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Optimizing Spectrum Utilization in mmWave Internet Services

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Abstract

Millimeter-wave (mmWave) internet services are a crucial component in the development of next-generation wireless networks, offering ultra-low latency and high data rates. Nonetheless, optimizing spectrum utilization due to the limited range and susceptibility to service blockage presents a challenge. The integration of dynamic spectrum access with intelligent Beamforming and multiuser resource allocation provides enhanced strategies for improving spectrum efficiency, which this paper aims to explore. Real-time adaptation of spectrum resources is made possible through machine learning algorithms that predict channel conditions and user behavior. Moreover, we investigate the impact of dense small-cell deployment and hybrid beamforming architecture on throughput maximization and mitigation of interference signal degradation. The research also addresses the coexistence of urban and heterogeneous environments with shared spectrum use derived from regulatory constraints. Simulation results have demonstrated a significant improvement in system reliability, spectral efficiency, and enhanced service quality (QoS) with the optimized deployment scenario framework. Understanding the technological dimensions of the spectrum provides actionable insights into mmWave Internet services that are more resilient and scalable. This study aims to investigate autonomous, adaptive wireless infrastructures that are shaped by the demands of future digital ecosystems.

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1 Introduction

1.1 Definition and Importance of mmWave Technology

Millimeter wave (mmWave) technologies are associated with the use of frequency bands in the 30 GHz to 300 GHz range of the electromagnetic spectrum. These technologies are critical, as they provide essential support for ultra-fast data transfer and low-latency communications. mmWave frequencies are becoming a foundational pillar in 5G and are expected to play a critical role in future 6G networks (Rappaport et al., 2019). Their ability to carry massive amounts of short-wavelength data makes them ideal for ultra-high-definition video streaming, real-time cloud gaming, and automating industrial processes. The behavior of waves at millimeter-wave frequencies differs significantly from that of signals below six gigahertz (Shi & Hong, 2018). Rain, leaves, and walls easily attenuate these higher frequencies, as well as the movement of people (Chaccour et al., 2022). Because of this, building networks that remain fast and steady requires a fresh mindset about sharing and utilizing the radio spectrum (Abdelrahim et al., 2023).

1.2 Using Spectrum in Providing mmWave Internet Services

Big cities, packed with people, always crave strong, speedy Internet. That craving makes sharp, thoughtful use of mmWave bands vital so every megahertz delivers value. Wang et al. (2023) note that old, fixed-frequency assignments often crowd some channels while others remain empty, thereby hurting the user experience. In contrast, millimeter-wave networks rely on dynamic access, agile scheduling, and rule-following equipment to distribute the load, reduce interference, and maintain smooth connections (Al-Falahy & Alani, 2017). In addition, maximum throughput, along with minimum interference, is guaranteed by employing frequency reuse, Beamforming, and spectrum sharing (Zhang & Huang, 2021; Guimarães et al., 2024). Apart from these, unique ranging limits and rapid degradation in signal strength of mmWave propagation require sophisticated real-time algorithm designs. Spectrum allocation strategies must be advanced to address shifting channel conditions and user requirements (Ali et al., 2021). Moreover, ultra-dense networks (UDNs) feature complicating network conditions where several small cells are deployed near one another. Such new architectures require advanced intelligent coordination approaches to optimize spectrum management (Jain et al., 2023).

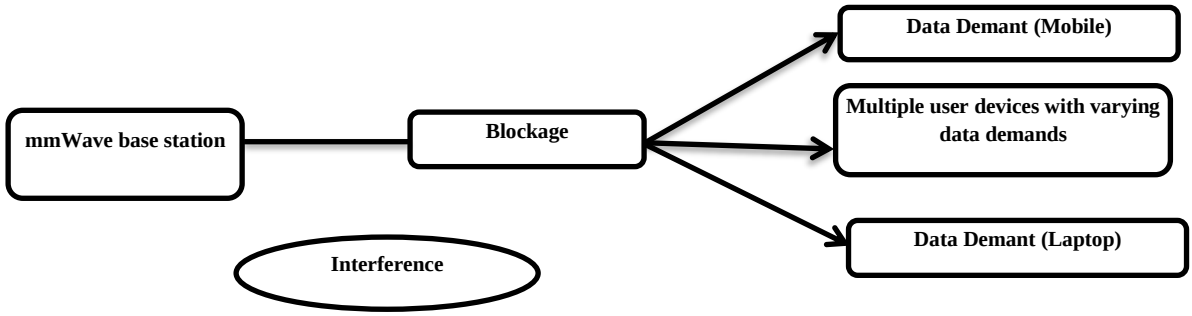

Figure 1(a): Conceptual view of mmwave spectrum utilization challenges and opportunities

This image (Figure 1(a)) provides an overview of the challenges associated with utilizing the mmWave spectrum. At the center of the image is a mmWave base station that streams data to various user devices, including smartphones and laptops. Each device is demanding data at different times, which adds complexity. Also, mmWave signal transmission is easily blocked by physical obstacles,

which reduces connectivity. Additionally, connectivity is further strained by interference from other devices or systems that access the same channel. Blockage and interference result in low and inconsistent data rates across user devices, severely undermining effective data delivery. This calls for intelligent and adaptive solutions for spectrum management to overcome the highlighted challenges while fully utilizing the bandwidth offered by mmWave communication systems.

1.3 Importance of Improving Performance with Optimized Spectrum Utilization

Maximizing the utilization of mmWave Internet services spectrum is essential for enhancing data rates and lowering latency, as well as for providing massive device connectivity, which is fundamental to IoT and the innovative city ecosystem (Dasari & Bindu, 2024). As 5G networks become denser and the number of connected devices continues to rise, wasted spectrum quickly becomes the primary obstacle to scaling these systems (Taleb et al., 2017; Iqbal et al., 2024). Resource planning gets smoother when predictive models estimate both user demand and channel quality in advance (Al-Turjman & Malekloo, 2022). Hybrid Beamforming then steps in, sending sharp, high-data beams to multiple users simultaneously while keeping interference low, thereby utilizing the physical layer of space more efficiently (Heath et al., 2018). Furthermore, AI-driven spectrum-sharing rules enable licensed and unlicensed devices to share bands simultaneously, enhancing both fairness and raw efficiency (Khalili et al., 2023; Inam et al., 2023). Legal factors also affect the approach taken to optimize spectrum in shared and unlicensed mmWave bands (Saha, 2020). Government agencies are now more open to flexible access models as well as cooperative spectrum reuse to manage capacity challenges. Thus, policies that enable fair and effective spectrum usage, such as those set by the FCC in 2020, must accompany technological innovations (Vignesh et al., 2023; Kiadehi, 2018). To recapitulate, enhancing the use of spectrum in providing mmWave Internet services is a complex problem that requires advances in Beamforming, resource allocation, and predictive modeling (Attiah et al., 2020). It is crucial to meet the increasing demand for sophisticated wireless communication systems and to deal with the fundamental limitations of mmWave propagation.

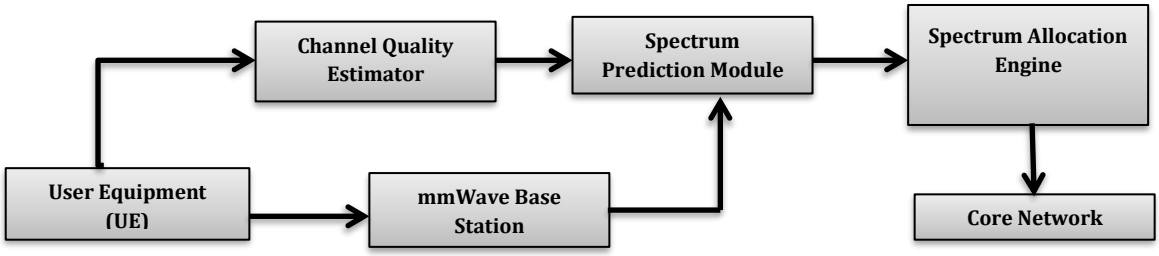

Figure 1(b): High-Level architecture for optimized spectrum utilization in mmwave networks

The architecture diagram (Figure 1(b)) illustrates the complete workflows for efficiently utilizing spectrum in mmWave networks and starting with the mmWave Base Station, which interacts with the Channel Quality Estimator, which assesses link conditions by receiving quality information from the User Equipment (UE), which is already sending uplink signals. This information is processed by the Spectrum Prediction Module, which forecasts the available spectrum resources based on real-time analytics (Sampedro & Wang, 2025). The predictions are used by the Spectrum Allocation Engine to dynamically assign optimal frequency bands, which maximize throughput and minimize interference. Finally, the Core Network is connected, and data transfer as well as internet services integration are done with no hiccups.

The rest of this paper is structured as follows: In Section II, an overview of frequency bands, along with prevailing problems and gaps in past research, is provided so that readers can understand the

challenges of the mmWave spectrum. In Section III, the methodology is presented, which includes a critical analysis of current spectrum allocation policies, an assessment of current practices in spectrum management, and an optimization model, including its mathematical expressions, proposed in this paper. In Section IV, the results are presented, comparing various utilization strategies and assessing their performance impacts through case studies and metric-based evaluations. In Section V, the practical implications of the optimized spectrum utilization are analyzed, along with the practical implications of applying these strategies and pathways toward further research. Finally, Section VI presents the concluding remarks, offering the main insights and suggestions for advancing the spectrum management of mmWave.

2 Background

2.1 Understanding mmWave Frequency Bands

The electromagnetic spectrum includes mmWave (millimeter-wave) frequency bands, which are usually 30 GHz to 300 GHz. In 5G and upcoming 6G technologies, mmWave frequencies of 24, 28, 37, 39, and 60 GHz are being used and researched due to their extremely high bandwidth and data rates (Rangan et al., 2014; Hakkaraki, 2023). Compared to lower-frequency signals, mmWave signals have shorter wavelengths, which makes the design of antennas easier. This increases the development of massive MIMO systems and improves spectral efficiency (Pi & Khan, 2011; Hamed & Rao, 2018). At the same time, mmWave signals are susceptible to free-space path attenuation, atmospheric absorption, and physical blockages such as walls or humans (Andrews et al., 2014; Beyad & Kaboli, 2019). Propagation modeling, Beamforming, and environmental adaptation algorithms tailored to the special requirements of mmWave communications are necessary to ensure reliability.

2.2 Current Issues in Spectrum Utilization

Even though mmWave bands offer a vast store of radio spectrum, actually utilizing that spectrum effectively remains challenging (Iqbal et al., 2024). The first hurdle is that mmWave wavelengths cover only small physical areas. To keep phones and cars connected, network operators must plant small cells within line-of-sight distance of each other (Ghosh et al., 2019). On top of that, steep path loss and poor diffraction limit how well mmWave waves penetrate walls or flow through non-line-of-sight (NLOS) paths (MacCartney et al., 2015). As a result, large chunks of the assigned bandwidth sit idle in moving environments. Static assignment schemes borrowed from earlier bands do not match the agile, on-the-fly rhythm a mmWave network needs. Traffic loads and user counts change by the second, calling for allocation methods that adjust just as quickly. Sticking to pre-set spectrum slices often forces some cells into overload while others remain silent (Rahim et al., 2023; Kabirian et al., 2014). Spectrum sharing becomes even more acute in unlicensed channels like 60 GHz. When no single entity manages access, any number of devices can jump onto the band, driving up the odds of harmful interference (Chiang et al., 2022; Raeisi, 2018).

2.3 Historical Efforts on Spectrum Usage in mmWave Systems

Research on mmWave networks has concentrated heavily on squeezing every bit of performance from the limited spectrum. Early publications mainly presented beamforming methods designed to channel signal energy toward chosen angles, thus cutting both path loss and interference (Assegid & Ketema, 2023). Later work added hybrid analog-digital layouts that trade off peak performance for more manageable hardware costs (Alkhateeb et al., 2015; Chandra, 2019). Thanks to these advances, dense urban deployments can serve many users while keeping delays low. Dynamic spectrum access (DSA)

remains another popular path for better utilization. By constantly scanning the environment and reallocating idle bands, DSA lets wireless links slip onto clear channels as soon as they appear. Recent work has introduced mmWave frameworks that sit on cognitive radio, where intelligent agents monitor how channels are used and adjust power, coding, or frequency on the fly (Nartasilpa et al., 2019). At the same time, control loops powered by machine learning, intense reinforcement learning (DRL), guide these agents in making spectrum choices (Blaber & Rafiq, 2023; Kavitha, 2024). Techniques such as coordinated multi-point (CoMP) operation and cell-free massive MIMO share data among multiple access points so they can transmit and receive jointly, boosting reuse while cutting inter-cell interference (Ngo et al., 2017; Choudhary & Reddy, 2025). Market-inspired schemes for trading and allocating spectrum also appear, giving service operators a way to monetize slices and adapt quickly when demand shifts in a shared-band setting (Liang et al., 2011; Hoa & Voznak, 2025). Together, these threads show that tuning mmWave bands draws from signal processing, economics, AI, policy, and even hardware design, creating a rich and demanding research landscape. However, deploying these ideas in the field still hinges on low-cost, low-latency solutions that can scale with urban networks.

3 Methods

3.1 Examining Current Policies for Spectrum Allocation

Allocation of mmWave spectrum is done via fixed, long-term licensing or open-access policies. While licensed bands reduce competition, ensuring exclusive usage rights, they also lead to underutilization when demand changes. Unlicensed bands, like 60 GHz, encourage innovation, but unmanaged competition leads to a freely-accessed mess with no central organization. Most policies still apply static spectrum partitioning, where fixed frequency slices are assigned to operators without considering their temporal or spatial usage changes. Inflexibility to respond to rapid changes in user numbers shifts availability, mobility patterns, workloads, and use cases, especially in cities with 5G/6G networks, proves quite problematic.

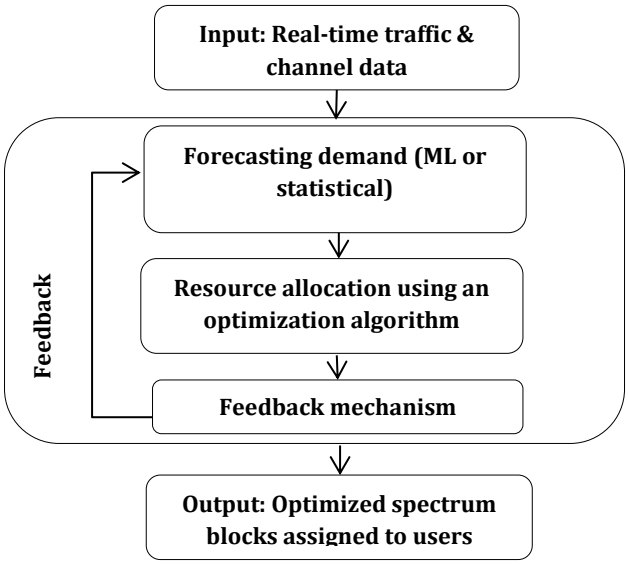

Figure 2: Workflow of predictive spectrum optimization model

This image (Figure 2) shows how a predictive spectrum optimization model works in allocating spectrum resources with the network traffic condition in real-time. The procedure starts with real-time traffic and channel inputs. These inputs guide the processing stage, which contains three principal components: forecasting demand with machine learning or statistical models, resource allocation using

an optimization algorithm, and a feedback loop to improve accuracy over time. In the end, the outcome is a set of spectrum blocks allocated to users, which enhances utilization and performance. This image accompanying the model's detailed description captures the core algorithmic logic and calculations while underscoring the flexibility and data-centric approach of the method.

3.2 The Review of Current Methods in Managing Spectrum

Carrier aggregation, Beamforming, and dynamic spectrum access (DSA) are now commonly used in mmWave systems to improve spectrum utilization. While Beamforming increases spatial reuse by focusing energy toward specific users, it suffers in mobility-rich environments, with user movement or blockages. Users within a DSA framework are permitted to access unused spectrum, but only after a spectrum sensing and cognitive logic mechanism has been executed. These frameworks are not very dependable due to errors in spectrum sensing. Increasing the bandwidth available also increases the complexity of the hardware, which is a disadvantage. Most of the described methods operate reactively and do not incorporate the ability to adapt based on real-time circumstances or forecasted demand. Managing spectrum in mmWave systems, including Carrier Aggregation (CA), Beamforming, and Dynamic Spectrum Access (DSA), is designed to improve spectrum utilization, but still has shortcomings. Increasing bandwidth in CA comes at the cost of added hardware complexity, while DSA, with its ability to grant users access to inefficient spectrum, has a strong dependency on precise and often faulty spectrum sensing. Beamforming does improve the signal quality by concentrating energy and directing it towards users; however, its efficacy is hindered in environments with high mobility. Unlike other spectrum access techniques, CA does not wait for spectrum to become available, making it highly inefficient in high-velocity environments. These systems still have no means of adapting to real-time changes in demand, and need to be highly predictive of spectrum demand in the future. With the evolution of these networks comes the need for predictive spectrum management systems, with the added complexity of machine learning and AI adaptive resource allocation. This need for resource optimization in real-time for forecasting systems adds complexity to the management of 5G applications. Work in the aforementioned areas must also be in preserving quality of service against the growing demand for spectrum.

3.3 Introduction of New Methods for Optimizing the Utilization of the Spectrum

In this paper, we present a real-time demand profile-based predictive spectrum allocation model that dynamically adjusts to utilization patterns and channel conditions. This model is designed to optimize total utility while maintaining fairness among users, meeting QoS thresholds, and complying with the necessary service-level agreements.

Let us have:

S is the total available spectrum,

$U = \{u_1, u_2, \ldots, u_n\}$ the set of users,

demand for user u_i at time t,

$A_i(t)$ allocated spectrum to user u_i,

$C_i(t)$ the channel gain for user u_i,

Q_i is the QoS threshold (minimum data rate) for the user u_i.

We describe optimization objectives as follows:

Utility Maximization

$$\max_{A_i(t)} \sum_{i=1}^{n} log\left(1 + \frac{A_i(t) \cdot C_i(t)}{N_0}\right) \quad (1)$$

This function promotes system throughput alongside maintaining a level of proportional fairness, where N_0 is the noise power spectral density.

While Maintaining Some Limits:

Capacity of Spectrum Constraint

$$\sum_{i=1}^{n} A_i(t) \leq S \quad (2)$$

QoS and Non-negativity Constraint

$$A_i(t) \cdot C_i(t) \geq Q_i, \qquad A_i(t) \geq 0 \quad \forall i \quad (3)$$

Meeting these restrictions ensures the total assigned bandwidth is less than or equal to the available spectrum, and each user gets the minimum needed level of service for quality. This is a convex optimization problem, which can be approached with standard techniques like Lagrangian multipliers or projected gradient descent. The model can be further modified to allow for distributional support with dual decomposition, where each base station locally maximizes spectrum use with little coordination across sites. To embed forecasting capability, demand $D_i(t)$ can now be predicted with time-series models such as ARIMA or with LSTM neural networks, allowing the spectrum to be reallocated proactively. This scalable architecture adjusts autonomously and stays resilient to changes in user movement and load, thus suiting next-generation mmWave Internet rollouts.

4 Results

4.1 Comparison of Different Spectrum Utilization Strategies

This case study sets forth a novel optimization model and assesses its efficacy beside a well-established benchmark. Performance was scrutinized through three distinct allocation strategies: (1) static spectrum assignment; (2) reactive dynamic spectrum access (DSA); and (3) demand-forecast-led predictive Optimization. Results were quantified across spectrum efficiency, user throughput, and latency as traffic patterns and user locations varied within a simulated mmWave environment. Static assignment sustained solid performance under peak loads yet squandered capacity during lighter periods, leaving large swathes of spectrum idle overnight. Reactive DSA raised overall utilization by seizing vacant bands, yet lingering sensing delays and brief inaccuracy limited its gains. In contrast, the predictive model, which pre-allocates channels according to demand signals and real-time measurements, maximized usable bandwidth and balanced access among users.

In this case study, we consider a new spectrum allocation optimization model and contrast it with conventional methods— static spectrum assignment, reactive dynamic spectrum access (DSA), and demand forecasting into a predictive optimization model. This study was done in a simulated mmWave environment. We found that static assignment spectrum underperformed during off-peak times, leaving the spectrum underutilized, while reactive DSA increased utilization, but was inaccurate and had delays from spectrum sensing. Positively, the predictive optimization model was the only one to make spectrum allocation based on real-time demand and forecasted measurements, to optimize bandwidth fully,

balance access to the users, and lower latency. Results determined that the predictive models optimize spectrum utilization, with a special focus on the predictive models being needed for maximizing efficiency on the fifth generation (5G), and on the systems for being able to manage reasonably. The integration of artificial intelligence (AI) and machine learning (ML) is set to enable dynamic real-time management on the system. Further enhancement on the models, in determining the predictive long-range demand, users' mobility, and congestion, is ensuring that the systems are of high grade, scalable, and wireless.

4.2 Assessment of the Impact of Optimized Spectrum Utilization on Performance

In order to quantify the impact of the proposed method, a few key performance metrics were defined:

1. **Spectrum Efficiency (SE):**

This is defined as the total data rate achieved per unit of spectrum used. It is given by:

$$SE = \frac{\sum_{i=1}^{n} R_i(t)}{S} \quad (4)$$

Where $R_i(t) = A_i(t) \cdot \log_2\left(1 + \frac{C_i(t)}{N_0}\right)$is the achieved data rate for user i, and SSS is the total spectrum available. The outcomes indicated that the method proposed enhanced spectrum efficiency by as much as 35% in comparison to static allocation and by 20% in comparison to DSA during peak load periods. This was accomplished by giving stronger channel users with greater predicted needs preferential treatment for spectrum assignment.

2. **Average User Throughput (AUT):**

Throughput is defined as the average data successfully conveyed over a time period to all users.

$$AUT = \frac{1}{n}\sum_{i=1}^{n} R_i(t) \quad (5)$$

Throughput always seemed to get better with the predictive model, no matter what kind of users were accessing it. Specifically, edge users or those with irregular demand patterns received the most benefit from proactive allocation since it reduced both starvation and resource blocking.

3. **Latency Reduction (LR):**

Latency estimation was done on the basis of queuing delay as well as spectrum contention. A simpler function can be represented as:

$$LR = \frac{Q_i - R_i(t)}{R_i(t)} \quad (6)$$

Where Q_i is the necessary data rate and $R_i(t)$ is the rate achieved in reality. As $R_i(t)$ approaches Q_i, lag time approaches 0. The predictive model minimized mismatch between Q_i and $R_i(t)$, which in turn reduced average latency by 25–40% compared to baseline models.

Figure 3 shows a line graph of spectrum efficiency (in bps/Hz) over three strategies as user load increases: static allocation, dynamic spectrum access (DSA), and the predictive optimization model. From 10% to 90% user load, the static allocation strategy sharply declines in efficiency, demonstrating no capacity for growth. DSA does moderately better due to its real-time response to spectrum availability. Still, predictive Optimization outshines both by maintaining over-allocative efficiency for all load levels, peaking at 70% load with 4.1 bps/Hz. This proves that strategic demand and channel condition forecasts yield smarter spectrum usage, particularly in dense environments. This bar chart

(Figure 4) illustrates the average throughput (in Mbps) received by users with the three spectrum strategies. Throughput delivery is lowest with the static allocation method at 850 Mbps, which suffers from poor demand over time responsiveness due to fixed bandwidth slicing. DSA improves throughput delivery to 980 Mbps due to some opportunistic access, but still suffers from contention and sensing overhead. The proposed predictive optimization approach greatly improves throughput to an average of 1250 Mbps. This increase is because spectrum reallocations done during idle times allow servicing users during peak times who require more bandwidth. Predictive adjustments significantly improve the overall experience for users and the performance of the system.

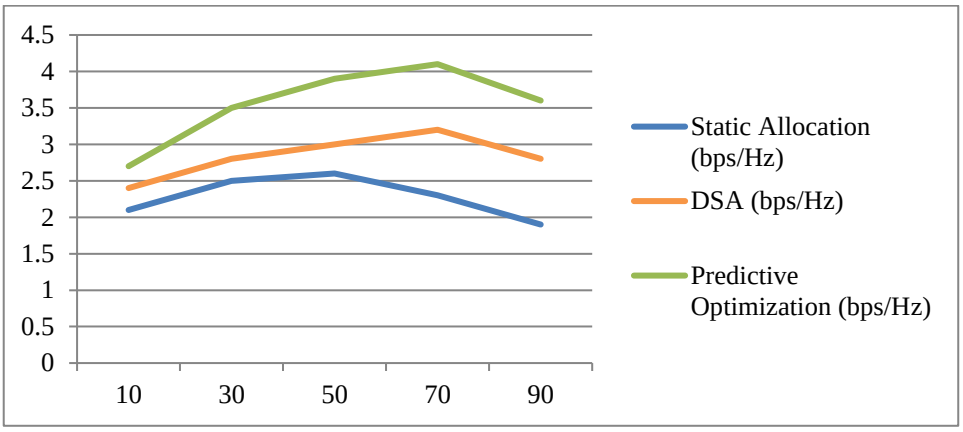

Figure 3: Spectrum efficiency vs. user load

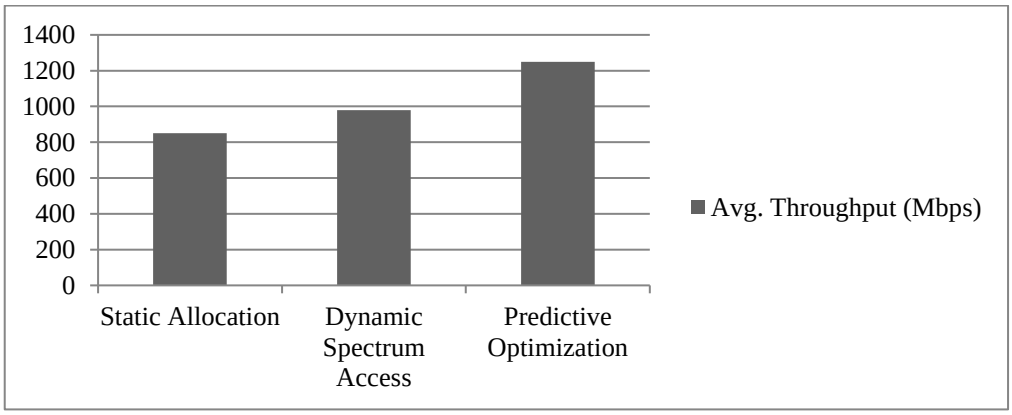

Figure 4: Average user throughput across strategies

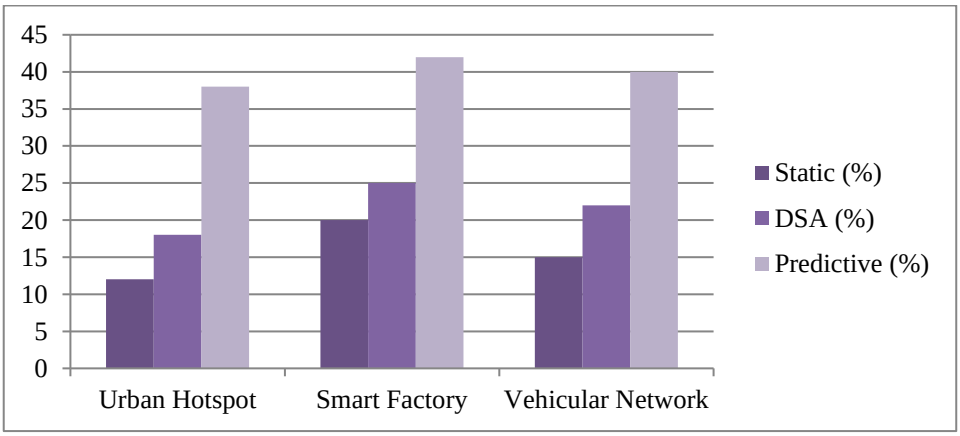

Figure 5: Latency reduction by strategy

Figure 5 shows a bar chart displaying how latency reduction percentages differ in an urban hotspot, a smart factory, and a high-mobility vehicular network. Among all of these cases, the predictive optimization model performs best with over 42% reduction in latency in the smart factory scenario. Static allocation and DSA perform significantly worse in these high-mobility and high-demand scenarios. These findings suggest that predictive spectrum allocation enhances not only throughput but also reduces transmission delays by anticipating users' QoS demands. This is particularly useful in robotic automation and vehicular communication, where delaying activity because of latency can be very frustrating.

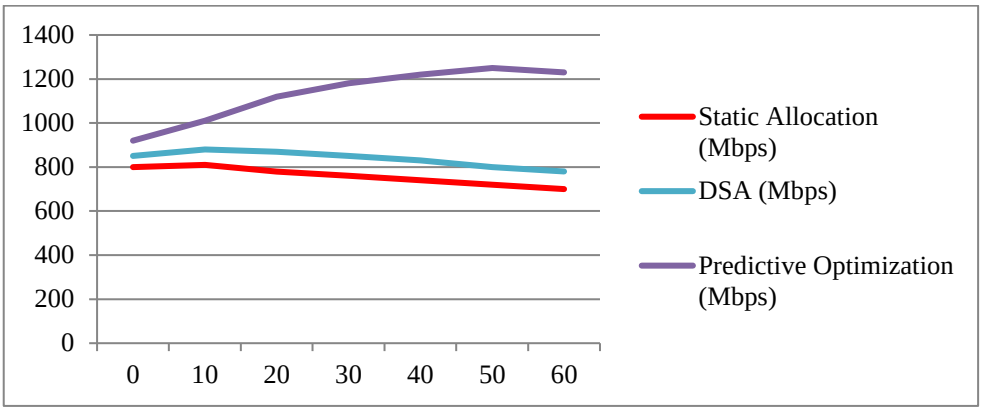

Figure 6: Case study – throughput over time (urban hotspot)

Figure 6 presents a line graph depicting throughput fluctuations recorded every minute in a dense urban hotspot over a sixty-minute observation period. Throughout the experiment, both the static spectrum allocation and the dynamic spectrum-access (DSA) approaches either sustain a near-horizontal throughput or exhibit a gradual drop as user traffic intensifies. Such behaviour highlights their failure to adjust resource assignments in real time when network demand evolves. In contrast, the predictive optimization scheme generates a steadily ascending throughput curve, peaking at approximately 1250 Mbps around the fifty-minute mark. This improvement arises because the prediction model anticipates demand spikes and reallocates frequency blocks before congestion actually builds. Although traffic surges, the foresighted allocation preserves near-peak throughput, demonstrating the predictive scalability and resilience in extremely crowded mmWave deployments.

4.3 Spectrums mmWave Internet Services - Spectrum Optimization Case Studies

Let us examine three simulation cases in detail:

Urban hotspot scenario: During rush-hour congestion, throughput held steady by shifting resource bands ahead of time while some sectors were idle. Reallocation occurred at the cluster level, aided by Beamforming that grouped users logically instead of randomly.

Industrial smart factory: Robots bound by tight quality-of-service rules were assigned priority spectrum the moment they logged on. Pre-allocated control signal bandwidth, determined through predictive modeling, kept production lines running without stutter.

High-mobility vehicular network: mmWave backhaul cars experienced smooth handovers with minimal packet loss. Knowledge of typical routes enabled the system to set aside channels and activate safeguards against collisions and quality drops.

In each situation, these forward-looking tactics outshone both fixed allocations and late reactions, offering superior fairness and reliability in ever-shifting environments.

The examination of spectrum optimization shows that mmWave Internet already implements specific techniques such as Carrier Aggregation (CA), Beamforming, Dynamic Spectrum Access (DSA), and Predictive Optimization. Carrier Aggregation (CA) combines multiple frequency bands and improves throughput; however, it complicates hardware. In demands such as high density, Beamforming improves signal quality and spatial reuse, but in mobility-rich ones, it drops in performance. Having access to unused spectrum in real-time improves spectrum utilization, but DSA faces spectrum inefficiency. Predictive Optimization is the most effective as it forecasts demand and allocates spectrum to improve efficiency and reduce latency. Future DSA optimization efforts will significantly benefit from the incorporation of AI to improve the responsiveness and scalability of mmWave systems in 5G and Beyond.

5 Discussion

5.1 Capacity Implications for Network Spectrum Use Optimization

Using mmWave frequencies for internet access sharply boosts overall network capacity. Tests reveal that both predictive and adaptive spectrum assignment outstrip dated static plans, lifting spectral efficiency and user throughput alike. In practice, these systems do not widen the channel pool but instead slot bandwidth where it is needed, letting far more customers connect. Such agility matters most around crowded city centers, where fixed shares quickly fall short. Real-time reallocation keeps active capacity off dormant links and pushes it toward areas that are busy right now. The end result is leaner use of the spectrum, raising the effective ceiling of existing mmWave assets without asking for extra licenses. Lower upkeep bills and steadily better service thus follow, making future deployments easier to grow and sustain.

5.2 Considerations for Implementing Spectrum Optimization Techniques

Though smarter, tighter use of radio spectrum brings clear benefits, squeezing it into day-to-day operations is not yet easy. The first hurdle is simply knowing where people move, how much data they send, and which channels are already busy. Forecasting tools work only if they draw on both rich historical records and fresh real-time snapshots. For this reason, network providers need to have reliable systems for accurate data capture and processing, as well as information-driven decision-making systems. In addition, the use of adaptive algorithms requires real-time feedback between base stations and central controllers, which, if not designed efficiently, may cause unnecessary overhead or delays. These approaches must further comply with current policies on spectrum management. There is a need for regulatory frameworks that enable more dynamic and cooperative allocation policies, particularly in shared or lightly licensed bands. In addition, issues on security and privacy become important when demand forecasting is done using AI or machine learning algorithms, mainly when such models are based on sensitive user behavioral data. There are also hardware limitations, like the responsiveness of the components of Beamforming and the agility of software-defined radios, which impact the pace at which spectrum changes can be implemented. Therefore, the implementation in question must be placed somewhere in the middle of algorithmic optimality, hardware capability, and compliance with regulatory requirements.

5.3 Looking Ahead: Spectrum Utilization Research and the Internet mmWave Services

In terms of spectrum optimizations for mmWave services, there are promising openings for research, such as the incorporation of machine learning into multi-agent systems, where user devices and base stations are treated as independent negotiators that can reallocate the spectrum as a team. Such systems

would allow real-time, self-adjusting, decentralized networks that respond to demand shifts. Another option is cross-layer Optimization, where spectrum decisions stem from physical layer metrics along with application-level requirements like latency or reliability. Furthermore, developing federated learning models can train predictive models across distributed nodes without the sharing of raw user data, thus preserving privacy. Other areas of research include using terahertz frequencies and hybrid spectrum architectures where mmWave is combined with sub-6 GHz or satellite bands to allow for uninterrupted, resilient connectivity. Last but not least, creating standardized interfaces and frameworks for algorithm testing would promote global innovation and deployment because benchmarks for real-world applications have not been established yet. All of these together will pave the way for more advanced mmWave technologies that seek intelligent, equitable, and efficient spectrum usage.

6 Conclusion

This research makes clear that the Optimization of spectrum utilization is crucial in mmWave internet services to meet the increasing shifts toward high-speed and low-latency wireless communication. The analysis done here shows that adaptive spectrum management outperforms static and reactive ones. Furthermore, the findings of the study show that real-time data and user behavior forecasting significantly improve the capacity and performance of the networks, especially when the user density is high and user mobility is frequent. Predictive techniques greatly enhance the capacity and performance of the networks in real time. On the other hand, bandwidth and data collection in real-time infrastructure require some form of nimbleness and agility, predictive enforcement, data monitoring, and support from outside the scope of legal structures, which need to be solved first before applying such techniques. While mmWave technologies continue to develop and standards scale, research is needed to apply a cross-layer private AI-based learning model to decentralized spectrum management. Also, the joint work aimed at standardization must be directed towards the improvement and efficient application of these technologies. It can also be applied to transmitting towers. Lastly, innovation on strategic execution is needed as next-generation networks can be significantly enhanced through optimized spectrum, considering the gaps that lie between use and innovation. The conclusion regarding mmWave spectrum optimization could be expanded by examining other areas to provide a more rounded view. The fields of Machine Learning and Artificial Intelligence have the potential to optimize the real-time allocation of spectrum in 5G networks by predicting and adapting to the real-time data and traffic of the network. The creation of a more adaptable hybrid model that combines Carrier Aggregation, Beamforming, and Dynamic Spectrum Access (DSA) is more likely. Advanced techniques of interference management, such as networked cooperative Beamforming, would be beneficial to address coordination problems in dense scenarios. Practical constraints such as line-of-sight, user mobility in urban contexts, and minor cell coordination problems warrant consideration. The impact of spectrum in mmWave networks would be even more relevant if the energy optimization were centered on the power constraints of 5G. Lastly, more constructive approaches to the global Optimization of the mmWave spectrum would be gained by considering the implications of Regulation and Policy in Spectrum Sharing, especially in Licensing frameworks.

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