wireless networks.

Despite these advancements, several research gaps remain. Many existing ML-based FFR solutions struggle with scalability in ultra-dense network deployments due to increased computational complexity and slow convergence. In addition, most studies rely heavily on simulation-based evaluations, with limited real-time or field implementation. High training overhead and strong dependence on large datasets also pose challenges for practical deployment in dynamic 5G environments.

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