# AN INTELLIGENT CALL ADMISSION CONTROL ALGORITHM FOR LOAD BALANCING IN 5G-SATELLITE NETWORKS

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# ABSTRACT

Cellular networks are projected to deal with an immense rise in data traffic, as well as an enormous and diverse device, plus advanced use cases, in the nearest future; hence, future 5G networks are being developed to consist of not only 5G but also different RATs integrated. In addition to 5G, the user's device (UD) will be able to connect to the network via LTE, WiMAX, Wi-Fi, Satellite, and other technologies. On the other hand, Satellite has been suggested as a preferred network to support 5G use cases. Satellite networks are among the most sophisticated communication technologies which offer specific benefits in geographically dispersed and dynamic networks. Utilising their inherent advantages in broadcasting capabilities, global coverage, decreased dependency on terrestrial infrastructure, and high security, they offer highly efficient, effective, and rapid network deployments. Satellites are more suited for large-scale communications than terrestrial communication networks. Due to their extensive service coverage and strong multilink transmission capabilities, satellites offer global high-speed connectivity and adaptable access systems. The convergence of 5G technology and satellite networks therefore marks a significant milestone in the evolution of global connectivity.

However, this integration introduces a complex problem related to resource management, particularly in Satellite – Terrestrial Integrated Networks (STINs). The key issue at hand is the efficient allocation of resources in STINs to enhance Quality of Service (QoS) for users. The root cause of this issue originates from a vast quantity of users sharing these resources, the dynamic nature of generated traffic, the scarcity of wireless spectrum resources, and the random allocation of wireless channels.

Hence, resource allocation is critical to ensure user satisfaction, fair traffic distribution, maximised throughput, and minimised congestion. Achieving load balancing is essential to guarantee an equal amount of traffic distributed between different RATs in a heterogeneous wireless network; this would enable optimal utilisation of the radio resources and lower the likelihood of call blocking/dropping. This research endeavours to address this challenge through the development and evaluation of an intelligent call admission control (CAC) algorithm based on Enhanced Particle Swarm Optimization (EPSO). The primary aim of this research is to design an EPSO-based CAC algorithm tailored specifically for 5G-satellite heterogeneous wireless networks. The algorithm's objectives include maximising the number of admitted calls while maintaining Quality of Service (QoS) for existing users, improving network resource utilization, reducing congestion, ensuring fairness, and enhancing user satisfaction. To achieve these objectives, a detailed research methodology is outlined, encompassing algorithm development, numerical simulations, and comparative analysis.

The proposed EPSO algorithm is benchmarked against alternative artificial intelligence and machine learning algorithms, including the Artificial Bee Colony algorithm, Simulated Annealing algorithm, and Q-Learning algorithm. Performance metrics such as throughput, call blocking rates, and fairness are employed to evaluate the algorithms' efficacy in achieving load-balancing objectives.

The experimental findings yield insights into the performance of the EPSO-based CAC algorithm and its comparative advantages over alternative techniques. Through rigorous analysis, this research elucidates the EPSO algorithm's strengths in dynamically adapting to changing network conditions, optimising resource allocation, and ensuring equitable distribution of traffic among different RATs. The result shows the EPSO algorithm outperforms the other 3 algorithms in all the scenarios.

The contributions of this thesis extend beyond academic research, with potential societal implications including enhanced connectivity, efficiency, and user experiences in 5G-Satellite heterogeneous wireless networks. By advancing intelligent resource management techniques, this research paves the way for improved network performance and reliability in the evolving landscape of wireless communication.

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# LIST OF ACRONYMS

| Acronym | Full Form |
|---|---|
| 3G | Third Generation |
| 4G | Fourth Generation |
| 5G | Fifth Generation |
| ABC | Artificial Bee Colony |
| AI | Artificial Intelligence |
| AP | Access Point |
| AR | Augmented Reality |
| BS | Base Station |
| BSR | Buffer Status Report |
| CAC | Call Admission Control |
| CLO | Cross-Layer Optimisation |
| CSI | Channel State Information |
| DSM | Dynamic Spectrum Management |
| D2D | Device-to-Device |
| EMBB | Enhanced Mobile BroadBand |
| EPSO | Enhanced Particle Swarm Optimisation |
| GEO | Geostationary Earth Orbit |
| HetNet | Heterogeneous Network |
| HTS | High Throughput Satellite |
| HWN | Heterogeneous Wireless Network |
| H2H | Human-To-Machine |
| IoT | Internet of Things |
| KPI | Key Performance Indication |

| | |
|---|---|
| LEO | Low Earth Orbit |
| LTE | Long-Term Evolution |
| LTE-A | Long-Term Evolution Advanced |
| MDP | Markov Decision Process |
| MEC | Multi-Access Edge Computing |
| MEO | Multi-Access Edge Computing |
| MIMO | Multiple Input Multiple Output |
| ML | Machine Learning |
| MMTC | Massive Machine Type Communication |
| mmWave | millimetre wave |
| MS | Mode Selection |
| MT | Mobile Terminal |
| M2M | Machine-To-Machine |
| NFV | Network Functions Virtualisation |
| NR | New Radio |
| NTN | Non-Terrestrial Network |
| OFDMA | Orthogonal Frequency-Division Multiple Access |
| PLF | Probabilistic Load Flow |
| PRB | Physical Resource Blocks |
| PSO | Particle Swarm Optimisation |
| QoE | Quality of Experience |
| QoS | Quality of Service |
| RAN | Radio Access Network |
| RAT | Radio Access Technology |

| | |
|---|---|
| RBs | Resources Blocks |
| RL | Reinforcement Learning |
| RRM | Radio Resource Management |
| RSRP | Reference Signal Received Power |
| RSSI | Received Signal Strength Indicator |
| RTT | Round-Trip Times |
| SDN | Software-Defined Networking |
| SatCOM | Satellite Communication |
| SINR | Signal-to-Interference-plus-Noise-Ratio |
| STIN | Satellite-Terrestrial Integrated Networks |
| UD | User Device |
| UE | User Equipment |
| URLLC | Ultra-Reliable Low Latency Communication |
| VBA | Virtual Basic for Applications |
| VHM | Vertical handover management |
| VNF | Virtual Network Functions |
| VR | Virtual Reality |
| Wi-Fi | Wireless Fidelity |
| WiMAX | Worldwide Interoperability for Microwave Access |
| WLAN | Wireless Local Area Network |

# ACKNOWLEDGEMENT

Reaching this point in my studies is underpinned by many enablers. I wish to start by acknowledging and pronouncing my gratitude to The Almighty God for the grace that enabled this great wonder – our existence – and the many blessings I enjoy.

I wish to acknowledge and thank my supervisory team – Prof Prashant Pillai and Dr Ali Safaa Sadiq for their contribution and support.

Last but certainly not least, I wish to acknowledge my family for their love, patience, support, and for making our journey joyful and fulfilling.

# DEDICATION

I dedicate this thesis to my beloved son, a beacon of inspiration; inspiring the resilience to persist and excel in this scholarly endeavour. May this thesis stand as a testament to the belief that hard work and determination pave the way for a brighter future, one that I aspire to build for you with love and perseverance.

# RESEARCH OUTPUT

- Bello, M., Pillai, P. and Sadiq, A.S., 2024. An intelligent load balancing algorithm for 5G-satellite networks. *International Journal of Satellite Communications and Networking*.
- Bello, M., Pillai, P. and Sadiq, A.S., 2022. AI-Based Call Admission Control Scheme For 5G-Satellite Network. In 2022 *Festival of Research (FSEFOR) Conference Proceedings*. pp.140 – 148.
- Bello, M., Pillai, P. and Sadiq, A., 2021, October. An Intelligent Hybrid Radio Access Technology Selection Algorithm for 5G-Satellite Network. In *2021 IEEE Mysore Sub Section International Conference (MysuruCon)* (pp. 42-49). IEEE.
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# CHAPTER 1: INTRODUCTION

## 1.1 OVERVIEW

There has been an exponential increase in cellular network data traffic over the last few years. New multimedia and broadband applications, as well as the Internet of Things (IoT) and mobile Internet technology, are all increasing quickly. The capacity, cost, data rate, coverage, and latency of the current communication system are all being challenged by emerging technologies like 4K ultra-high-definition video, virtual reality, tactile internet, remote surgery, smart devices, augmented reality, and machine-type communications [1].

Ericson Mobility report forecasts that the global monthly average mobile data usage will be 19GB in 2023 and is expected to increase to 46GB by the end of 2028 [2].

As a result of the rising demand for wireless services, mobile technology has advanced quickly towards the fifth-generation (5G) networking framework, which will allow rapid network connectivity for a wide range of applications. With regard to present demands, the implementation of 5G technologies will significantly increase cellular capacity.

Huge data exchanges are anticipated to be supported by 5G networks and their evolution. According to [3], 5G networks are planned to accommodate billions of Machine-to-Machine (M2M) and Ultra Reliable Low Latency Communication (URLLC) devices in addition to enhanced Mobile BroadBand (eMBB) connections. With the introduction of 5G, users will be able to share data anytime, anywhere, with any other users, or with any connected objects, with improved reliability and extremely low latency. In comparison to earlier generations, 5G also allows an extremely high connection density. The connection and control of self-drive vehicles, virtual and augmented reality, the smart city, factory automation, telemedicine, etc.

are only a few examples of the applications that are now available thanks to this technology [4].

A single network, however, is unable to meet customer demand for high speed, low latency, and large capacity services because of the explosion in traffic, particularly in remote areas and low-density areas where it is challenging to build ground base stations (BSs). Thus, 5G networks are being developed with heterogeneity concepts; numerous RATs, including those from the 3GPP and IEEE families, are being combined and controlled collaboratively [5].

Each Radio Access Technology (RAT) has different attributes, such as coverage range, security, data rate, energy consumption, and protocol support for mobility and security. Therefore, by employing multimode terminals (MTs), mobile users will be able to roam between several RATs and communicate using any of them [6].

Seamless traffic transfer between heterogeneous wireless access technologies will be a fundamental attribute of 5G, as well as the utilisation of multiple radio access technologies simultaneously to boost capacity, connectivity and reliability [7].

Today, the concept of integrating satellite components into a 5G network is gaining more attention. Satellite communication (SatCOM), which may provide communication services for areas that base stations cannot reach, has drawn the attention of researchers due to its properties of broad coverage, minimal delay, and high bandwidth. To offer continuous connectivity, Satellite-Terrestrial Integrated Networks (STINs) emerge as a new paradigm [8].

In addition to providing pervasive coverage, emergency/disaster recovery and broadcast/multicast delivery, SatCOM will be a key component of the 5G network [9]. Satellites will have unique opportunities as a result of their ability to support 5G services in remote regions. In addition, machine-type communications enabled by satellites will create new opportunities for smart agriculture, animal tracking, transportation, and environmental protection, among other applications [7]. A general 5G-Satellite integration network is shown in Figure 1-1 below.

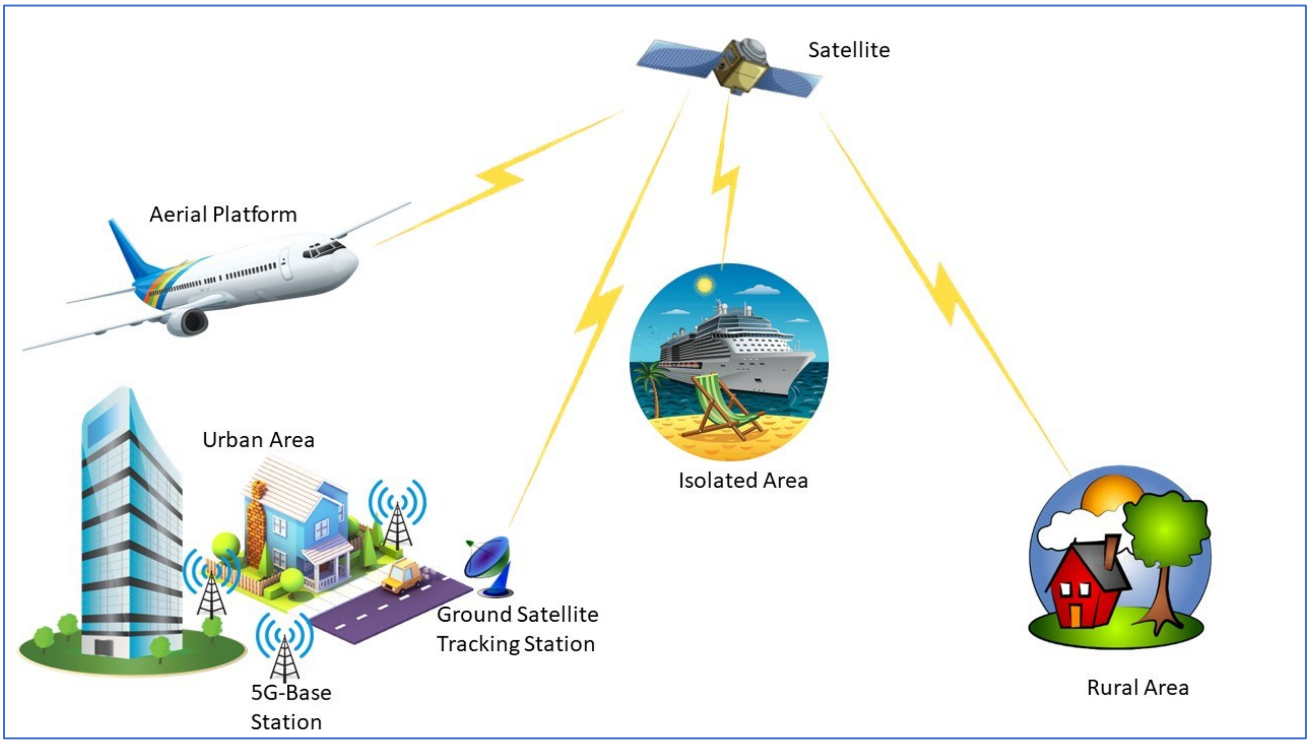


*Figure 1-1: 5G -Satellite Integration*

The key feature of 5G-Satellite heterogeneous wireless networks (HWNs) lies in their integrated framework, which blends terrestrial and SatCOM infrastructure. This combination made it possible to have higher capacity, wider coverage and enhanced network stability. Additionally, in order to guarantee effective use of spectrum, 5G-satellite HWNs utilise frequency bands appropriate for both terrestrial and SatCOM. By using this strategy, interferences may be reduced, resources can be allocated optimally, and network performance is improved overall.

However, apart from the use of spectrum, standardisation of protocols and frameworks is also essential to the smooth coexistence of satellite and terrestrial networks. Hence, cooperative efforts among industry stakeholders, standardisation bodies, and regulatory bodies are essential to guarantee network compatibility, interoperability, and a smooth user experience between various locations and service providers.

In conclusion, 5G-Satellite HWNs offer a very promising framework for achieving uninterrupted global connections. By utilising the benefits of both terrestrial and SatCOM, these networks can provide higher capacity, increased coverage, and pervasive connection. Even though there are still obstacles to overcome, cooperation and technical developments will make it possible for this game-changing technology to become a reality. As the world moves towards an increasingly connected future, 5G-Satellite HWNs hold the potential to revolutionise wireless communication and reduce the digital gap.

## 1.2 PROBLEM STATEMENT

The rapid growth in cellular network data traffic driven by emerging technologies like 4K ultra-high-definition video, virtual reality, IoT, and 5G connectivity has raised significant challenges in terms of capacity, cost, data rate, coverage, and latency [10]. As the global demand for mobile data usage continues to escalate, traditional cellular networks are struggling to keep up. To address these challenges, the integration of satellite communication into 5G networks has gained attention due to its potential to provide broad coverage, minimal delay, and high bandwidth, especially in remote and underserved areas.

However, this integration introduces a complex problem related to resource management, particularly in STINs. The key issue at hand is the efficient allocation of resources in STINs to enhance QoS for users [8]. The root cause of this issue originates from a vast quantity of users sharing these resources, the dynamic nature of generated traffic, the scarcity of wireless spectrum resources, and the random allocation of wireless channels [11].

Hence, resource allocation is critical to ensure user satisfaction, fair traffic distribution, maximised throughput, and minimised congestion. Moreover, the integration of multiple Radio Access Networks (RANs) in STINs introduces the challenge of load balancing, which aims to evenly distribute User Devices (UDs) among cells or access points (APs).

Existing load-balancing techniques often rely on manually chosen rules and expert knowledge, which may become inadequate as communication networks become more advanced [12]. Additionally, advanced communication networks need to be able to scale to support a large number of users and devices, and manually chosen rules may not be scalable to large networks. Moreover, new technologies, such as 5G and network function virtualisation (NFV), are introducing new challenges for load balancing, and manually chosen rules may not be able to effectively address these challenges.

Several traditional load-balancing techniques have been proposed in the literature. [13] incorporates two functional units into Media Independent Handover (MIH) to improve energy efficiency and seamless handover of mobile nodes across heterogeneous networks. The first unit optimises network scanning decisions and the second functional unit computes handover decisions using a utility function-based TOPSIS algorithm.

In a cellular-wireless local area network (WLAN) heterogeneous network, a novel load-balancing scheme was proposed that employs a cell-breathing technique for the WLAN network. The user association is controlled by the scheme, which balances the load among the cells [14].

In [15], the authors suggested a two-stage load balancing mechanism based on two biases to adjust the layer and RAT selection in multi-tier HetNets of LTE-A macro cells and mmWave small cells.

[16] proposed a cell selection algorithm for load balancing in two-tier HetNets based on Physical Resources Blocks (PRBs), Signal -to- Interference -plus-Noise Ratio (SINR), and reference signal received power. The algorithm uses estimated signal strength and biased pilot signals from base stations, preparing a list of candidate FAPs under the critical SINR condition. The algorithm allocates qualified Resources Blocks (RBs) to users, and its performance was evaluated for throughput and fairness index.

In [17], the user association is defined as a local optimisation problem in macro BS. Only a limited channel state information (CSI) feedback user association scheme was proposed, developing a low complexity successive offloading scheme. A distance-based load balancing algorithm was employed to enable users to connect with the closest BS when load imbalance is identified in Heterogeneous Networks (HetNets).

[18] study explores downlink resource allocation in two-tier HetNets with macrocells transmitting at microwave frequency and dual-band small cells using both frequencies. A novel architecture with dual-band small-cell base stations, serving users in inner and outer regions is proposed. A two-layer game theory approach is

used to maximise energy efficiency and spectral efficiency, focusing on non-cooperative frequency assignment and multi-objective optimisation.

[19] propose a vertical handoff algorithm based on load balance to address network congestion caused by large users connecting to partial networks in HetNets. The algorithm uses an analytic hierarchy process to weight networks, ensuring average load distribution and close network utilisation, based on user demands.

Another promising approach for load balancing is biased user association. This approach offloads users from macro base stations to small cell base stations, thereby reducing the load on macro base stations. It involves adding a positive bias value to small cell BSs, making them appear stronger to users. This bias influences user choice, encouraging more users to connect to small-cell BSs instead of macro-BSs. This redistribution alleviates the load on macro-BSs and improves network capacity and performance [20].

Although these algorithms improve load balancing performance, and provide flexibility and control, they also have drawbacks including scaling issues, restricted automation, lack of adaptability, reliance on specialist knowledge, inadequate performance, and difficulty in optimising trade-offs. These methods may not adapt well to unanticipated changes in network configuration or traffic fluctuations, and they might necessitate extensive reconfiguration work to support network evolution.

In light of these challenges, there is a pressing need to develop intelligent solutions that can dynamically manage resources in STINs. New load-balancing techniques that are more intelligent and adaptive have therefore emerged. Artificial Intelligence (AI) and Machine Learning (ML) algorithms, such as reinforcement learning, genetic algorithms, and neural networks, have shown promise in solving complex system control and resource management problems. These AI techniques offer the potential to adapt to dynamic network conditions and optimise resource allocation effectively. They automatically learn the traffic patterns on the network and dynamically adjust the load balancing rules accordingly.

Hence, this thesis addresses the resource management and load balancing challenges in 5G-Satellite HWNs using artificial intelligence to ensure quality of service, fair distribution of users, and efficient network performance, as well as optimising resource allocation in a dynamic network environment.

## 1.3 RESEARCH AIM AND OBJECTIVES

To address the challenges posed by the exponential increase in cellular network data traffic and the integration of SatCOM into 5G networks, this thesis proposes a dynamic solution that optimises resource management in 5G-Satellite HWNs. In this thesis, the resource management and load balancing problem in 5G-Satellite HWNs is solved by call admission control (CAC).

The aim of this research is to develop and evaluate an intelligent call admission control (CAC) algorithm for load balancing in 5G-satellite heterogeneous wireless networks. This algorithm aims to optimise resource management by maximising call admission, improving network resource utilisation, reducing congestion, maximising throughputs, ensuring fairness, and enhancing user satisfaction, while dynamically adapting to changing network conditions and traffic loads.

To achieve the aim of this thesis, the following objectives are pursued:

**Research Objectives:**

- Develop an intelligent call admission control algorithm based on Enhanced Particle Swarm Optimization (EPSO) to maximise the number of admitted calls while maintaining Quality of Service (QoS) for existing calls in 5G-Satellite HWNs.

- Investigate methods to improve network resource utilisation through dynamic resource allocation and load balancing techniques integrated into the EPSO-based CAC algorithm.
- Evaluate the effectiveness of the proposed EPSO-based CAC algorithm in reducing network congestion and minimising call dropping by efficiently sharing the load between co-located wireless networks.
- Assess the performance of the EPSO-based CAC algorithm in maximising throughputs to ensure efficient use of resources, improved data transmission rates, and increased user satisfaction.
- Investigate methods to ensure fairness in resource allocation among users within 5G-Satellite HWNs, while maintaining high system throughput and user satisfaction levels.
- Compare the performance of the EPSO-based CAC algorithm with other artificial intelligence and machine learning algorithms, including the Artificial Bee Colony Algorithm, Simulated Annealing Algorithm, and Q-Learning Algorithm, to evaluate its efficacy and suitability for real-world deployment.
- Implement the EPSO-based CAC algorithm and evaluate its performance through simulation experiments, considering various network scenarios and traffic conditions.

## 1.4 RESEARCH QUESTION

Given the research background, problem statement, aim and objectives, the research questions are as follows:

**RQ1:** How can dynamic radio resource allocation algorithms be tailored to effectively balance the load across 5G-Satellite HWNs, ensuring optimal utilisation of available spectrum resources?

**RQ2**: What decision-making mechanisms can be employed to accurately determine whether incoming calls should be admitted or rejected within the network, considering factors such as network congestion, user priority, and QoS requirements?

**RQ3**: How can intelligent call admission control strategies be devised to make optimal decisions regarding connectivity handover, including pre-emptive switching to maintain quality before degradation, automated quality assessment and selection prior to connection establishment, and reactive switching post-degradation?

**RQ4**: What criteria and metrics should be considered in selecting a unified solution capable of harmonising the diverse design paradigms prevalent in next-generation wireless networks, including the integration of SatCOM systems with terrestrial 5G networks, to ensure seamless interoperability and performance optimisation?

**RQ5**: How can ML and AI techniques be leveraged to enhance the intelligence and adaptability of call admission control mechanisms in 5G-Satellite HWNs, enabling proactive decision-making, real-time optimisation, and adaptive resource allocation in dynamic network environments?"

## 1.5 RESEARCH DESIGN

The research methodology followed a positivist approach, emphasising empirical observation and quantitative analysis to provide insights into CAC for load balancing in 5G-Satellite HWNs. Data was collected through simulation-based experiments. The sampling strategy used was the non-probability sampling technique to select simulation scenarios based on predefined criteria such as network topology, traffic patterns, and algorithm parameters.

Data analysis was conducted using statistical techniques to analyse the numerical data collected from simulations and derive empirical findings Finally, a CAC framework for load balancing in 5G-Satellite HWNs was developed as the output of the research findings. A summary of the methodology is presented in the following table (Table 1-1).

*Table 1-1: Summary of the Research Methodology*

| | |
|---|---|
| **Research Classification** | Experimental Study |
| **Research Philosophy** | Positivism |
| **Research Approach** | Quantitative approach |
| **Research Strategy** | Numerical simulation |
| **Data Collection Method** | Simulation experiment |
| **Sampling Methodology** | Non-probability sampling |
| **Data Analysis** | Quantitative analysis |
| **Research Instrument** | Simulation tools |
| **Research Outputs** | • The importance of efficient CAC for load balancing in 5G-Satellite HWNs.<br>• The key drivers behind the need for effective CAC for load balancing in 5G-Satellite HWNs.<br>• The key strategies for optimising network performance and resource allocation in 5G-Satellite HWNs.<br>• A CAC assessment tools and methodologies for evaluating the |

| | |
|---|---|
| | performance of the proposed algorithm in 5G-Satellite HWNs.<br>• The development of an intelligent CAC framework for load balancing in 5G-Satellite HWNs. |

The outcomes of the study have been published in peer-reviewed journal papers and conferences attended by academics and practitioners. This process allowed for the enhancement and improvement of the research techniques used in this investigation.

## 1.6 SCOPE AND LIMITATIONS

**Scope:**

- The scope of this research includes the development and evaluation of an intelligent CAC algorithm based on Enhanced Particle Swarm Optimization (EPSO) for load balancing in 5G-Satellite HWNs.
- The study focused on optimising resource management by maximising call admission, improving network resource utilisation, reducing congestion, maximising throughputs, ensuring fairness, and enhancing user satisfaction.
- The research involves numerical simulations to assess the performance of the EPSO-based CAC algorithm under various network conditions and traffic scenarios.
- The study considered the dynamic adaptation of the CAC algorithm to changing network conditions and traffic loads.
- The research compared the performance of the EPSO-based CAC algorithm with other benchmarked artificial intelligence and machine learning

algorithms, including the Artificial Bee Colony Algorithm, Simulated Annealing Algorithm, and Q-Learning Algorithm, in terms of call admission efficiency, resource utilisation, network congestion mitigation, fairness, and user satisfaction.

- The implementation and performance evaluation of the EPSO-based CAC algorithm and the other algorithms was conducted through numerical experiments.

**Limitations:**

Despite the innovative insights provided by this research, it still has some limitations:

- The research focused on numerical simulations and may not encompass real-world deployment scenarios. Actual implementation in live 5G-Satellite HWNs may encounter additional challenges not addressed in the simulations.
- The study considered a limited range of network scenarios and traffic conditions, which may not fully capture the diversity and complexity of real-world environments.
- The performance evaluation of the EPSO-based CAC algorithm is based on simulated results, which may differ from actual operational outcomes due to simplifications and assumptions made in the simulation model.
- The scope of comparison with other algorithms is limited to selected AI and ML, and the study may not encompass all possible algorithms used in related literature.
- The research may not address specific hardware or implementation constraints associated with deploying the EPSO-based CAC algorithm in practical 5G-Satellite HWNs environments.

- The study may not cover all aspects of network management and optimisation in 5G-Satellite HWNs, focusing primarily on the call admission control aspect.

## 1.7 THESIS CONTRIBUTION

This thesis covers the problems of resource management in 5G-Satellite HWNs and proposes a solution to tackle the aforementioned problem. The main contributions are as follows:

**Development of an Intelligent Call Admission Control (CAC) Algorithm**: This research contributes to the field by designing and implementing an intelligent CAC algorithm based on EPSO algorithm specifically tailored for call admission control to facilitate load balancing in 5G-satellite heterogeneous wireless networks. The algorithm aims to optimise resource management by maximising call admission while maintaining QoS for existing calls, thereby addressing the challenge of efficient resource allocation in dynamic network environments.

**Evaluation of EPSO-based CAC Algorithm Performance**: The study provides a comprehensive evaluation of the proposed EPSO-based CAC algorithm through numerical simulations. By assessing its performance under various network conditions and traffic scenarios, the research offers insights into the algorithm's effectiveness in reducing network congestion, maximising throughputs, ensuring fairness, and enhancing user satisfaction for 5G-Satelliet HWNs.

**Comparison with Other AI and ML Algorithms**: This thesis contributes to the literature by comparing the performance of the EPSO-based CAC algorithm with other AI and ML algorithms commonly used in call admission control. Through rigorous evaluation and benchmarking, the research identifies the strengths and weaknesses of different algorithms, thereby guiding future research and practical deployment decisions.

**Insights into Dynamic Resource Management**: By focusing on dynamic adaptation to changing network conditions and traffic loads, the research provides valuable insights into the challenges and opportunities associated with resource management in 5G-Satellite HWNs. The findings contribute to the advancement of knowledge in network optimisation and inform the development of more adaptive and efficient resource allocation strategies.

**Practical Implications for 5G-Satellite Networks**: This thesis offers practical implications for the design and implementation of call admission control mechanisms in 5G-Satellite HWNs. By considering factors such as computational complexity, scalability, and real-time decision-making requirements, the research provides guidance for network engineers and policymakers seeking to enhance the performance and reliability of next-generation wireless networks.

Overall, the contributions of this thesis advance the state-of-the-art in intelligent CAC for 5G-Satellite HWNs, offering novel insights, innovative algorithms, and practical recommendations for optimising resource management and enhancing network performance.

## 1.8 ORGANISATION OF THE THESIS

The thesis starts with this introductory section in Chapter 1 and finishes with the conclusions and recommendations in Chapter 6. To begin understanding the structure of this thesis, Figure 1-2 shows a visual representation which indicates the organisation of the thesis. The rest of the thesis is organised as follows:

**Chapter 2 – Literature Review Background. Chapter 2** offers a comprehensive overview of 5G Hetnets: Motivation and Vision. The chapter explores the concept of 5G-Satellite heterogeneous wireless networks, emphasising on the integration. Building on this, the section elaborates on the role of satellites within 5G networks, highlighting their significance as well as the challenges of integrating satellite components into 5G networks.

Moving forward, the chapter explores resource management methods, focusing on their relevance in HWNs. Subsequently, it delves into the importance of CAC in such networks and the need for efficient management. This section also introduces the concept of intelligent load balancing CAC as a solution to address resource allocation challenges. Additionally, it highlights the significance of AI algorithms in improving wireless network performance.

**Chapter 3 – CAC Framework In 5G – Satellite HWNs.** This chapter provides a comprehensive explanation of the proposed CAC model, emphasising its architecture and components. Furthermore, it discusses the integration of AI algorithms into the CAC framework. Additionally, this section details the use of the EPSO algorithm for CAC and RAT selection. Lastly, it explains the practical implementation and operation of the proposed CAC model.

**Chapter 4 - Simulation Framework.** This chapter outlines the simulation environment and its configuration for testing the proposed CAC model. Additionally, it discusses the scenarios and usage patterns considered in the simulation to evaluate the CAC model's performance. Furthermore, the chapter explains the metrics used for evaluating the performance of the CAC model. Finally, this section provides technical insights into the implementation of the simulation framework.

**Chapter 5. Results and Discussion.** This chapter presents the results of the simulations and analyses them in detail. Furthermore, it compares the performance of the proposed CAC model with existing AI-based algorithms. In addition, this chapter discusses the implications of the results on resource optimisation and network performance. Lastly, the chapter offers insights into the significance of the findings and their potential impact.

**Chapter 6. Conclusion & Future Work.** This chapter summarises the achievements and contributions of the proposed CAC model. Additionally, it identifies potential future research directions and areas for improving resource management in 5G-Satellite networks. Lastly, the chapter concludes with closing remarks on the significance of the research in addressing the challenges of 5G-Satellite heterogeneous wireless networks.

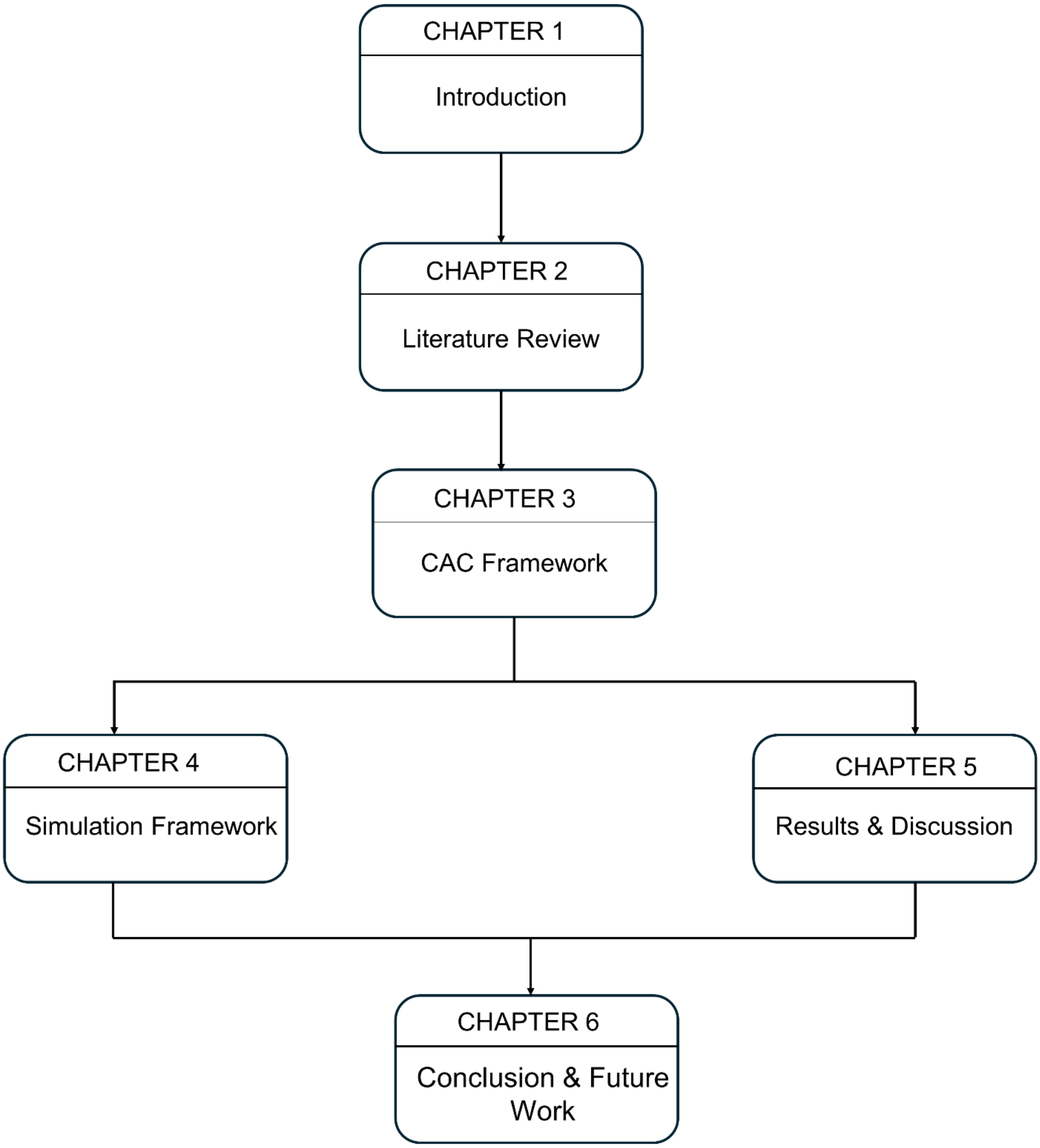


*Figure 1-2: Thesis Structure*

# CHAPTER 2: LITERATURE REVIEW

## 2.1 BACKGROUND

The swift growth and adoption of wireless network technologies have now made it possible for users to connect to networks via a variety of devices, whenever they want from anywhere. 5G technology is anticipated to have features including low-latency services, high-speed internet, and numerous devices connected to the Internet at once. The needs for various forms of communication are used to classify the 5G use cases [21].

The newly developed 5G network was deployed as a result of the enormous demand for more bandwidth and data speeds from the growing user base. 5G networks must be able to support enormous device connections, increased traffic flow capacities, and customised user service experiences in comparison to fourth-generation (4G) long-term evolution advanced (LTE-A) systems [22].

5G technologies are bringing about a fundamental change in the architecture of the core and access networks. The 5G system is directly tailored and optimised to serve a multitude of services and applications of specialised markets, in contrast to previous general-purpose standards to which applications and services were adapted [22].

5G networks are expected to support higher connectivity, improved capacity, high-speed data rates, and low latency. According to the International Telecommunications Union, 5G networks aim to deliver: 1,000 times higher mobile data volume per area; 100 times the number of connected devices; 100 times higher user data rate; ten times longer battery life for low-power massive-machine communications; and five times reduced end-to-end latency [23].

It has been projected to have higher capacity and increased user data rates than current capabilities, to satisfy the increasing needs of users. In addition, an essential key objective of 5G is to offer improved resilience, continuity, and much higher resource efficiency including a substantial reduction in energy consumption [24].

In recent years, 5G technology has advanced quickly, and numerous 5G BSs have been installed simultaneously. As a result, 5G network communication services are available everywhere, including urban and metropolitan areas. However, no single technology will be able to meet all of these requirements, and not every 5G application will need every one of these features [24]. In addition, it is challenging to offer network connection services to people in remote regions without internet connection infrastructure, such as oceans, deserts, and other locations.

Hence, to enable the vast range of use cases, including both global and local markets with highly diverse requirements, 5G needs to merge within the extensive system of all current communication technologies, utilising their particular strengths and services, next to the New Radio (NR) [25].

5G will come equipped with a built-in feature for seamless handover between heterogeneous wireless access technologies and the simultaneous usage of several radio access technologies to boost capacity, availability, and reliability [7].The 5G infrastructure will be a framework of interconnected networks that require several distinct but complementary technologies to succeed and satisfy user demands [26]. Thus, many organisations, including the European Commission identify that a component of the 5G infrastructure will include satellite networks. Among others, the role of satellites in 5G has been studied in the European Union (EU) Technology Platform NetWorld2020 SatCOM WG as well as in relevant R&D projects, such as SPECSI, MENDHOSA and INSTINCT, CloudSat, SANSA, VITAL, RIFE, and

SCORSESE. Moreover, the EMEA Satellite Operators Association (ESOA) has released a 5G White Paper on the SatCOM services' role as an integral part of the 5G framework.

Satellite networks are among the most sophisticated communication technologies which offer specific benefits in geographically dispersed and dynamic networks. Utilising their inherent advantages in broadcasting capabilities, global coverage, decreased dependency on terrestrial infrastructure, and high security, they offer highly efficient, effective, and rapid network deployments [26].

Satellites are more suited for large-scale communications than terrestrial communication networks. Due to their extensive service coverage and strong multilink transmission capabilities, satellites offer global high-speed connectivity and adaptable access systems [17].

The convergence of 5G technology and satellite networks therefore marks a significant milestone in the evolution of global connectivity. As the demands for high-speed data, ultra-low latency, and ubiquitous coverage continue to grow, the fusion of these two powerful communication paradigms offers a new horizon of possibilities. The marriage of 5G's terrestrial capabilities with the expansive reach of satellite networks creates a synergy that can reshape industries, reduce digital gaps, and connect even the most remote corners of the world.

Thus, by intelligently allocating traffic between several RATs, the integration of satellites into 5G systems will improve the QoS for UDs [27]. Furthermore, this integration gives the 5G network extra spectrum and broadband access in remote and rural regions [27].

However, the new challenge is how to effectively manage resources in STINs so that users can get improved Internet services. A crucial technology that influences how well STINs perform is resource allocation. According to the above 5G and satellite integration, a potentially poor load balancing decision could result in a reduction in Quality of Experience (QoE) for users and QoS for M2M [3]. In this chapter, the issue of resource management in 5G-Satellite HWNs is addressed. Figure 2-1 presents an overview of all the topics reviewed in this chapter.

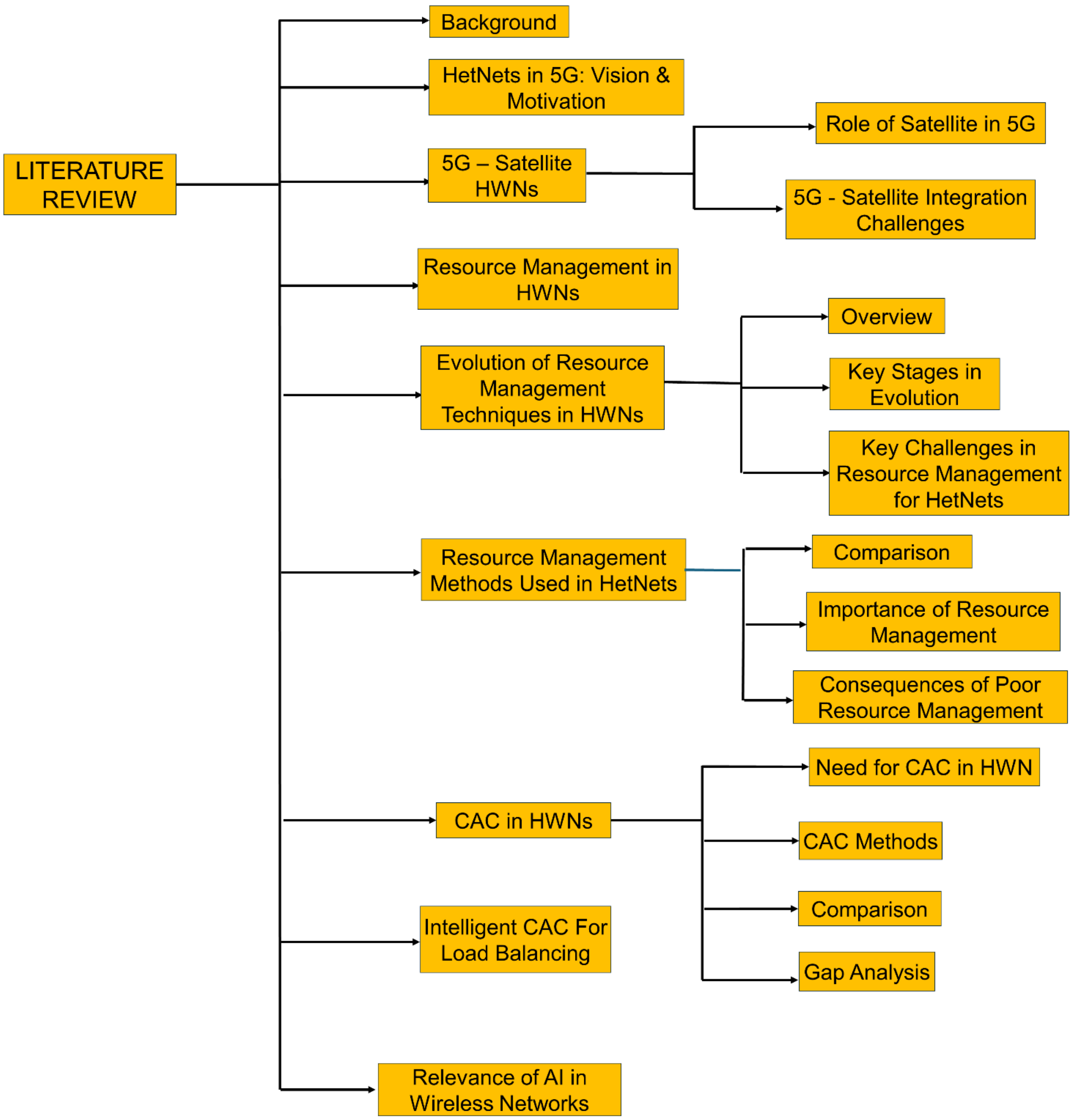


*Figure 2-1: Literature Review Overview*

## 2.2 HETNETS IN 5G: VISION AND MOTIVATION

The evolution of wireless communication systems has been progressing rapidly, with the imminent launch of 5G network. The transition to 5G technology has sparked significant interest in the research community, particularly in the context of IoT applications within the 5G wireless systems [28]. The integration of heterogeneous network technologies in 5G networks plays a crucial role in improving spectrum resources and overall network capacity [29]. 5G HetNets combines various types of cellular base stations – macrocells (traditional large towers), small cells (microcells, picocells, femtocells), as well as Wi-Fi, satellite amongst others to create a seamless and adaptable network.

The vision and motivation for 5G heterogeneous networks are driven by the need for improved performance, including high capacity, low latency, network virtualisation , and ubiquitous connectivity in modern wireless connectivity [30] .This technology is expected to support a wide range of applications, from smart homes and autonomous driving to health and mission-critical applications [31]. The vision and motivation behind HetNets in 5G encompass several key aspects:

**Enhanced Capacity**: One of the primary motivations for HetNets in 5G is to enhance the network capacity [32]. 5G promises a massive surge in connected devices; however, the explosion of connected devices and exponential growth in data traffic will strain traditional cellular networks [33]. Traditional macrocellular networks alone struggle to cope with the exponential growth in data traffic. By integrating small cells into the network architecture, 5G HetNets can distribute traffic across different cell types alleviating congestion and ensuring smooth operation for all users.

**Improved Coverage**: 5G HetNets aim to improve coverage, especially in areas with high user density or where macrocellular networks face coverage challenges [34]. Small cells, such as femtocells and picocells, as well as other cell types such as Wi-Fi, Satellite amongst others can be strategically deployed to fill coverage gaps, providing high-quality signals, improve indoor coverage, and enhance overall network performance [35]. This approach ensures that users experience consistent connectivity and high data rates across diverse environments, including urban, suburban, and indoor settings.

**Enhanced User Experience**: 5G HetNets promises to deliver a superior user experience by providing faster data rates, reduced latency, and improved reliability [36]. By leveraging the combined coverage and capacity of macrocells and small cells, users can enjoy seamless connectivity and high-quality services, even in densely populated urban areas or indoor environments.

**Support for Diverse Applications**: 5G applications span a wide range of use cases, from eMBB to URLLC and massive [37]. Figure 2-2 represents the main 5G use cases. 5G HetNets are designed to support these diverse applications by offering tailored network solutions optimised for specific requirements, such as high throughput, low latency, or massive connectivity.

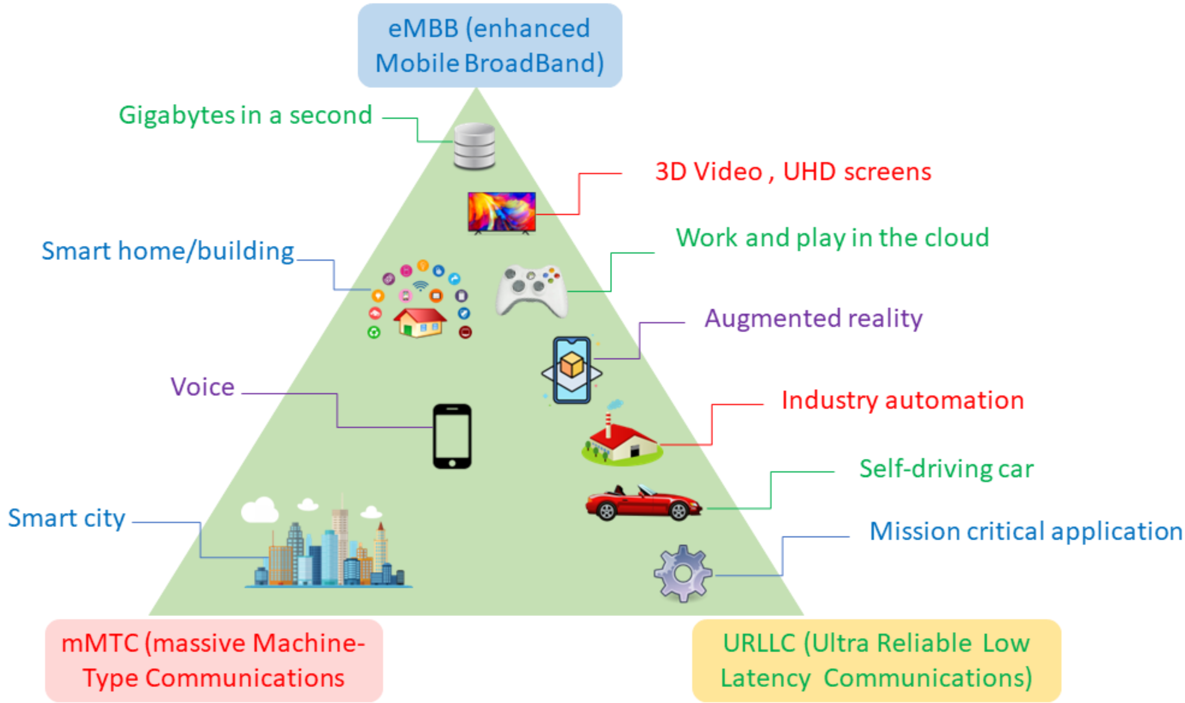


*Figure 2-2: 5G Network Use Cases*

**Accommodating Diverse Needs**: 5G caters to a wide range of applications, each with different requirements. 5G HetNets enable network slicing, where virtual networks are created on top of the physical infrastructure, allowing for customised performance for different services (e.g., high bandwidth for video streaming, ultra-low latency for autonomous vehicles) [38]. By providing low-latency, high-bandwidth connectivity, 5G HetNets support innovative use cases that rely on real-time communication, massive connectivity, and high reliability [21]. This enables new business opportunities and revenue streams for operators while unlocking transformative capabilities for industries and society as a whole.

**Improved Quality of Service (QoS)**: HetNets in 5G aim to enhance the QoS for users by optimising network resources and minimising interference [39]. By dynamically adjusting transmit power, resource allocation, and handover parameters, 5G HetNets can ensure that users receive the best possible service quality, even in challenging radio conditions [40]. Additionally, advanced interference management techniques, such as coordinated multipoint (CoMP) transmission and reception, help mitigate interference and improve spectral efficiency.

**Enhanced Quality of Experience (QoE)**: 5G HetNets aim to enhance the QoE for users by ensuring consistent connectivity, low latency, and high reliability [41]. By deploying small cells closer to users, 5G HetNets reduce signal attenuation and improve signal strength, resulting in better indoor coverage and higher data speeds. Additionally, 5G HetNets employs advanced mobility management and handover algorithms to maintain seamless connectivity during user mobility, ensuring uninterrupted service delivery and a superior user experience [42].

**Efficient Spectrum Utilization**: 5G HetNets enable more efficient spectrum utilisation by dynamically allocating resources based on demand and traffic patterns [43]. By leveraging both licensed and unlicensed spectrum bands, 5G HetNets can optimise spectral efficiency and maximise the utilisation of available resources, leading to better overall network performance.

**Scalability and Flexibility**: 5G HetNets provide scalability and flexibility to accommodate future growth and evolving network requirements [44]. The modular nature of HetNet architecture allows for easy deployment and expansion, enabling operators to adapt to changing demands and technology advancements seamlessly. Moreover, 5G HetNets leverages network intelligence and automation to optimise resource allocation, load balancing, and mobility management, enhancing overall network efficiency and performance [45].

In conclusion, the vision and motivation behind HetNets in 5G revolve around addressing the challenges of increasing data traffic, improving network performance, and delivering a superior user experience across diverse applications and environments. By integrating macrocells and small cells into a unified network architecture, 5G HetNets pave the way for a more connected, intelligent and responsive wireless ecosystem.

## 2.3 5G-SATELLITE HETEROGENEOUS WIRELESS NETWORKS

According to Ericsson, 5G networks will be carrying 45% of the world's mobile data traffic by 2025 [2]. Also, 5G systems will need to achieve important Key Performance Indicators (KPIs), such as consistent QoS provisioning, high level of security, low latency, and massive device connectivity [46]. For example, 5G is anticipated to offer user bitrates up to 10 Gbps and to have Round-Trip Times (RTTs) as small as 1 – 10 ms for some application scenarios [46].

However, the available spectrum will not be able to meet this enormous demand. The cost of pure terrestrial coverage will soon become too expensive. Therefore, SatCOM will play a significant role in 5G as a complementary solution for ubiquitous coverage, broadcast/multicast provision, and emergency/disaster recovery thanks to their attractive features such as their very wide coverage area and short service deployment time [47]. Satellites will have unique opportunities for providing 5G services in remote locations.

Additionally, satellites will support machine-type communications, paving the way for new applications, ranging from transportation, environmental protection, animal tracking, and smart agriculture, amongst others [48].

By 2020-2025 there will be more than 100 High Throughput Satellite (HTS) systems using GEO orbits but also mega-constellations of LEO satellites, delivering Terabit per second (Tbps) of capacity across the world. These upgraded satellite systems are anticipated to supply RANs, also known as Satellite RANs, which will be incorporated into the 5G system together with other wireless technologies, like Wi-Fi, cellular systems, and so forth [49]. By utilising SatCOM's diverse strengths, 5G systems can achieve greater range, capacity, and capabilities.

### 2.3.1 Role of Satellite in 5G Networks

The role of satellites in 5G networks is still evolving, but it is clear that satellites will play an important role in the future of 5G. Satellites can provide redundancy, support high-bandwidth applications, and complement and enhance the terrestrial 5G infrastructure and services, particularly in terms of coverage, capacity, and connectivity. They will address challenges related to reaching remote, rural and underserved areas. Below is a brief overview of the role of satellites in 5G networks. Figure 2-3 presents the visual overview of the Satellite roles discussed below.

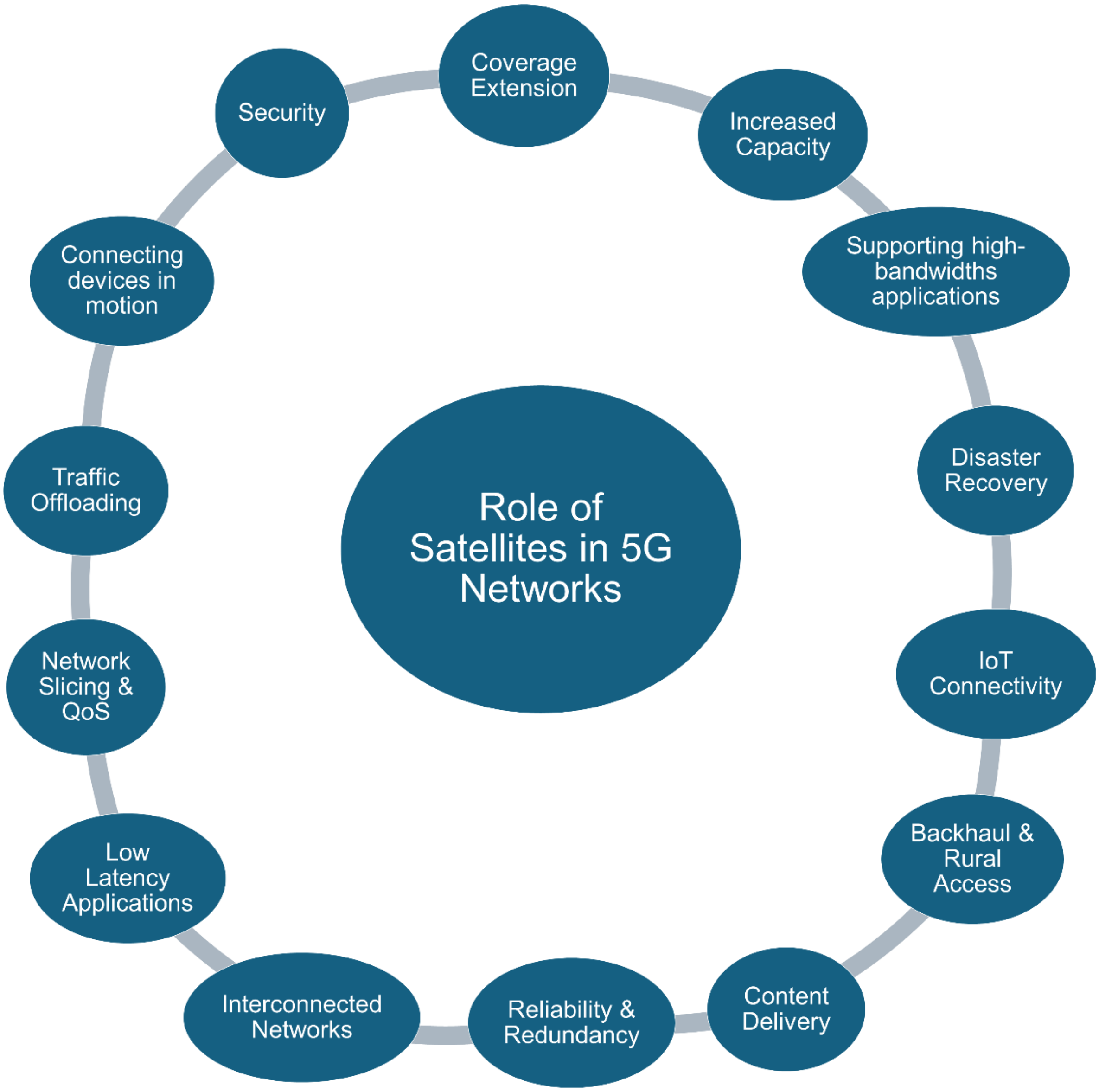


*Figure 2-3: Role of Satellites in 5G Networks*

**Coverage Extension**: Satellites provide wide-area coverage that complements the limited coverage of terrestrial 5G networks [50]. They can be used to extend 5G networks to areas that are not well served by terrestrial networks such as high latitudes, polar regions, oceans, air space, rural and remote areas, as well as any other geographically challenging areas where building extensive terrestrial infrastructure is not feasible.

**Increased Capacity**: Satellites can provide capacity, which is the amount of data that can be transmitted or received, to support various applications and services that require high throughput, low latency, or global reach, such as smart cities, IoT, e-health, or public safety [51].

**Supporting high-bandwidth applications**: Satellites can be used to support high-bandwidth applications, such as Virtual Reality (VR) and Augmented Reality (AR), that require more bandwidth than terrestrial networks can provide [52].

**Disaster Recovery**: During natural disasters or emergencies when terrestrial networks are disrupted, satellites provide a reliable communication link for disaster response and recovery efforts [53].

**IoT Connectivity**: Satellites extend 5G's IoT capabilities by connecting devices in remote or hard-to-reach locations, such as sensors in remote agricultural fields or equipment in remote industrial sites [54].

**Backhaul and Rural Access**: Satellites can serve as a backhaul link to connect remote cell towers and provide connectivity to areas where terrestrial backhaul is challenging to deploy, especially in remote, rural or hard-to-reach areas where terrestrial backhaul is not available or cost-effective [55].

**Content Delivery**: Satellites can support content delivery and broadcasting by reaching a wide audience, including areas where terrestrial distribution is limited [56].

**Reliability and Redundancy**: Satellites can be used to provide redundancy and backup for 5G networks in case of a terrestrial network outage to ensure the reliability and availability of 5G services [57]. This is important for critical applications, such as emergency services and financial services.

**Interconnected Networks**: Satellites can be integrated into multi-access edge computing (MEC) and distributed cloud architectures to optimise data processing and minimise latency for remote users [58].

**Low Latency Applications**: While traditional SatCOM introduces latency due to the signal travel distance, certain advanced satellite constellations in LEO are designed to reduce latency, making them suitable for low-latency applications like remote surgery and autonomous vehicles [59].

**Network Slicing and QoS**: Satellites can be integrated into network slicing strategies to allocate dedicated slices for specific services, ensuring QoS for different applications [60].

**Traffic Offloading**: Satellites can offload traffic from congested terrestrial networks, especially during peak usage times, improving the overall user experience [61].

**Connecting devices in motion**: Satellites can be used to connect devices that are in motion, such as ships and aeroplanes, which are not well-served by terrestrial networks [62]. For instance, Satellites can offer reliable in-flight connectivity for passengers during air travel, enabling in-flight entertainment, internet access, and real-time communication.

**Security**: Satellite networks can offer effective solutions for secure, highly reliable, rapid and resilient deployment in difficult communication situations like emergency response [63].

### 2.3.2 5G – Satellite Integration Challenges

Integrating 5G terrestrial networks with satellite networks poses several challenges due to the distinct characteristics, technical differences, and operational considerations of both technologies.

Addressing these challenges requires close collaboration among terrestrial and satellite network operators, technology vendors, regulatory bodies, and standards organisations. Overcoming these hurdles is essential to create a seamless, reliable, and efficient 5G-Satellite integrated network ecosystem that benefits users across various scenarios and regions. Below are some key challenges associated with 5G-Satellite integration. Figure 2-4 presents the visual overview of the 5G-Satellite integration challenges discussed below.


*Figure 2-4: 5G-Satellite Integration Key Challenges*

**Limited Spectrum**: The radio spectrum is a finite resource, and it is becoming increasingly crowded as more and more devices and applications are using wireless communication. This makes it difficult to find new frequency bands for 5G-Satellite HWNs, and it also makes it difficult to harmonise frequency bands between different countries and regions [23].

**Interference Mitigation**: When two or more wireless networks operate in the same frequency band, they can interfere with each other. This can cause problems such as dropped calls, degraded data rates, and even service outages. There are a number of techniques that can be used to mitigate interference, such as power control, beamforming, and frequency reuse [23]. However, these techniques can be complex and expensive to implement, and they may not always be effective in all situations.

**Seamless Handover**: Seamless handover is a critical challenge in 5G-Satellite HWNs. This is because the two networks have different characteristics, such as different propagation delays, different radio link budgets, and different mobility patterns [64]. This makes it difficult to ensure that a handover between the two networks will be smooth and seamless.

**Latency:** Latency variability is a major challenge in 5G-Satellite HWNs. This is because the distance between the user and the satellite is much greater than the distance between the user and a terrestrial base station. This results in longer propagation delays, which can lead to higher latency [65].

The latency of a SatCOM link can vary depending on a number of factors, such as the distance between the user and the satellite, the elevation angle of the satellite, and the atmospheric conditions. This variability can make it difficult to maintain low latency for applications that are sensitive to delay, such as real-time gaming and video streaming [65].

**Orbital Consideration:** Different types of satellite orbits (LEO, MEO, GEO) have varying latency, coverage, and bandwidth characteristics, which must be optimised for different use cases. The choice of satellite orbit depends on the specific application [66]. For example, LEO satellites are well-suited for applications that require low latency, such as real-time gaming and video streaming. MEO satellites are well-suited for applications that require a balance of latency and coverage, such as maritime and aviation communications. GEO satellites are well-suited for applications that require large coverage areas, such as rural broadband access [66].

**Coverage Alignment**: For satellite networks, coordination of satellites in different orbits (LEO, MEO, GEO) to provide uniform coverage can be challenging. Aligning satellite coverage areas with terrestrial cells is a technical challenge [67]. This is because the satellite coverage areas are constantly changing due to the movement of the satellites. The network must be able to dynamically adjust the coverage areas to ensure that users always have a connection.

**Protocol Compatibility:** The protocols and interfaces between terrestrial and satellite networks must be compatible to ensure seamless communication and handover [68]. This is a complex challenge, as there are many different protocols and interfaces in use.

**Roaming Management**: Roaming management is the process of managing user roaming across different network types while maintaining connectivity, quality, and billing consistency. This is a complex challenge, as it requires the coordination of multiple networks [69].

**QoS Across Networks:** QoS is the ability to provide a certain level of performance for different types of traffic. This is important in 5G-Satellite HWNs, as users may be moving between terrestrial and satellite networks. It is important to ensure that the QoS of the service is maintained even when the user is moving between networks [70].

**Network Slicing**: Network slicing is the process of partitioning a network into multiple virtual networks, each with its own dedicated resources. This can be used to allocate dedicated resources for different services across integrated networks [71]. Network slicing can help to improve the efficiency of the network by allocating resources to different services only when they are needed.

**Security:** Secure handover is the process of ensuring that data is kept confidential and secure when a user is handed over from one network to another. This is a challenge in 5G-Satellite HWNs because the two networks have different security protocols and mechanisms [72].

**Authentication Complexity**: Authentication is the process of verifying the identity of a user or device. This is a challenge in 5G-Satellite HWNs because the two networks have different authentication protocols and mechanisms [73]. There are a number of techniques that can be used to implement robust authentication mechanisms. These techniques include using strong passwords, two-factor authentication, and biometrics amongst others [72].

**Network Management**: Network management is the process of managing the integrated network, including resource allocation, load balancing, and real-time network monitoring [74]. This is a challenge because the network is heterogeneous and consists of different types of nodes, such as terrestrial base stations and satellite gateways. There are a number of techniques that can be used to manage the integrated network. These techniques include using software-defined networking (SDN), artificial intelligence and virtualisation.

**Satellite Tracking**: Satellite tracking is the process of accurately tracking the positions of satellites to ensure proper connectivity and handover between different coverage areas [75]. This is a challenge because the satellites are moving, and the coverage areas are constantly changing.

There are a number of techniques that can be used to track satellites. These techniques include using ground-based tracking stations, using satellite-based tracking systems, and using machine learning [75]. The development of these techniques will help to make it possible to track satellites accurately in 5G-Satellite HWNs.

**Cost and Investment:** Deploying and maintaining heterogeneous networks can be complex and costly due to the need for infrastructure, equipment, and coordination [76]. The cost of establishing the infrastructure for 5G-Satellite HWNs is significant. This includes the cost of ground stations, satellite constellations, and related infrastructure. The operational expenses for 5G-Satellite HWNs are also significant. This includes the cost of operating and maintaining the ground stations, satellite constellations, and related infrastructure.

**Uniform User Experience:** Ensuring a consistent and satisfactory user experience across integrated networks, regardless of whether users are on terrestrial, or satellite connections is a key challenge in 5G-Satellite HWNs. This is because the two networks have different characteristics, such as latency, bandwidth, and coverage [77]. There are a number of techniques that can be used to ensure a uniform user experience. These techniques include using network slicing, caching, QoS, AI and ML [70].

Despite these challenges, 5G-Satellite HWNs have the potential to be a valuable asset for a variety of applications. As the technology continues to develop, it is expected that 5G-Satellite HWNs become more widespread and affordable.

## 2.4 RESOURCE MANAGEMENT IN HWN

As discussed above, one of the main challenges for 5G-Satellite HWNs is radio resource management, which tackles the allocation of radio resources to various users while assuring user satisfaction. [78] argue that the primary challenge is the heterogeneity itself, including the number of different devices and technologies, different service requirements, and increasing complexity. The combination of these technologies in the same network, with their complementary characteristics, to afford complete coverage to users can cause various challenges such as seamless handover, resource management and CAC. This problem emanates from the increasing number of users and devices sharing these available resources, the heterogeneity of the network, the random distribution of wireless channels, the scarcity of wireless spectral resources, and the dynamic behaviour of generated traffic.

Resource management in HWNs is vital for optimising network performance, ensuring QoS, and preventing congestion. Effective management enhances user experiences, reduces costs, and supports the seamless operation of diverse wireless technologies. Poor resource management, on the other hand, leads to network issues, wasted resources, and an unsatisfactory user experience.

Hence, resource management in HWN has become a hot research topic in the last decade. [79] proposes a radio resource management framework that can be supported by future network architectures to guarantee QoS requirements, reduce new call blocking probability, and maintain efficient resource utilization. [10] proposes an efficient resource allocation algorithm to address the inefficient allocation of available resources versus QoS challenges. The authors in [80] provide a comprehensive review of resource management in 6G HetNets, identifying severe challenges associated with current resource management methods and proposing suitable solutions. One of the proposed solutions is Mode Selection (MS). MS methods are essential for determining the best mode for users in cellular and D2D networks due to the availability of multiple communication modes, as illustrated in Figure 2-5. Dynamic MS methods, such as fuzzy clustering, multi-hop cellular network communications, and context-aware strategies have been used to improve network efficiency, system throughput, and network capacity.

In [81], the authors used resource management to allocate radio resources to users and applications in LTE/LTE-A heterogeneous networks. The resource allocation criteria are based on device priority, power, channel quality, Buffer Status Report (BSR), etc. This is done to ensure that all users have a good QoE.

The authors in [82] aim to improve Wi-Balance in Wi-Fi heterogeneous networks by adjusting the AP load threshold and introducing two new indicators for station reassociation. The SDN controller gathers uplink RSSI and channel usage for each AP, computes total channel occupancy, and triggers user reassociation or channel reassignation processes based on average RSSI, AP load, and Channel Occupancy. The algorithm maximizes the product by selecting the best trade-off between signal quality and network resources used, reducing transmission time and improving performance. Figure 2-6 shows a scenario where this indicator triggers a reassociation process. Figure 2-7 shows an AP load indicator triggering a handover as a condition. Figure 2-8 shows a scenario where this indicator triggers a channel reassignation as the subtraction of the channel occupancy of Channel Y (the minimum) from the channel occupancy of Channel X (the maximum) is bigger than the median.

In [83], resource management is used to allocate spectrum, power, and other resources to users and applications in 5G heterogeneous networks. In 5G networks, resource management is used to allocate spectrum, power, and other resources to users and applications. This is done to meet the demands of high-speed data applications, such as AR and VR.

Therefore, resource management is an important part of ensuring the efficient and reliable operation of HWNs. By carefully managing the available resources, it is possible to improve the QoS for users and applications, reduce congestion, and improve the overall performance of the network.

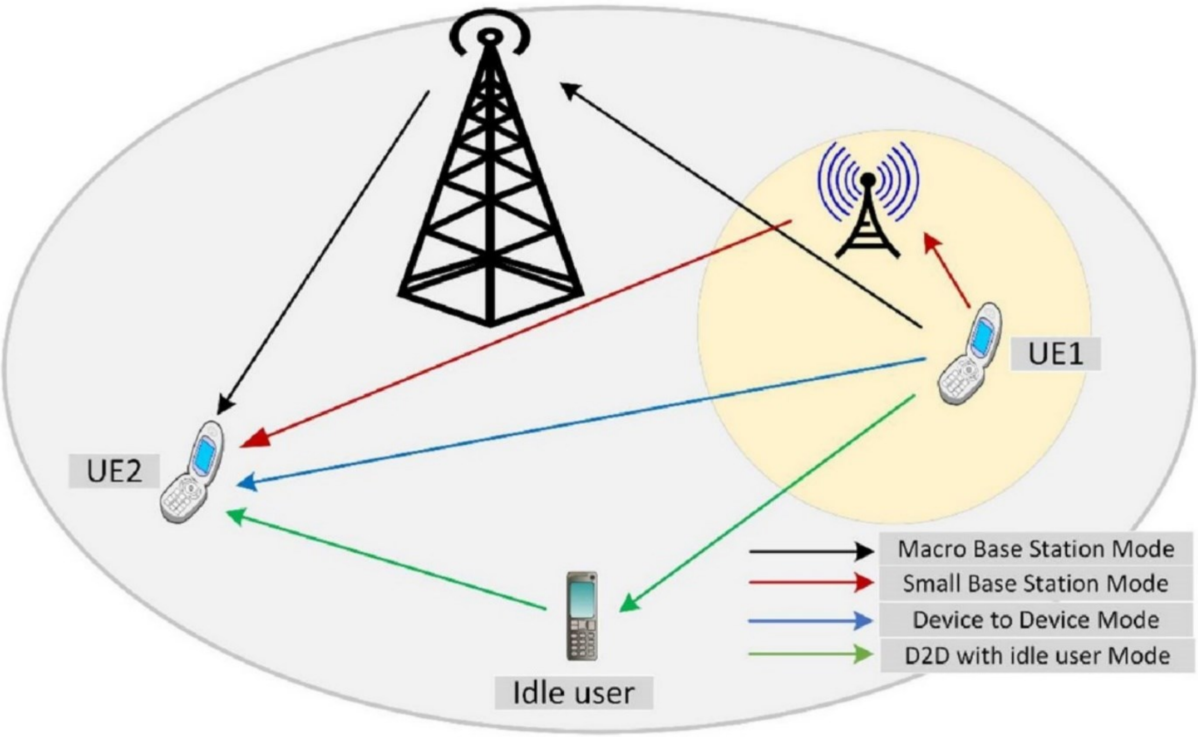


*Figure 2-5 : Mode Selection in Hetnet [80]*

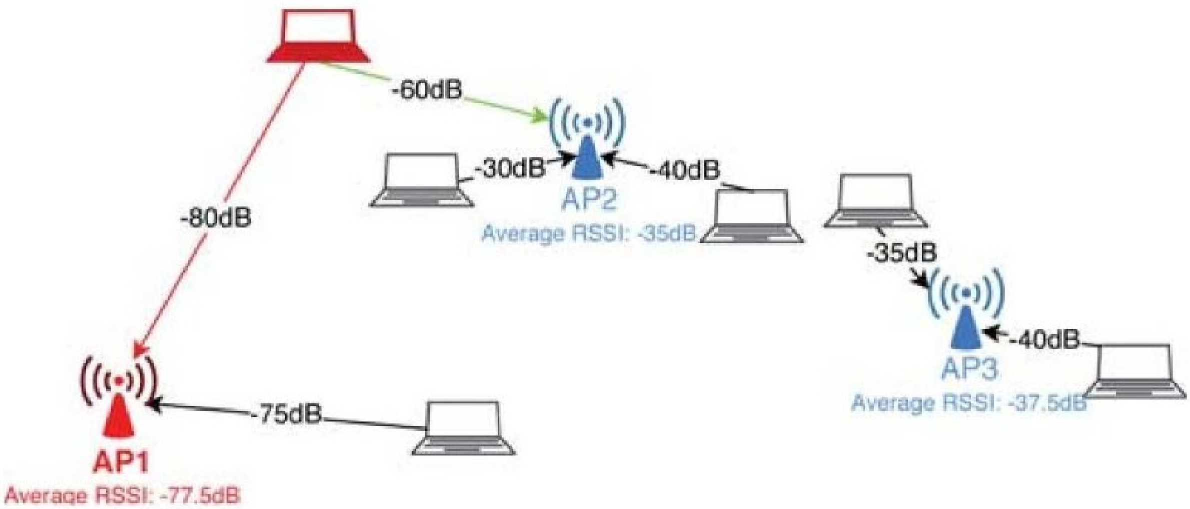


*Figure 2-6: Average RSSI indicator triggering a handover as condition [82]*

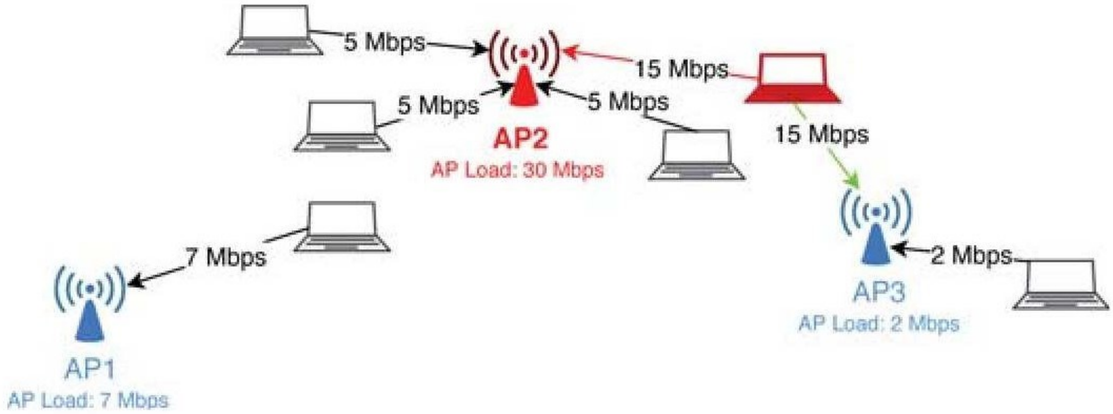


*Figure 2-7: AP Load indicator triggering a handover as condition [82]*

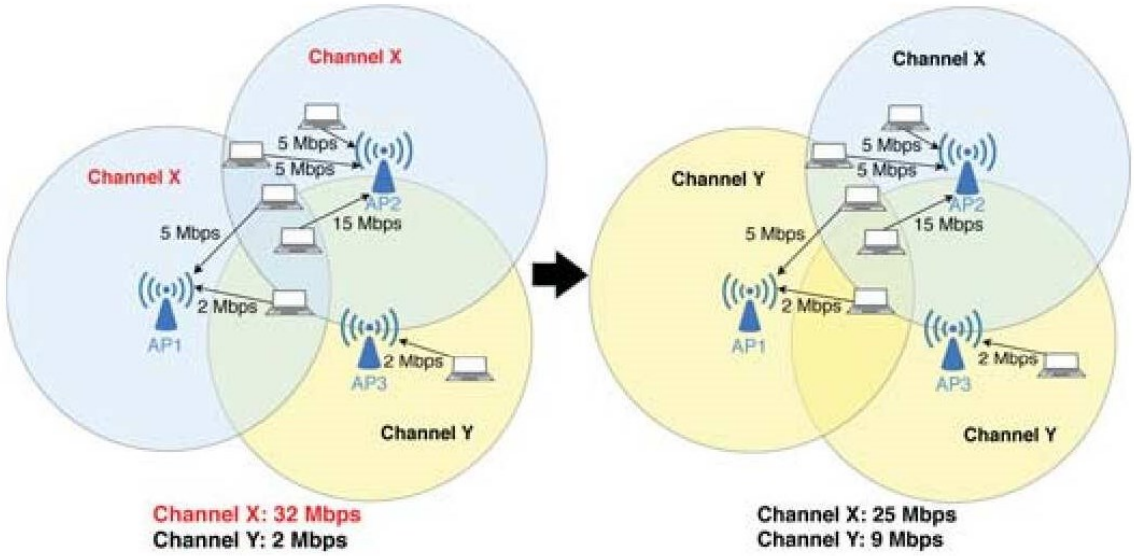


*Figure 2-8: Channel Occupancy indicator triggering a channel reassignation as condition [82]*

## 2.5 EVOLUTION OF RESOURCE MANAGEMENT TECHNIQUES IN HWN

### 2.5.1 Overview

The evolution of resource management techniques in HWNs has been a topic of significant interest in recent literature. The authors in [84] proposed an Enhanced Resource Allocation (ERA) algorithm to address inefficient resource allocation and QoS challenges in heterogeneous wireless networks, demonstrating significant improvements in bandwidth allocation, end-to end delay, bandwidth allocation, end-to-end delay, packet loss, and throughput performance. [85] introduced the concept of service-oriented wireless virtualised networks, which utilize the virtualisation of wireless access and resources to achieve efficient operation. [86] further enhanced resource management in heterogeneous wireless networks by introducing the resource-optimised network selection (RONS) method, which focuses on load balancing, dynamic slot optimisation, and tradeoffs between high performance and quality of experience. [87] focused on handover management challenges in dense heterogeneous 5G networks, specifically addressing handover decision algorithms between eNB and HeNB. [88] introduced a deep learning framework for multi-dimensional intelligent multiple access (MD-IMA) in beyond 5G and 6G wireless networks to meet diverse quality of service requirements efficiently. [89] proposed a hierarchical and modular radio resource management architecture for 5G and beyond to address the increasing complexity of radio resource management in HetNets.

Overall, the literature review indicates a growing interest in developing innovative resource management techniques to improve energy efficiency, quality of service, and overall performance in heterogeneous wireless networks.

### 2.5.2 Key Stages in Evolution

The evolution of resource management techniques in heterogeneous wireless networks has been a fascinating journey driven by the ever-increasing demand for wireless connectivity and the diverse characteristics of network elements. Here's a brief overview of the key stages in this evolution:

**Traditional Resource Allocation**:

In the early stages, resource allocation in wireless networks was mainly based on fixed channel assignment and power control schemes [90]. These networks were homogeneous in nature, with similar devices and technologies, making resource management relatively simple. It focused on the basic interworking of different network types and simple user multi-homing solutions to improve coverage and data rates.

**Introduction of Heterogeneity**:

With the proliferation of diverse wireless technologies like Wi-Fi, cellular, and Bluetooth, HWNs emerged [91]. These networks comprise various types of devices with different capabilities, coverage areas, and QoS requirements.

**Dynamic Spectrum Access (DSA)**:

DSA techniques were introduced to efficiently utilise the scarce radio spectrum by dynamically allocating spectrum bands to users based on their needs and availability [92]. Cognitive radio networks are a prime example, where secondary users opportunistically access underutilised spectrum bands without interfering with primary users.

**Software-Defined Networking (SDN):**

SDN decouples the control plane from the data plane, enabling centralised control and programmability of network resources. In HetNets, SDN facilitates dynamic resource allocation and management across different access technologies, improving flexibility and efficiency [93].

**Network Function Virtualisation (NFV):**

NFV abstracts network functions from dedicated hardware appliances and implements them as software-based virtual network functions (VNFs) running on commodity hardware. In HetNets, NFV enables the deployment of network functions (e.g., base stations, gateways) as virtualised instances, enhancing scalability and cost-effectiveness [94].

**Edge Computing:**

Edge computing brings computational capabilities closer to the network edge, reducing latency and enhancing responsiveness. In HetNets, edge computing facilitates localised resource management decisions, enabling faster response times and better QoS provisioning [95].

**Machine Learning (ML) and Artificial Intelligence (AI):**

ML and AI techniques are increasingly being applied to optimise resource management in heterogeneous networks. These techniques can dynamically learn network traffic patterns and user demand, enabling intelligent decision-making based on real-time network conditions, traffic patterns, and user behaviours, leading to improved performance and user experience [96].

**5G and Beyond:**

5G networks further enhance resource management capabilities through features like network slicing, which allows the creation of isolated virtual networks optimised for specific use cases [97]. Beyond 5G, technologies like terahertz communication and massive MIMO promise even greater flexibility and efficiency in resource management.

Overall, the evolution of resource management techniques in HWNs has been driven by the need to efficiently utilise resources, accommodate diverse technologies and devices, and meet the ever-growing demands of users and applications.

These advancements aim to create a more intelligent and adaptable network that can cater to the exploding demand for data services while ensuring a seamless and high-quality user experience.

### 2.5.3 Key Challenges in Resource Management for HetNets

Resource management in HetNets poses several challenges due to the diversity of network elements and the need for efficient utilisation of resources. Figure 2-9 presents the visual overview of the key challenges discussed below. The key challenges in resource management for HetNets include:


*Figure 2-9: Key Challenges in Resource Managements for HetNets*

**Heterogeneity:**

The primary challenge is the heterogeneity itself, with the large number of different devices, technologies, and service requirements, leading to increasing complexity [78].

**Interference Management:**

HetNets consist of a mix of macrocells, microcells, picocells, and femtocells, leading to interference among neighbouring cells [98]. Signals transmitted from one device might interfere with other devices that communicate in the same or nearby frequency bands that are being used. Coordinating resource allocation to mitigate interference while ensuring efficient spectrum utilisation is a significant challenge. It's crucial to ensure that signals from different cells do not negatively impact each other's performance [99].

**Heterogeneous QoS Requirements**:

Different types of devices and applications have diverse QoS requirements in terms of latency, throughput, reliability, and energy efficiency [100]. Balancing these heterogeneous QoS requirements while optimising resource allocation poses a significant challenge.

**Mobility Management**:

HetNets accommodate devices with varying mobility patterns, from stationary sensors to high-speed vehicles. Seamless handover between different cell types and technologies without service disruption is crucial but challenging, especially in dense deployment scenarios [101], [99]. As users move across different cells and network types, maintaining a seamless connection and service quality requires sophisticated mobility management strategies. This includes handover decisions and maintaining QoS during these transitions [80].

**Spectrum Allocation**:

Spectrum scarcity is a fundamental challenge in wireless communication, exacerbated by the increasing demand for bandwidth-intensive applications [102]. Efficiently allocating the limited available spectrum among a large number of devices and network nodes is another critical issue. This involves dynamic spectrum sharing and ensuring fair access to the spectrum for all users.

**User Association:**

In HetNets, each user is associated with one of the available networks; to choose the best network for the user, a user association scheme is implemented. Determining which network node, a device should connect to for optimal performance is a complex decision that involves just not signal strength but also factors like the current load on the node and the device's data needs [103]. The association of the user is based on their demands, the distance from the BSs, and channel quality. User association is important to improve the spectrum efficiency, energy efficiency and load balancing of the network [104].

Hence, developing effective user association schemes to optimize SINR and data rate, considering multiple features like channel conditions and user preferences, is an important challenge.

**Resource-Power Allocation**:

Allocating resources and power in an energy-efficient manner while still meeting the service requirements of users is a delicate balance. This includes optimising the use of power to extend battery life of devices and reduce the overall energy consumption of the network [105]. Techniques like particle swarm optimization and deep deterministic policy gradient algorithms have been explored to enhance energy efficiency while satisfying QoS requirements.

**Load Balancing:**

In highly dense HetNets, there is a load imbalance between the cells due to the random positioning of the cells and the mobility of the UEs. Load imbalance within the network reduces network performance [99]. Hence, distributing the network load evenly across all the available resources to prevent congestion and ensure all users receive adequate service levels is a key aspect of resource management in HetNets [106]. Non-uniform traffic distribution across different cells and technologies can lead to uneven resource utilisation and congestion in certain areas [107].

Therefore, dynamic load balancing mechanisms are required to evenly distribute traffic and resources among cells to optimise network performance and avoid overloading specific nodes.

**Handover Problems:**

The extensive deployment of small cells in the network also brings new challenges that negatively impact QoS, such as interference, frequent and unnecessary handover, handover failure, and Ping Pong handover [107].

Inter-cell handover occurs more frequently due to the intense deployment of huge numbers of small cells in HetNet. During handover operation, reciprocal signal packets must be sent between the source cell, the target cell, and the UE, so that users can be registered with the target cell by performing handover. More frequent occurrences of handover will create an additional signal load on the network and lead to more interruptions during data transfer [108]. This causes a trade-off to occur between the additional signal load from the frequent handover and the network coverage [109].

**Signalling Overhead:**

The increased communication between network elements due to dynamic resource allocation can lead to increased signalling overhead, impacting network efficiency [36].

**Energy Efficiency:**

HetNets include energy-constrained devices such as IoT sensors and battery-powered mobile devices. Optimising resource allocation to minimize energy consumption while maintaining performance and QoS requirements is essential for prolonging device battery life and reducing overall energy consumption [110].

**Security and Privacy:**

HetNets introduce additional security challenges due to the heterogeneous nature of network elements and the increased attack surface [111]. Ensuring secure and private communication across different technologies while accommodating diverse security requirements is crucial but complex.

Malevolent users use mutual authentication between UEs and BS to protect themselves from network effects such as Man-in-the-Middle attacks, Denial of Service attacks, impersonation attacks, and repeat attacks. Secure transport authentication is required to protect against these attacks and to provide reliable communication when moving between networks [99].

**Scalability and Manageability**:

HetNets often comprise a large number of heterogeneous network elements deployed in diverse environments. Scalable and manageable resource management mechanisms are needed to efficiently handle the complexity and scale of HetNets while ensuring ease of deployment and operation [112].

Addressing these challenges requires innovative approaches and technologies such as dynamic spectrum access, ML, NFV, SDN, among others. Various research efforts and technological advancements aim to create more intelligent and autonomous networks capable of self-optimization and real-time resource management. Effective resource management in HetNets is essential for delivering reliable, high-performance wireless connectivity across diverse use cases and applications.

## 2.6 RESOURCE MANAGEMENT METHODS USED IN HWN

Resource management in HWNs involves strategies and techniques to efficiently allocate and manage various network resources, such as bandwidth, spectrum, power, and computing capacity. These methods are essential to ensure optimal performance, QoS, and overall network efficiency.

A range of resource management methods have been proposed for HWNs. [86] introduces the resource-optimised network selection (RONS) method, which focuses on load balancing and dynamic slot optimisation to enhance performance. [113] present a resource allocation scheme that leverages big data technology to select the most suitable radio access technology, considering various parameters. [114] proposes a data-driven joint resource allocation method that integrates different radio access technologies to reduce energy consumption. Lastly, [115] emphasises the importance of radio resource management (RRM) in satellite communication networks, highlighting the need for effective RRM approaches to maximise network performance and minimise interference. This section presents some resource management methods commonly used in HWNs.

Figure 2-10 presents the visual overview of the resource management discussed below.


*Figure 2-10: Resource Management Methods Used in HWNs*

**Load Balancing:**

Load balancing is a resource management method that distributes network traffic across different network resources, such as BS, APs and servers to prevent congestion and ensure even resource utilization [116]. This helps to ensure that no single resource is overloaded, maintain network stability, and enhance user experience.

Load balancing enhances network performance, efficiency, and reliability by optimising throughput, distributing workload evenly, preserving node energy, and improving QoS by reducing congestion and interference [117].

**Call Admission Control (CAC):**

Another resource management method that is commonly used in HWNs is CAC. It is a significant resource management method in heterogeneous wireless networks. CAC is responsible for controlling the admission of new connections to the network, ensuring that the network's resources are allocated efficiently and that QoS commitments are maintained [118].

CAC works by evaluating the current state of the network and determining whether or not there are enough resources available to support a new call. If there are not enough resources available, the call will be rejected. If there are enough resources available, the call will be admitted [119].

By regulating the number of connections and ensuring that the network is not overloaded, CAC plays a crucial role in managing resources such as bandwidth, spectrum, and computing capacity. It helps prevent congestion and maintain optimal performance by only admitting new connections when there are sufficient resources available to meet their QoS requirements. CAC aims to optimise resource utilisation by admitting more calls while maintaining the QoS of ongoing services [119].

CAC enhances network performance by efficiently allocating radio resources, reducing call-blocking probability, enhancing QoS for users, and supporting heterogeneous services across multiple wireless access technologies [120].

**Traffic Offloading:**

Traffic offloading is a resource management technique that transfers some of the data traffic from a congested or overloaded network to a less congested network [121]. This helps to improve the performance of the congested network and ensure that all users have a good experience. Traffic offloading aims to reduce the network load, improve the user experience, and save the energy consumption of the network. Traffic offloading enhances network performance by distributing traffic among networks, improving user QoS through higher data rates and lower latency, and conserving energy through energy-efficient devices [122].

**Vertical Handover Management:**

Vertical handover management (VHM) is a resource management method that enables a mobile user to switch from one RAT to another without losing the connection or the QoS [123]. VHM aims to provide seamless and uninterrupted services in HWNs, especially in scenarios where the user is moving fast, or the network connectivity is poor [124]. This helps to ensure that the user's traffic is always connected to the best available RAT, regardless of their location or the traffic load. Vertical handovers between different wireless technologies (e.g., Wi-Fi to cellular) require efficient decision-making to maintain a seamless user experience. Algorithms consider factors such as signal strength, available bandwidth, and user preferences to optimize handover decisions.

VHM enhances network performance by maintaining seamless connections, optimizing resource utilisation, and enhancing reliability by avoiding congestion and interference while optimising network coverage based on user preferences and bandwidth [125], [126].

**Dynamic Spectrum Management:**

Dynamic Spectrum Management (DSM) is a resource management method commonly used in heterogeneous wireless networks. It is a set of techniques that dynamically allocate radio spectrum resources to different users and applications based on their needs and requirements [127].

DSM can use various methods, such as cognitive radio, blockchain, and AI, to sense, monitor, and control spectrum usage dynamically and efficiently [128]. Cognitive radio techniques and spectrum sensing can be used to detect unused or underutilised spectrum bands, allowing for more efficient utilisation of the spectrum. This has been used in cognitive radio networks to maximise spectrum efficiency. DSM is a complex and challenging problem, but it is essential for the efficient and effective use of spectrum in heterogeneous wireless networks. By dynamically allocating spectrum resources to different users and applications, DSM can improve the efficiency and overall performance of the network, providing better QoS to users.

**Power Management:**

Power management is a resource management method that aims to reduce the energy consumption of the network and devices such as base stations and mobile devices, especially wireless user equipment (UE) that have limited battery power [80]. Power management can improve network performance, user experience, and the environmental sustainability.

Managing power resources involves optimising the transmission power of wireless devices to minimise interference, extend battery life, and improve overall network performance. It's used in cellular networks to ensure optimal coverage and capacity.

Power control algorithms adjust transmit power based on factors such as distance, signal strength, and interference [80].

Power management enhances network performance by reducing device energy consumption, improving QoS for users, and reducing operational costs and environmental impact. It extends battery life, improves network QoS, and reduces the carbon footprint and greenhouse gas emissions of the network.

**Cross-Layer Optimisation:**

Cross-layer optimisation (CLO) is a technique that exploits the collaborative operation among the different layers of the network protocol stack, such as the physical layer, the MAC layer, the network layer and the application layer [129]. Cross-layer techniques consider parameters from multiple layers of the protocol stack to make resource allocation decisions. For instance, dynamic modulation adaptation adjusts the modulation scheme based on channel conditions.

CLO enhances network performance by adapting to dynamic network conditions and user requirements. It improves resource efficiency by reducing resource wastage and improving QoS for users through flexible resource allocation and control schemes. It also increases network capacity and throughput by exploiting spatial diversity and multiplexing gains of MU-MIMO and OFDMA technologies [130].

**Context-Aware Resource Management:**

Context-aware resource management is a technique that leverages information about the network, the user and the environment to optimise resource allocation and control in an HWN [131].

The context of the network can include factors such as the traffic load, the available resources, and the user's location. The context of the users can include factors such as their QoS requirements, their battery level, and their mobility.

This approach considers contextual information, such as user location, device capabilities, and application requirements, to make resource allocation decisions. Context-aware techniques adapt to changing conditions to provide an optimal user experience and provide users with the resources they need when they need them [131].

It can improve the network performance by adapting to the dynamic and diverse network conditions and user requirements; optimising resource allocation and improving QoS by providing more flexible and adaptive resource allocation based on user context information. It also increases network capacity and throughput through spectrum diversity and multiplexing gains of multi-band technologies [132].

Hence, resource management methods in HWNs are crucial for maintaining network efficiency, QoS, and user satisfaction. The choice of methods depends on the network's characteristics, technology diversity, and specific goals, with the ultimate aim of achieving optimal resource utilisation and performance.

### 2.6.1 Comparison

As explained earlier, managing resources efficiently in HWNs is crucial for ensuring seamless connectivity and optimal performance. Several resource management methods have been developed to address the unique challenges posed by the coexistence of multiple network technologies (e.g.,5G, LTE, Wi-Fi) with diverse characteristics. Table 2-1 shows the comparison of different resource management methods in heterogeneous wireless networks.

*Table 2-1: Comparison of Resource Management Methods*

| Method | Key Features | Use Cases | Advantages | Disadvantages |
|---|---|---|---|---|
| Load Balancing [133] | Distributes traffic evenly across different network resources. | Congestion mitigation | Improved resource utilisation | Complexity in implementation |
| Call Admission Control [119] | Determines whether to admit a new call | Quality of service (QoS) preservation | QoS assurance, network stability | This can lead to call rejection |
| Traffic Offloading [134] | Redirects traffic from one network to another | Offloading data from congested cells | Congestion relief, enhanced user experience | Handover delays, network coordination |
| Vertical Handover Management [135] | Switches between different access technologies | Seamless mobility | Improved coverage, user experience | Handover complexity, latency during handover |
| Dynamic Spectrum Management [136] | Optimises spectrum allocation dynamically | Spectrum efficiency | Efficient spectrum usage, reduced interference | Complexity, coordination with other methods |
| Power Management [137] | Adjusts transmission power to conserve energy | Battery life improvement | Extended device battery life | Potential coverage and QoS reduction |

| | | | | |
|---|---|---|---|---|
| Cross-layer optimisation [129] | Optimises network parameters across protocol layers | Performance enhancement | Enhanced end-to-end performance | Implementation complexity, tuning challenges |
| Context-Aware Resource Management [131] | Considers context information for resource allocation | User-specific QoS provision | Personalised QoS, improved user satisfaction | Context data availability, overhead |

### 2.6.2 Importance of Resource Management:

**Optimal Utilisation**: Resource management prevents wastage of limited resources like spectrum, bandwidth, power, and computing capacity. For example, the spectrum is a valuable resource, and efficient allocation allows multiple technologies to coexist within the same frequency bands [138].

**QoS Assurance**: Proper resource allocation guarantees that each user's QoS requirements are met. Users experience consistent performance regardless of their location or the technology they are using [139].

**Load Balancing**: Resource management techniques distribute traffic evenly across network nodes. This prevents congestion and ensures uniform utilisation, preventing certain nodes from becoming overloaded while others remain underutilised [140].

**Network Stability**: Efficient resource management prevents network instability, congestion, and crashes caused by resource exhaustion. It ensures a reliable and responsive network environment [141].

**Cost Efficiency**: By optimising resource usage, network operators can reduce operational costs. For example, effectively managing power consumption can extend the battery life of mobile devices [142].

**Enhanced User Experience**: Proper resource allocation leads to a seamless and uninterrupted user experience, regardless of the user's location or the specific wireless technology in use [143].

### 2.6.3 Consequences of Poor Resource Management:

**Network Congestion**: Improper resource allocation can lead to network congestion, resulting in slow data rates, dropped calls, and delayed communications [144].

**QoS Degradation**: Inadequate resource allocation can lead to poor QoS, affecting applications like video streaming or VoIP, where low latency is essential [144].

**Uneven Utilization**: Poor load balancing can cause certain nodes or APs to become overwhelmed, leading to performance issues for users connected to those nodes [145].

**Wasted Resources**: Inefficient resource usage results in wasted spectrum, bandwidth, and energy. This inefficiency impacts the overall network capacity and scalability [146].

**Service Interruptions**: Unmanaged resources can cause service disruptions and failures, resulting in dissatisfied users and potential revenue loss for network operators [147].

**Interference**: Improper spectrum allocation can cause interference between technologies, affecting performance and leading to a suboptimal user experience [148].

## 2.7 CALL ADMISSION CONTROL IN HWN

The study of radio resource management (RRM) is important in HWNs because radio resources are frequently expensive and scarce, making their effective utilisation an ongoing research topic [149].

The effective use of resources in any RAN is due to RRM solutions. According to [119], one of the resource management techniques that play a significant part in efficiently managing resources is called admission control.

CAC schemes are central elements for resource management with QoS support in heterogeneous wireless systems. CAC schemes are part of networks that make decisions that ensure users receive services of guaranteed quality. This decision-making process also reduces network congestion and call-blocking probabilities, which results in more effective resource utilisation [150]. The CAC algorithm decides whether or not to accept an incoming call. Additionally, it determines whether the existing RANs are adequate to handle incoming calls [150]. An effective CAC algorithm aims to maintain the ongoing connections' QOS while also ensuring the best possible use of the radio spectrum.

There have been numerous investigations on CAC in 4G and 5G, both in academia and industries. As a result, many ideas have been made by researchers in these domains.

A novel CAC technique for VoIP is presented by the authors in [151] within the Wi-Fi access network environment and implemented with Unmanned Aerial Vehicles (UAVs) which connect to a backhaul 5G network. In response to its evaluation of the Wi-Fi network's level of congestion and the minimal level of VoIP call quality necessary, it intercepts VoIP call control signals and chooses whether to accept each incoming call. The CO-CAC optimises the codec settings of active calls regularly to improve the number of concurrent calls by exchanging signalling with VoIP users.

The authors in [152] proposed an algorithm focused mostly on minimum energy usage that was modelled in a CAC environment and supplied by three classes of services in a 5G access network. This method will support the development of the IoT by enabling connected, low-energy gadgets to connect to the network with a suitable quality of service.

A Dynamic Handover Control Parameter for LTE-A/5G Mobile Communications was proposed in [153], the study presented flexible handover control variables in heterogeneous wireless settings with dense small cells. It seeks to improve radio link performance by reducing the likelihood of ping-pong handovers.

An intelligent Call Admission Control Algorithm (CACA) is presented in [154] to ensure a smooth transition in 5G networks with a suitable QoS for end-users. The "cell breathing" phenomenon, which causes the overloaded cell coverage to decrease, is considered in the current CACA. The criteria used to decide whether the user is accepted are the minimum bit rate that must be obtained, the farthest distance from the base station, and the largest number of active users in the cell.

[155] presented a flexible resource management and predictive handover algorithm based on the target BS's load and data attributes of the network point of connection. The fundamental goal of combining different heterogeneous network connections is to improve handover performance and more effectively utilise radio resources, which improves system performance as a whole.

To provide an effective forecast approach without placing undue strain on the mobile station and the whole network, the proposed work in [101] presented an innovative vertical handover prediction strategy. Two separate thresholds are used by the prediction strategies. The first is determined by the current base station's signal strength, while the second is obtained by the user signal strength as detected by the mobile station.

[156] suggested CAC for Real-Time and Non-real-time Traffic for Vehicular LTE Downlink Networks. Based on user priority, the algorithm seeks to accept or reject calls. Additionally, it divided calls into handoff and new calls, and real-time and non-real-time traffic demands.

[157] proposed an effective resource allocation and admission control technique for public safety communication across a 5G network slice. The authors give a general outline of how resource allocation and CAC can be implemented effectively in a 5G network. An Adaptive CAC with Bandwidth Reservation for Downlink LTE Networks was given by [158]. When there is a high volume of traffic, the algorithm utilises an adjustable threshold value to modify the network environment. Best-effort traffic (BE) throughput was maximised, while CBP and CDP were reduced.

A novel vertical handover method based on a multi-attribute and neutral network for heterogeneous integrated networks is presented in [159]. The model's framework is developed by adjusting the network environment in which the network resources are used to accommodate the switch between UMTS, GPRS, WLAN, 4G, and 5G for device connection.

### 2.7.1 Need for CAC In HWN

In HWNs, the need for CAC is paramount due to the complex nature of coexisting wireless technologies and the varying capabilities of different network components. CAC is a crucial mechanism that regulates the admission of new connections into the network based on available resources, QoS requirements, and network conditions.

As described above, CAC is a technique used to control the number of calls that are admitted into a wireless network. This is important to ensure that the network does not become overloaded and that all users have a good QoS.

Here are some key reasons highlighting the need for CAC in HWNs. Figure 2-11 also presents the visual overview of the key reasons for CAC in HWNs.

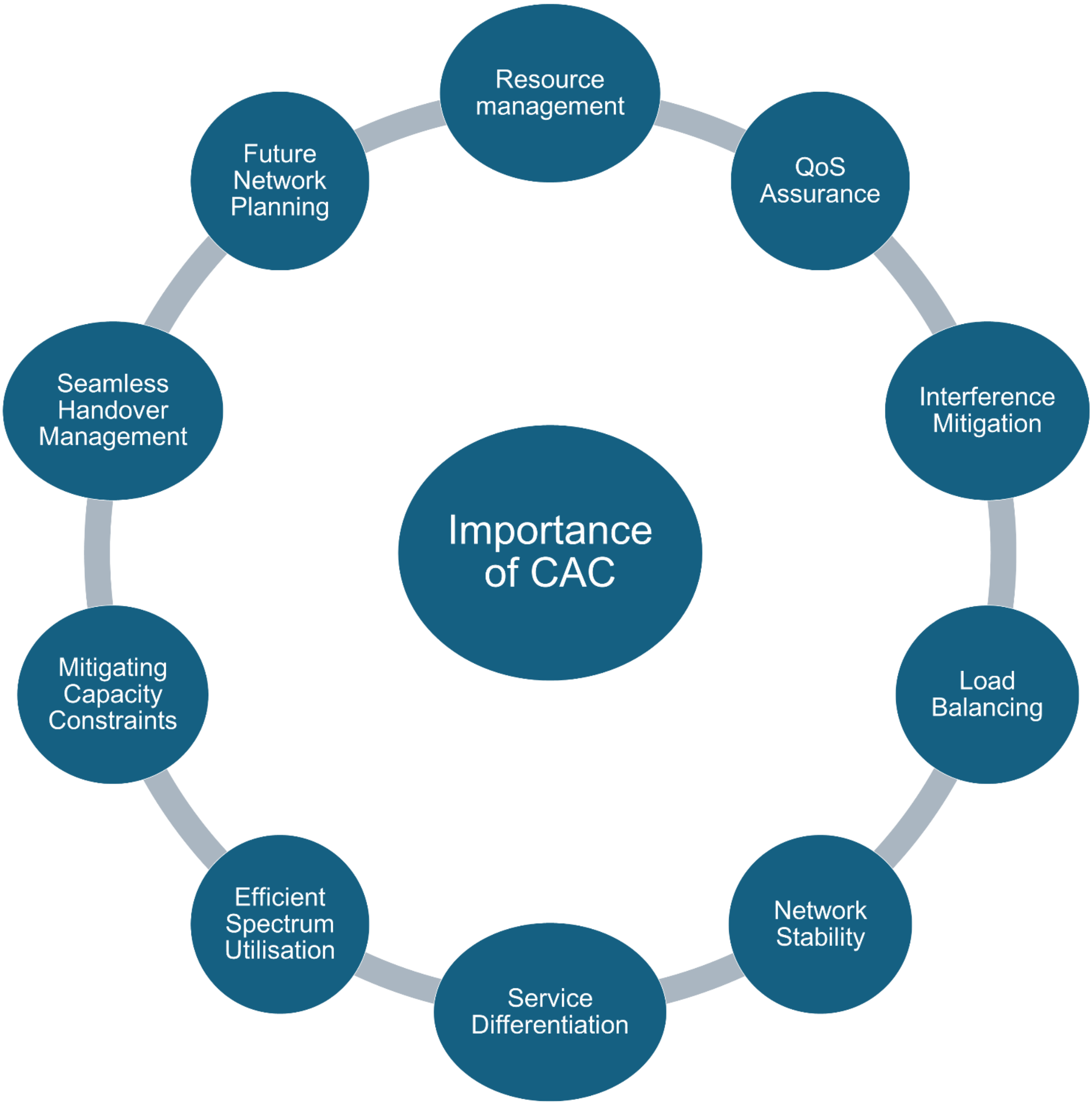


*Figure 2-11: Importance of CAC in HWNs*

**Resource Management**: Heterogeneous wireless networks consist of diverse access technologies, such as Wi-Fi, cellular, and satellite, each with its own set of resources and limitations. CAC prevents network congestion and resource overutilisation by ensuring that new connections are only admitted if sufficient resources are available to maintain acceptable QoS levels [119].

**QoS Assurance**: Different wireless technologies offer varying QoS capabilities. CAC helps maintain consistent QoS by admitting connections that can be supported within the network's available resources. This prevents the degradation of service for existing users due to an influx of new connections [160].

**Interference Mitigation**: In a heterogeneous environment, multiple wireless technologies often share the same frequency spectrum. CAC considers interference levels and helps prevent excessive interference caused by adding new connections that could disrupt existing connections and degrade network performance [161].

**Load Balancing**: CAC contributes to load balancing by distributing connections evenly across available access points or base stations. By controlling the number of connections in each area, CAC prevents certain nodes from becoming overloaded while others remain underutilised [162].

**Network Stability**: Effective CAC prevents network instability by avoiding scenarios where a sudden surge in new connections could lead to excessive traffic, congestion, and even network crashes. By regulating the admission of new connections, CAC maintains the overall stability of the network [162].

**Service Differentiation**: Heterogeneous networks serve a wide range of applications with diverse requirements, from real-time communication to non-real-time data transfer. CAC allows operators to prioritize certain types of traffic and manage connections, accordingly, ensuring that each service class receives its required resources [124].

**Efficient Spectrum Utilisation**: In networks where spectrum is a limited and valuable resource, CAC optimizes its use by admitting connections only when necessary. This prevents unnecessary spectrum consumption and allows for more effective utilisation of available frequency bands [163].

**Mitigating Capacity Constraints**: Different wireless technologies have different capacities and coverage areas. CAC prevents nodes or APs from reaching their capacity limits, which could lead to service degradation and dissatisfaction among users [164].

**Seamless Handover Management**: Heterogeneous networks often require seamless handovers between different technologies to maintain connectivity as users move. CAC plays a role in coordinating handovers by assessing the capacity and availability of target networks before allowing a handover [165]

**Future Network Planning**: CAC data can inform network planning and expansion efforts. By analysing admission requests and resource utilization patterns, operators can better allocate resources and plan for network growth [119].

In conclusion, the need for CAC in HWNs is driven by the diverse range of technologies, QoS requirements, and resource constraints that characterize such networks. By regulating new connection admissions based on available resources and network conditions, CAC ensures a balanced and optimised network performance, delivering a seamless and satisfying user experience across various wireless technologies.

### 2.7.2 Call Admission Control Methods In HWNs

CAC methods in heterogeneous wireless networks are designed to effectively manage and regulate the admission of new connections to ensure optimal resource utilisation, maintain QoS requirements, and prevent network congestion. These methods consider the diverse nature of wireless technologies and their varying capabilities. Below are some common CAC methods used in heterogeneous wireless networks. Figure 2-12 presents the visual overview of the CAC methods used in HWNs.

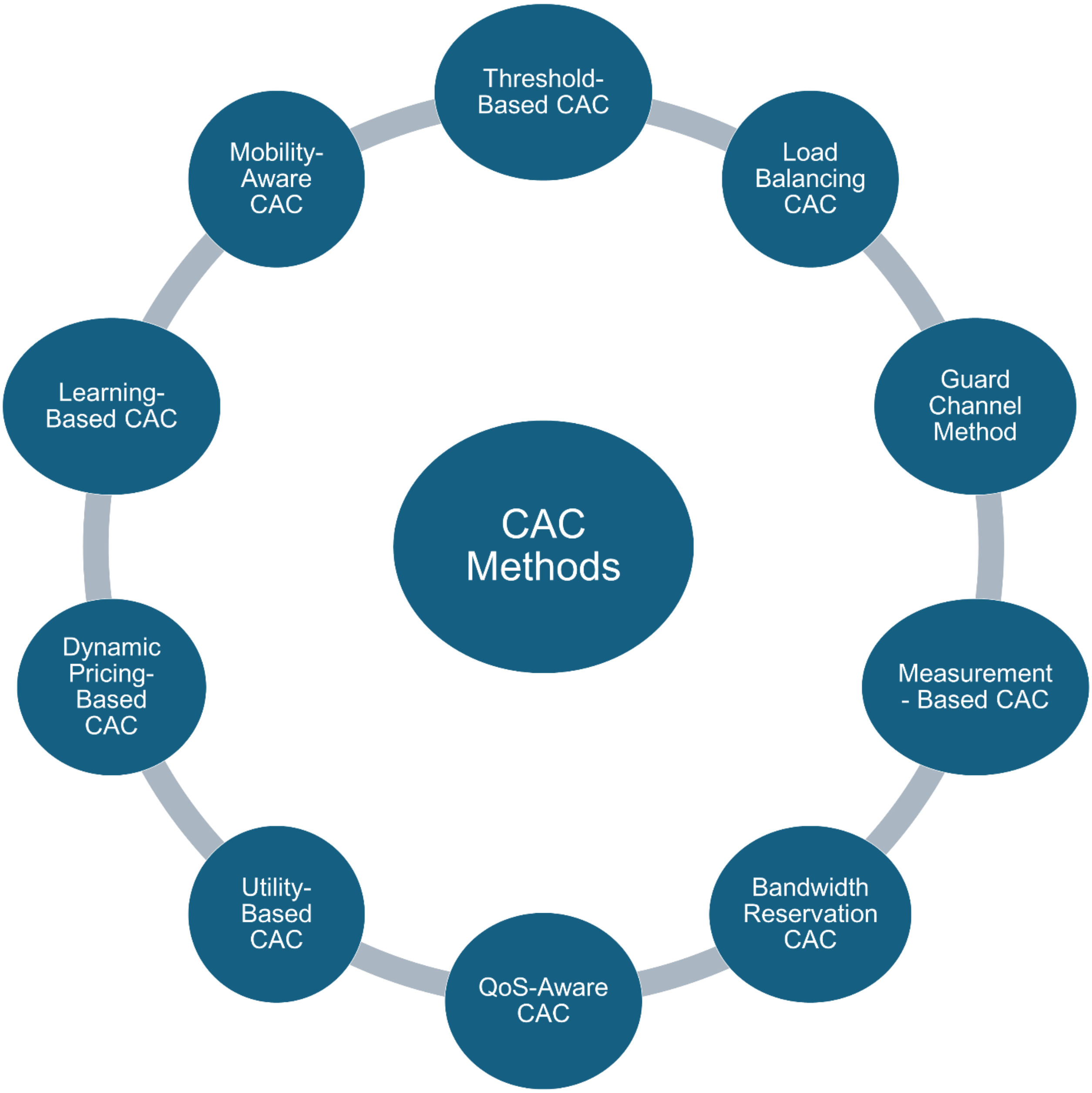


*Figure 2-12: Call Admission Control Methods*

**Threshold-Based CAC**: This method sets predefined thresholds for various network parameters, such as available bandwidth, SINR, and node capacity. When a new connection request arrives, the CAC algorithm checks whether admitting the connection would cause any of these parameters to exceed their thresholds. If so, the request might be rejected or redirected to a less congested access point. Incoming connection requests are admitted if they satisfy these thresholds, ensuring that the network's resources are not overloaded [169].

Threshold-Based CAC is a simple and effective technique for managing network resources. It can be implemented quickly and easily in most wireless networks. It can help to ensure that the QoS is maintained for existing calls. However, there are also some disadvantages to using threshold-based CAC. It can be difficult to set the threshold value correctly, which can lead to either too many or too few calls being admitted to the network. It does not take into account the specific needs of individual users or applications. It can lead to a reduction in the overall capacity of the network, as calls are rejected when the threshold value is exceeded [119].

**Load Balancing CAC**: This method considers load balancing across different network nodes or access points. The load-based CAC algorithm considers the current load on different access points or cells. If a certain AP is heavily loaded, the algorithm may redirect new connection requests to less congested APs. Incoming connections are admitted to nodes with lower traffic loads, ensuring even distribution of traffic and preventing network bottlenecks [154].

Load-based CAC can improve the utilisation of network resources by admitting more calls while maintaining the QoS of ongoing calls [167]. It can provide better performance than other CAC schemes in terms of call-blocking probability, handoff-dropping probability and resource utilisation. It can handle the issue of resource allocation in a heterogeneous wireless environment where resources are always scarce.

However, it has some drawbacks. Load-based CAC requires a lot of computational power to calculate the load of the network. It can be difficult to implement load-based CAC in a heterogeneous wireless network due to the different types of wireless networks and the varying QoS requirements of multimedia applications. Load-based CAC can also be less effective in handling bursty traffic and may lead to congestion. It also requires additional network infrastructure and expertise. Hence, proper implementation and configuration are crucial to maximise its benefits.

**Guard Channel Method**: In this method, a certain number of channels or resources are designated as "guard" channels, reserved for emergency or high-priority traffic. New connections are admitted if sufficient guard channels are available, preventing resource exhaustion during critical situations [168].

This leads to improved call quality, enhanced user experience, simplified network management, and improved network capacity.  The guard-channel method can reduce the rate of dropped handover calls by reserving channels specifically for them. It can provide better QoS for handover calls by reducing the number of blocked calls. It can also improve the overall network performance by reducing the number of handovers.

However, it also has disadvantages, such as reduced spectrum utilisation, increased network complexity, potential underutilisation, and limited scalability. The guard-channel method can increase the call-blocking rate for new calls, it can lead to inefficient use of network resources [169]. Also, it can be difficult to determine the optimal number of guard channels to use.

**Measurement-Based CAC**: This method involves real-time measurement of network conditions, including signal strength, interference, and load. Admission decisions are made based on these measurements to ensure that new connections can be accommodated without degrading the performance of existing connections [151].

Measurement-based CAC offers different advantages. It is more accurate than other methods because it uses real-time measurements to determine the available bandwidth and the QoS. It is flexible and can be adapted to different network conditions. It can handle a wide range of traffic types, including voice, video and data [150].

However, it also has some disadvantages. Measurement-based methods require more computational resources than other methods because they need to continuously monitor the network [170]. They are more complex to implement than other methods because they require sophisticated algorithms to analyse the measurements. They may not be suitable for networks with high mobility because the measurements may not be accurate enough to predict future network conditions.

**Bandwidth Reservation CAC**: Bandwidth reservation CAC methods allocate a specific amount of bandwidth for certain types of traffic, ensuring that the reserved bandwidth is available when needed. This approach is particularly useful for real-time applications with stringent QoS requirements [171].

The bandwidth reservation method offers several benefits. It ensures that the required bandwidth is reserved for the call before it is admitted into the network, thereby reducing the likelihood of call drops due to insufficient bandwidth. It helps to maintain the QoS of ongoing services by admitting only those calls that can be supported by the available resources [172]. It is particularly useful in HWNs where the bandwidth requirements of different types of calls may vary significantly. However, it has some drawbacks. It may lead to inefficient utilisation of network resources as the reserved bandwidth may not be fully utilised. It may result in higher blocking probabilities for new calls as the reserved bandwidth may not be available for new calls [173]. It may be difficult to implement in practice as it requires a mechanism for reserving bandwidth for each call.

**QoS-Aware CAC**: QoS-aware methods consider the QoS requirements of incoming connection requests. The QoS-aware CAC algorithms evaluate the QoS requirements of incoming connection requests and compare them with the available resources. This algorithm ensures that new connections are admitted only if the network can meet its QoS demands [174]. Different access technologies may have varying QoS capabilities, so the algorithm needs to consider the capabilities of each technology when making admission decisions. If the requested QoS can be guaranteed without compromising existing connections, the request is granted. Otherwise, it may be denied or admitted with a lower priority [175].

QoS-aware methods for call admission control in heterogeneous wireless networks have both advantages and disadvantages. One of the main advantages is that they can provide better QoS to users by improving the rate of transmission, increasing the quality of signal, and reducing the rate of packet loss and delay rate of packet [176]. However, these methods can be complex and resource-intensive to implement which can lead to higher costs and longer development times. Additionally, QoS-aware methods may not be effective in all situations, such as when there is a high degree of network congestion or when there are significant variations in channel quality

[176]. Despite these challenges, QoS-aware methods remain an important area of research in wireless networks, and many researchers are working to develop new and more effective methods for CAC.

**Utility-Based CAC**: Utility-based CAC algorithms assign utility values to different connections based on factors like QoS requirements, user priorities, and available resources. The algorithm selects connections with higher utility values for admission, ensuring that connections with higher priority or better QoS requirements are given precedence [177]. Utility-based method for call admission control in heterogeneous wireless networks has its own advantages and disadvantages. One of the advantages is that it provides a more flexible and efficient way of managing network resources by taking into account the utility of different types of traffic. It allocates resources to calls that provide the most benefit to the network and users, potentially leading to higher bandwidth utilization and improved overall performance [177]. Different call types can be assigned different utility values based on their QoS requirements, ensuring that critical calls, like emergency services, are prioritised over less urgent ones. Also, Utility functions can be customised to reflect the specific needs and priorities of the network and its users, allowing for adjustments as network conditions or user preferences change. By considering the utility of both the network and individual users, utility-based CAC can promote fairer resource allocation compared to methods solely focused on maximising network utilisation. However, it has some disadvantages such as the complexity of the algorithm and the difficulty of determining the utility function. Defining and accurately measuring utility can be challenging, requiring detailed knowledge of network performance, user preferences, and service characteristics [178]. Assigning utility values involves subjective judgment, potentially leading to biases and inconsistent decision-making. Also, implementing and maintaining utility-based CAC systems can require additional computational resources and network overhead. Users may attempt to manipulate the system by misrepresenting their call priorities or utility values, potentially impacting its effectiveness.

**Dynamic Pricing-Based CAC**: This approach involves dynamically adjusting admission decisions based on pricing mechanisms. Users willing to pay more for better QoS might be admitted even when resources are limited. This technique can balance revenue generation with resource allocation [179].

Dynamic Pricing-Based CAC offers several benefits. It improves resource utilisation by dynamically adjusting prices based on network conditions and user demand, this can incentivize users to choose less congested cells or adjust their call times, leading to more efficient use of network resources [180]. Users can benefit from predictable pricing based on network congestion, allowing them to make informed decisions about when and how long to call to avoid high charges during peak times. Dynamic pricing can generate additional revenue for operators by capturing the value of their network resources during periods of high demand. By discouraging excessive use during peak times, dynamic pricing can help to prevent network congestion and maintain call quality for all users. Dynamic pricing allows operators to fine-tune pricing strategies based on specific network conditions, user profiles, and service tiers.

However, it also has some drawbacks. Implementing and managing dynamic pricing systems can be complex, requiring sophisticated algorithms and infrastructure to track network conditions and user behaviour in real time [181]. Some users, such as those with limited budgets or inflexible call patterns, may be disproportionately affected by dynamic pricing, potentially leading to accusations of unfairness. High prices during peak times could make essential communication services less accessible to low-income users, raising concerns about affordability and the digital divide. Users may not have complete or accurate information about network conditions and pricing, potentially leading to confusion and frustration. Users may try to game the system by finding ways to avoid high prices, such as using alternative networks or delaying calls until off-peak times [181].

**Learning-Based CAC**: Some CAC methods leverage predictive analytics and ML algorithms to forecast future resource availability and demand. The learning-based CAC algorithm uses ML techniques to adapt admission decisions based on historical data, user behaviour, and network conditions. These algorithms can optimize over time and handle complex scenarios [182]. By anticipating congestion or resource shortages, the network can make proactive admission decisions.

Learning-based methods for call admission control in heterogeneous wireless networks have both advantages and disadvantages. One of the main advantages is that they can adapt to the changing network conditions and traffic patterns, which makes them more efficient than traditional methods. Additionally, learning-based methods can be used to optimise the performance of the network by predicting future traffic and allocating resources; accordingly, this can result in higher call success rates, lower call drops, and better overall network performance [183]. Also, Learning-based methods can consider diverse factors like user priorities, service types, and traffic patterns to ensure fair access to network resources. This can prevent issues like starvation for low-priority users or congestion caused by high-bandwidth applications. By analysing historical data and real-time network usage, learning algorithms can predict future traffic patterns and proactively adjust admission control thresholds. This can help prevent congestion before it occurs, leading to a more stable and predictable network experience. Learning-based methods can be easily adapted to diverse network architectures and technologies, making them suitable for HWNs with various cell sizes, RATs, and user devices [184]. ML algorithms can continuously learn and improve over time as they are exposed to new data and network dynamics [184]. This allows for ongoing optimization of call admission control strategies for better performance.

However, one of the main disadvantages of learning-based methods is that they require a large amount of data to train the model, which can be difficult to obtain in some cases. The accuracy and effectiveness of learning algorithms depend heavily on the quality and quantity of available data. Insufficient or inaccurate data can lead to suboptimal performance or even negative consequences.

Furthermore, learning-based methods can be computationally expensive, especially for complex models; this can be a challenge for resource-constrained devices or networks with limited processing power [185]. This can lead to increased latency and reduced throughput. Implementing and maintaining learning-based systems can be more complex than traditional admission control methods. This requires expertise in ML and network engineering, as well as access to appropriate computational resources. Some ML models can be difficult to interpret, making it challenging to understand the reasoning behind their decisions. This can raise concerns about transparency and fairness in CAC decisions.

**Mobility-Aware CAC**: Mobility-aware CAC algorithms consider user mobility patterns and handover mechanisms when making admission decisions. Users transitioning between different access technologies should experience smooth handovers without degradation of service [186].

Mobility-Aware CAC offers some benefits. It provides better QoS by improving the rate of transmission, increasing the quality of the signal and reducing the rate of packet loss and delay rate of the packet [187]. By predicting user movement, Mobility–Aware CAC can allocate resources more efficiently, preventing handovers during calls and reducing dropped calls. This leads to a smoother and more reliable user experience. It can optimize resource utilization by admitting calls only if the network can maintain its QoS throughout the expected user trajectory. This prevents overloading specific cells and ensures efficient use of limited spectrum. Proactive call admission based on mobility patterns helps prevent congestion hotspots in the network, further improving overall performance and user satisfaction [187]. It is sensitive to geographical constraints and to users' common habits. It does not require any control message and additional load for the Mobile Switching Centre (MSC).

However, this has some drawbacks and limitations. Implementing and managing Mobility-Aware CAC algorithms can be complex, requiring accurate user mobility prediction models and integration with network infrastructure. The method may not be effective in highly congested networks. It may require additional computational resources [188]. Also, it may not be suitable for real-life applications. The effectiveness of Mobility-Aware CAC heavily relies on the accuracy of mobility prediction models. Any errors in these models can lead to suboptimal call admission decisions, potentially impacting QoS. Running complex mobility prediction algorithms on network devices can introduce additional computational overhead, potentially impacting overall network performance.

### 2.7.3 Comparison

Table 2-2 below presents the comparison of different CAC methods in HWNs discussed above; showing their key features, use cases, strengths and weaknesses.

*Table 2-2: Comparison of CAC Methods in HWNs*

| CAC Method | Key Features | Use Cases | Advantages | Disadvantages |
| --- | --- | --- | --- | --- |
| Threshold-Based CAC [119] | Compares incoming request parameters to predefined thresholds | Resource allocation | Simple implementation, resource protection | May lead to underutilisation or congestion |
| Load Balancing CAC [154] | Distributes load evenly across network nodes | Congestion management | Efficient ressource utilisation, congestion control | Requires continuous monitoring and adaptation |
| Guard Channel Method [189] | Reserves specific channels for handoff attempts | Handover support | Reduced handover failure rates, improved QoS | Channel underutilisation, complexity |
| Measurement-Based CAC [151] | Uses real-time measurements to determine admission | QoS-sensitive applications | Accurate resource allocation, QoS preservation | Requires reliable measurement mechanisms |

| | | | | |
|---|---|---|---|---|
| Bandwidth Reservation CAC [190] | Reserves bandwidth for admitted connections | Multimedia applications | Guaranteed QoS, better user experience | Inefficient bandwidth usage, inflexibility |
| QoS Aware CAC [191] | Prioritises admission based on QoS requirements | QoS-sensitive applications | Enhanced QoS, application satisfaction | Complex QoS mapping, potential resource issues |
| Utility-Based CAC [192] | Assigns utility values to different types of traffic | Traffic prioritisation | Customisable to traffic types, QoS optimisation | Utility function design complexity |
| Dynamic Pricing-Based CAC [179] | Adapts pricing based on network conditions | Revenue maximisation | Efficient network utilisation, revenue generation | Complexity in pricing model integration |
| Learning-Based CAC [182] | Uses ML to make admission decisions | Adaptive network management | Adaptive to changing conditions, improved QoS | Training data requirement, model complexity |
| Mobility-Aware CAC [170] | Considers user mobility for admission decisions | Mobile networks | Seamless mobility support, improved handover | Mobility prediction challenges |

### 2.7.4 CAC Gap Analysis In 5G-Satellite HWNs

In the rapidly evolving wireless communication field, the integration of 5G terrestrial networks with satellite systems has garnered significant attention due to its potential to provide seamless and ubiquitous connectivity. This integration introduces a complex and dynamic environment known as 5G-Satellite HWN, where terrestrial BSs and satellite nodes collaborate to cater to diverse communication needs.

5G-Satellite HWNs are expected to provide seamless and ubiquitous connectivity for various applications and services, such as IoT, vehicular communications, smart cities, and emergency communications. However, the integration of 5G and satellite networks poses several challenges in terms of network selection, resource allocation, handover management, QoS provisioning, and security. Table 2-3 shows some of the identified research gaps for CAC in HWN.

However, this thesis focuses on one of the greatest challenges to address in a 5G-Satellite HWN, which is how to allocate resources (e.g., bandwidth, power) fairly and efficiently to meet the QoS requirements of different users.

Within this scenario, one critical aspect that requires further investigation is the efficient allocation of network resources through CAC mechanisms. While CAC mechanisms are well-established in terrestrial 5G networks, their adaptation and optimisation for 5G-Satellite HWN pose unique challenges.

Despite some initial research in CAC for 5G-Satellite HWN, several critical research gaps remain unaddressed. Most of the existing solutions for these challenges are either based on centralised or heuristic approaches that may not be scalable, efficient, or robust in dynamic and complex scenarios. They assume that the network parameters are static and do not consider the dynamic changes in the network conditions, such as traffic load, user mobility, channel quality, and network availability. This may lead to suboptimal performance and inefficient resource utilisation in the network.

Also, another research gap is the inadequate exploration of ML and AI techniques for adaptive admission control that anticipate network congestion and user mobility to make proactive resource allocation decisions. Therefore, there is a need to develop intelligent and adaptive solutions that can leverage the advantages of AI and ML techniques to optimize the performance and reliability of 5G-Satellite HWNs. This can learn the traffic patterns and network conditions and dynamically adjust the admission criteria and parameters according to the network conditions and user requirements.

To address this research gap, a novel load balancing, adaptive, and intelligent CAC scheme that can dynamically adapt to the traffic and network conditions in HWNs is proposed. The scheme takes into account the different types of traffic, the available network resources, the user QoS requirements, and the characteristics of the 5G and satellite networks. This study seeks to enhance resource allocation efficiency, improve user experiences, and ultimately contribute to the realisation of a robust and efficient 5G-Satellite HWN.

Addressing these research gaps is imperative to unlock the transformative capabilities of 5G-Satellite HWN, accommodate diverse user demands and applications, and pave the way for a new era of ubiquitous and interconnected communications.

Table 2-3: Research Gap in the CAC for 5G-Satellite HWNs

| Research Gap | Description |
|---|---|
| Resource allocation | How to allocate resources (e.g., bandwidth, power) fairly and efficiently to meet the QoS requirements of different users [194], [193], [80]. |
| Mobility management | How to manage the mobility of users seamlessly, while ensuring that their QoS requirements are met [195],[33]. |
| Security | How to secure the 5G-Satellite HWNs against cyberattacks. Inadequate focus on security aspects in |

| | |
|---|---|
| | admission control protocols for 5G-satellite networks, such as ensuring user authentication, data confidentiality, and protection against potential satellite-specific vulnerabilities [1970, [196],[73], [72] |
| Interference management | How to manage interference between different users and links in the network. Absence of comprehensive studies on the coexistence and interference management between terrestrial 5G networks and satellite networks in the context of call admission control, especially when they operate in overlapping frequency bands [198], [39]. |
| Artificial intelligent | Inadequate exploration of ML and AI techniques for predictive admission control that anticipates network congestion and user mobility to make proactive resource allocation decisions [199], [187] |
| Handover management | How to manage handovers between different networks (e.g., 5G, satellite) seamlessly, while ensuring that the QoS requirements of users are met [200], [32]. |
| Energy efficiency | How to design the 5G-Satellite HWNs in an energy-efficient manner. Lack of energy-efficient call admission control schemes that take into account the limited power resources of SatCOM systems while maintaining acceptable QoS levels [202], [201]. |
| Cost optimisation | How to optimise the cost of the 5G-Satellite HWNs. Insufficient investigation into the economic implications of CAC decisions, including pricing strategies, resource allocation auctions, and incentives for collaboration between terrestrial and satellite service providers [204], [203]. |
| Scalability and manageability | Limited consideration of scalability and manageability of CAC mechanisms as the number of connected devices and satellites increases, potentially leading to bottlenecks and performance degradation [205], [27]. |

## 2.8 AN INTELLIGENT CAC FOR LOAD BALANCING IN 5G-SATELLITE NETWORKS

Load balancing CAC aims to regulate the amount of call requests and balance the load of heterogeneous wireless networks. It can improve the network performance and guarantee the QoS. It is an active research topic, especially with the emergence of 5G networks. There are many papers published on this topic in recent years, proposing different algorithms and methods to improve network performance and QoS.

In [206] presents a load-balancing algorithm for a multi-RAT network including an NTN and a TN, which performs intra-RAT and inter-RAT load balancing based on the relative resource utilisation ratio (RRUR) of each cell.

In [162] presents a collaboration algorithm for CAC with load-balancing in ultra-dense small-cell networks, which uses a fuzzy logic system to decide the call acceptance or rejection and a load-balancing algorithm to handover some of the UEs from a fully occupied cell to its neighbouring cells.

In [150] presents a genetic neuro-fuzzy controller for CAC in 5G networks, which applies a hybrid approach of genetic algorithm and neuro-fuzzy system to optimise the call admission decision based on the QoS requirements and network conditions.

In [154] presents a load-balancing CAC algorithm based on soft-handover in 5G networks, which uses a soft-handover procedure to maintain the connection of the UEs to the radio link and a load-balancing algorithm to distribute the traffic load among different cells.

In [207] presents a multi-RAT load balancing function for 5G integrated satellite-terrestrial networks, which uses different algorithms such as weighted fair queuing, proportional fair scheduling, or max-min fairness to balance the load among different RATs based on the QoE requirements.

Hence, in this thesis, an intelligent load-balancing CAC technique is used to address the problem of resource management in 5G-Satellite networks. This combines load balancing and AI methods to create an efficient mechanism for admission control and resource allocation.

The load balancing CAC algorithm is an artificial intelligent algorithm which aims to optimise the resource utilization and QoS in 5G – Satellite HWN by balancing the traffic load among different cells and RATs.

This is done by admitting calls to the network with less load and rejecting calls to the network with more load. The admission parameter is based on a pre-defined threshold for each of the network parameters (signal strength, network cost, network load and available bandwidth). The load balancing algorithm typically works by first calculating the threshold of the network based on the chosen parameter. When a new connection request arrives, the CAC algorithm checks whether admitting the connection would cause any of these parameters to exceed their thresholds. If the new call meets the admission criteria, it is admitted to the cell with the least load. If the new call does not meet all of the admission criteria, it is rejected, this is to ensure that the network's resources are not overloaded. Full details of the call admission process are given in Chapter 3.

The intelligent load balancing CAC algorithm can be used to improve the performance of a cellular network by preventing overloaded cells from becoming congested. It can improve the network performance by enhancing resource efficiency by reducing the congestion and blocking probability in overloaded cells; improving the QoS for users by providing more reliable and consistent service levels across different cells and RATs; and increasing the network capacity and throughput by exploiting the diversity and flexibility of 5G-Satellite networks.

### 2.8.1 Relevance Of Artificial Intelligent In Wireless Networks

The application of intelligent techniques has grown significantly for complex and nonlinear time-varying problems that presented a major obstacle to researchers when using conventional approaches.

Evolutionary approaches and other AI-related techniques have been used to optimise computer systems in a variety of challenging situations [208]. These techniques may include multidisciplinary ML methods, bioinspired algorithms, and fuzzy neural networks. Recursive feedback-based learning and local interactions make these methods very simple [208].

The demand for intelligence has pervaded the future of HWNs. Moreover, the need for mobile traffic is increasing, which is adding to the complexity of network operation procedures. Existing resource management approaches are often based on the experiences of human specialists and depend on manually pre-selected rules; they are neither autonomous for network access nor flexible to the dynamic wireless network environment. Such human task control can become challenging to execute as communication networks get more sophisticated. The network must be able to continuously change its strategy to the real environmental conditions to achieve network resource self-management [209].

Future networks will be able to use AI techniques for complicated decision-making, advanced learning, information finding, and performance optimisation. Strong skills in analysis, learning, optimisation, and intelligent recognition are present in these techniques [210].

Modern AI techniques are being used in 5G networks to increase their capacity to manage traffic. When a network is overloaded, AI can help with decision-making. Thus, AI combined with 5G can meet both the anticipated needs and the new technical obstacles [211]. In [212], the authors proposed a framework which offers an intelligent decision-making support system based on Fuzzy Logic for mobile device energy conservation within an integrated LTE and Wi-Fi network; to ensure that users in this scenario receive a quality experience (QoE).

A fuzzy logic-based vertical handover decision-making framework is suggested in [213] to accomplish seamless vertical handover in HetNets. The suggested method is utilised to address the issue of ping-pong handovers and enhance the networks' overall performance.

In [214], handover prediction is used to address the issue of providing full mobility in WLAN and LTE heterogeneous networks without degrading the QoS. The model relies on inspecting the signal strength between the mobile user and all base stations in close proximity. A new prediction strategy employing a neural network model is given. The efficiency of the suggested plan is improved primarily by reducing the number of unnecessary/redundant handovers.

While [215] uses multiple actor-learner pairs with diverse exploration techniques to train a DRL-based MLB (Mobility Load Balancing) algorithm in an ultra-dense network to learn the best load-balancing strategy.

In recent years, reinforcement learning (RL) which develops a control strategy that maximises its long-term estimated reward through interactions with the environment has been applied to address the nonconvex problems in wireless networks. The agent can carry out specific activities based on the most recent information about the environment at a given time.

In [216], it was suggested to use AI techniques for energy optimization with multi-sleeping control in 5G heterogeneous networks. This was done by using an RL for tiny cells that adjust their operations in response to a service delay limit. To determine the optimum Sleep Mode policy, the algorithm automatically acquires information from the environment based on the anticipated cell throughput, the cell buffer size and the co-channel interference.

The authors in [217] examine the issue of distributed resource management in two-tier heterogeneous networks, where each cell decides on its joint device association, spectrum allocation, and power allocation strategy solely based on information that is locally obtained, without the aid of a central controller. To efficiently learn the optimal intelligent resource management strategy, a distributed coordinated learning algorithm built on a multi-agent duelling deep-Q network is suggested.

A context-aware mobility management approach using RL is proposed for small-cellular networks in [218]; the BSs learn their long-term traffic loads and the best way to increase their cell range collectively, and they schedule their UDs in accordance with the speed and rate of historical data which is transferred in bits while also taking into account QoS for the users.

The authors in [219] presented interference control and handover techniques with RL in HetNet to solve the problem of controlling interference between the macro-BS and the small cell BS. Each BS learns parameters for the transmission power, activation pattern, and bias to achieve the best network performance in HetNet.

In [220], the authors introduced a deep Q-network and employed an evolution strategy to tackle the network's backpropagation initial parameters, with the aim of maximising the system's benefits. This improved both the complicated computations and the connection speed as well as the accuracy of parameter learning.

To address load and energy imbalance,[221] integrate two Q-learning-based selection techniques in HetNets. Distributed Q-learning-based selection algorithms are used in this case to determine bias levels and routing choices. In the downlink, a Q-learning model is created to choose bias values using the energy received from BSs and the number of outages UEs. To construct a Q-learning model which chooses routing targets in the uplink, neighbour energy sorting and variations of each mobile UE's remaining energy are utilised.

The authors in [222] proposed a novel Clipped Double Q-Learning-based load balancing framework to increase total network throughput and resource block usage; while also improving packet loss ratio, jitter and latency.

In [223], Deep Q-learning is used to handle load balancing in the device-to-device (D2D) communication scenario. In [224], the bandwidth adaptation problem in a network is formulated as a partially observable Markov decision process.

A distributed optimisation strategy based on multi-agent RL was developed by the authors in [225] to handle the computationally expensive problem with the vast action space in heterogeneous cellular networks. To attain the nearly optimal policy, the duelling double deep Q-network method is implemented after the state, action, and reward functions for UEs are defined.

In [226], an online RL-based user association strategy for vehicular networks is presented. [227] investigated an RL-based method to provide power control and rate adaptation in cellular networks. A technique for learning was examined in [228] to determine the optimal resource allocation and network access strategy in LAA-LTE-based HetNets.

An algorithm for VHO based on Q-learning was proposed by the authors in [229]. The QoE is further enhanced by the algorithm's suggestion of an RNN-based QoE evaluation system. However, the intricate calculations render them inappropriate for terminal devices with constrained computer power.

To address the problems of better mobility management and handover and to offer an excellent service for end users' throughput, call dropping probability, handover delay and energy consumption, the authors in [230] examined the application of metaheuristics algorithms like grey wolf optimisation (GWO) and Mayfly optimisation (MFO) techniques.

A new hybrid cuckoo search and genetic algorithm that maximises the capacity of heterogeneous wireless networks in terms of lowering latency, increasing throughput, and reducing handover failure probability was proposed in [231]. The performance of the suggested system is encouraging for situations where it is necessary to optimise the handoff mechanisms to limit regular handover as well as cut down on the power consumption of user equipment.

[232] proposes an improved approach that uses an ant colony optimisation technique to lower the call-dropping percentage in heterogeneous wireless networks. Although there are numerous ways to boost network performance that have been suggested in the literature, an emerging area of study is how to autonomously control complicated mobile networks using evolutionary algorithms and methods.

As a result, enhancing load balance and user association procedures in a HetNet can be accomplished by integrating bioinspired methodologies with network operating techniques [233].

Particle Swarm Optimisation (PSO) is one of the bio-inspired algorithms, it is straightforward in its search for the best solution in the problem area. PSO has been successfully applied in a variety of research and application fields. It has been demonstrated that PSO can generate superior outcomes more rapidly and affordably than other methods [234].

The history optimal information is mostly used by the traditional PSO technique to direct its optimisation. However, the traditional PSO algorithm is readily caught in a local optimum when it investigates high-dimensional difficult situations because inaccurate information about the position of the best particles can quickly cause most of the particles to migrate towards the incorrect space [235].

In this thesis, EPSO is suggested to improve the traditional PSO algorithm's optimisation performance. EPSO is different from other optimisation methods because it does not rely on the gradient or any differential form of the objective and simply requires the objective function [236]. Additionally, it contains a small number of hyperparameters, which makes implementation simpler. EPSO is a very strong and adaptable algorithm that may be used for a very wide range of applications. The information sharing of EPSO can immediately identify more accurate global and local information, minimising particles restricted to local optimum and increasing the algorithm’s precision throughout the optimisation. Therefore, EPSO is used to solve the CAC problem for load balancing in this thesis.

*Table 2-4: Taxonomy of AI & ML Algorithms For Resource Management in Wireless Networks*

| Algorithm | Objective | Merits | Demerits | Future Works |
|---|---|---|---|---|
| Fuzzy Logic [213], [212] | To ensure that users in this scenario receive a quality experience; to accomplish seamless vertical handover in HetNets | Optimises mobile device battery life by balancing energy consumption and network performance; enables intelligent vertical handovers and real-time energy conservation for longer device usage times. | Uncertainty, complexity, validation and verification, noise sensitivity, and scalability. | Algorithm enhancement, machine learning integration, IoT, user behaviour analysis, multi-criteria decision-making, consensus facilitation, and FinTech applications. |
| Neural Network Model [214] | To address the issue of providing full mobility in WLAN and LTE heterogeneous networks without degrading the QoS | Improves accuracy, reduces unnecessary handovers, enhances throughput, and adapts to changing network conditions. | Complexity, overfitting, transparency, dynamic environments, data dependency, and resource-intensiveness, necessitate careful management. | Integrating emerging technologies, optimising deep learning algorithms, developing hybrid models, enhancing energy efficiency, and improving coverage and QoS. |
| DRL-based MLB (Mobility Load Balancing) [215] | To learn the best load-balancing strategy | Effectively manages complex and dynamic challenges in ultra-dense networks, | Complexity, overfitting, stability, safety concerns, and scalability issues | Optimisation, generalisation, scalability, reward function design, safety, stability, integration, |

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| | | offering self-organized clustering, optimal policy learning, efficiency, stability, and a safeguard mechanism. | | energy efficiency, and real-world testing to improve practicality and effectiveness. |
| Reinforcement Learning [218], [216] | To determine the optimum Sleep Mode policy; to learn long-term traffic loads and the best way to increase cell range collectively | Effective in wireless network optimisation due to their adaptability, real-time learning, resource efficiency, and user privacy, making them a promising approach for intelligent network management. | Complexity, computational intensity, convergence issues, and non-stationarity | 5G advancement, distributed learning, resource management, security, optimisation, hardware implementation, energy efficiency, and latency reduction, |
| Q-learning [221] | To handle vertical handover | Adaptability, ability to learn from the environment, and its ability to optimize handover decisions | Convergence time, high overhead, and balancing exploration and exploitation. | Convergence enhancement, time, computational overhead reduction, hyperparameter optimisation automation, non-stationary environments adaptability, integration with other machine |

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|---|---|---|---|---|
| | | | | learning techniques |
| Multi-agent Duelling Deep-Q Network [217] | To efficiently learn the optimal intelligent resource management strategy | Enhances resource management in Heterogeneous Networks, improves efficiency, reducing energy consumption, and facilitates precise policy evaluation and resource allocation decisions | Complexity, communication overhead, non-stationarity, scalability issues, partial observation, convergence, and interference management | Improving scalability, communication efficiency, non-stationarity, power control, interference management, meta-learning, and adaptive user association to enhance performance and efficiency |
| Deep Q-Network [220] | To tackle the network's backpropagation initial parameters, with the aim of maximising the system's benefits. | Enables better generalisation over high-dimensional environments. | Inefficient sample efficiency, overestimation bias, stability issues, hyperparameter sensitivity, and partial observability | Improving adaptability, efficiency, and applicability, growing Q-Networks for adaptive control resolution, optimising workload planning in cloud networks, and developing dual-embedding-based DQNs. |
| Distributed Q-Learning-Based Selection Algorithms [221] | To address load and energy imbalance | Effectively manage load and energy imbalance in heterogeneous networks (HetNets) | Computational complexity, scalability, robustness, and finding optimal balance between exploration and exploitation. | Optimisation, scalability, communication efficiency, robustness, integration, energy harvesting, and |

| | | | | |
|---|---|---|---|---|
| | | | | advanced QoS management. |
| Clipped Double Q-Learning-based [222] | To increase total network throughput and resource block usage; while also improving packet loss ratio, jitter and latency. | Optimizes wireless network operations, particularly load balancing, by addressing overestimation issues and enhancing throughput, resource utilization, and QoS quality | Unpredictable network dynamics, overestimation bias, slow policy changes, and may not be as data efficient as other algorithms. | Improving algorithmics, reducing bias, adapting to policy changes, enhancing data efficiency, and integrating with other techniques for robust solutions |
| Deep Q-Learning [223] | To handle load balancing in the device-to-device (D2D) communication scenario | Adaptability, optimization, predictive capabilities, autonomy, and performance improvement | Complexity, overfitting, delayed convergence, non-stationarity, and sample inefficiency, | Improving adaptability, reducing complexity, enhancing sample efficiency, addressing non-stationarity, integrating novel techniques, and optimising performance for device-to-device communication |
| Multi-agent RL [225] | To handle the computationally expensive problem with the vast action space in heterogeneous | Offers decentralisation, scalability, efficiency, adaptability, robustness, learning from interaction, and | Training instability, coordination complexity, and policy heterogeneity, necessitating careful design | Improve performance, reliability, and applicability, integrating with emerging technologies, and considering |

| | | | | |
|---|---|---|---|---|
| | cellular networks | convergence to a Nash Equilibrium | and implementation. | ethical and societal impacts |
| Hybrid Cuckoo Search and Genetic Algorithm [231] | To maximise the capacity of heterogeneous wireless networks in terms of lowering latency, increasing throughput, and reducing handover failure probability | Optimises wireless networks by reducing latency, increasing throughput, and minimizing handover failure probability, ensuring reliable service continuity. | Complex, computationally intensive, and requires regular updates, requiring careful design and implementation. | Optimising parameters, real-time applications, integrating with emerging technologies, improving mobility management, energy efficiency, scalability, and robustness to network variability. |
| Ant Colony Optimisation [232] | To lower the call-dropping percentage in heterogeneous wireless networks | Efficiently finds optimal routing paths in wireless networks, reducing call-dropping percentages and improving its robustness, dynamic adaptation, and real-time optimisation | Computational complexity, slow convergence speed, resource constraints, overhead costs, and optimization limitations. | Involve hybrid approaches, energy conservation, routing path optimisation, enhanced algorithms, and reducing overhead to improve coverage and efficiency. |

## 2.9 CONCLUSION

This chapter provides a detailed analysis of resource management in HWNs. This chapter begins with an exploration of 5G HetNets: Vision and Motivation. It then looks at the role of Satellite in 5G Hetnet, as well as some of the integration challenges. Also, a comprehensive analysis of the different resource management strategies employed in HWNs to shed light on the difficulties of improving network efficiency and performance. The discussion then shifts to CAC, a crucial idea that plays a vital role in guaranteeing smooth operations in HWNs.

The chapter highlights the critical necessity for CAC in HWNs by outlining the challenges and complications that arise in dynamic network environments. To pinpoint areas in need of enhancement and improvement, a gap analysis is provided. The scope is expanded to include a detailed assessment of CAC within the framework of the 5G-Satellite HWN paradigm.

An innovative approach is introduced with an exploration of Intelligent Load Balancing CAC in 5G-Satellite Networks. To ensure a balanced and effective use of network resources, this part reveals a strategic integration of intelligence for load distribution optimisation. An effective way to improve network performance and deal with the problems caused by wireless networks' diverse structure is the intelligent load balancing mechanism.

The final section of the chapter explores AI’s applicability to wireless networks. It opens the door for future advancements in resource management, CAC, and load-balancing techniques across diverse wireless settings by recognising the revolutionary potential of AI.  AI integration is being positioned as a critical enabler for meeting the changing needs of wireless communication, including improved intelligence, efficiency, and agility in resource management.

Building on this foundation, the subsequent chapters will cover more detail on the proposed Load-balancing CAC framework for 5G-Satellite HWN.

# CHAPTER 3: CAC FRAMEWORK FOR LOAD BALANCING IN 5G-SATELLITE HETEROGENEOUS NETWORK

## 3.1 OVERVIEW

This chapter explains the load balancing framework and algorithm design. Load balancing is a major problem in 5G-Satellite HWNs because of the increased demand for data and constrained resources. Network effectiveness and performance can be enhanced by using load balancing frameworks to distribute traffic equally across the networks.

The load balancing framework in 5G-Satellite HWNs is a framework that aims to balance the traffic load among different network components, such as satellites, macro base stations, small cell base stations, etc. A load balancing framework can improve the network performance, efficiency, and reliability in 5G-Satellite HWNs. One of the crucial challenges in managing these networks is efficiently allocating network resources, ensuring QoS, and maintaining a high level of network performance. Load balancing in this thesis is achieved using the CAC mechanism. Hence, the design of the load balancing mechanism is described elaborating on the CAC algorithm which is used to ensure equitable distribution of traffic between the networks. The chapter also discusses the network architecture and proposed system model to be used in the thesis, the call admission policy, the performance metrics as well as the mathematical problem formulation in the 5G-Satellite HWNs.

## 3.2. 5G-SATELLITE NETWORK LOAD BALANCING ARCHITECTURE

The load balancing architecture of the 5G-Satellite HWNs is a critical component for ensuring the performance and reliability of the network. The architecture must be able to distribute traffic efficiently across the different RATs in the network, while also taking into account the user's location and preferences. The load balancing in this thesis is done by using CAC to manage the flow of traffic on the 5G-Satellite networks.

The CAC determines whether or not a new call can be admitted to the network. If the network is not able to handle the new call, it will be rejected. By rejecting calls that would overload the network, CAC can help to improve the performance of the network by preventing overload, ensuring that all users have a consistent level of performance, and reducing the number of dropped calls.

The literature survey shows that three main types of architecture can be used for CAC in HWNs, this includes centralised architecture, distributed architecture and hybrid architecture [119].

In a centralised approach, a central entity such as a gateway or server acts as the central controller and is responsible for making all CAC decisions for the whole HWNs. Therefore the CAC algorithm is implemented in the network core. The network core has a global view of the network and can make more informed decisions about whether to admit a call [237]. This approach is typically used in small to medium-sized networks with predictable traffic patterns. A centralised CAC architecture has some advantages, such as simplicity, scalability, and global optimisation. This can be efficient because it eliminates the need to communicate with multiple systems servers. However, a centralised CAC system can be a single point of failure. If the central system server fails, then no new calls can be admitted to the network. It also has other disadvantages such as high signalling overhead, and lack of flexibility. It involves cooperation among all wireless BSs and users such as the sharing of substantial data overhead, and this might not be possible when the networks are operated by competing operators. In addition, different network operators adopt a different method for transmitting the network; and this will also make any close cooperation among the heterogeneous wireless network difficult [238].

Another drawback with the centralised architecture is the fact the central controller communicates more often with all the network systems which causes overload in the centralised system and slows down the processing and connection time. A centralised architecture also has to deal with the issue of performance degradation, which causes network instability and rapid fluctuation [239].

The problem of excessive communication overheads can be solved with distributed architecture. In this architecture, the CAC algorithm is implemented on mobile devices. This approach is more scalable and efficient, as it does not require the network core to make admission decisions for every call. Mobile users aim to improve their own performance by selecting the network themselves based on their preferences. A distributed CAC architecture has some advantages, such as low signalling overhead, high fault tolerance, and high flexibility. However, mobile device-based CAC can be less reliable, as it depends on the accuracy of the information on the mobile device. It also has some disadvantages, such as complexity, coordination, and suboptimal performance.

In addition, the problem of load balancing emerges when the UD performs network selection, as users have a greedy approach, that is, they select the best network among the available options without taking into account the network’s actual load. It is also likely that the network selected does not have the bandwidth or other network resources to handle the incoming call. This leads to inefficient use of resources, performance degradation, network instability, increased call blocking, and dropping probability. Therefore, a distributed architecture may not guarantee an equitable distribution of traffic.

A major issue is to develop a load-balancing architecture that increases network efficiency and improves user satisfaction while reducing the burden of signalling and processing. To tackle this issue, a hybrid architecture should be considered.

A hybrid CAC architecture combines the benefits of centralised and distributed CAC systems. This is mobile device-based CAC with feedback from the network. The mobile device makes an initial decision about whether to admit a call, based on its own local information and preferences such as battery level, signal strength, supported technologies, service cost etc. If the mobile device is not sure whether to admit the call, it can request feedback from the network core. The network core can then provide the mobile device with more information about the network conditions and the admission status, such as the signal strength of different RATs, the load on different RATs, the available bandwidth on different RATs and the number of active users. This feedback can help the mobile device to make a more informed decision about whether to admit the call; the UD can use this information to select the RAT that is most likely to provide the best experience for the user.

The hybrid CAC architecture is a promising approach to CAC for HWNs. The proposed load balancing algorithm in this thesis is based on hybrid CAC. There are a number of benefits to providing UDs with network information. First, it allows UDs to make more informed decisions about which RAT to use; this can lead to improved performance and satisfaction for users. Second, it helps to ensure that radio resources are used effectively; this can help to improve the overall performance of the network. It ensures fairness in the allocation of radio resources among the HWN; it can be used to support a variety of QoS requirements for all admitted calls and reduce call blocking /dropping probability.

## 3.3 CAC ARCHITECTURE NETWORK COMPONENT

The CAC architecture in 5G-Satellite HWNs is a complex system. However, it is essential for ensuring the QoS of the network. The architecture must be able to adapt to changes in traffic load and user QoS requirements. It must also be able to handle unexpected events, such as network outages.

The following are some of the key components of the CAC architecture in 5G-Satellite HWNs:

**5G Cellular Network**: The 5G cellular network provides the primary network for the system. It is responsible for providing high-speed, low-latency connectivity to devices in urban and suburban areas.

**Satellite Network**: The satellite network provides the secondary network for the system. It is responsible for providing connectivity to devices in remote areas and areas that are not served by the 5G cellular network.

**Gateway**: The gateway is the point of interconnection between the 5G cellular network and the satellite network. It is responsible for routing traffic between the two networks. The gateway forwards the call request from the BS to the CAC server. It can be located on the ground or in space.

**User Device (UD)**: The UD is the device that connects to the network. It can be a smartphone, tablet, laptop, or other device that is capable of connecting to a wireless network. The UD sends a call request to the CAC server. The call request includes information about the user's location, the QoS requirements of the call, and the type of service that the user is requesting.

**Base Station (BS)**: The BS is the node in the 5G cellular network that is responsible for communicating with the UD. It is responsible for transmitting and receiving data between the UD and the core network. The BS forwards the call request from the UD to the CAC server. BSs can be located on the ground, on rooftops, or in space.

**Satellite Ground Station**: A satellite ground station, also known as an Earth station or Earth terminal, is designed to communicate with satellites in orbit. These stations play a crucial role in the operation of satellites, as they are responsible for sending commands to the satellite, receiving data from the satellite, and monitoring its status. Satellite ground stations are essential components of satellite operations, enabling communication and control of satellites for a wide range of applications, including Earth observation, telecommunications, scientific research, and navigation.

**Satellite**: In a satellite network, the satellite is the node that is responsible for communicating with the UD. The satellite acts as a relay between the UD and the ground station. It receives data from the UD and then transmits it to the ground station, or vice versa. The satellite is also responsible for routing data through the satellite network. When the UD sends data to the ground station, the satellite will determine the best route for the data to take through the network. This may involve routing the data through other satellites or the ground station.

**Core Network**: The core network is the backbone of the 5G-Satellite HWNs. It is responsible for routing traffic between the different parts of the network and providing services to the UDs. The core network forwards the call request from the gateway to the CAC server.

**Control Plane**: The control plane is responsible for managing the network. It includes functions such as CAC, handover, and resource allocation.

**User Plane**: The user plane is responsible for carrying user traffic. It includes functions such as data delivery and QoS management.

**CAC Algorithm**: The CAC algorithm is responsible for making decisions about whether to admit a call or not. It also decides which of the available RATs is most suitable to accommodate the incoming call. The CAC algorithm ensures that the network resources are not overloaded, which can lead to poor call quality or even call drops. It takes into account a number of factors, such as the current traffic load on the network, the type of traffic, the user’s location, as well as the user's QoS requirements. When a new call request is received, the CAC algorithm will first check to see if there are enough network resources available to support the call. If there are not enough resources available, the call request will be denied. Figure 3-1 shows a simple CAC procedure in 5G-Satellite HWNs.

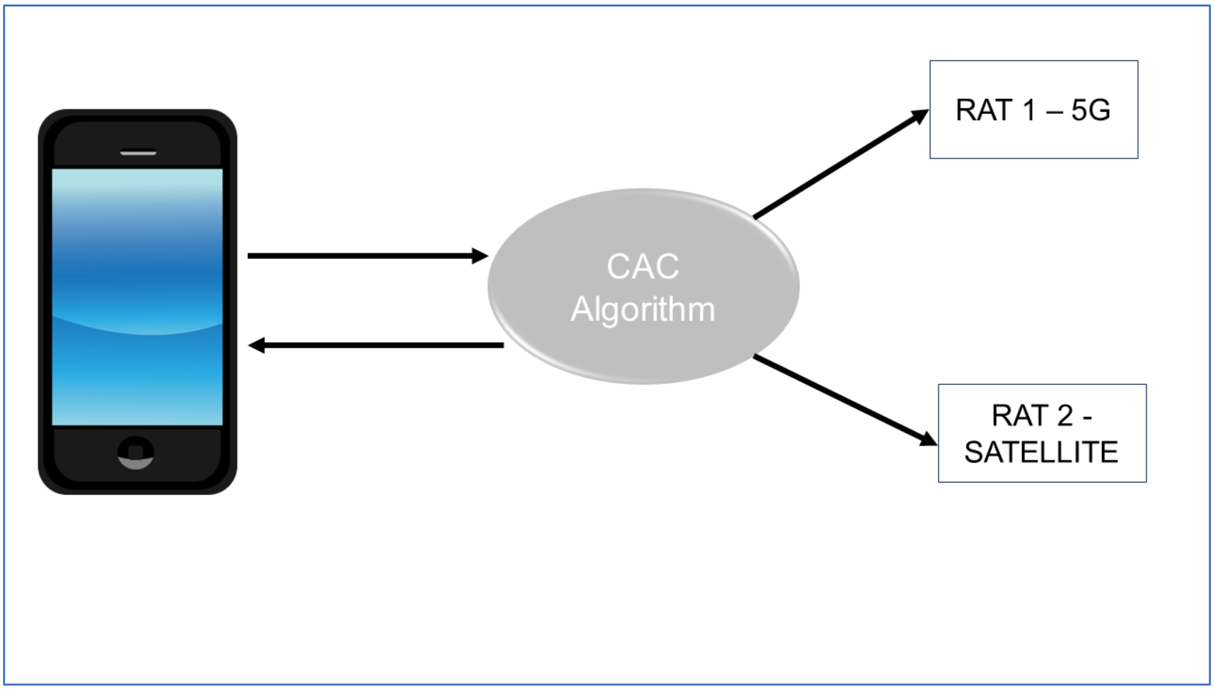



*Figure 3-1: CAC Procedure in 5G-Satellite HWNs*

**CAC Controller**: The CAC controller is a device or software application that implements a CAC algorithm. CAC controllers are used to control the number of calls that are allowed in the network. CAC controllers typically work by monitoring the current load on the network and the estimated bandwidth requirements of new calls. If there are not enough network resources available to support a new call, the CAC controller will deny the call request. The CAC controller executes the CAC algorithm and selects the most suitable RAT for the incoming call.

CAC controllers can be used to improve the QoS in a telecommunications network. By limiting the number of calls that are allowed to be established, CAC controllers can help to prevent congestion and ensure that all calls can be completed with good quality.

**Handover decision-making**: The handover decision-making process is also a critical component of load balancing in 5G-Satellite HWN. The handover decision-making process determines when a user should be handed over from one RAT to another. This process must take into account the load-balancing algorithm's decisions about how to route traffic. A full handover event and trigger scheme are beyond the scope of this thesis; however, the algorithm must consider this during call admission. Figure 3-2 presents the CAC architecture of the 5G-Satellite HWN.

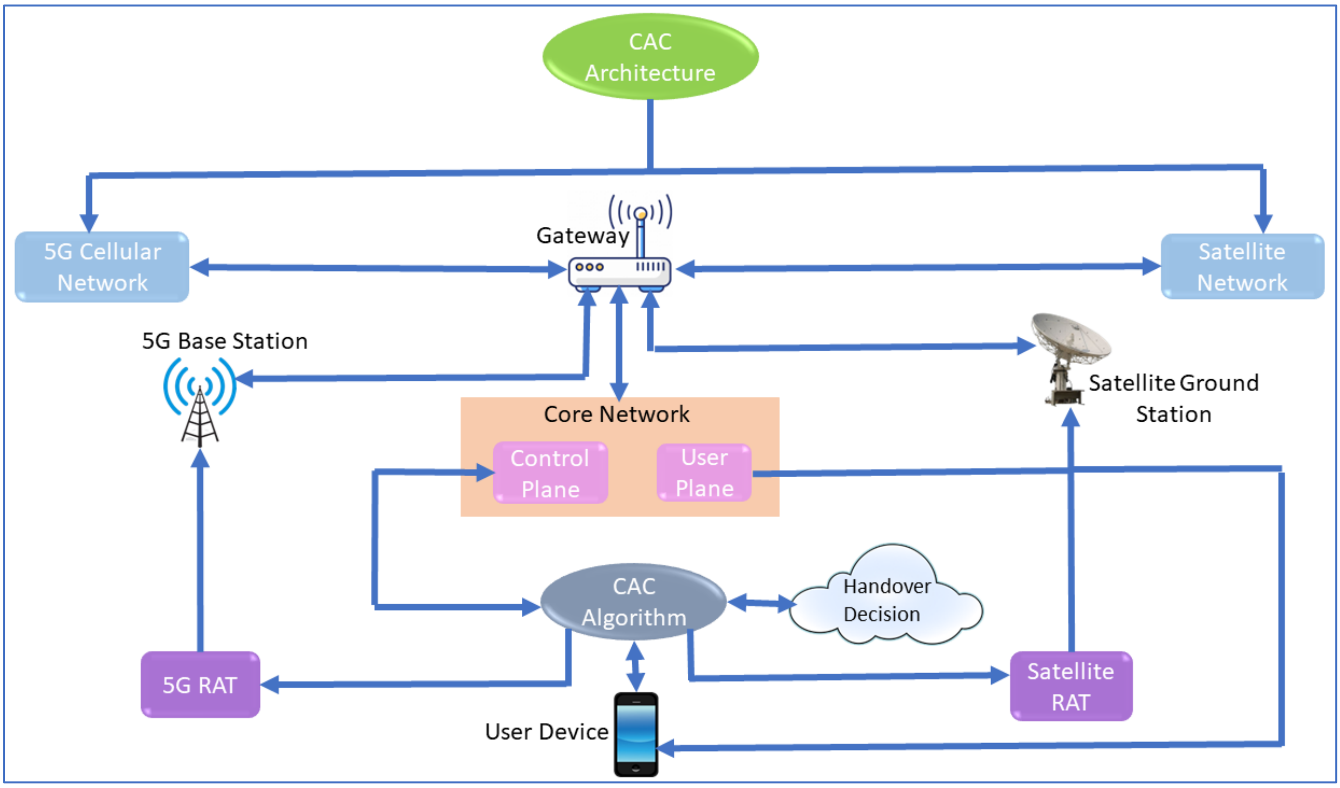



*Figure 3-2: CAC Architecture in 5G-Satellite HWNs*

## 3.4 PROPOSED LOAD BALANCING FRAMEWORK

This section discusses the proposed CAC model, the decision epoch and the call admission policy for the 5G-Satellite HWN.

### 3.4.1 Call Admission Control Model

In this section, a geographic region completely covered by two broadband RATs is considered: a primary RAT such as 5G and a secondary RAT serviced by Satellite; typically, a 5G cell will be covered with several satellite gateway links (access points). A common example of such coverage areas overlapping with heterogeneous wireless networks can be observed in urban areas, especially in busy town centres, train stations and marketplaces.

These HWNs offer different coverage, bitrates, capacity, etc. In addition, the signal coverage of these wireless networks overlaps. Figure 3-3 shows the 5G-Satellite HWNs model.

It is assumed that the mobile users are randomly positioned at any point in the Satellite and 5G BS coverage area. The set of users is represented by N = {1, 2, ..., N}. Each user in the network has a choice between the two available RATs in the scenario under consideration. Additionally, it is expected that the user uses any one of the three service types—voice, video, and data—and the user can run any of the three services on their device.

It is also assumed that the arrivals of the video, voice, and data users follow a Poisson distribution and the channel holding times for video, voice and data calls are exponentially distributed. The mean arrival rate $\lambda$ is 1(calls/s) and the average call holding time $1/\mu$ =100(s).

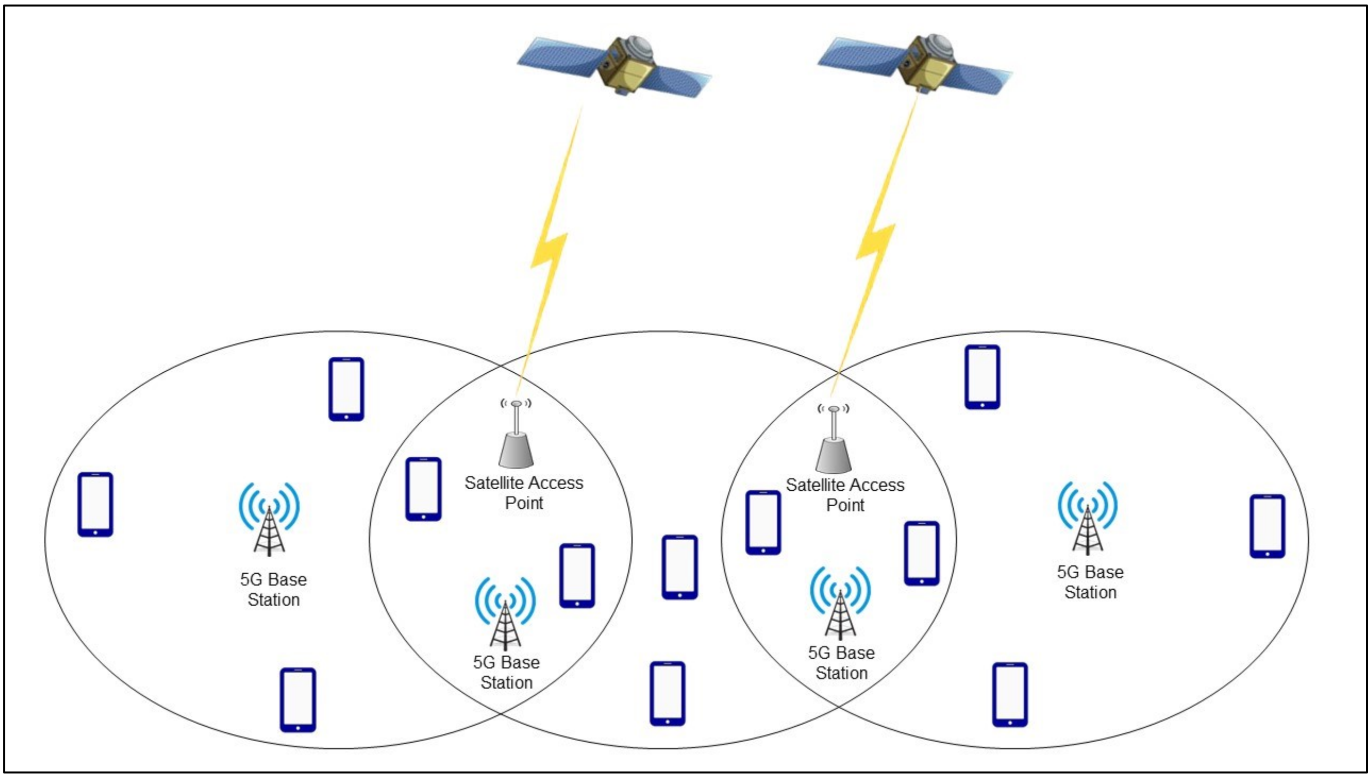



*Figure 3-3: 5G -Satellite HWNs Model*

An intelligent CAC framework using the EPSO algorithm is used to balance the load in the 5G-Satellite HWNs. The novel hybrid CAC scheme in the HWN utilises two controlling entities: CCN running on the network entity, and controller at UD.

The UD is also treated as multi-mode mobile terminals, and they can connect to a single network or multi-RATs simultaneously. Also, only users present within the overlapping coverage area of 5G, and Satellite are taken into account; users outside the dual coverage area of 5G BS and the Satellite AP are always connected to either 5G or Satellite and no decision is taken in this case.

The load balancing process starts when there is an arrival of a new call. The proposed CAC algorithm decides to admit or decline a call once a request is received from an arriving mobile user. In this way, the CAC algorithm evaluates the resource availability using the network attributes. Here it is assumed that there are four network attributes collected by the CAC (namely signal strength, network cost, network load and available bandwidth) and these are used as the decision variables. Before the CAC can choose or admit a call, it needs to observe the information from the network; this is because a bad decision can lead to load imbalance, degraded network, and bad quality of service. The core ideas are to sample the network state information in a decision epoch, evaluate the defined threshold and decide if there are enough resources to admit the incoming call.

In addition to the available resources, the network also considers the handover probability for each RAT. If the handover probability is high, it means the call is more likely to experience a handover. This can degrade the QoS of the call, so the network may be less likely to admit the call to a RAT with a high handover probability. By carefully considering the handover probability, the network can make more informed decisions about whether or not to admit new calls. It can help to reduce the number of dropped calls. If the network knows that a call is likely to experience frequent handovers, it can avoid admitting the call to a RAT that is prone to handovers. Hence the network calculates the handover score for each RAT using the handover probability.

Specifically, when a new call arrives, the CAC algorithm receives as input information of all the network's status in terms of signal strength, network cost, network load and available bandwidth. It then evaluates the defined network status value for each RAT and checks if it is ≤ ηthreshold. It also checks the handover score for each RAT to see if it's lower than the call's QoS. If the network status value is ≤ ηthreshold and the handover call is lower than the call's QoS, the service is admitted to 5G or Satellite (depending on the network that meets the threshold and handover requirement), the call is admitted; if none of the networks meets the threshold and handover requirement, the call is blocked and the user should try to request that service again.

The EPSO algorithm, embedded within the CAC framework, continuously monitors the network state, including parameters like signal strength, network load, and available bandwidth. In response to fluctuations in user density and mobility patterns, the algorithm dynamically reallocates network resources to ensure optimal performance and QoS across diverse scenarios. By leveraging information about user density and mobility patterns, the algorithm adjusts its parameters and optimization criteria to suit the specific characteristics of urban and rural areas. For instance, in urban areas with high user density and frequent mobility, the algorithm prioritizes efficient resource allocation and congestion management to prevent network overload and degradation of service quality; the algorithm may adopt more conservative admission policies to account for increased handover probability, thus maintaining seamless connectivity and minimizing call drops. Similarly, in rural areas with lower user density and potentially different mobility patterns, the algorithm adapts its resource allocation strategies to ensure equitable access and optimal utilization of available network resources. Hence, the EPSO algorithm is designed to be scalable and adaptable to varying network conditions, including changes in user density and mobility patterns over time.

The proposed CAC scheme is designed to improve the overall performance of 5GSatellite HWNs by reducing call blocking and improving QoS. The CAC scheme is also designed to be fair to all users, regardless of their location or the type of network they are using. Figure 3-4 shows the algorithm flowchart.

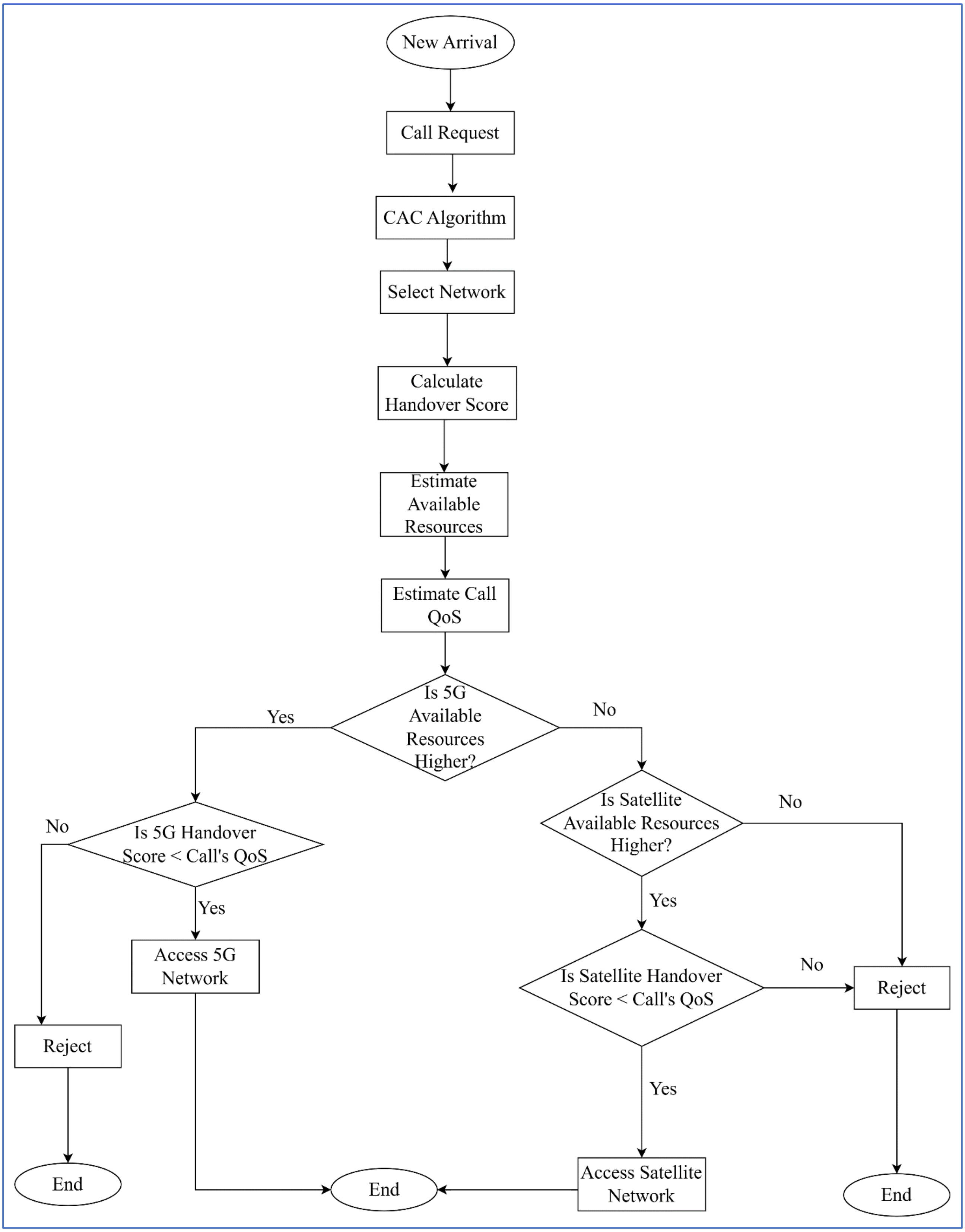



*Figure 3-4: CAC Flowchart*

### 3.4.2 Decision Epochs and Admission Control Policy

The proposed CAC model consists of seven elements: network state, call arrival process, decision epoch, possible actions, call processing time, call admission policy and handover probability.

**(1) The call arrival process:**

The call arrival process is a stochastic process that models the arrival of calls to the network. The call arrival process is typically modelled as a Poisson process, which means that the calls arrive independently and randomly in time. The rate of the Poisson process, also known as the arrival rate, is the average number of calls that arrive at the network per unit of time. The call arrival process can be used to model the arrival of calls to a variety of networks, including 5G-satellite HWN. The arrival rate of the call arrival process can be adjusted to reflect the expected number of calls that will arrive on the network in a given time period. This allows the network to be designed to handle the expected load.

The call arrival process is an important input to the CAC scheme. The CAC scheme uses the call arrival process to estimate the future load on the network and make decisions about whether to admit calls to the network. The CAC scheme can be more effective if it has a good estimate of the call arrival process.

**(2) States:**

The state includes all relevant information about the network environment that the CAC algorithm needs to know to make a decision. There are 4 network information used in this thesis; these are also the decision variables: signal strength, network cost, network load and available bandwidth.

**3) Decision epoch:**

A decision epoch is defined as the specific time in which an arrival request occurs. Under the network state, **t**he decision epochs are the points in time when the proposed algorithm makes a call admission decision on whether to admit the new call. The decision epochs are typically spaced evenly in time, but they can also be adaptive, depending on the traffic load of the network.

**(4) Actions:**

At each decision epoch, the CAC algorithm decides for each possible call arrival that may occur in the time. These decisions are collectively referred to as an action. These are sets of all possible actions that the proposed algorithm can take. The actions of the proposed algorithm include block the call, accept the call in 5G RAT, accept the call in Satellite RAT.

**(5) The call processing time:**

The call processing time is the time it takes for a call to be established and completed. The call processing time can be divided into two parts. The first part is the call setup time which is the time it takes for the CAC to make a decision about whether to admit the call and for the network to set up the call. The second part is the call holding time which is the time that the call is connected and active.

**(6) Handover Probability**

Handover probability is the likelihood that a mobile user's call will be handed over from one network to another. The handover probability is important for CAC in the HWNs. If the network does not consider any future events, such as handovers, when making this decision, this means that the network can become overloaded if there is a sudden influx of new calls or if a large number of calls are handed over to the network at the same time. Also, If the handover probability is high, then the call admission control algorithm needs to be more conservative to avoid blocking calls. This is because there is a higher chance that a call will be handed over to a different network and then blocked. For example, if the algorithm predicts that a handover is likely to occur in the near future, it might be more likely to block a new call, even if there is currently enough bandwidth available. This is because the algorithm knows that the bandwidth will be needed for the handover, and it does not want to risk overloading the network.

The handover probability can be incorporated into the CAC algorithm in a number of ways. In this thesis, the handover probability is added to the decision-making process. For example, if the handover probability is high, then the CAC algorithm might be more conservative to avoid blocking calls.

The handover probability is calculated using the formula below:

Handover Probability = 1 - e^ (-(Difference in Signal Strength) / Handover Threshold)

where:

- Difference in Signal Strength is the difference in signal strength between the home network and the visited network.
- Handover Threshold is the minimum difference in signal strength that will trigger a handover.

It is assumed that there is a 50% chance that a user will be handed over from the 5G network to the satellite network.

**(7) Call Admission Policy:**

Call admission policy in heterogeneous wireless networks is a set of rules that determines whether or not to admit a new call in a heterogeneous wireless network based on the available resources, the QoS requirements, and the network selection of the user. It aims to make full use of the spectrum resources in different RATs, under the constraint of seamless QoS. The goal of the call admission policy is to improve network performance such as resource utilisation, call blocking probability, and call dropping probability as well as ensure that the network can provide a satisfactory level of service to all users, while also avoiding congestion [119].

The call admission policy uses a decision rule which maps the action to be chosen at different states and decision epochs. The goal is to determine an association policy which maximises the total system throughput and minimises call blocking. The decision rule considers available resources in the network, the handover probability for the call and the QoS requirements of the call. The set of rules is applied to determine if a new call should be admitted on the network or not.

The decision rule considers the following:

Args:

handover_probability: The handover probability for the call.

available_resources: The available resources in the network (the four options considered are signal strength, network cost, network load and available bandwidth).

call_qos: The QoS requirements of the call.

Returns:

True if the call is admitted, False otherwise.

**Calculate the handover score for the call.**

handover_score = handover_probability * available_resources

**If the handover score is greater than the call's QoS, reject the call.**

if handover_score > call_qos: return False.

**Otherwise, admit the call.**

return True

The given code snippet above is a simplified representation of a decision-making process related to call handovers in 5G -Satellite HWNs where handovers might occur between different network segments (5G and Satellite). Below is a breakdown of the logic:

**1) Handover Score Calculation:**

handover_score = handover_probability * available_resources

This formula calculates a handover score by multiplying two factors:

**handover_probability**: Represents the likelihood or probability that a handover will be needed. It could be influenced by factors such as user mobility patterns, signal strength fluctuations, or other dynamic network conditions.

**available_resources**: Represents the resources available in the target network segment, which might include bandwidth, power, or other capacity-related metrics.

**2) Decision Making:**

**if handover_score > call_qos: return False.**

This condition checks if the calculated handover score is greater than the QoS (call_qos) required for the call. The QoS is a predefined threshold representing the acceptable level of service quality for the ongoing call. If the handover score exceeds this threshold, it indicates that the target network may not have enough resources to maintain the desired call quality. In such a case, the decision is to reject the call (return False).

**Otherwise, admit the call: return True.**

If the handover score is equal to or below the call's QoS, it suggests that the target network has sufficient resources to handle the call adequately. In this scenario, the call is admitted, and the function returns True.

In conclusion, the purpose of this decision-making process is to evaluate the feasibility of a handover for an incoming call based on the calculated handover score. If the resources in the target network are deemed inadequate (as indicated by a high handover score), the call is rejected. Otherwise, the call is admitted to the network. This logic helps optimise the handover process by considering the probability of handover and the available resources in the target network segment, ensuring seamless QoS while maximising resource usage and minimising call blocking.

### 3.4.3 Summary of Call Admission Process

The call admission process is summarised below:

1. **Call Request Initiation**: A new call request is initiated from the mobile device to the network. The request contains information about the call's QoS requirements, such as desired bandwidth, latency tolerance, priority level etc.

2. **CAC Algorithm Assessment**: The CAC algorithm embedded within the mobile device receives the call request. The algorithm considers various factors, including the device's current resources (e.g. available processing power, memory, battery), ongoing calls and their resource requirements.
3. **Initial Decision**: The CAC algorithm evaluates whether admitting the new call on 5G or Satellite network is feasible without causing undue resource strain. It compares the QoS requirements of the new call with the available resources on the different RATs and ongoing call loads.
4. **Network Feedback Request**: If the CAC algorithm tentatively approves the call, the mobile device sends a feedback request to the network. The request seeks real-time feedback on handover probability and the different RATs network conditions, including congestion levels, available bandwidth, latency and overall QoS metrics.
5. **Network Feedback Acquisition**: The network infrastructure processes the feedback request from the mobile device. It gathers relevant information about the handover probability score and the current state of the different networks, such as the number of active calls, resource utilisation, and any signs of congestion. It identifies the available resources in the different radio access technologies (RATs) that can support the call.
6. **Network Selection**: The network identifies the RAT that can provide the best QoS for the call. The network determines if the selected RAT has the lowest handover probability and enough resources to support the call using the call admission policy.

7. **Feedback Integration**: The CAC algorithm receives the network feedback and analyses it. The feedback provides insights into the current network conditions and the potential risks of admitting a new call.
8. **Dynamic Decision Adjustment**: Based on the network feedback, the CAC adjusts its initial admission decision. If the network is experiencing congestion or resource scarcity, the algorithm might tighten its admission criteria to prevent network degradation.
9. **Final Admission Decision**: The CAC algorithm makes a final decision on whether to admit the new call. This decision considers the handover probability, the mobile device's resources and the real-time network feedback to ensure optimal QoS. If the selected RAT has enough resources and the lowest handover score, the call is admitted. If the selected RAT does not have enough resources and the lowest handover score, then RAT 2 is considered. However, if both RATs do not have enough resources to admit the call, the call is rejected.
10. **Admission Notification**: If the call is approved, the CAC algorithm notifies the network infrastructure about the admission decision. The network reserves the necessary resources for the new call and allocates them to the suitable RAT.
11. **Call Session Monitoring**: Throughout the call session, the mobile device continually monitors QoS parameters and network conditions. It tracks factors like latency variations, signal strength and satellite handovers.
12. **Feedback Loop Activation**: If the mobile device detects any degradation in call quality or network conditions, it sends real-time feedback to the network. The network receives the feedback and assesses call quality and network

conditions. If required, the network undertakes actions such as adaptive resource allocation or handover to ensure optimal QoS.

## 3.5 DISCUSSION OF THE ALGORITHMS

To achieve efficient load balancing between 5G-Satellite HWNs, an intelligent CAC algorithm has been proposed as part of the proposed overall load balancing framework. Intelligent CAC is a more advanced form of CAC that uses AI to make more informed decisions about whether or not to admit a call. The intelligent CAC takes into account factors such as the current traffic load in the network, the user's location, and the user's desired QoS. It is particularly important in 5G – Satellite HWNs because it can help to ensure that the network can handle the increased traffic load that is associated with these networks. It can also help to improve the QoS for users who are located in areas with poor cellular coverage. It is a valuable tool that can help to improve the performance and reliability of 5G-Satellite HWNs. By intelligently distributing traffic across the different network nodes, the framework can minimize congestion and maximize performance. This can lead to improved user experience and reduced costs for network operators. This section gives full details of the proposed algorithm as well as the benchmarking algorithms.

### 3.5.1 Proposed Algorithm

The EPSO algorithm is proposed in this thesis to handle the CAC. EPSO is a very strong and adaptable algorithm that may be used for a very wide range of applications. The information sharing of EPSO can immediately identify more accurate global and local information, minimising particles restricted to local optimum and increasing the algorithm’s precision throughout the optimisation.

EPSO utilises parameters collected using call admission policy to seamlessly admit new calls and choose the suitable RAT to allocate the UD, to ensure there is equitable distribution on the networks. The advantage of this proposed algorithm is that it improves throughput and fairness and reduces call blocking, enhancing resource allocation and network utilisation.

Its performance is compared with three other intelligent algorithms which include: the Artificial Bee Colony algorithm, the Simulated Annealing algorithm and the Q-Learning algorithm. Each of these algorithms is discussed below.

#### 3.5.1.1 Enhanced Particles Swarm Optimization

EPSO is a variant of the standard PSO algorithm that aims to improve its performance and overcome its limitations [236]. PSO is a population-based metaheuristic algorithm that mimics the social behaviour of birds or fish to find the optimal solution in a search space. It is a popular algorithm for optimisation problems. It works by simulating the behaviour of a swarm of particles, where each particle represents a potential solution to the problem. The particles move around in the search space, and their movement is influenced by their own personal best solution and the best solution of the swarm. However, traditional PSO has some weaknesses such as high sensitivity to the initial conditions, local optima trapping, low density, and decline of solutions' variety [236].

Hence EPSO is proposed to address the weaknesses of the traditional PSO. EPSO is designed to improve the exploration and exploitation powers of the algorithm by using several strategies such as segmentation of search apace, modification of solution's updating rule, using an intelligent probabilistic function, accepting and removing regions with poor solutions, and focusing the solutions on the local search after removing all regions with poor solutions [240] . The enhancement includes parameter adaptation, hybridization with local search techniques, diversity maintenance, memory mechanisms, adaptive neighbourhood topologies, niching and multi-swarm approaches [241]. The parameters can be dynamically adjusted during the optimisation process, balancing exploration and exploitation. Local search techniques can be applied to refine solutions, while memory mechanisms help particles retain and exploit information. Adaptive neighbourhood topologies allow particles to adjust interactions during the optimization process, improving information sharing and exploration-exploitation balance. These enhancements help EPSO handle multimodal optimization problems more effectively. EPSO employs niching and multi-swarm approaches to tackle multimodal optimization problems, enabling particles to explore different search regions and handle multiple peaks or solutions. The enhancements in EPSO make it a more powerful and efficient algorithm than PSO. EPSO is effective in solving a variety of optimization problems in various fields and domains such as ML, engineering, robotics, health care, image processing, finance amongst others [240].

It has been tested on various optimisation problems and has shown superior performance compared to other algorithms. For example, EPSO has been used to solve the Probabilistic Load Flow (PLF) problem in a distribution network and has achieved 89% similarity of the results to those of the most accurate method i.e. Monte Carlo Simulation (MCS) [236]. EPSO has been used for feature selection of microarray data and has required less processing time to select the optimal features than PSO [242]. EPSO can also be adapted and enhanced in HWNs to optimise various parameters such as network topology, resource allocation, power control, and mobility management [243]), [242].

It is a promising solution for CAC in 5G-Satellite HWNs due to these unique features. EPSO's adaptive inertia weight, cognitive and social learning, randomness and diversity, and suitability for numerical optimization make it a strong candidate for CAC. Its parallel processing nature allows for faster convergence to optimal solutions, making it a critical choice for CAC tasks in dynamic and unpredictable scenarios. Additionally, EPSO's strong and convergence properties make it reliable for optimising CAC strategies in 5G-Satellite networks, where strong decision-making is essential for maintaining network stability and performance.

It models the network as a search space and the call admission policies as potential solutions to the problem [244]. The particles in the swarm represent different call admission policies, and their movement is influenced by their own personal best solution, the best solution of the swarm, and the current state of the network. The EPSO algorithm can take into account the traffic load, the QoS requirements, the fairness of the call admission decision, and the utility of the call admission decision. The EPSO algorithm is also able to adapt to changes in the network.

EPSO is designed to be robust and flexible, capable of adapting to evolving network requirements and deployment scenarios. By incorporating feedback mechanisms and adaptive learning capabilities, EPSO continuously improves its performance and adapts to changing environmental conditions, ensuring long-term scalability and adaptability in heterogeneous network environments. Hence EPSO algorithm can adapt to changes in the network.

#### 3.5.1.2 Enhanced Particle Swarm Optimization Algorithm Process for CAC in 5G-Satellite Networks

The EPSO algorithm has emerged as a promising optimisation technique for addressing resource allocation and management challenges in communication networks. The proposed research aims to develop an EPSO algorithm tailored specifically for addressing the CAC problem in 5G-Satellite HWNs. The algorithm seeks to improve resource allocation efficiency, maximise network utilisation, and enhance the overall QoS for users. Below is the Enhanced Particle Swarm Optimization algorithm process for CAC in 5G-Satellite networks:

1) **Problem Formulation**: Define the objective function to be optimized. It could be a utility function that considers various performance metrics like throughput, latency, energy efficiency, or fairness in the heterogeneous wireless network.
2) **Define Constraints**: Consider any constraints imposed by the wireless network, such as limited resources or QoS requirements. Employ suitable mechanisms to ensure that particle updates adhere to these constraints.
3) **Initialisation**: Initialise the EPSO algorithm parameters, including the number of particles, maximum iterations, inertia weight, cognitive and social parameters, and other relevant parameters. Generate a swarm of particles, each representing a potential call request, with random initial positions and velocities.
4) **Fitness Evaluation**: For each particle (call request), evaluate the fitness based on network parameters such as available bandwidth, signal-to-noise ratio, congestion level, and the estimated handover probability. Incorporate

the handover probability as an additional parameter in the fitness evaluation, which affects the likelihood of successful handovers during a call's lifetime.

5) **Position and Velocity Updates**: Update the particle's velocity and position based on the EPSO equations, which take into account the particle's current position, velocity, and the best positions achieved by itself and its neighbouring particles. Adjust the velocity and position updates to accommodate the handover probability as a factor in the decision-making process.
6) **Local and Global Best Selection**: Update each particle's local best position based on its individual fitness evaluation. Update the global best position based on the best fitness values obtained by all particles in the swarm.
7) **Adaptive Inertia Weight**: Calculate an adaptive inertia weight based on the iteration number, allowing a balance between exploration and exploitation during the optimisation process. Incorporate this adaptive inertia weight into the velocity update equation.
8) **Dynamic Neighborhood Topology**: Implement a dynamic neighbourhood topology that defines which particles influence the position update of each particle. Neighbours can be selected based on their proximity in the search space, fostering information sharing and cooperative behaviour among particles.
9) **Termination Condition**: Set a termination condition based on the maximum number of iterations or a predefined convergence criterion. If the termination condition is not met, return to step 2; otherwise, proceed to the next step.
10) **Call Admission Decision**: Once the EPSO algorithm converges, each particle's final position represents a potential call admission decision. Analyse

the positions of particles in terms of their fitness values to determine which calls should be admitted into the network.

11) **Network Resource Allocation**: Allocate network resources (e.g., bandwidth, power) to the admitted calls based on the corresponding particle positions obtained from the EPSO algorithm. Ensure that the allocated resources fulfil the QoS requirements of each admitted call.
12) **Performance Evaluation**: Simulate the performance of the network with the admitted calls and allocated resources. Evaluate performance metrics such as call blocking rate, handover success rate, network throughput, and resource utilization.
13) **Analysis and Optimization**: Analyse the performance results to understand the effectiveness of the EPSO algorithm for CAC in 5G-Satellite Networks with handover probability. Consider fine-tuning the algorithm parameters and handover probability modelling to optimize network performance further.
14) **Iteration or Deployment**: If the network conditions change over time, consider running the EPSO algorithm iteratively to adapt to dynamic changes in call arrival rates, network load, and handover probabilities. Alternatively, deploy the optimised CAC system using the learned EPSO parameters and strategies for ongoing network management.

### 3.5.1.3 Pseudo-code for EPSO Algorithm for Heterogeneous Wireless Networks

```
Initialize parameters and constants
Initialize particle swarm with random positions and velocities
Initialize particles and their velocities randomly
Initialize global best position
Define the objective function
Define the constraints function
Define Fitness Function

function FitnessEvaluation(particle):
    Calculate fitness based on network parameters and handover
probability
    return fitness

function UpdatePositionAndVelocity(particle):
    Update velocity and position based on EPSO equations with handover
probability
    return updated_velocity, updated_position


Main Loop:
for iteration in range(max_iterations):
    for each particle in swarm:
        fitness = FitnessEvaluation(particle)
        if fitness > particle.local_best_fitness:
            particle.local_best_fitness = fitness
            particle.local_best_position = particle.position

    global_best_particle = Particle with highest local_best_fitness in
the swarm

    for each particle in swarm:
        updated_velocity, updated_position =
UpdatePositionAndVelocity(particle)
        particle.velocity = updated_velocity
        particle.position = updated_position

    Update global_best_particle if applicable

Admission Decision:
for each particle in swarm:
    if particle == global_best_particle:
        Admit call corresponding to particle's position
    else:
        Reject call

Allocate resources to admitted calls
Simulate network performance with admitted calls and allocated resources
```

*Figure 3-5: EPSO Algorithm Pseudocode*

### 3.5.2 Benchmark Algorithms

The performance of the proposed algorithm is benchmarked with three other AI algorithms in order to evaluate its performance. Details of these algorithms are given below.

#### 3.5.2.1 Artificial Bee Colony Algorithm

Artificial Bee Colony algorithm is an optimisation technique that simulates the foraging behaviour of honeybees [245]. It belongs to the group of swarm intelligence algorithms and has been successfully applied to various practical problems. It is a relatively simple algorithm to implement and can be easily parallelised.

The ABC algorithm has been shown effective in solving a variety of optimisation problems in signal, image and video processing fields. Additionally, it has been applied to other optimisation problems in different areas such as engineering, economics and biology [246].

The Artificial Bee Colony algorithm can be used for CAC in HWNs by finding the optimal selection of RATs for each cell based on the QoS requirements and network conditions. It can be used to find a good solution to the CAC problem by exploring the search space and finding a solution that minimises the blocking probability and maximises the network capacity. However, it may have some limitations, such as slow convergence speed, premature convergence, and sensitivity to parameter settings [247].

The Artificial Bee Colony algorithm can be used for CAC in heterogeneous wireless networks by simulating the three types of bees in a honey bee colony: employed bees, onlooker bees, and scout bees.

- **Employed bees**: Employed bees are responsible for exploring the search space and finding new call admission policies. They start with a randomly generated call admission policy and then iteratively improve it by making small changes.
- **Onlooker bees**: Onlooker bees observe the employed bees and choose the call admission policy that they think is most likely to have the lowest blocking probability and highest network capacity. They then copy the solution of the chosen call admission policy and make small changes to it.
- **Scout bees**: Scout bees are responsible for exploring new areas of the search space if the employed bees do not find any good call admission policies. They randomly generate new call admission policies and add them to the population.

#### 3.5.2.1.1 Artificial Bee Colony Algorithm Process for CAC in 5G-Satellite Networks

The Artificial Bee Colony algorithm is a powerful and versatile metaheuristic algorithm that can be used to solve the CAC problem in HWNs. This algorithm's ability to explore and exploit solution spaces makes it a promising candidate for enhancing CAC in 5G-satellite networks. Below is the Artificial Bee Colony Algorithm process for CAC in 5G-Satellite Networks.

1. **Problem Formulation**: Define the objective function to be optimised. It could be a utility function that considers various performance metrics like throughput, latency, energy efficiency, or fairness in the heterogeneous wireless network.

2. **Define Constraints**: Consider any constraints imposed by the wireless network, such as limited resources or quality-of-service requirements. Employ suitable mechanisms to ensure that the constraints are adhered to.
3. **Initialization**: Define the Artificial Bee Colony algorithm parameters, including the number of employed bees, onlooker bees, scout bees, maximum iterations, and others as needed. Initialise a population of potential call requests as solutions, represented by bee positions.
4. **Fitness Evaluation**: For each employed bee (call request), calculate the fitness based on network parameters such as available bandwidth, signal quality, congestion levels, and the estimated handover probability. Integrate the handover probability as an additional consideration in the fitness evaluation to capture its impact on call quality and network performance.
5. **Employed Bee Phase**: Update the positions of employed bees based on local search mechanisms, such as exploiting the current best solution for each bee. Modify the position updates to incorporate the handover probability as a decision factor.
6. **Onlooker Bee Phase**: Allocate onlooker bees based on the quality of solutions (fitness values) discovered by employed bees. Determine the probability of selecting a particular solution for onlooker bees using fitness-based probabilities. Update onlooker bee solutions by applying local search operations, considering handover probability.
7. **Scout Bee Phase**: Identify solutions (call requests) that have not been improved after a certain number of iterations. Replace these solutions with new randomly generated solutions (call requests) to enhance exploration.

8. **Termination Condition**: Set a termination condition based on a predefined maximum number of iterations or a convergence criterion. If the termination condition is not met, go back to step 2; otherwise, proceed to the next step.
9. **Call Admission Decision**: Once the Artificial Bee Colony algorithm converges, the final positions of the employed and onlooker bees represent potential call admission decisions. Analyse these positions considering fitness values and handover probabilities to determine which calls should be admitted.
10. **Resource Allocation**: Allocate network resources (e.g., bandwidth, power) to the admitted calls based on the corresponding bee positions obtained from the ABC algorithm. Ensure that allocated resources satisfy the Quality of Service (QoS) requirements, considering potential handovers.
11. **Performance Evaluation**: Simulate the network's performance with the admitted calls and allocated resources. Evaluate important performance metrics, such as call blocking rate, handover success rate, network throughput, and resource utilisation.
12. **Analysis and Optimisation**: Analyse the performance results to assess the effectiveness of the Artificial Bee Colony algorithm for CAC in 5G-Satellite Networks, considering handover probability. Fine-tune algorithm parameters and handover probability modelling for performance optimisation.
13. **Iterative Adaptation or Deployment**: Consider applying the Artificial Bee Colony algorithm iteratively to adapt to dynamic changes in network conditions over time, including call arrival rates, network load, and varying handover probabilities. Alternatively, deploy the optimised CAC system using

the learned Artificial Bee Colony parameters and strategies for ongoing network management.

#### 3.5.2.1.2 Pseudo-code for Artificial Bee Colony Algorithm for CAC in 5G-Satellite Networks

```
Initialize parameters and constants
Initialize employed bees, onlooker bees, and scout bees
Define the objective function
Define the constraints function
Define Fitness Function

function FitnessEvaluation(solution):
    Calculate fitness based on network parameters and handover
probability
    return fitness

function GenerateNeighboringSolution(solution):
    Generate a neighboring solution by perturbing the current solution
    return neighboring_solution


Main Loop:
for iteration in range(max_iterations):
    for each employed bee:
        fitness = FitnessEvaluation(solution)
        if fitness > employed_bee.local_best_fitness:
            employed_bee.local_best_fitness = fitness
            employed_bee.local_best_solution = solution

    onlooker_bees = SelectOnlookerBees(employed_bees)
    for each onlooker bee:
        solution = employed_bee.solution
        neighboring_solution = GenerateNeighboringSolution(solution)
        if FitnessEvaluation(neighboring_solution) >
FitnessEvaluation(solution):
            solution = neighboring_solution
            employed_bee.trials = 0
        else:
            employed_bee.trials += 1

    if any employed_bee.trials >= max_trials:
        ReplaceSolutionWithRandom(employed_bee)

Admission Decision:
for each employed bee:
    if employed_bee == best_employed_bee:
        Admit call corresponding to employed_bee's solution
    else:
        Reject call

Allocate resources to admitted calls
Simulate network performance with admitted calls and allocated resources
```

*Figure 3-6: Artificial Bee Colony Algorithm Pseudocode*

### 3.5.2.2 Simulated Annealing Algorithm

The simulated annealing algorithm is a metaheuristic algorithm inspired by the annealing process of metals. It is a probabilistic algorithm that can be used to find good solutions to optimisation problems [248]. It is a relatively simple algorithm to implement and can be easily parallelised.

The simulated annealing algorithm can be used for solving various optimisation problems with large and complex search spaces, such as travelling salesman problems, image processing, machine learning etc [249].

Simulated annealing can also be used for CAC in HWNs. It can be used to find a good solution to the CAC problem by exploring the search space and finding a solution that minimises the blocking probability and maximises the network capacity. Simulated annealing can be used for CAC in HWNs by simulating the annealing process of metals. It works by starting with a random call admission policy. It then repeatedly generates new call admission policies by making small changes to the current call admission policy. The new call admission policies are accepted if they are better than the current call admission policy. If the new call admission policies are not better than the current call admission policy, they may still be accepted with a certain probability. This probability decreases as the algorithm progresses, which helps to prevent the algorithm from getting stuck in local optima.

The Simulated annealing algorithm works by starting with a random solution to the problem. It then repeatedly generates new solutions by making small changes to the current solution. The new solutions are accepted if they are better than the current solution. If the new solutions are not better than the current solution, they may still be accepted with a certain probability. This probability decreases as the algorithm progresses, which helps to prevent the algorithm from getting stuck in local optima.

Overall, the Simulated Annealing algorithm is a powerful and versatile metaheuristic algorithm that can be used to solve a variety of optimisation problems. It is simple to implement and understand, and it is effective in practice. However, it may also have some drawbacks, such as slow convergence, sensitivity to parameter settings, and difficulty in finding the optimal colling schedule [250].

#### 3.5.2.2.1 Simulated Annealing Algorithm Process for CAC in 5G -Satellite Networks

The application of the Simulated Annealing algorithm to the CAC problem in 5G-satellite networks holds substantial promise for optimizing resource allocation decisions while accommodating diverse QoS constraints. By capitalising on the algorithm's exploration capabilities, gradual refinement through annealing, and the ability to avoid local optima, the algorithm seeks to enhance the efficiency and effectiveness of CAC mechanisms within the evolving landscape of 5G-satellite networks. Below is the Simulated Annealing Algorithm process for CAC in 5G-Satellite networks.

1. **Problem Formulation**: Define the objective function to be optimised. It could be a utility function that considers various performance metrics like throughput, latency, energy efficiency, or fairness in the heterogeneous wireless network.
2. **Define Constraints**: Consider any constraints imposed by the wireless network, such as limited resources or QoS requirements. Employ suitable mechanisms to ensure that these constraints are adhered to.
3. **Initialization**: Define the initial temperature, cooling rate, maximum iterations, and other relevant parameters for the Simulated Annealing algorithm.

Generate an initial solution, where each solution represents a call admission decision, and initialise the current best solution.

4. **Fitness Evaluation**: Evaluate the fitness of the initial solution based on network parameters such as available bandwidth, signal quality, congestion levels, and the estimated handover probability. Incorporate the handover probability as an additional parameter in the fitness evaluation to account for the potential impact of handovers.
5. **Annealing Process**: Start the annealing process by iteratively exploring neighbouring solutions. During each iteration, generate a neighbouring solution by perturbing the current solution, possibly considering changes in call admission decisions and resource allocations while maintaining constraints. Calculate the fitness of the neighbouring solution, including the handover probability factor.
6. **Acceptance Probability**: Calculate the acceptance probability based on the fitness difference between the current solution and the neighbouring solution, along with the current temperature. Decide whether to accept the neighbouring solution as the new current solution, considering the acceptance probability. A higher temperature allows more exploration.
7. **Cooling Schedule**: Decrease the temperature according to the cooling rate to control the exploration-exploitation trade-off. A slower cooling rate allows for more exploration initially, which gradually shifts towards exploitation.
8. **Termination Condition**: Set a termination condition based on reaching a predefined maximum number of iterations or a convergence criterion. If the termination condition is not met, repeat steps 3 to 5; otherwise, proceed to the next step.

9. **Call Admission Decision**: Once the Simulated Annealing algorithm converges, the final solution represents a set of call admission decisions. Analyze the solution based on fitness values and handover probabilities to determine which calls should be admitted into the network.
10. **Resource Allocation**: Allocate network resources (e.g., bandwidth, power) to the admitted calls based on the solution obtained from the SA algorithm. Ensure that allocated resources meet the QoS requirements, considering potential handovers.
11. **Performance Evaluation**: Simulate the network's performance with the admitted calls and allocated resources. Evaluate key performance metrics, such as call blocking rate, handover success rate, network throughput, and resource utilization.
12. **Analysis and Optimisation**: Analyse the performance results to assess the effectiveness of the Simulated Annealing algorithm for CAC in 5G-Satellite Networks with handover probability. Fine-tune algorithm parameters and handover probability modelling for optimisation.
13. **Iterative Adaptation or Deployment**: Consider applying the Simulated Annealing algorithm iteratively to adapt to dynamic changes in network conditions, including call arrival rates, network load, and varying handover probabilities. Alternatively, deploy the optimised CAC system using the learned Simulated Annealing parameters and strategies for ongoing network management.

#### 3.5.2.2.2 Pseudo-code for Simulated Annealing Algorithm for CAC in 5G-Satellite Networks

```
Initialize parameters and constants
Initialize initial solution and temperature
Initialize cooling rate and termination condition
Define the objective function
Define the constraints function
Define Fitness Function

function FitnessEvaluation(solution):
    Calculate fitness based on network parameters and handover
probability
    return fitness

function GenerateNeighborSolution(solution):
    Generate a neighboring solution by perturbing the current solution
    return neighboring_solution


Main Loop:
while temperature > termination_temperature:
    for iteration in range(max_iterations_per_temperature):
        neighbor_solution = GenerateNeighborSolution(current_solution)
        current_fitness = FitnessEvaluation(current_solution)
        neighbor_fitness = FitnessEvaluation(neighbor_solution)

        if neighbor_fitness > current_fitness:
            current_solution = neighbor_solution
        else:
            probability =
calculate_acceptance_probability(current_fitness, neighbor_fitness,
temperature)
            if random_number() < probability:
                current_solution = neighbor_solution

    temperature *= cooling_rate

Admission Decision:
Admit call corresponding to the current_solution

Allocate resources to admitted calls
Simulate network performance with admitted calls and allocated resources
```

*Figure 3-7: Simulated Annealing Algorithm Pseudocode*

#### 3.5.2.3 Q-Learning Algorithm

Reinforcement Learning (RL) is a machine-learning concept, where agents learn through trial-and-error interactions with their environment the strategies that work best over the long term [251]. The Q-learning algorithm is the most prominent RL algorithm [252]. Q-learning is a model-free reinforcement learning algorithm that learns the value of an action in a particular state. The Q-learning algorithm allows agents to learn the best actions in an environment by the table of Q-values continuously. Q-values define the expected cumulative reward of taking a particular action in a given state**.** The algorithm also uses an exploration-exploitation trade-off, which is a balance between choosing random actions to explore new states and choosing greedy actions to exploit known values [253].

Q-learning algorithm is frequently employed because it does not require knowledge of the state transition probability. By using less prior knowledge of the environment, the Q-learning approach can determine the best policy to solve intelligent decision problems [254]. The goal is to maximise the expected reward by seeking the best of all possible actions.

Q-learning can be applied to a variety of problems that involve sequential decision-making under uncertainty. Some examples of Q-learning applications are Pathfinding in a maze, Robot Navigation, Game playing, Traffic light control amongst others.

The Q-learning algorithm has also been applied in HWNs to solve the problem of resource management [255], [256], [258]. Q-learning has been shown to be effective in solving the CAC problem in heterogeneous wireless networks. It can find policies that minimise the blocking probability and maximise the network capacity [259], [260].

Hence, Q-learning can be used for call admission control (CAC) in 5G-Satellite HWNs by modelling the network as a Markov decision process (MDP). The idea is to use Q-learning to learn the optimal admission policy that balances the trade-off between blocking new requests and dropping ongoing requests, while considering the network conditions, traffic characteristics and user preferences [260].

The states of the MDP would represent the current state of the network, such as the number of users in each cell, the amount of available bandwidth, and the traffic load. The actions of the MDP would represent the decisions that the CAC algorithm can make, such as whether to admit a call or not. The rewards of the MDP would represent the cost of admitting a call, such as the cost of dropping a call or the cost of increasing the blocking probability. The Q-learning algorithm can then be used to find a policy that maximises the expected reward over time, which would be the policy that minimizes the cost of admitting calls.

The algorithm would start by randomly initialising the Q-values. Then, it would repeatedly iterate through the following steps:

1. Choose an action in the current state based on the Q-values.
2. Take the action and observe the reward and next state.
3. Update the Q-values for the current state and action using the equation above.
4. Go to step 1.

The algorithm would continue to iterate until it converges to a policy that minimises the cost of admitting calls.

Overall, Q-learning is a powerful algorithm that can be used to solve the CAC problem in HWNs. It is relatively simple to implement and can be easily parallelised. Q-learning is suitable for 5G-Satellite HWNs due to its dynamic environment, multi-connectivity, and balance between exploration and exploitation. Q-learning's iterative learning process allows the agent to continuously adapt to evolving network states and make optimal decisions. The process is repeated iteratively, allowing the agent to learn optimal actions over time. The update rule modifies the Q-values and iteratively applies this rule to learn which actions lead to the most rewarding outcomes in the complex world of 5G-Satellite HWNs. However, it can be slow to converge to a good policy, especially for large networks.

#### 3.5.2.3.1 Key Components of the Q-Learning

As discussed in the previous section, Q-learning involves a state, action, reward, and Q-table, which store expected rewards for each state-action pair. The learning process involves initialising Q-values for all state-action pairs, exploring the environment, selecting actions randomly or based on best-known actions, taking an action, receiving an immediate reward, and transitioning to a new state. The reward obtained from the selected action and the resulting state transition is calculated afterwards using the Q-Learning equation. The agent updates the Q-values in its table based on these experiences.

The key components of the Q-Learning equation include the Q-Value (Q (s, a)), Learning Rate (α), Immediate Reward (r), Permanence Reward (r (s, a)), and Discount Factor (γ). A brief detail of these components is given below.

**Q-Value (Q (s, a))**: Represents the expected cumulative reward of taking action 'a' in state 's.' It is updated iteratively based on the agent's experience. The state is the current situation the agent is in (e.g., network resources, network congestion, available RAT). The action is the possible decisions the agent can make (e.g. admit call, block call).

**Learning Rate (α):** Denotes the rate at which the agent updates its Q-values. A higher learning rate allows for quicker adaptation to new information, but it may lead to instability. A lower rate provides stability but may slow down adaptation.

**Immediate Reward (r):** The immediate feedback the agent receives after taking an action in a given state (e.g., improved data speed, reduced delay). It is a crucial factor influencing the update of Q-values. If an action leads to a good reward, its Q-value increases, making it more likely to be chosen again in similar situations. If an action results in a negative reward, its Q-value decreases, discouraging the agent from repeating it.

**Discount Factor (γ):** Represents the importance of future rewards. A higher discount factor emphasises long-term rewards, encouraging the agent to consider future consequences when making decisions.

#### 3.5.2.3.2 Q-learning Algorithm Process for CAC in 5G-Satellite Networks

The Q-learning algorithm is a central component of reinforcement learning which enables agents to learn optimal strategies through interactions with their environment, aiming to maximize cumulative rewards over time. This adaptability and learning capability make Q-learning a viable candidate for enhancing CAC in the context of 5G-satellite networks. By harnessing the algorithm's learning and adaptation capabilities, the Q-learning approach aims to enhance the efficiency and effectiveness of CAC mechanisms within the dynamic landscape of 5G-satellite networks. Below is the Q-learning algorithm process for CAC in 5G-Satellite networks:

1. **Initialisation**: Define the state space, action space, and initial Q-values for the Q-learning algorithm. States represent network conditions, and actions

correspond to call admission decisions. Initialise the Q-table with zeros or small random values.

2. **State Representation**: Represent the state of the network based on features like available bandwidth, signal quality, congestion levels, and estimated handover probability. Discretise the continuous state space into discrete states for efficient learning.
3. **Action Selection**: Select an action (call admission decision) based on the Q-values associated with the current state. Employ exploration-exploitation strategies (e.g., ε-greedy) to balance between trying new actions and selecting the best-known actions.
4. **Fitness Evaluation**: Evaluate the fitness of the selected action based on network parameters. Integrate the handover probability as an additional factor in the fitness evaluation to account for the potential impact of handovers.
5. **Q**-value Update: Calculate the reward obtained from the selected action and the resulting state transition. Update the Q-value for the current state-action pair using the Q-learning update equation, considering the handover probability factor.

The standard Q-learning update equation without considering handover probability is:

$$Q(s, a) = (1-\alpha) \cdot Q(s,a) + \alpha \cdot (r + \gamma \cdot max_a\, Q(s',a))$$

where:

Q (s, a) is the Q-value of state s and action a.

α is the learning rate, determining the balance between new and old information.

r is the immediate reward obtained from taking action a in state s.

γ is the discount factor, indicating the importance of future rewards.

s' is the next state after taking action a in state s

$max_a$ Q(s′,a)) is the maximum Q-value for all possible actions a in the next state s'

To incorporate the handover probability factor, you can modify the reward r as follows:

r = FitnessEvaluation(s,a) x (1 – HandoverProbability(s,a))

where:

FitnessEvaluation (s, a) calculated fitness of tracking action a in state s based on network parameters.

HandoverProbability (s, a) estimates the handover probability associated with the action a in state s.

Substituting the modified reward into the Q-learning update equation:

Q (s, a) = (1 - α). Q(s,a) + α

FitnessEvaluation(s,a) x (1 – HandoverProbability(s,a)) + γ. $max_a$ Q(s',a)

This equation updates the Q-value for the current state-action pair, considering the impact of handover probability on the immediate reward.

6. **Transition to Next State**: Transition to the next state based on the action taken and the network dynamics. Update the state representation based on the new network conditions.
7. **Termination Condition**: Set a termination condition based on a predefined number of iterations or a convergence criterion. If the termination condition is not met, repeat steps 3 to 6; otherwise, proceed to the next step.

8. **Call Admission Decision**: Once the Q-learning algorithm converges, the Q-values represent the learned policy for call admission decisions. Determine the call admission decisions by selecting actions with the highest Q-values for each state.
9. **Resource Allocation**: Allocate network resources (e.g., bandwidth, power) to the admitted calls based on the Q-learning policy obtained. Ensure allocated resources meet QoS requirements, considering potential handovers.
10. **Performance Evaluation**: Simulate the network's performance with the admitted calls and allocated resources. Evaluate key performance metrics, such as call blocking rate, handover success rate, network throughput, and resource utilization.
11. **Analysis and Optimisation**: Analyse the performance results to assess the effectiveness of the Q-learning algorithm for CAC in 5G-Satellite Networks with handover probability. Fine-tune algorithm parameters and handover probability modelling for optimization.
12. **Iterative Adaptation or Deployment**: Consider applying the Q-learning algorithm iteratively to adapt to dynamic changes in network conditions, including call arrival rates, network load, and varying handover probabilities. Alternatively, deploy the optimised CAC system using the learned Q-values and strategies for ongoing network management.

### 3.5.2.3.3 Pseudo-code for Q-Learning Algorithm for CAC in 5G-Satellite Networks

```
Initialize Q-values with small random values or zeros
Initialize state space, action space, and other parameters
Initialize exploration rate and learning rate

function FitnessEvaluation(state, action):
    Calculate fitness based on network parameters and handover
probability
    return fitness

Main Loop:
for episode in range(total_episodes):
    current_state = initial_state
    while not is_terminal_state(current_state):
        if random_number() < exploration_rate:
            selected_action = choose_random_action()
        else:
            selected_action =
choose_action_with_highest_q_value(current_state)

        reward = FitnessEvaluation(current_state, selected_action)
        next_state = perform_transition(current_state, selected_action)

        max_next_q_value = max_q_value_for_next_state(next_state)
        updated_q_value = (1 - learning_rate) * current_q_value +
learning_rate * (reward + discount_factor * max_next_q_value)

        update_q_value(current_state, selected_action, updated_q_value)

        current_state = next_state

Admission Decision:
Choose call admission decision based on the action with the highest Q-
value for the current state

Allocate resources to admitted calls
Simulate network performance with admitted calls and allocated resources
```

*Figure 3-8: Q-Learning Algorithm Pseudocode*

### 3.5.3 Comparison Of Algorithms

Below is a comparison table of the four algorithms discussed above.

*Table 3-1: Algorithm Comparison*

| Algorithm | Nature | Optimization Type | Exploration vs Exploitation | Handling Discrete Variables | Handling Uncertainty | Parameter Sensitivity |
|---|---|---|---|---|---|---|
| EPSO | Swarm-based optimization | Continuous | Balanced | Limited | Limited | High |
| ABC | Swarm-based optimization | Continuous | Balanced | Limited | Limited | Moderate |
| Simulated Annealing | Probabilistic optimization | Continuous & Discrete | Exploration early, Exploitation later | Yes | Yes | Moderate |
| Q-learning | Reinforcement learning | Sequential Decision | Exploration and Exploitation | Yes | Yes | Moderate |

## 3.6 CONCLUSION

This chapter provides a detailed description of the proposed load balancing framework using the CAC model. The network architecture is explained in the beginning and major components in the architecture have been described.

The proposed CAC model for load balancing in 5G – Satellite HWN using an intelligent hybrid CAC algorithm is a promising approach that can achieve better network performance, reliability, and cost-effectiveness. The intelligent CAC scheme in HWN utilises two controlling entities: CCN running in the network entity, and controller at UD.

As the call admission process is a vital part of the load balancing framework, therefore a detailed explanation of the process is given, which is also illustrated using a flow chart. The proposed EPSO along with the three benchmark algorithms; ABC algorithm, Simulated Annealing algorithm and the Q-Learning algorithm are discussed. Details of the processes of these algorithms for CAC as well as the pseudocode are provided.

Overall, the proposed system model is a promising approach to optimising the performance of 5G-Satellite HWNs. The use of AI allows the proposed framework to make more informed decisions about how to admit new calls to ensure equal distribution of traffic between the two networks. This can lead to significant improvements in the performance of the heterogeneous wireless network.

# CHAPTER 4: SIMULATION FRAMEWORK

## 4.1 OVERVIEW

This chapter describes the simulation framework developed to study the performance of the proposed EPSO-CAC framework. Its performance is compared with three other AI algorithms namely the Artificial Bee Colony algorithm, Simulated Annealing algorithm and Q- Learning Algorithm. This chapter also presents different simulation scenarios and parameters. To evaluate performance, a series of tests in various settings are used. The suggested algorithm's performance is evaluated using four key metrics: throughput, call-blocking probability, fairness and user satisfaction. Finally, this chapter presents a detailed analysis of the obtained results for the various simulation scenarios.

## 4.2 SIMULATION SET UP

Numeric simulation is performed for a heterogeneous wireless network consisting of 5G and Satellite networks. The performance of the EPSO Algorithm for CAC is illustrated using Visual Basic for Applications (VBA) and Python programming language and representation as a platform for simulation and experimentation; and a Windows operating system with an Intel Core i3-6100U, 8GB RAM, 128GB SSD and Nvidia GeForce 940M. The VBA is used to model the call arrival and decision rule, while Python is used to model the algorithms using the decision rule results.

A 5G multi-RAT network including a satellite RAT and a 5G RAT is considered. It is assumed that SatCOM uses either several LEO satellites or a single GEO satellite to accomplish coverage, the specifics are outside the scope of this paper. The RANs have different coverage areas. Only resource management in the common area is considered, which means that all users in this area have two RANs from which to choose.

In this thesis, an urban hotspot scenario is considered, where a 5G cell will be covered with several satellite gateway links. The mobility of UDs leads to the dynamic of the network load. No interference is assumed between 5G and Satellite networks, given different spectrum bandwidths are used between the two networks. The approximated simulation area size is 1000 x 1000 $m^2$ with BS randomly deployed. In this thesis, 200 UEs are considered and the required data rates for each UD were 5 Mbps to 30 Mbps. These data rate requirements reflect the diverse communication needs of different UDs in the urban hotspot scenario. As UDs move within the urban hotspot, their data rate requirements may change, leading to dynamic fluctuations in network load. Meeting the data rate requirements ensures that the network can provide the necessary resources to fulfil the diverse communication needs of UDs. Each mobile node represents a mobile device equipped with two radio interfaces, one simulating 5G and the other one simulating Satellite.

The simulation parameters are listed in Table 4-1.

*Table 4-1: Simulation Parameters*

| Parameter | Value |
|---|---|
| Simulation area size | 1000 x 1000 $m^2$ |
| Confidence Level | 95% |
| Number of runs | 30 |
| Number of users | 200 |
| Data rate per user | 5 – 30 Mbps |
| User's distribution | Random |
| Lower Bound | -5 – 6 |
| Upper Bound | 0 – 15 |
| inertia coefficient (**w**) | 1.4 |
| cognitive coefficient (**c1**) | 0.5 |
| social coefficient (**c2**) | 1.6 |
| Gamma | 0.4 |
| Alpha | 0.99 |
| Beta | 0.95 |
| Simulation time | 6000s |

## 4.3 SIMULATION TOOLS

The simulation setup for evaluating the performance of the proposed algorithm as well as the other benchmarked algorithms involves the use of both VBA and Python programming languages. The experiment is a numerical simulation and most of the data are generated via code (VBA and Python) which modelled a real-life telecoms data gotten from kaggle.com. A detailed explanation of how these tools are used is provided in the following sub-sections:

### 4.3.1 VBA

In the simulation setup, VBA serves as a pivotal component for modelling various aspects of the call admission process and the random distribution of users within the heterogeneous wireless network. It handles the logic related to when calls arrive, how they are processed, and the decision-making process for call admission. These functionalities collectively contribute to the realistic representation of network behaviour and performance, enabling comprehensive analysis and evaluation of resource management strategies within heterogeneous wireless networks.
Detailed functionality of the VBA is provided below:

**Modelling Call Arrival:**

VBA is responsible for simulating the arrival of calls within the network. The call arrival rate is modelled using Poisson distribution, this call pattern emulates real-life scenarios where users initiate calls at different times and frequencies.
The call arrival process modelled by VBA determines when new calls are introduced into the network, influencing the overall network load and resource utilisation.

**Modelling Call Admission:**

VBA governs the call admission process; wherein incoming calls are evaluated against predefined criteria to determine whether they should be admitted into the network or rejected.

The call admission decision, based on factors such as network capacity, QoS requirements, and resource availability, is formulated within the VBA script. This decision-making process ensures efficient utilisation of network resources while maintaining QoS standards.

Additionally, VBA may implement specific call admission policies or algorithms to govern the admission of users based on dynamic network conditions and performance metrics.

**Random Distribution of Users:**

VBA facilitates the random distribution of users within the simulation environment, simulating the spatial distribution of mobile devices or UDs across the coverage area.

By randomly deploying users within the network coverage area, VBA creates a realistic representation of user mobility patterns and spatial distribution, crucial for evaluating network performance and resource management strategies.

This random distribution of users ensures that the simulation reflects the dynamic nature of wireless networks, where users move within the coverage area, impacting network load and resource allocation.

**Predefined Call Admission Policy:**

The call admission policy, predefined within the VBA script, outlines the criteria and thresholds for admitting users into the network.

This policy includes parameters such as signal strength, available bandwidth, network load, and network costs.
By adhering to the predefined call admission policy, VBA ensures consistency and repeatability in the simulation experiments, enabling systematic evaluation of network performance under various conditions.

### 4.3.2 Python

Python is used to model the Algorithms for CAC and to analyse the results obtained from the VBA simulation. Python allows for the implementation of complex algorithms, such as EPSO, and facilitates data analysis and visualisation.
Detailed below is how the Python code is customised for the specific use case of call admission in 5G-satellite networks:

**VBA Output as Python Input**:

The output generated by the VBA script, including data related to call arrivals, admission decisions, and user distribution, serves as the input data for the Python simulation implemented in the Anaconda development environment.
This input data is typically formatted in a structured manner using CSV files and import CSV library in Python. Python code reads and processes this input data to perform further analysis, optimisation, and visualisation tasks relevant to the simulation scenario.

**Customisation of Python Code:**

While Python libraries such as NumPy, Matplotlib amongst others provide foundational tools for numerical computation and data visualisation, the actual code implementation is written from scratch and customised to suit the specific requirements of call admission scenarios in 5G-Satellite networks.

Custom functions and algorithms are developed in Python to handle tasks such as optimising resource allocation, evaluating network performance metrics, and visualising simulation results.

The Python code is tailored to integrate seamlessly with the output generated by the VBA script, ensuring compatibility and continuity in the simulation workflow.

Specific parameters and constraints unique to 5G-satellite networks, such as dual-radio interfaces, dynamic network load, and QoS requirements, are incorporated into the Python code logic.

**Integration of VBA and Python:**

The integration between VBA and Python facilitates a cohesive simulation framework where VBA handles the initial setup, call admission modelling, and basic data processing, while Python performs advanced analysis and optimisation tasks.

Output data generated by VBA, such as user locations, call admission decisions, and network performance metrics, are seamlessly passed to Python for further processing and analysis.

Python code leverages the input data to execute complex algorithms, visualise simulation results, and derive insights into network behaviour, thereby enhancing the overall simulation capability and accuracy.

This collaborative workflow ensures a holistic approach to simulating and optimising call admission in 5G-satellite networks, leveraging the strengths of both VBA and Python to achieve comprehensive simulation outcomes.

## 4.4 CASE STUDY

Below is an urban hotspot scenario for critical communication in an overlapping scenario for 5G-satellite networks:

A major city is hosting large-scale outdoor event, such as a music festival or marathon. It is anticipated that the city's 5G network will be overloaded with participant and spectator traffic. The city has installed a satellite network to offer more capacity and coverage to address this. Because the satellite network is situated in a geostationary orbit, it stays fixed on the Earth. Because of this, it's perfect for covering a big region, like a city.

In the vicinity of the event, the satellite network is set up to overlap with the city’s 5G network. This makes it possible for critical communication users, such as first responders and event organizers, to seamlessly switch between the two networks depending on which one has a stronger signal.

Here is an example of how this might work:

A paramedic is attending to a medical emergency at the event. Their device is linked to the 5G network in the city. As they get closer to the scene of the emergency, the 5G signal strength weakens. After identifying the satellite network with the strongest signal, their device switches to it. Without interfering with their service, the paramedic can keep in contact with dispatch and other first responders present at the scene.

The 5G-satellite network also provides additional capacity for critical communication users. This means that more users can access the network simultaneously, which is important in emergencies where there may be a high demand for critical communication services.

Overall, the deployment of a 5G-satellite network in an urban hotspot can significantly improve the reliability and capacity of critical communication infrastructure. This can be essential in life-or-death situations. A 5G-satellite HWNs can help to ensure that first responders and other critical communication users have the resources they need to stay connected and coordinate their response.

## 4.5 SCENARIO

To evaluate the proposed mechanism performance four simulation scenarios are used. The time of decision is always the arrival time of any type of call and possible actions in these moments are 0 (reject the call), 1(accept the call on 5G Network) and 2 (accept the call on Satellite Network). CAC plays a crucial role in ensuring network efficiency and user satisfaction by determining when to accept or reject incoming calls. The four scenarios examine different aspects of decision-making and their impact on throughput, fairness, and call blocking.

**Scenario 1: Variation in network resources**

The network resources used in this thesis are signal strength, network cost, network load and available bandwidth. Hence the admission of a new call into the network is based on the availability of these resources. This scenario aims to assess how variations in these factors affect CAC outcomes. This scenario is evaluated in two parts. The first part focuses on using a single network resource as a decision variable for call admission. The second part introduces variations in network conditions by combining multiple network resources as decision variables. Network resources which include signal strength, network cost, network load, and available bandwidth are incorporated into the decision-making process. This scenario evaluates if the algorithm is algorithm is resource-efficient, maintains accuracy, and scales appropriately as network conditions become more complex.

This scenario evaluates the impact of these variations on throughput, call blocking, and fairness shedding light on the trade-offs involved in using multiple decision variables for CAC.

**Scenario 2: Variation in the Number of Users**

In the second scenario, how changes in the number of users influence fairness within the network is explored. The number of devices from 10 to 200 is gradually increasing, providing insights into the scalability of our CAC approach and its ability to maintain fairness as the user population grows.

**Scenario 3: Variation in Network Load**

The impact of network load variation on user satisfaction in a heterogeneous wireless network like the 5G-satellite scenario can be significant. User satisfaction is closely tied to the QoS they receive, and network load fluctuations can directly influence this.

In this scenario, the user starts in the stadium with a congested 5G network and is redirected to the satellite network for their call. The simulation introduces varying levels of network congestion and load throughout the user's time at the stadium. The CAC algorithm continually assesses and adjusts the network selection, demonstrating its ability to adapt to changing network conditions in real-time. As the user eventually leaves the stadium, the simulation illustrates the seamless transition back to the 5G network once it becomes the optimal choice, ensuring user satisfaction and high-quality calls throughout the dynamic network environment.

**Scenario 4: Dynamic QoS-Based Admission Control**

In this scenario, you explore the dynamic adjustment of call admission decisions based on QoS metrics. Instead of primarily considering resource availability and handover probability, the CAC algorithm can adaptively control admissions by continuously monitoring and optimizing for QoS parameters such as network load, signal strength, and bandwidth. The scenario assesses how dynamic QoS-based admission control affects network performance and user satisfaction.

## 4.6 PROBLEM FORMULATION

Since there are limited amounts of resources, an inaccurate distribution of resources could affect both the network's performance and the users' satisfaction. Therefore, to achieve the main goal of balancing the load across several networks while making sure QoS prerequisites are fulfilled, it is important to build a mathematical model that incorporates the user's specification and network constraints. The goal of the considered CAC problem is to maximise the throughput of all UDs, maximise fairness and minimise call dropping.

In this section, the mathematical model's variables, functions, and parameters are defined, along with a solution that provides an ideal load distribution across the 5G-Satellite networks while adhering to QoS requirements.

### 4.6.1 Throughput

The number of data/ packets that successfully reach their destination is referred to as throughput. Packet arrival within a network is necessary for high-performance service. Low throughput suggests problems like packet loss, which hinders or slows down networks. Having a high network throughput increases the speed and reliability of data transmission; reduces latency, or delay between data sent and received; and reduces the risk of packet loss or other errors due to slow transmission speeds.

Due to the importance of the network's overall throughput, load balancing is required to boost the data rate for each user connected to 5G and satellite heterogeneous networks. By doing load balancing, the objective is to increase throughput per user, and as a result, throughput on the entire network will be efficiently raised. Both operators and users will gain from this.

The variable $R_i$ is defined as the expected data rate (Maximum throughput) for a user i for a time period t. Equation (1) can be used to determine the maximum throughput ratio ( $M_i$) for a given time interval t [3].

.$r_i(t)_{5g}$: Data rate in 5G for time period t

$r_i(t)_{sat}$ : Data rate in Satellite for time period t

$$M_i(\text{t}) = \frac{r_{i\,(t)5g} + r_{i(t)sat}}{R_i} \quad \text{- (1)}$$

The maximum throughput ratio is extended for all users and all channels. For a particular time period, a user may be connected to either 5G or Satellite or may not be connected to any network. The following variables are defined.

$X_{i\ 5g}^{c}(\text{t}) \longrightarrow$ 0 or 1 { 0: No 5G Access, 1: 5G Access available}

$X_{i\ sat}^{c}(\text{t}) \longrightarrow$ 0 or 1 { 0: No Satellite Access, 1: Satellite Access available}

TTN $\longrightarrow$ Total throughput of the network (which includes 5G and Satellite)

$$\text{TTN} = \sum_i \sum_c [\ x_i^c\ (t)_{sat} \quad [\frac{r_i\,(t)_{sat}}{R_i\,(t)}\,] + \ x_i^c(t)_{5g} \quad [\frac{r_i(t)_{5g}}{R_i\,(t)}\,]\ ] \quad \text{- (2)}$$

**Date rate in 5G**

This variable represents the rate at which data can be transmitted over the 5G network for that particular user at the given time interval. To calculate or estimate

$r_i(t)_{5g}$, factors such as the available bandwidth, modulation scheme, signal quality, and other parameters that affect the data transfer rate in a 5G network are considered.

**Data rate in Satellite**

This variable represents the rate at which data can be transmitted over the satellite link for that particular user at the given time interval. The specific formula for calculating the data rate in a satellite system would depend on various factors, including the characteristics of the satellite link, modulation and coding schemes, signal propagation conditions, and other parameters. It's common to use metrics such as satellite link efficiency, available bandwidth, and SINR to estimate the achievable data rate.

**Maximum Throughput Ratio**

This equation essentially calculates the ratio of the sum of data rates in 5G and satellite to the expected maximum throughput for that user. It gives you an indication of how efficiently the user is utilizing the available network resources.

If $M_i$(t) is close to 1, it suggests that the user is achieving close to the expected maximum throughput. If it's significantly less than 1, it may indicate that the user is not fully utilizing the available resources, possibly due to network conditions or other factors.

**Total Throughput of the Network**

This equation calculates the total throughput of the network by summing up the contributions from all users and channels. It takes into account whether a user is connected to 5G or Satellite, and the associated data rates are adjusted based on the expected maximum throughput for each user.

TTN represents the combined throughput from both 5G and Satellite for all users in the network, considering their connectivity status and the data rates in the respective channels.

### 4.6.2 Load Balancing: Jain's Index Functions

Achieving a balanced distribution of UDs among cells is the goal of load balancing. It would be ideal to have a system or index that could be used to quantify the level of fairness. Fairness is a term frequently used in numerous study domains, including those in wireless networks, to refer to "equality" in the distribution of resources.

The fairness of resource distribution among networks can be measured using Jain's Index function, which can provide a precise assessment of how evenly distributed the network load is in the cellular system.

Fairness is a value between 0 and 1, where a value closer to 0 indicates an unbalanced load in the system, whilst a value near 1 indicates a fairer resource distribution, and 1 means perfect fairness.

This function can be formulated as follows:

$$\frac{\left(\sum_{i=1}^{n} x_1\right)^2}{\sum_{i=1}^{n} x_1^2} \qquad - (3)$$

### 4.6.3 Call Blocking

Call-blocking probabilities are one of the most important performance indicators in mobile communication. Some calls in a cellular network system are lost. When a user requests service, there is a minimal call set-up time and if a channel is available, the user has immediate access to it. A call is deemed to be blocked and lost if all channels are busy when it attempts to connect. Although the user does not have access to any service, they are free to try again later. All blocked calls are returned immediately to the user set.

Call Blocking ($C_b$) :

$$= \frac{\frac{E^m}{m!}}{\sum_{i=0}^{m} \frac{E^i}{i!}} \quad - (4)$$

where

E = total traffic offered

m = number of resources in the service system

### 4.6.4 User Satisfaction

User satisfaction is a crucial metric in telecommunications that directly reflects the QoS experienced by users. It encompasses a user's overall contentment with their call experience, including factors like call quality, call setup time, call success rate, and network responsiveness. In this scenario, the primary aim is to investigate how CAC decisions affect user satisfaction, shedding light on the critical relationship between network performance and user experience.

For this scenario, user satisfaction is categorized into two values: "1" for successfully admitted calls and "0" for blocked calls. This binary classification simplifies user satisfaction assessment while allowing for differentiation between satisfied and dissatisfied users.

Successfully Admitted Call (1) represents user satisfaction when a call is successfully admitted, indicating that the user is content with the call quality and overall experience. Blocked Call (0) reflects user dissatisfaction due to call blocking, signifying disappointment with the network's performance and the inability to make the desired call.

### 4.6.4 Constraints

In this model, several constraints are considered to ensure that it may be adapted to work with real-world networks. Some constraints are connected to QoS specifications, while others are to service connectivity.

#### 4.6.4.1 QoS constraints

There are four QoS parameters considered in the modelling: Signal Strength, Network Cost, Network Load and Available Bandwidth. However, it is important to remark that the model can be extended by including any other QoS requirements. The QoS parameters are limited, therefore it is essential to check that the network service is within the specified threshold before a new call may be accepted. If it is not, the network must decline the connection.

**A) Received Signal Strength**

The Received Signal Strength Indication (RSSI) is the corresponding signal strength received in a wireless environment. It determines the power level being received by the antenna; hence, when the value of the RSSI is very high, this indicates the received signal is very strong. A receiver in wireless communication needs a strong signal. The optimal received signal strength for a cellular connection depends on several factors including the technology being used (e.g., 3G, 4G, 5G), the network provider, the distance from the nearest cell tower, and the presence of obstacles or interference [261]. However, for 4G LTE networks, a good signal strength is typically -85 dBm to -95 dBm, while for 5G networks, it's -80 dBm to -90 dBm. These values may vary slightly depending on network conditions, the specific device being used and activity type. Voice calls require less bandwidth and can function with weaker signals. Streaming video requires strong signals for uninterrupted playback. Web browsing and social media use moderate bandwidth. Factors like phone models, network congestion, and obstructions can affect signal strength.

In general, when the RSSI value is closer to zero, this means the received signal strength is stronger. However, even with slightly weaker signals, users can still maintain a usable connection depending on their needs and the quality of service provided by the network operator. In reality, the received signal power determines the quality of calls made or received, i.e., at −113 dBm RSRP; a call can probably go uninterrupted, while when the signal fluctuates below −119 dBm, the request is dropped but reconnected after re-dial in a few seconds [261].

In this thesis, the threshold for the received signal strength is set at <= -80dbm. If this value is below the predefined threshold RSSIth, it is assumed that the quality of the connection between the base station and the mobile is very bad.

Therefore, calls will be forwarded to the RAT that has the received signal strength <= -80dbm. If the chosen RAT is unable to accommodate the call, another RAT will be chosen. The call will be blocked if none of the RATs can handle it.

**B) Network Cost**

The decision on which RAT to assign a call to is based on minimizing the total cost associated with both network and user aspects. Calls will be assigned to the RAT that has the lowest total cost. This ensures efficient resource utilization and potentially improves user experience by considering factors like battery life and call quality. Hence, If the chosen RAT does not have sufficient resources to accommodate the call, another RAT will be chosen. If there is no RAT available to admit the call, it will be declined.

The cost of allocation is calculated by the following equation:

C = $C_N$ + $C_U$

Total_Cost = min (C_N_5G + w_5G * C_U, C_N_Satellite + w_Satellite * C_U)

where C is the cost function for the allocation of radio resources.

$C_N$ is the cost of network.

$C_U$ is the cost of user.

C_N_5G is the network cost for 5G

w_5G is the weighting factor for 5G

C_N_Satellite is the network cost for Satellite

w_Satellite is the weighting factor for Satellite

The **Network Cost (C_N)** refers to the cost incurred by the network operator in allocating resources for a call. It encompasses various factors like energy consumption, spectrum usage, backhaul capacity, and signalling overhead.

The **User Cost (C_U)** represents the cost experienced by the user for making the call. It can include device battery consumption, call quality, and data charges.

The **weighting factors** between 0 and 1 reflect the relative importance of user cost for each network in the decision-making. These weights can be adjusted based on user's priorities. For example, if minimising user cost like battery consumption is crucial, a higher weight to C_U might be assigned in both terms.

**C) Network Load**

The amount of data transmitted over a network at any given time is known as the network load. The network is an essential element in network control, traffic monitoring, and simulation. The QoS in a particular network is ensured by properly managing the network load. Load balancing helps to reduce resource breakdown created by resource congestion by distributing network traffic equally.

The UD accesses the network load status through feedback provided by the network. There is a periodic exchange of signalling messages between the UD and the network, such as measurement reports, which include information about the current network conditions, including load. These reports may contain metrics like signal strength, signal quality, and network congestion levels, which collectively provide insights into the network load. Additionally, network protocols may incorporate mechanisms for the UE to query the network directly for load information. Therefore, calls will be assigned to the RAT that has the lowest network load. If the RAT that was initially chosen lacks the resources to accept the call, a different RAT will be picked. If none of the RATs can handle the call, it will be blocked.

**D) Available Bandwidth**

Network bandwidth is an essential network measurement for figuring out how fast and reliable a network is. Network bandwidth is a measurement that connotes the largest capacity of a wireless communications link to transfer data over a network connection in a specified period. The higher the bandwidth for data connectivity, the higher the data it can send and receive at one time.

The bandwidth is also a limited resource; therefore, it is important to check that all the selected networks have enough bandwidth to accept the call; otherwise, the network must reject the connection.

#### 4.6.4.2 Actived Services Constraint

This constraint confirms that all activated services of each user's device D must be connected to some network in N.

#### 4.6.4.3 Connectivity Constraint

Through this constraint, it is guaranteed that each service used by the user's device D is connected to only one network.

**Objective Function Summary**

A summary of the objective function is presented as follows:

*Maximise*

TTN =

$$\sum_i \sum_c [\, x_i^c \ (t)_{sat} \quad [\frac{r_i\,(t)_{sat}}{R_i\,(t)}\,] + \ x_i^c(t)_{5g} \quad [\frac{r_i(t)_{5g}}{R_i\,(t)}\,]\,] \quad - \ (2)$$

*Maximise*

$$\text{f(x)} = \frac{(\sum_{i=1}^{n} x_1)^2}{\sum_{i=1}^{n} x_1^2} \quad - \ (3)$$

*Minimise*

$$C_b = \frac{\frac{E^m}{m!}}{\sum_{i=0}^{m} \frac{E^i}{i!}} \quad - (4)$$

## 4.7 CONCLUSION

This chapter has provided a comprehensive overview of the simulation framework developed to assess the performance of the proposed ESPO-CAC framework in comparison to other AI algorithms. The simulation setup, including the network configuration, and programming languages used, has been detailed. The urban hotspot scenario for critical communication in an overlapping 5G-satellite network has been presented as a case study, illustrating the practical application of the proposed framework.

Four simulation scenarios were introduced to evaluate the ESPO-CAC mechanism, each focusing on different aspects of decision-making and their impact on network performance. These scenarios cover variations in network resources, the number of users, network load, and dynamic QoS-based admission control, providing a thorough examination of the proposed framework's capabilities.

The problem formulation section defined the goals of the CAC problem, emphasising the importance of balancing network load, maximising throughput, ensuring fairness, and minimizing call dropping. Mathematical models and constraints were presented, including throughput calculation, Jain's Index for load balancing, call-blocking probability, and user satisfaction metrics. Constraints, ensure that the model aligns with real-world network conditions.

In conclusion, this chapter has laid the foundation for the subsequent analysis by presenting a well-defined simulation framework, scenarios, and mathematical models. The following chapters will delve into the results and analysis of the simulation experiments, providing insights into the performance of the proposed ESPO-CAC framework in various practical scenarios.

# CHAPTER 5: RESULTS AND DISCUSSION

## 5.1 OVERVIEW

To analyse the performance of the CAC algorithm in the 5G-Satellite heterogeneous network, three scenarios have been simulated. This chapter examines the effect of the number of users, network information and user satisfaction to determine the CAC's effectiveness in improving the system's performance. Finally, this chapter presents a detailed analysis of the obtained results for the various simulation scenarios.

## 5.2 RESULTS

This section presents the results obtained for the scenarios simulated to evaluate the proposed algorithm's performance. Also, in order to assess the performance of the suggested load-balancing algorithm, three other existing load-balancing algorithms have been used for benchmarking.

The figures demonstrate the results for different performance parameters such as throughput, call blocking, and fairness. The results are cross-compared in order to study the performance of each algorithm with respect to each other.

### 5.2.1 Impact On Throughput

Throughput represents the amount of data conveyed by the system in a given time. When the throughput is high, this means the transmission capability of the system is also high. It is a crucial performance indicator of the network.

The simulation aims to measure the effect of the CAC algorithms on throughput. The objective function of these algorithms which is stated in Equation 1 is to maximise throughput.

The figures show the throughput results under the four types of CAC algorithms; EPSO, Artificial Bee, Simulated Annealing and Q-Learning when users were admitted using the single-decision variable as well as multiple-decision variables and how these algorithms maximised throughput using the decision variables. The decision variables as discussed in Chapter 4 are the network resources which include signal strength, network cost, network load, and available bandwidth. These decision variables are varied during simulation to obtain different results. Also, 200 users were simulated on the network for 6000 seconds. The total number of users on the network is varied every minute following Poisson distribution and call arrival rate as discussed in Chapter 4.

Figure 5-1 shows the total throughput result for the single decision call admission scenario based on signal strength, network cost, network load and available bandwidth. Figures 5-2 and 5-3 show the total throughput result for the multiple decision call admission scenario based on network cost and available bandwidth; network cost and network load; network cost and signal strength; network load and available bandwidth; signal strength and network load; signal strength and available bandwidth; network cost, network load and available bandwidth.

In the single decision scenarios (Figure 5-1), because of the simplicity of the call admission process, the throughput increases because the networks could accommodate more users. The network only considers one decision variable at the point of admission. However, with multiple decision scenarios (Figures 5-2 & 5-3), because of the variation in the network resources which added to the complexity of the decision-making, it shows there is a decrease in the total throughput maximised. The network had to combine multiple decision variables at the point of call admission. However, the result shows that the proposed EPSO algorithm always has the highest throughput in all the scenarios.

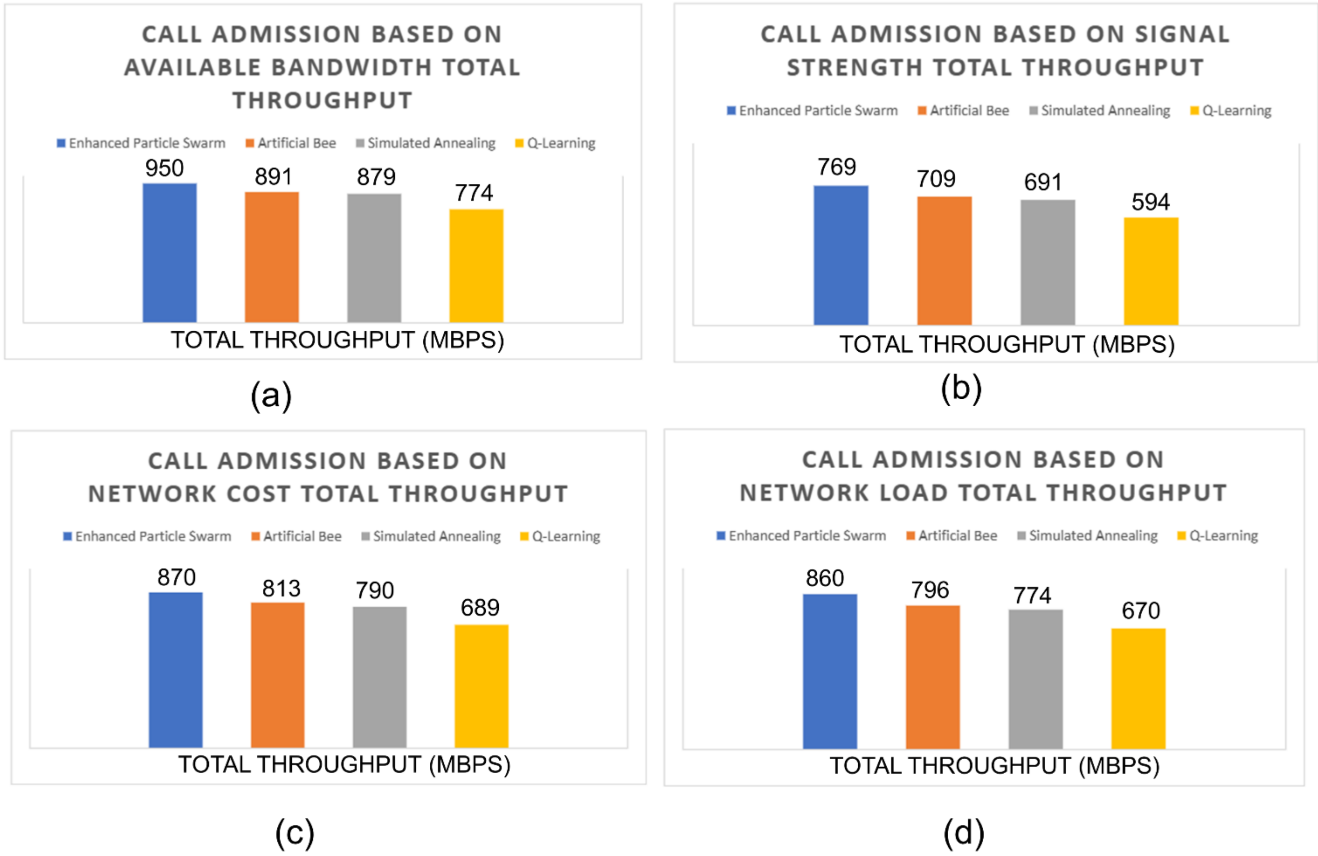



*Figure 5-1: Throughput Results 1*

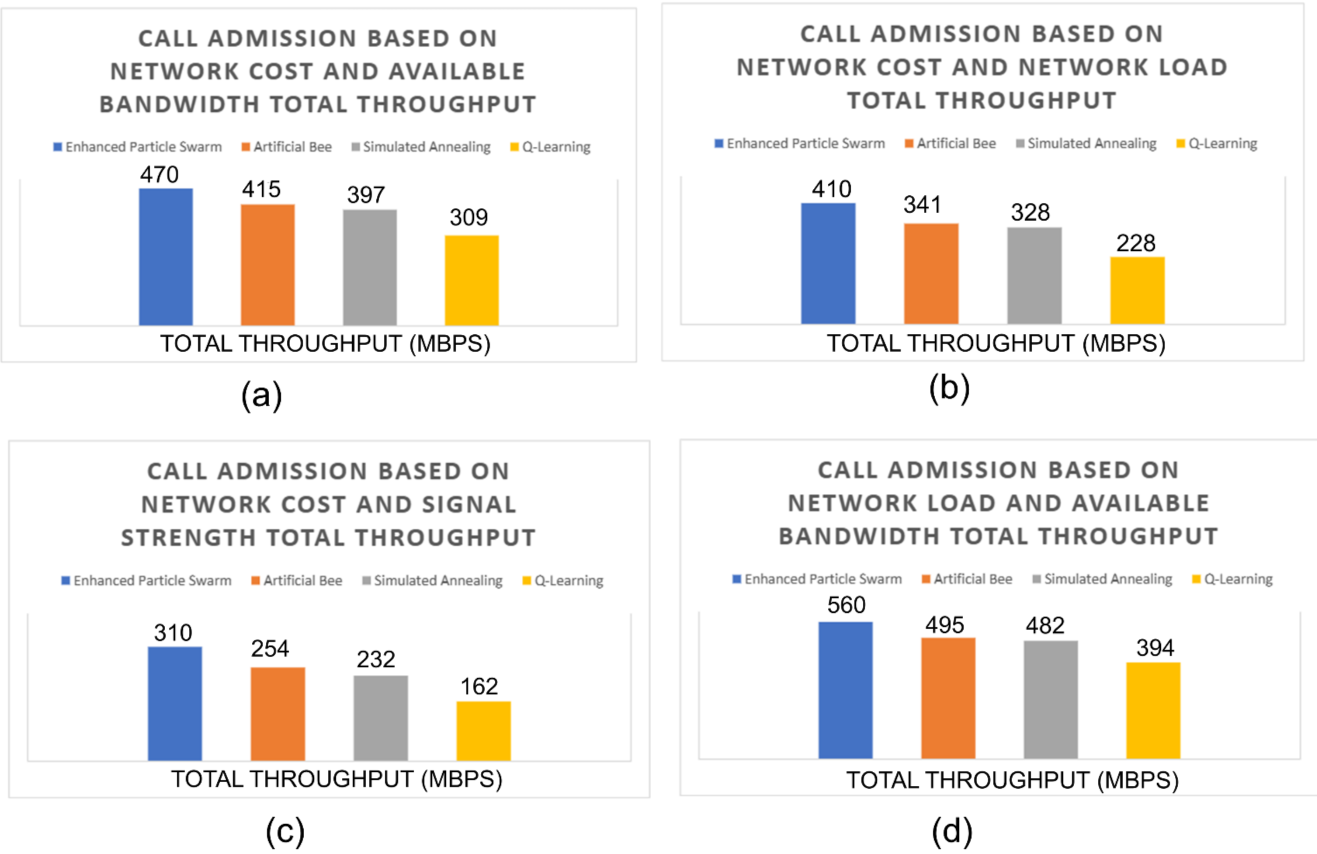
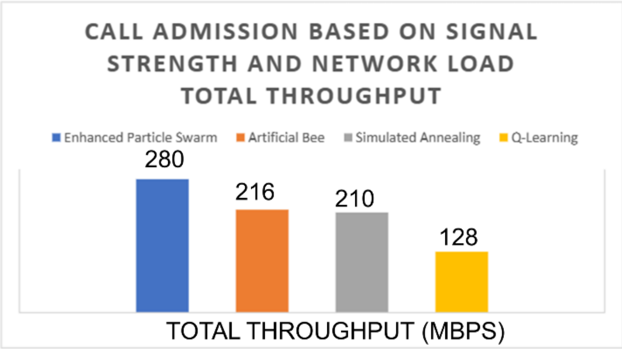
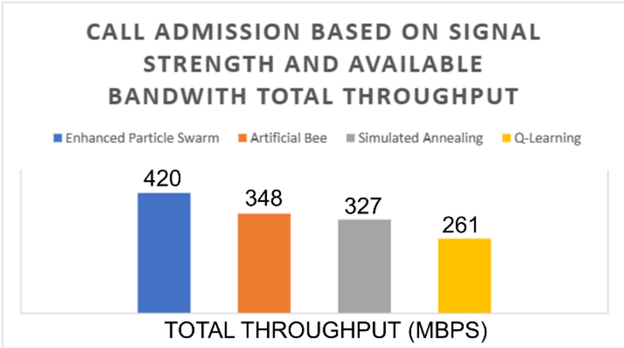


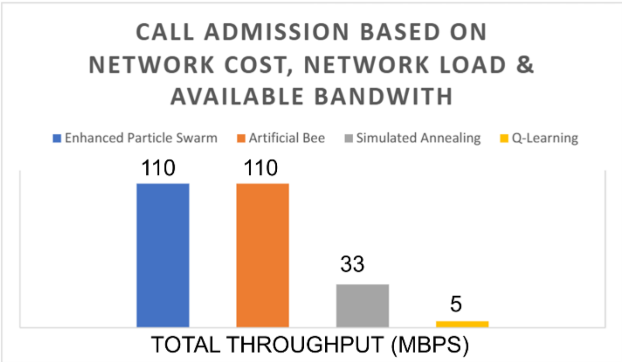

*Figure 5-2: Throughput Results 2*




(e)




(f)




(g)

*Figure 5-3: Throughput Results 3*

### 5.2.2 Impact On Call Blocking

Call Blocking is another important indicator of the scheme. In this section, the impact of call blocking is presented, Figure 5-4 to 5-6 shows the results of call blocking. The result is evaluated based on the single-call admission scenario, and the multiple-call admission scenario while simulating 200 users on the network for 6000 seconds. The total number of users on the network is varied every minute following Poisson distribution and call arrival rate as discussed in Chapter 4. The objective of the algorithms which is stated in equation 2 is to minimise call blocking. Figure 5-4 shows the total throughput result for the single decision call admission scenario based on signal strength, network cost, network load and available bandwidth. Figures 5-5 & 5-6 show the total throughput result for the multiple decision call admission scenario based on network cost and available bandwidth; network cost and network load; network cost and signal strength; network load and available bandwidth; signal strength and network load; signal strength and available bandwidth; network cost, network load and available bandwidth.

However, EPSO has the best overall performance in all the scenarios as it has the lowest call-blocking instances as well as the lowest number of calls blocked.

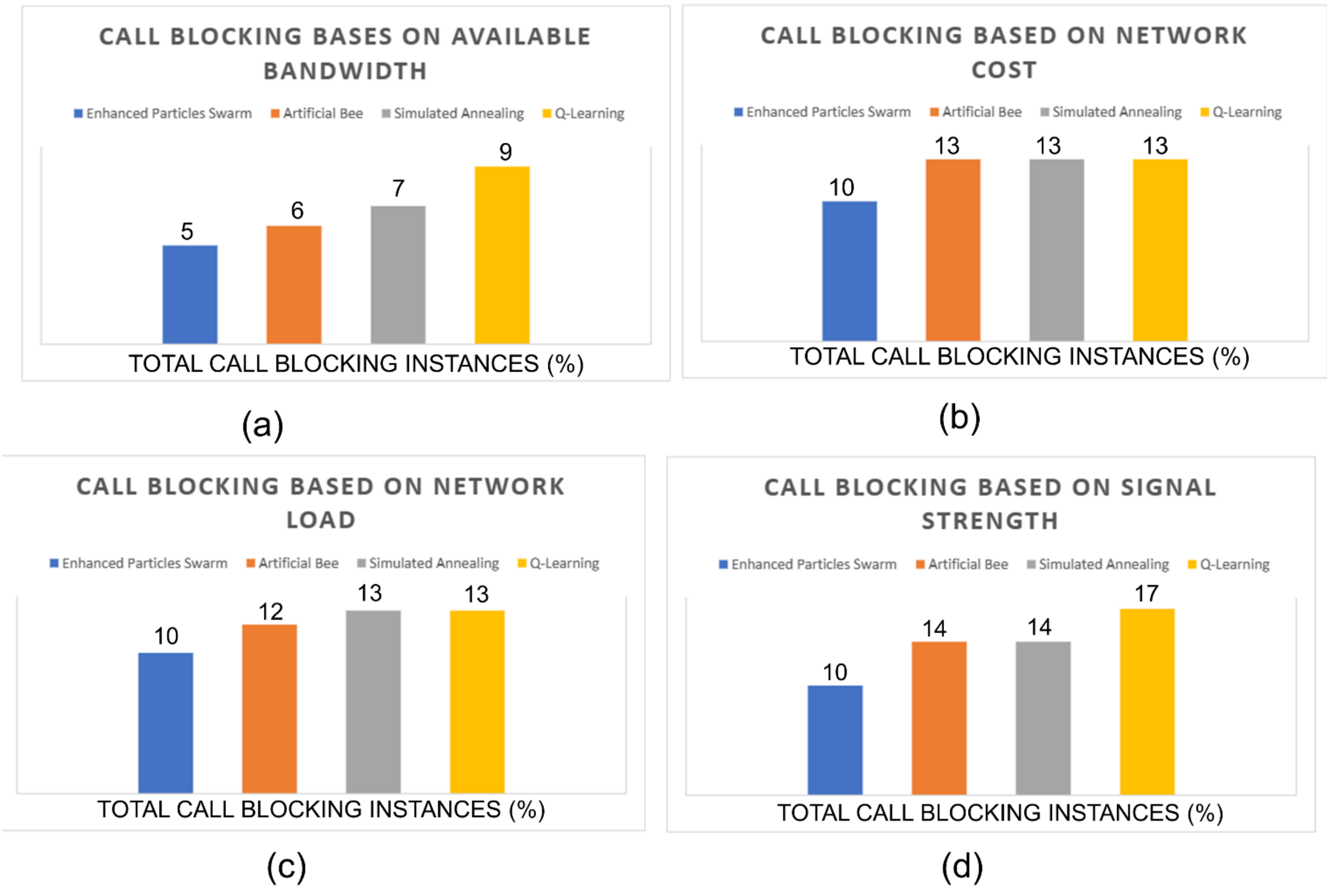
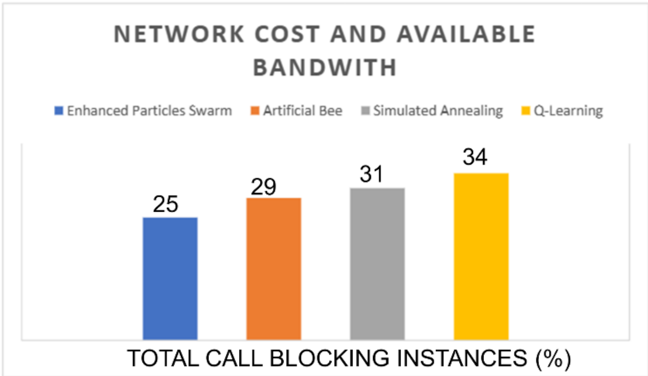
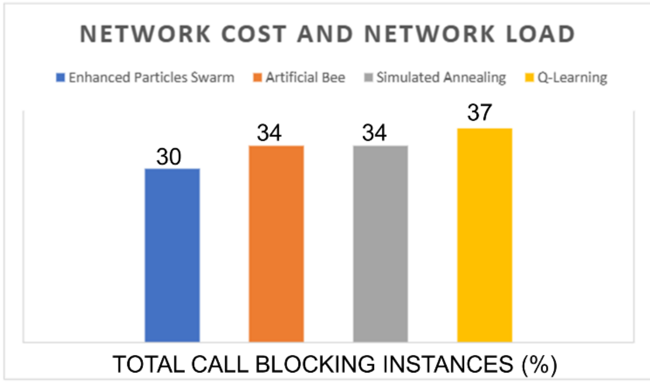


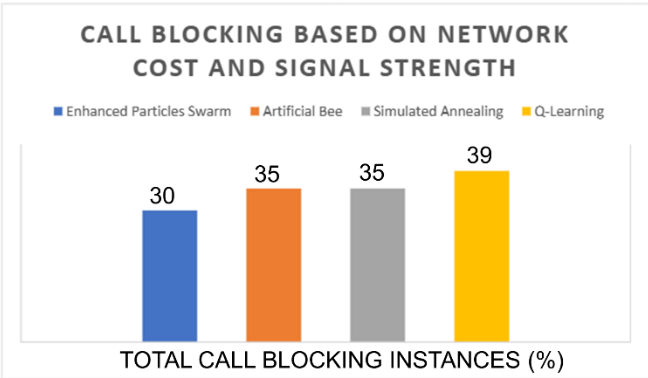

*Figure 5-4: Call Blocking Results 1*



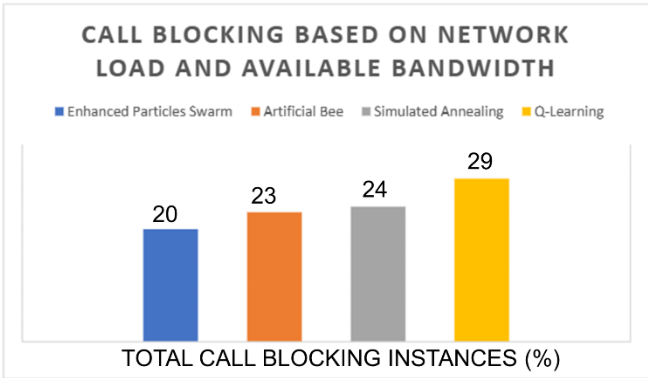

(a)




(b)

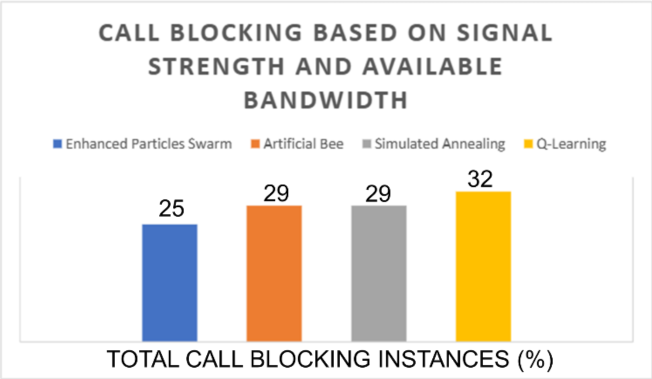



(c)

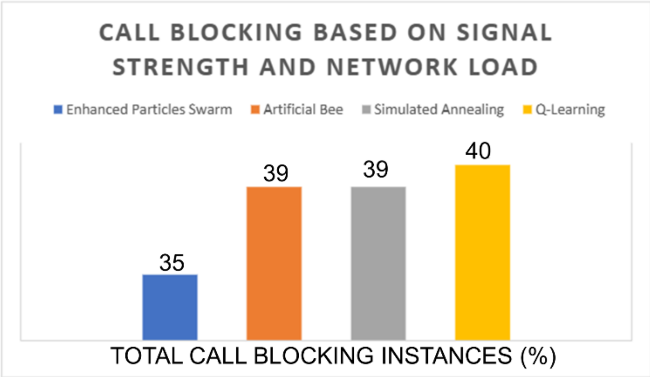



(d)

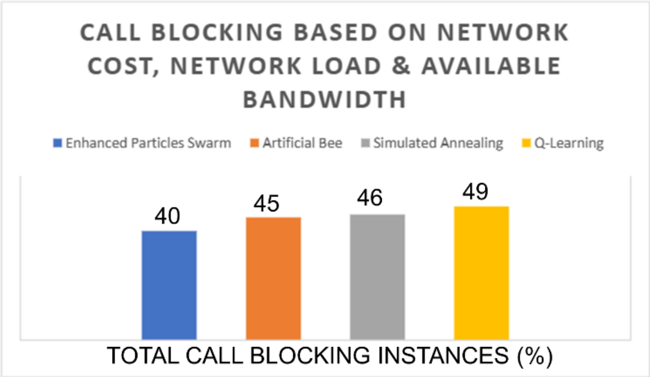
*Figure 5-5: Call Blocking Results 2*




(e)




(f)




(g)

*Figure 5-6: Call Blocking Results 3*

### 5.2.3 Impact On Fairness With Different Numbers Of Users

The effect of increasing numbers of UDs in the network on the different approaches to fairness is examined. The impact on fairness is evaluated based on the single and multiple-call admission decisions made as well as the varied number of users. The objective of the algorithms which is stated in equation 3 is to maximise fairness. Tables 5-1 to 5-11 show the fairness computed using Jain's index for the four algorithms; this is evaluated based on the increasing number of users accessing the network for the different decision variables.

Jain’s fairness index is a metric for evaluating the fairness of resource allocation among participants. It is a value between 0 and 1, where 1 means perfect fairness and 0 means complete unfairness.

Figures 5-7 to 5-9 show the fairness performance of the four algorithms when the number of users is increased is increased from 10 – 200, as well as varied decision variables. Figure 5-7 shows the fairness result for the call admission scenario based on single decision variables - signal strength, network cost, network load and available bandwidth. Figure 5-8 & 5-9 shows the fairness result for the call admission scenario based on multiple decision variables - network cost and available bandwidth; network cost and network load; network cost and signal strength; network load and available bandwidth; signal strength and network load; signal strength and available bandwidth; network cost, network load and available bandwidth the signal strength and network load.

The x-axis of the graphs represents the number of users simulated for each scenario, while the y-axis represents Jain’s Fairness Index. The results show that the EPSO algorithm has the best performance compared to the other algorithm, it has a perfect fairness value of 1 in all the scenarios and the increasing number of users does not affect its performance. Artificial Bee Colony algorithm and Simulated Annealing also have good fairness index in some of the scenarios, however, their performance is affected by the increasing number of users as the value dropped when users increased. Q-Learning has the lowest index value among all the algorithms and its performance is mostly affected by the increasing number of users. EPSO achieves a steady and consistently high performance of 100% for the fairness metric in the simulation environment because it converges faster and stably to an optimal solution than the other algorithms. The algorithm's convergence behaviour is influenced by factors like the swarm size, inertia weight, and acceleration coefficients. A well-balanced setting of these parameters contributes to consistent and reliable performance. EPSO's inherent properties, such as the ability to explore and exploit the solution space effectively, enable it to align perfectly with the characteristics of the simulation. Also, its adaptability to the dynamic nature of the network and its robustness to variations in network conditions contribute to its consistent high performance. Random initialisation and sensitivity to network characteristics also contribute to its success.

*Table 5-1: Computed Jain's Index For CAC Based On Signal Strength*

| No of users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.90 | 0.85 | 0.62 |
| 20 | 1 | 0.90 | 0.87 | 0.49 |
| 30 | 1 | 0.88 | 0.83 | 0.54 |
| 50 | 1 | 0.88 | 0.83 | 0.53 |
| 70 | 1 | 0.88 | 0.88 | 0.51 |
| 100 | 1 | 0.90 | 0.87 | 0.48 |
| 120 | 1 | 0.90 | 0.92 | 0.46 |
| 150 | 1 | 0.90 | 0.92 | 0 |
| 170 | 1 | 0.92 | 0.92 | 0.47 |
| 200 | 1 | 0.92 | 0.92 | 0.46 |

*Table 5-2: Computed Jain's Index For CAC Based On Network Load*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.820 | 0.880 | 0.616 |
| 20 | 1 | 0.838 | 0.876 | 0.574 |
| 30 | 1 | 0.867 | 0.833 | 0.576 |
| 50 | 1 | 0.860 | 0.851 | 0.504 |
| 70 | 1 | 0.879 | 0.867 | 0.512 |
| 100 | 1 | 0.853 | 0.840 | 0.474 |
| 120 | 1 | 0.866 | 0.854 | 0.487 |
| 150 | 1 | 0.871 | 0.880 | 0.481 |
| 170 | 1 | 0.872 | 0.868 | 0.467 |
| 200 | 1 | 0.896 | 0.877 | 0.475 |

*Table 5-3: Computed Jain's Index For CAC Based On Available Bandwidth*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.983 | 0.879 | 0.646 |
| 20 | 1 | 0.957 | 0.991 | 0.634 |
| 30 | 1 | 0.949 | 0.898 | 0.619 |
| 50 | 1 | 0.905 | 0.932 | 0.643 |
| 70 | 1 | 0.935 | 0.930 | 0.564 |

| | | | | |
|---|---|---|---|---|
| 100 | 1 | 0.916 | 0.950 | 0.551 |
| 120 | 1 | 0.925 | 0.938 | 0.544 |
| 150 | 1 | 0.929 | 0.939 | 0.526 |
| 170 | 1 | 0.923 | 0.933 | 0.530 |
| 200 | 1 | 0.931 | 0.936 | 0.538 |

*Table 5-4: Computed Jain's Index For CAC Based On Network Cost*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.998 | 0.968 | 0.766 |
| 20 | 1 | 0.968 | 0.910 | 0.641 |
| 30 | 1 | 0.943 | 0.973 | 0.650 |
| 50 | 1 | 0.881 | 0.934 | 0.515 |
| 70 | 1 | 0.894 | 0.906 | 0.475 |
| 100 | 1 | 0.882 | 0.894 | 0.494 |
| 120 | 1 | 0.901 | 0.897 | 0.488 |
| 150 | 1 | 0.903 | 0.934 | 0.494 |
| 170 | 1 | 0.910 | 0.935 | 0.492 |
| 200 | 1 | 0.933 | 0.915 | 0.505 |

*Table 5-5: Computed Jain's Index For CAC Based On Network Cost and Network Load*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.936 | 0.889 | 0.517 |
| 20 | 1 | 0.941 | 0.895 | 0.400 |
| 30 | 1 | 0.856 | 0.868 | 0.405 |
| 50 | 1 | 0.824 | 0.840 | 0.312 |
| 70 | 1 | 0.850 | 0.906 | 0.303 |
| 100 | 1 | 0.828 | 0.851 | 0.276 |
| 120 | 1 | 0.827 | 0.847 | 0.262 |
| 150 | 1 | 0.831 | 0.824 | 0.245 |
| 170 | 1 | 0.795 | 0.793 | 0.193 |
| 200 | 1 | 0.820 | 0.811 | 0.243 |

*Table 5-6: Computed Jain's Index For CAC Based On Network Cost and Signal Strength*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.970 | 0.942 | 0.616 |
| 20 | 1 | 0.988 | 0.738 | 0.185 |
| 30 | 1 | 0.852 | 0.874 | 0.328 |
| 50 | 1 | 0.979 | 0.828 | 0.167 |

| | | | | |
|---|---|---|---|---|
| 70 | 1 | 0.797 | 0.837 | 0.187 |
| 100 | 1 | 0.775 | 0.831 | 0.267 |
| 120 | 1 | 0.769 | 0.833 | 0.200 |
| 150 | 1 | 0.795 | 0.806 | 0.211 |
| 170 | 1 | 0.775 | 0.782 | 0.199 |
| 200 | 1 | 0.792 | 0.771 | 0.194 |

*Table 5-7: Computed Jain's Index For CAC Based On Network Cost and Available Bandwidth*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.996 | 0.976 | 0.616 |
| 20 | 1 | 0.875 | 0.876 | 0.458 |
| 30 | 1 | 0.892 | 0.911 | 0.463 |
| 50 | 1 | 0.872 | 0.872 | 0.404 |
| 70 | 1 | 0.829 | 0.867 | 0.290 |
| 100 | 1 | 0.851 | 0.863 | 0.317 |
| 120 | 1 | 0.842 | 0.866 | 0.309 |
| 150 | 1 | 0.848 | 0.839 | 0.280 |
| 170 | 1 | 0.830 | 0.823 | 0.268 |
| 200 | 1 | 0.855 | 0.843 | 0.309 |

*Table 5-8: Computed Jain's Index For CAC Based On Network Load and Available Bandwidth*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.987 | 0.927 | 0.616 |
| 20 | 1 | 0.947 | 0.952 | 0.530 |
| 30 | 1 | 0.875 | 0.871 | 0.542 |
| 50 | 1 | 0.878 | 0.862 | 0.445 |
| 70 | 1 | 0.893 | 0.902 | 0.454 |
| 100 | 1 | 0.875 | 0.895 | 0.413 |
| 120 | 1 | 0.871 | 0.917 | 0.412 |
| 150 | 1 | 0.802 | 0.801 | 0.374 |
| 170 | 1 | 0.838 | 0.833 | 0.351 |
| 200 | 1 | 0.837 | 0.838 | 0.354 |

*Table 5-9: Computed Jain's Index For CAC Based On Signal Strength and Available Bandwidth*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.919 | 0.853 | 0.616 |
| 20 | 1 | 0.817 | 0.890 | 0.534 |
| 30 | 1 | 0.823 | 0.781 | 0.504 |
| 50 | 1 | 0.835 | 0.807 | 0.423 |
| 70 | 1 | 0.767 | 0.771 | 0.392 |

| | | | | |
|---|---|---|---|---|
| 100 | 1 | 0.877 | 0.837 | 0.350 |
| 120 | 1 | 0.862 | 0.844 | 0.353 |
| 150 | 1 | 0.784 | 0.785 | 0.309 |
| 170 | 1 | 0.843 | 0.836 | 0.299 |
| 200 | 1 | 0.882 | 0.894 | 0.277 |

*Table 5-10: Computed Jain's Index For CAC Based On Signal Strength and Network Load*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 1 | 0.794 | 0 |
| 20 | 1 | 0.951 | 0.795 | 0.261 |
| 30 | 1 | 0.803 | 0.842 | 0.250 |
| 50 | 1 | 0.763 | 0.743 | 0.220 |
| 70 | 1 | 0.819 | 0.740 | 0.252 |
| 100 | 1 | 0.827 | 0.820 | 0.257 |
| 120 | 1 | 0.798 | 0.770 | 0.237 |
| 150 | 1 | 0.797 | 0.780 | 0.205 |
| 170 | 1 | 0.783 | 0.795 | 0.168 |
| 200 | 1 | 0.761 | 0.759 | 0.158 |

*Table 5-11: Computed Jain's Index For CAC Based On Network Cost, Network Load and Available Bandwidth*

| No of Users | Enhanced Particles | Artificial Bee | Simulated Annealing | Q-Learning |
|---|---|---|---|---|
| 10 | 1 | 0.929 | 0.856 | 0.517 |
| 20 | 1 | 0.886 | 0.891 | 0.400 |
| 30 | 1 | 0.811 | 0.832 | 0.405 |
| 50 | 1 | 0.782 | 0.829 | 0.236 |
| 70 | 1 | 0.732 | 0.755 | 0.083 |
| 100 | 1 | 0.762 | 0.750 | 0.084 |
| 120 | 1 | 0.648 | 0.648 | 0 |
| 150 | 1 | 1 | 0.602 | 0 |
| 170 | 1 | 1 | 1 | 0 |
| 200 | 1 | 0.988 | 0.503 | 0 |

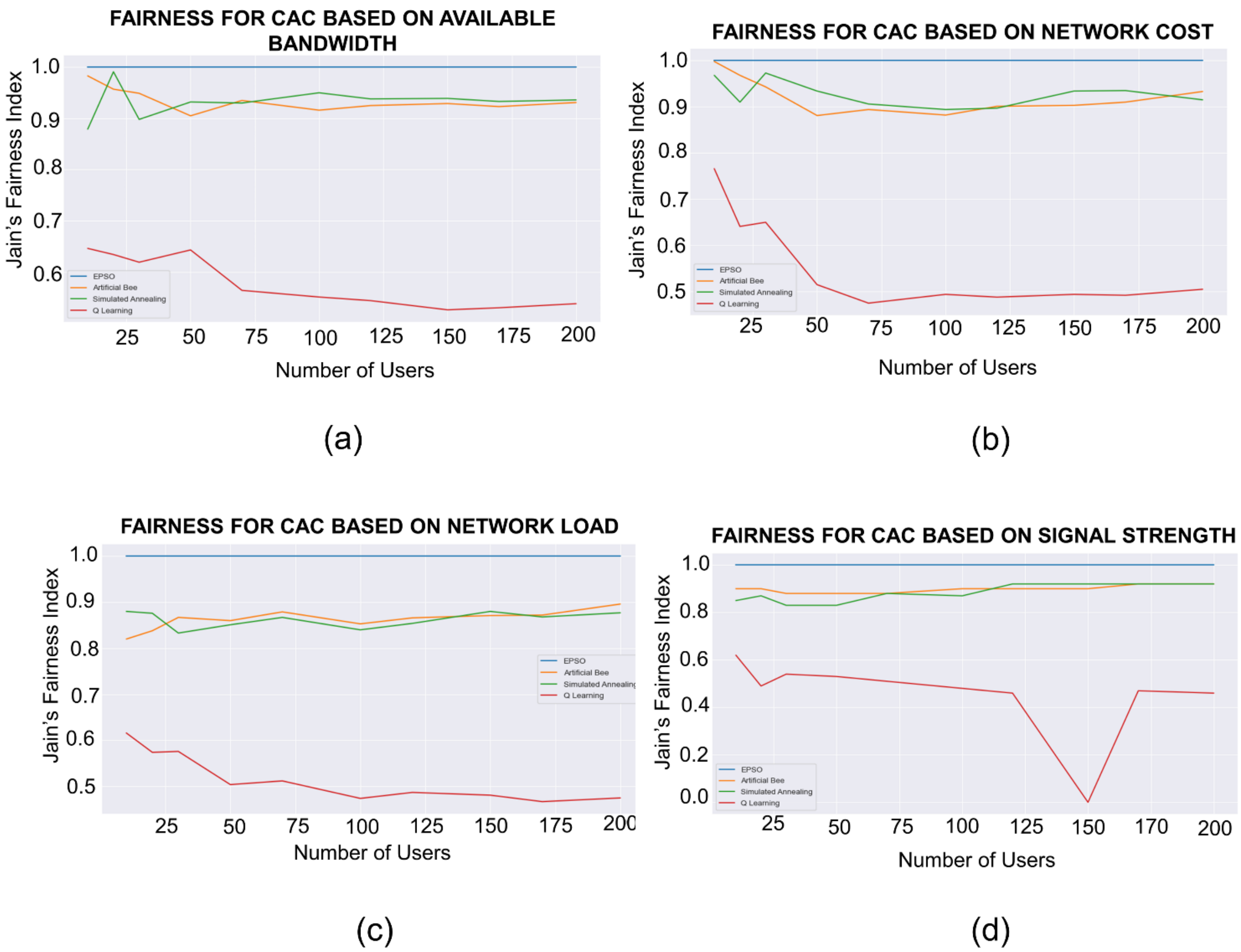
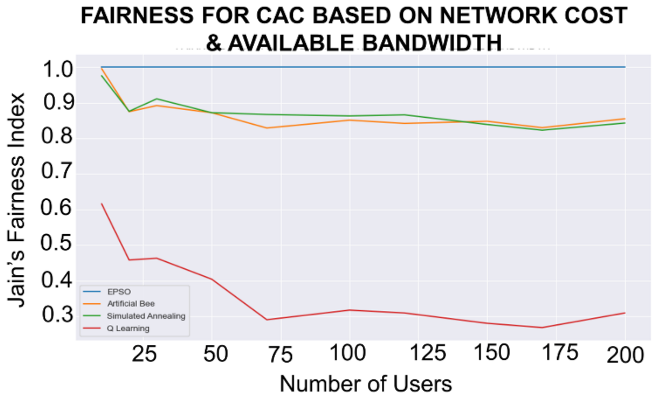
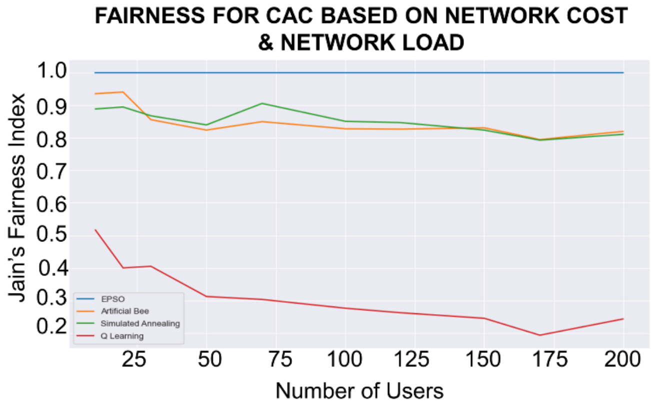


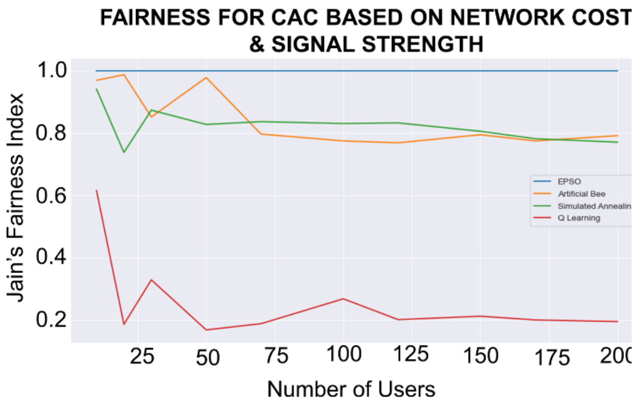

*Figure 5-7: Fairness Results 1*




(a)




(b)

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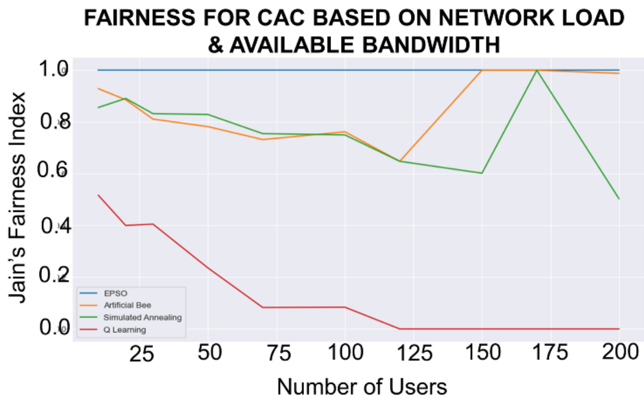
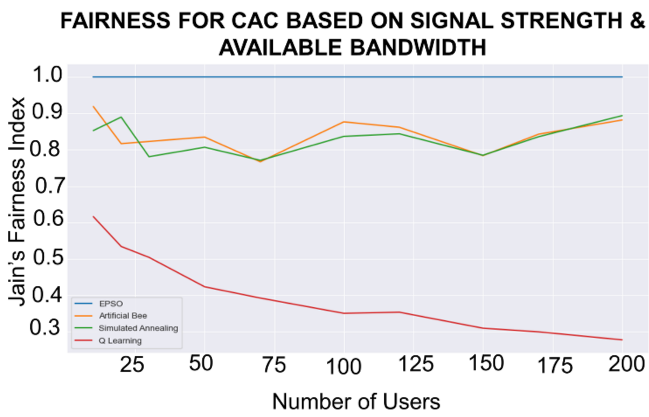



(d)

*Figure 5-8: Fairness Results 2*

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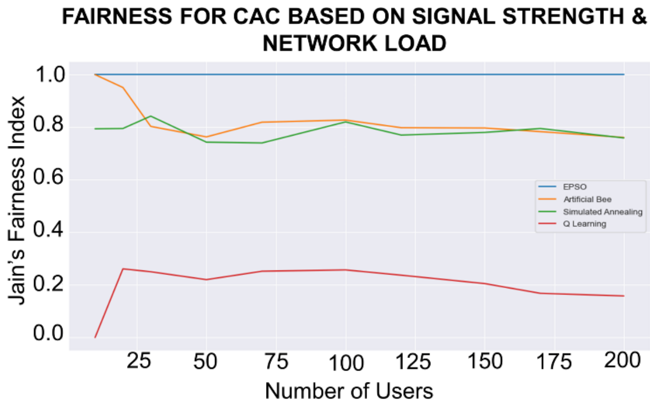


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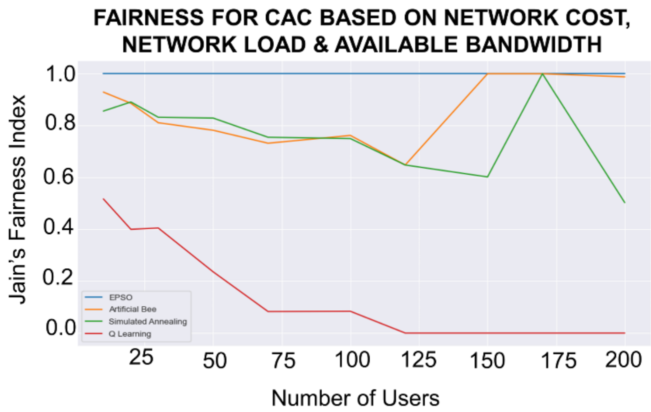


(g)

*Figure 5-9: Fairness Results 3*

## 5.3 PERFORMANCE COMPARISON

This section presents a detailed comparison of the performance of the proposed load-balancing algorithms and the three benchmarking algorithms presented in the previous section. The results of all the load-balancing algorithms are compared and the percentage difference is calculated to prove that the proposed algorithm outperforms the other algorithms significantly.

**A) Throughput Comparison**

Table 5-12 to 5-14 compares the performance of the proposed algorithm EPSO with the benchmarking algorithms - Artificial Bee Colony, Simulated Annealing and Q-Learning respectively for Throughput results using the absolute percentage difference and relative performance difference. The absolute and relative difference is calculated for each of the scenarios.

The results show there is a significant increase in the performance of the proposed algorithm compared to the other algorithms.

For absolute difference, the EPSO improvement rate is on average 12% higher than the Artificial Bee Colony algorithm; 26% higher than the Simulated Annealing algorithm; and 60% higher than the Q-Learning algorithm. For relative difference, the EPSO improvement rate is on average 12% higher than artificial bee; 21% higher than the simulated annealing algorithm; and 40% higher than the Q-Learning algorithm. The findings demonstrate that the proposed algorithm offers a significant performance advantage over the other three benchmarking algorithms.

*Table 5-12: Artificial Bee Colony vs EPSO (Throughput Performance Comparison)*

| **Decision Variables** | **Absolute Difference (%)** | **Relative Difference (%)** |
|---|---|---|
| Available Bandwidth | 6% | 6% |
| Network Cost | 7% | 7% |
| Network Load | 8% | 7% |
| Signal Strength | 8% | 8% |
| Network Cost and Available Bandwidth | 12% | 12% |
| Network Cost and Network Load | 18% | 17% |
| Network Cost and Signal Strength | 20% | 18% |
| Network Load and Available Bandwidth | 12% | 12% |
| Signal Strength and Available Bandwidth | 19% | 17% |
| Signal Strength and Network Load | 26% | 23% |
| Network Cost, Network Load and Available Bandwidth | 0% | 0% |

*Table 5-13: Simulated Annealing vs EPSO (Throughput Performance Comparison)*

| Decision Variables | Absolute Difference (%) | Relative Difference (%) |
|---|---|---|
| Available Bandwidth | 8% | 7% |
| Network Cost | 10% | 9% |
| Network Load | 11% | 10% |
| Signal Strength | 11% | 10% |
| Network Cost and Available Bandwidth | 17% | 16% |
| Network Cost and Network Load | 22% | 20% |
| Network Cost and Signal Strength | 29% | 25% |
| Network Load and Available Bandwidth | 15% | 14% |
| Signal Strength and Available Bandwidth | 25% | 22% |
| Signal Strength and Network Load | 29% | 25% |
| Network Cost, Network Load and Available Bandwidth | 108% | 70% |

*Table 5-14: Q-Learning vs EPSO (Throughput Performance Comparison)*

| **Decision Variables** | **Absolute Difference (%)** | **Relative Difference (%)** |
|---|---|---|
| Available Bandwidth | 20% | 19% |
| Network Cost | 23% | 21% |
| Network Load | 25% | 22% |
| Signal Strength | 26% | 23% |
| Network Cost and Available Bandwidth | 41% | 34% |
| Network Cost and Network Load | 57% | 44% |
| Network Cost and Signal Strength | 63% | 48% |
| Network Load and Available Bandwidth | 35% | 30% |
| Signal Strength and Available Bandwidth | 47% | 38% |
| Signal Strength and Network Load | 75% | 54% |
| Network Cost, Network Load and Available Bandwidth | 183% | 95% |

**B) Call Blocking Comparison**

Table 5-15 to 5-17 compares the performance of the proposed algorithm EPSO with the benchmarking algorithms - Artificial Bee Colony, Simulated Annealing and Q-Learning respectively for Call Blocking results using the absolute percentage difference and relative performance difference. The absolute and relative difference is calculated for each of the scenarios.

The results show there is a significant increase in the performance of the proposed algorithm compared to the other algorithms.

For absolute difference, the EPSO improvement rate is on average 17% higher than the ABC algorithm; 20% higher than the Simulated Annealing algorithm; and 30% higher than the Q-Learning algorithm. For relative difference, the EPSO improvement rate is on average 19% higher than the ABC algorithm; 23% higher than the simulated annealing algorithm; and 37% higher than the Q-Learning algorithm. The findings depict that the proposed algorithm outperforms other algorithms in terms of call blocking. When compared with the other three algorithms, it shows it offers a significant performance advantage.

*Table 5-15: Artificial Bee Colony vs EPSO (Call Blocking Instances Performance Comparison)*

| **Decision Variables** | **Absolute Difference (%)** | **Relative Difference (%)** |
|---|---|---|
| Available Bandwidth | 18% | 20% |
| Network Cost | 26% | 30% |
| Network Load | 18% | 20% |
| Signal Strength | 33% | 40% |
| Network Cost and Available Bandwidth | 15% | 16% |
| Network Cost and Network Load | 13% | 13% |
| Network Cost and Signal Strength | 15% | 17% |
| Network Load and Available Bandwidth | 14% | 15% |
| Signal Strength and Available Bandwidth | 15% | 16% |
| Signal Strength and Network Load | 11% | 11% |
| Network Cost, Network Load and Available Bandwidth | 12% | 13% |

*Table 5-16: Simulated Annealing vs EPSO (Call Blocking Instances Performance Comparison)*

| Decision Variables | Absolute Difference (%) | Relative Difference (%) |
|---|---|---|
| Available Bandwidth | 33% | 40% |
| Network Cost | 26% | 30% |
| Network Load | 26% | 30% |
| Signal Strength | 33% | 40% |
| Network Cost and Available Bandwidth | 21% | 24% |
| Network Cost and Network Load | 13% | 13% |
| Network Cost and Signal Strength | 15% | 17% |
| Network Load and Available Bandwidth | 18% | 20% |
| Signal Strength and Available Bandwidth | 15% | 16% |
| Signal Strength and Network Load | 11% | 11% |
| Network Cost, Network Load and Available Bandwidth | 14% | 15% |

*Table 5-17 Q-Learning vs EPSO (Call Blocking Instances Performance Comparison)*

| Decision Variables | Absolute Difference (%) | Relative Difference (%) |
|---|---|---|
| Available Bandwidth | 57% | 80% |
| Network Cost | 26% | 30% |
| Network Load | 26% | 30% |
| Signal Strength | 52% | 70% |
| Network Cost and Available Bandwidth | 31% | 36% |
| Network Cost and Network Load | 21% | 23% |
| Network Cost and Signal Strength | 26% | 30% |
| Network Load and Available Bandwidth | 37% | 45% |
| Signal Strength and Available Bandwidth | 25% | 28% |
| Signal Strength and Network Load | 13% | 14% |
| Network Cost, Network Load and Available Bandwidth | 20% | 23% |

### C) FAIRNESS COMPARISON

Table 5-18 to 5-20 compares the performance of the proposed algorithm EPSO with the benchmarking algorithms – Artificial Bee Colony, Simulated Annealing and Q-Learning respectively for Fairness results using the absolute percentage difference and relative performance difference. The absolute and relative difference is calculated for each of the scenarios.

The results show there is a significant increase in the performance of the proposed algorithm compared to the other algorithms.

For absolute difference, the EPSO improvement rate is on average 14% higher than the ABC algorithm; 16% higher than the Simulated Annealing algorithm; and 93% higher than the Q-Learning algorithm.  For relative difference, the EPSO improvement rate is on average 13% higher than the Artificial Bee Colony algorithm; 15% higher than the simulated annealing algorithm; and 61% higher than the Q-Learning algorithm.  From the findings, the performance advance of EPSO over the other three benchmarking algorithms is significant. The proposed load balancing algorithm ensures that users are evenly distributed in the 5G-Satellite HWNs.

*Table 5-18 Artificial Bee Colony vs EPSO (Fairness Performance Comparison)*

| Decision Variables | Absolute Difference (%) | Relative Difference (%) |
|---|---|---|
| Available Bandwidth | 7% | 6% |
| Network Cost | 8% | 8% |
| Network Load | 15% | 14% |
| Signal Strength | 11% | 10% |
| Network Cost and Available Bandwidth | 14% | 13% |
| Network Cost and Network Load | 16% | 15% |
| Network Cost and Signal Strength | 17% | 15% |
| Network Load and Available Bandwidth | 13% | 12% |
| Signal Strength and Available Bandwidth | 17% | 16% |
| Signal Strength and Network Load | 19% | 17% |
| Network Cost, Network Load and Available Bandwidth | 17% | 15% |

*Table 5-19 Simulated Annealing vs EPSO (Fairness Performance Comparison)*

| **Decision Variables** | **Absolute Difference (%)** | **Relative Difference (%)** |
|---|---|---|
| Available Bandwidth | 7% | 7% |
| Network Cost | 8% | 7% |
| Network Load | 15% | 14% |
| Signal Strength | 13% | 12% |
| Network Cost and Available Bandwidth | 14% | 13% |
| Network Cost and Network Load | 16% | 15% |
| Network Cost and Signal Strength | 19% | 18% |
| Network Load and Available Bandwidth | 13% | 12% |
| Signal Strength and Available Bandwidth | 19% | 17% |
| Signal Strength and Network Load | 24% | 22% |
| Network Cost, Network Load and Available Bandwidth | 28% | 23% |

*Table 5-20: Q-Learning vs EPSO (Fairness Performance Comparison)*

| Decision Variables | Absolute Difference (%) | Relative Difference (%) |
|---|---|---|
| Available Bandwidth | 53% | 42% |
| Network Cost | 59% | 45% |
| Network Load | 64% | 48% |
| Signal Strength | 79% | 54% |
| Network Cost and Available Bandwidth | 93% | 63% |
| Network Cost and Network Load | 105% | 68% |
| Network Cost and Signal Strength | 121% | 74% |
| Network Load and Available Bandwidth | 77% | 55% |
| Signal Strength and Available Bandwidth | 86% | 59% |
| Signal Strength and Network Load | 135% | 80% |
| Network Cost, Network Load and Available Bandwidth | 150% | 83% |

## 5.4 CONCLUSION

Chapter 5 has delved into an in-depth analysis of the results obtained from simulating the CAC algorithm in the 5G-Satellite HWNs. The evaluation focused on three key scenarios, assessing the impact of the number of users, network information, and user satisfaction on the effectiveness of the CAC algorithm in enhancing system performance.

This chapter offered a comprehensive view of the algorithm's performance across various parameters, including throughput, call blocking, and fairness. The investigation into the impact on throughput revealed in Figures 5-1 to 5-3 that the proposed EPSO algorithm consistently outperformed other algorithms in both single and multiple decision scenarios. The detailed comparisons provided in Tables 5-12 to 5-14 underscored the superiority of EPSO, showcasing its effectiveness in maximizing throughput across different decision variables. The results show there is a significant increase in the performance of the proposed algorithm compared to the other algorithms.

Examining call blocking, Figures 5-4 to 5- 6 demonstrated that EPSO exhibited the lowest instances of call blocking and the fewest number of calls blocked, reinforcing its robust performance in preventing service denials even as the number of users increased. Comparative analyses in Tables 5-15 to 5–17 confirmed the significant advantages of EPSO over other algorithms in minimizing call blocking.

Furthermore, the examination of fairness, as outlined in Figures 5-7 to 5-9 showcased EPSO's ability to maintain a high level of fairness, with Jain's fairness index consistently reaching a perfect value of 1. The comparisons presented in Tables 5-18 to 5–20 reinforced the notion that EPSO outperformed Artificial Bee

Colony, Simulated Annealing and Q-Learning in achieving fair resource allocation, even as the number of users in the network increased.

The comprehensive performance comparison in Section 5.3 reinforced the conclusion that the proposed EPSO algorithm consistently outperformed benchmarking algorithms, including Artificial Bee, Simulated Annealing, and Q-Learning. The detailed assessments across throughput, call blocking, and fairness revealed that EPSO offered significant improvements. For throughput, the performance gain of the EPSO algorithm on average when compared with the Artificial Bee Colony algorithm, Simulated Annealing and Q-Learning algorithm is 12%, 23% and 46% respectively. For call blocking, the performance gain of the EPSO algorithm on average when compared with the Artificial Bee Colony algorithm, Simulated Annealing and Q-Learning algorithm is 18%, 22% and 34% respectively. For fairness, the performance gain of the EPSO algorithm on average when compared with the Artificial Bee Colony algorithm, Simulated Annealing and Q-Learning algorithm is 13%, 15% and 77% respectively.

In conclusion, the findings of this chapter underscore the effectiveness of the proposed EPSO algorithm in optimizing the performance of the 5G-Satellite heterogeneous network. The consistent performance across various scenarios and performance metrics position EPSO as a promising solution for enhancing system efficiency, maximising throughput, minimizing call blocking, ensuring fairness, and ultimately maximizing user satisfaction in dynamic and complex network environments.

# CHAPTER 6: CONCLUSION AND FUTURE WORK

## 6.1 CONCLUSION

The aim of this research work is to design an intelligent CAC algorithm for load balancing in 5G-Satellite HWNs which satisfies the following requirements:

- Maximises the number of calls that can be admitted to the network while ensuring that the QoS for existing calls is not degraded.
- Improves utilisation of network resources in 5G – Satellite HWNs.
- Reduce the congestion in the networks by sharing the load between co-located wireless networks; hence minimises call dropping.
- Maximises throughputs to ensure efficient use of resources, improved data transmission rates and heightened user satisfaction.
- Maximises fairness to ensure equitable distribution of resources among the users.

In this thesis, the resource management and load balancing problem in 5G-Satellite heterogeneous wireless networks is solved by CAC. The different components of the proposed load balancing CAC framework running on the mobile node with assisted feedback from the network, work together to efficiently balance the load between co-located HWNs. The architecture of the 5G-Satellite HWNs is shown in Figure 3-2 The mobile device makes an initial decision about whether to admit a call, based on its own local information and preferences such as battery level, signal strength, supported technologies, service cost etc. If the mobile device is not sure whether to admit the call, it can request feedback from the network core. The network core can then provide the mobile device with more information about the network conditions and the admission status, such as the signal strength of different RATs, the load on different RATs, the available bandwidth on different RATs and the number of active users. This feedback can help the mobile device to make a more informed decision about whether to admit the call; the UD can use this information to select the RAT that is most likely to provide the best experience for the user.

There are a number of benefits to providing UDs with network information. First, it allows UDs to make more informed decisions about which RAT to use; this can lead to improved performance and satisfaction for users. Second, it helps to ensure that radio resources are used effectively; this can help to improve the overall performance of the network. It ensures fairness in the allocation of radio resources among the HWN.

An intelligent EPSO algorithm for CAC is proposed to admit users' calls as well as select the most suitable RAT to ensure equal distribution of users on the network and avoid congestion. The proposed strategy takes into consideration network attributes such as signal strength, network cost, available bandwidth and network load to aid in decision-making for call admission.

The study evaluates the EPSO-based CAC algorithm through numerical simulations, comparing its performance with other AI and ML algorithms which include Artificial Bee Colony Algorithm, Simulated Annealing Algorithm and Q-Learning Algorithm; and offering insights into dynamic resource management. The proposed scheme provides better results for maximising throughput, fairness, user satisfaction and minimizing call blocking.

For throughput, the improvement rate of the EPSO algorithm on average when compared with the Artificial Bee Colony algorithm, Simulated Annealing and Q-Learning algorithm is 12%, 23% and 46% respectively. For call blocking, the improvement rate of the EPSO algorithm on average when compared with the Artificial Bee Colony algorithm, Simulated Annealing and Q-Learning algorithm is

18%, 22% and 34% respectively. For fairness, the improvement rate of the EPSO algorithm on average when compared with the Artificial Bee Colony algorithm, Simulated Annealing and Q-Learning algorithm is 13%, 15% and 77% respectively. Hence, the findings contribute to network optimization and inform the development of more adaptive and efficient resource allocation strategies. The thesis offers practical implications for 5G-satellite network design and implementation.

However, it is essential to acknowledge the limitations of the research, such as simplified network models, parameter sensitivity, and practical deployment challenges. Addressing these limitations and collaborating with stakeholders in academia, industry, and network operators will further refine the framework and pave the way for its practical implementation in real-world scenarios.

The overall conclusions of these algorithms are as follows:

**EPSO:**

The EPSO algorithm serves as a fundamental component of the intelligent CAC scheme. EPSO, inspired by the flocking behaviour of birds and fish, was chosen due to its simplicity and suitability for solving complex optimization problems.

Furthermore, EPSO is renowned for its rapid convergence, a crucial attribute in dynamic network environments. Its capability to swiftly converge to near-optimal solutions ensures network adaptability to changing conditions, effectively preventing congestion and ensuring seamless user experiences.

In addition to rapid convergence, another noteworthy aspect of the algorithm is its low complexity. This simplicity, both in terms of parameter tuning and implementation, renders it a practical choice for resource management in large-scale

5G-Satellite networks. Its ease of implementation further enhances its real-world applicability.

Building upon these performance characteristics, EPO's efficient resource allocation significantly contributes to the overall effectiveness of the CAC system. This ensures that resources are optimally allocated while maintaining minimal computational overhead.

Furthermore, as an integral part of the CAC framework, EPSO aligns with the core objectives of maximizing network throughput, minimising call blocking and ensuring fairness among users. By intelligently admitting user calls and selecting the most suitable RAT, EPSO facilitates efficient resource utilization and equitable user distribution across the network.

Additionally, the successful implementation and evaluation of the EPSO-based CAC scheme in simulations set the stage for its potential real-world applicability. The algorithm's scalability and adaptability position it as a promising candidate for addressing resource management challenges in large-scale 5G-Satellite networks. However, it has disadvantages such as parameter sensitivity, limited handling of constraints, and dependency on initialization. The algorithm's success depends on factors like parameter settings, problem structure, and search space characteristics. It is also susceptible to suboptimal choices, which can affect convergence and solution quality. The effectiveness of EPSO for call admission control in 5G-satellite networks depends on the specific problem and network environment, and careful tailoring is essential to ensure effective application.

Hence, these contributions advance the understanding and practical implementation of resource management strategies in 5G-Satellite networks, ultimately benefiting both users and network operators.

**Artificial Bee Colony Algorithm:**

The Artificial Bee Colony algorithm made a significant contribution to the research by providing an exploration and optimization technique inspired by the foraging behaviour of bees. It played a crucial role in dynamically allocating network resources within the intelligent CAC scheme.

Artificial Bee Colony's population-based approach enabled the exploration of multiple resource allocation solutions simultaneously. This characteristic allowed it to effectively search for optimal solutions in complex and dynamic network environments.

Through rigorous simulations, the Artificial Bee Colony algorithm's performance was compared with other AI-based algorithms, including EPSO. This comparative analysis provided valuable insights into the strengths and weaknesses of the Artificial Bee Colony algorithm in the context of resource management and load balancing.

Artificial Bee Colony is simple, easy to implement and less sensitive to initial values. It is known for global optimization capabilities, parallelizability and adaptability. However, it has slower convergence speed, parameter tuning, and difficulty achieving an exploration-exploitation balance. It also lacks memory for past solution information, which can be disadvantageous in dynamic network scenarios.

**Simulated Annealing Algorithm:**

Simulated Annealing contributed by offering a global search strategy based on the principles of annealing in metallurgy. This strategy allowed the algorithm to explore a wide solution space, potentially identifying globally optimal resource allocation configurations.

Simulated Annealing's unique feature of adjusting temperatures during the search process contributed to its adaptability. It was able to balance exploration and exploitation effectively, making it suitable for dynamically changing network conditions.

Simulated Annealing's performance was evaluated alongside other algorithms in the simulation environment. The results of this evaluation provided insights into the algorithm's efficacy in managing network resources and optimizing the CAC system. The algorithm is easy to implement and can provide optimal solutions for CAC in 5G-Satellite HWNs. Simulated Annealing can be used to find the optimal allocation of resources that maximises throughput while minimising delay and the blocking probability. However, it suffers from a slow convergence rate. It requires a large number of iterations to converge to the optimal solution which can be computationally expensive affecting real-life performance [249]. It also suffers from improper parameter tuning which can lead to sub-optimal performance or network instability. As network size and complexity increase, scalability may become an issue, necessitating exploring alternative mechanisms. Simulated annealing's heuristic nature does not guarantee finding the global optimal solution.

**Q-Learning Algorithm:**

Q-Learning, a reinforcement learning algorithm, made a distinctive contribution to the research by introducing a learning-based approach to resource management. This approach allowed the algorithm to adapt its resource allocation decisions based on network feedback.

Q-Learning learned from past interactions and optimized resource allocation strategies over time. It adapted to changes in network conditions and user behaviour, which is crucial in ensuring consistent QoS for users.

Q-Learning's performance was systematically compared with EPSO, Artificial Bee Colony, and Simulated Annealing in the simulation environment. This analysis helped identify how the reinforcement learning approach stacked up against other optimization techniques in the 5G-Satellite HWNs.

It offers advantages such as adaptability to dynamic environments, learning from experience, optimal decision-making, decentralized decision-making, and versatility. However, it also has disadvantages such as the exploration-exploitation trade off, training time, convergence issues, state and action space complexity, high dimensionality, initial policy dependency, and limited incorporation of domain knowledge. It is not suitable for systems with large states and actions, as the Q-table size grows exponentially. It is not guaranteed to converge to the optimal policy, and it may not converge to a suboptimal policy or not at all.

## 6.2 FUTURE WORK AND RECOMMENDATION

The research work presented in this thesis provides the foundation for future studies in load-balancing CAC for 5G-Satellite heterogeneous wireless networks. This work may be extended, and further research studies can be done to improve and enhance the scope of this research. Some of the potential directions following this research are discussed as follows:

**Dynamic AI-driven Resource Management**: Future work can focus on enhancing the proposed intelligent CAC scheme by integrating more advanced AI algorithms such as deep reinforcement learning, graph neural networks or federated learning for other resource management techniques such as handover, interference management, traffic engineering etc. These algorithms can adapt in real-time to changing network conditions and user behaviour, providing even more efficient resource management.

**Multi-Objective Optimization:** Extend the research to consider multiple conflicting objectives in resource management, such as optimizing energy efficiency, reducing latency, and maximizing network throughput simultaneously. Investigate how multi-objective optimization techniques can be incorporated into the CAC framework to balance these competing goals.

**Machine Learning for Network Anomaly Detection**: Develop machine learning models for proactive network anomaly detection and fault prediction in 5G-Satellite networks. By identifying issues before they impact service quality, these models can contribute to more reliable and resilient network operations.

**Energy-Efficient Communication:** Investigate energy-efficient communication strategies, especially in satellite components, to address the sustainability challenges associated with increased data traffic. Explore energy-efficient transmission protocols and low-power satellite technologies.

**Profiling of User Traffic:** Investigate how AI-driven approaches can predict the nature of a user’s traffic, and this can be incorporated to make smart decisions.

**Real-World Deployment:** Conduct field trials and real-world deployments of the intelligent load balancing framework in collaboration with network operators to evaluate its performance and scalability in live 5G-Satellite HWNs.

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# APPENDIX A

## Code Base

The code and data used in this thesis are available as follows:

1) Enhanced Particles Swarm Optimization (EPSO) Algorithm

https://github.com/bebetemmy/epso

2) Artificial Bee Colony (ABC) Algorithm

https://github.com/bebetemmy/abc

3) Simulated Annealing Algorithm

https://github.com/bebetemmy/sa

4) Q-Learning Algorithm

https://github.com/bebetemmy/qlearning