

AN INTELLIGENT LOAD BALANCING ALGORITHM FOR 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, WiFi, Satellite, and other technologies. On the other hand, Satellite has been suggested as a preferred network to support 5G use cases. However, 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 study presented an artificial intelligent-based application in heterogeneous wireless networks and proposed an Enhanced Particles Optimization (EPSO) algorithm to solve the load balancing problem in 5G-Satellite networks. The algorithm uses a call admission control strategy to admit users into the network to ensure that users are evenly distributed on the network.

The proposed algorithm was compared with the Artificial Bee Colony and Simulated Annealing algorithm using three performance metrics: throughput, call blocking and fairness. Finally, based on the experimental findings, results outcomes were analysed and discussed.

Keywords

5G Network, Satellite Network, Load Balancing, Call Admission Control, Artificial Intelligent, RAT Selection, Heterogeneous Wireless Network

1.0 INTRODUCTION

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 M2M and URLLC (Ultra Reliable Low Latency Communication) devices in addition to ultra-mobile broadband 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 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 radio access technologies (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 [8]. To offer continuous connectivity, Satellite-Terrestrial Integrated Networks (STINs) emerge as a new paradigm [9]. In addition to providing pervasive coverage, emergency/disaster recovery and broadcast/multicast delivery, satellite communications will be a key component of the 5G network [10]. 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 [11]. The 5G-Satellite integration architecture is shown in Figure 1 below.

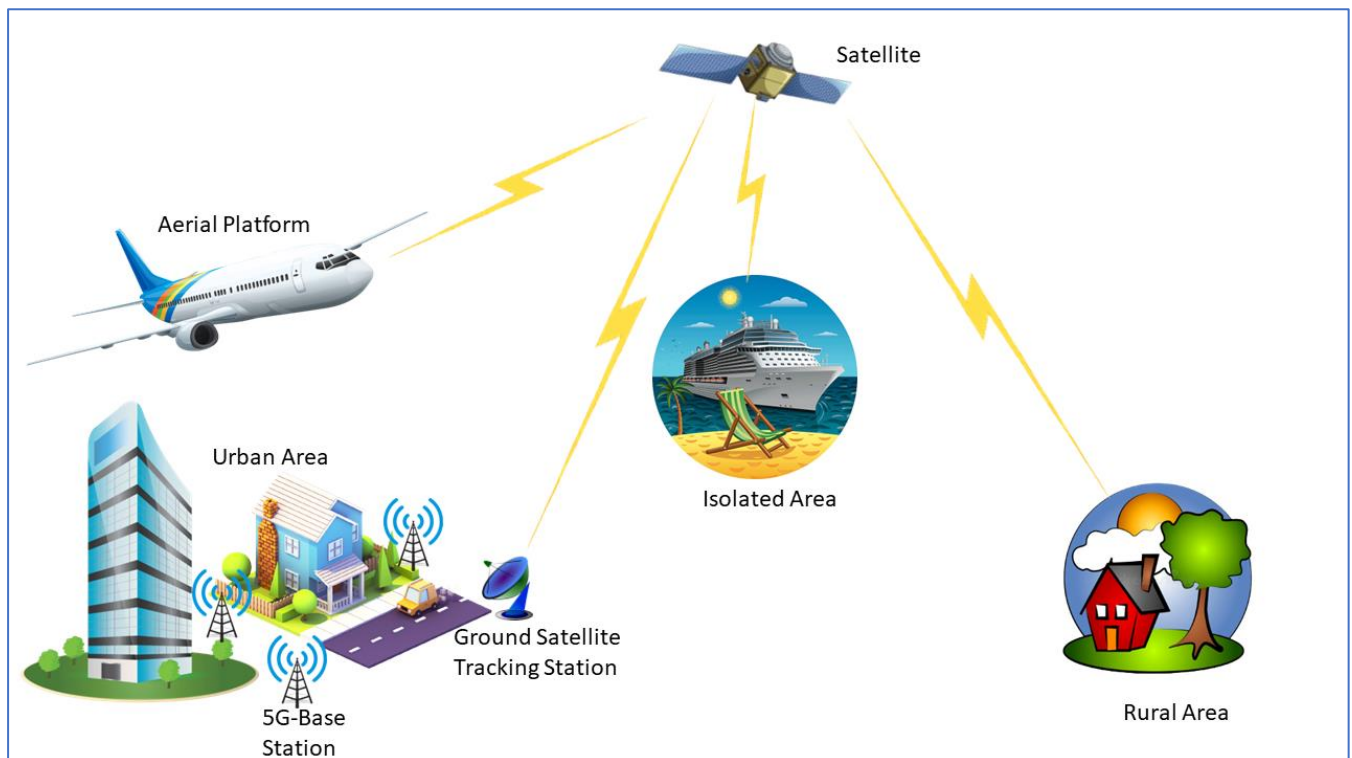


Figure 1: 5G - Satellite Integration

As a result, a new challenge has arisen regarding how to effectively manage resources in STINs to offer users improved Internet services [9]. A crucial technology that influences how well STINs perform is resource allocation.

One of the main concerns for 5G-Satellite networks is radio resource management, which involves allocating the radio resource to various users while guaranteeing user satisfaction [12]. If one RAN (Radio Access Network) resource is handled separately without considering other RANs, imbalanced traffic allocation is quite likely to occur. Load balancing comes into play when more than one access point is available for a user to connect to, or when multiple access points cover the same area. Load balancing is a method that makes it possible to evenly balance the network load among connected users and all accessible access points, based on predefined policies [13].

Load balancing aims to provide a fair allocation of traffic between cells or move some of the cell load from overloaded cells to less congested cells to boost overall system capacity and network performance metrics [13]. With load balancing, the load can be distributed among networks more evenly, leading to increased resource

utilisation of the entire network, increased system capacity, and improved QoS provisioning.

To address the issue of evenly distributing User Devices (UDs) among cells, many load-balancing methods have been put forth. The majority of current LB techniques are predicated on manually chosen rules and human experts' experiences. Such human task control can become cumbersome and exceedingly challenging as communication networks get more advanced [14].

Therefore, using artificial intelligence in network resource management is also very necessary in today's world. Thankfully, artificial intelligence algorithms like reinforcement learning (RL), genetic algorithms, neural networks, etc. have advanced quickly and have been used in a variety of fields recently. System control issues have been solved using AI algorithms [15]. It has also been used in other fields, such as combinatorial optimisation [16], resource management [17], and capacity management [18], [19]. Additionally, AI algorithms perform well in a dynamic network context. This serves as inspiration for the AI technique utilised to develop the best strategy for STINs [20].

In this paper, the load balancing problem is solved by call admission control which aims to guarantee the QoS requirements of services, maximise throughput, maximise fairness and minimise call blocking. An intelligent Call Admission Control (CAC) scheme using the Enhanced Particles Swarm Optimisation (EPSO) algorithm 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. EPSO is an algorithm that resembles the feeding behaviour of a flock of birds or the swimming patterns of fish [21]. It is simple to implement because there aren't many parameters that need to be changed. EPSO exhibits strong performance, quick convergence, and low complexity.

The performance of the proposed scheme is simulated numerically. The result of the intelligent framework is compared with other AI-based algorithms and the simulation results further validate the advantage of the proposed scheme.

The rest of the paper is organized as follows. A review of the related works in resource management, load balancing and call admission control is presented in Section 2. The system model is introduced and discussed in Section 3. Section 4 details the performance evaluation, simulation and results while section 5 concludes the paper.

2.0 RELATED WORKS

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. The fifth generation (5G) of 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 [22]. One of the use cases is Enhanced mobile broadband (eMBB), which needs high throughput and bandwidth [23].

In recent years, 5G technology has advanced quickly, and numerous 5G base stations have been installed simultaneously. As a result, 5G network communication services are available everywhere, including urban and metropolitan areas. It is challenging to offer network connection services to people in remote regions without internet connection infrastructure, such as oceans, deserts, and other locations [24]. The cellular network needs to be redesigned to manage the high bandwidth demand, high data rate requirements, and servicing of remote places that could be inaccessible. As a result, cellular networks utilise non-terrestrial networks (NTNs). By offering services in underserved areas, the NTN's function in 5G networks creates a diverse comprehensive system and expands the wide range and coverage area [24]. To provide uninterrupted connectivity and to allow data offloading and high data-rate transmissions, several RATs, including 5G and NTNs, are combined. By 2020–2025, it's anticipated that satellite systems will offer radio access networks (RANs), also known as satellite RANs, with over 100 high-throughput satellite systems using a geostationary earth orbit (GEO) [7].

Additionally, by broadcasting extremely high data rates (100 Mbps to 1 Gbps) to outdoor radio access points, satellites can enable the eMBB usage scenarios of 5G [25].

Thus, by intelligently allocating traffic between several RATs, the integration of satellites into 5G systems will improve the quality of service (QoS) for user devices (UDs) [26]. Furthermore, this integration gives the 5G network extra spectrum and broadband access in remote and rural regions [26].

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 above-5G and satellite integration, a potentially poor load balancing decision could result in a reduction in QoE for users and QoS for M2M [3].

2.1. RESOURCE MANAGEMENT IN HETEROGENEOUS WIRELESS NETWORK

One of the main challenges for 5G heterogeneous wireless networks is radio resource management, which tackles the allocation of radio resources to various users while assuring user satisfaction. If one RAN (Radio Access Network) resource is handled separately from the other RANs, imbalanced traffic allocation is quite likely to occur.

Load balancing can be employed to address the issue of uneven allocation of heterogeneous network resources, and on the other hand, it can be used to improve the utilisation of increasingly scarce resources, which has become a hot research topic; as well as to increase the service quality and system capacity.

Load balancing can increase network capacity, fairness, throughput, and utilisation concurrently while reducing processing delays. Even with a simple load-balancing method, radio resources remain highly utilised and have significant improvement in cell-edge user throughput and call blocking [27].

Uniform allocation of traffic load among several RATs in heterogeneous wireless networks enables improved radio resource utilisation and lowers the likelihood of call blocking or dropping [28].

Different load-balancing techniques have been suggested to address the resource allocation issues presented by heterogeneous wireless networks.

For heterogeneous LTE networks, a cluster-based mobility load balancing technique was suggested in [29]. By taking into account overloaded cells and their neighbours, the algorithm creates clusters of cells and then executes load balancing in those clusters.

In [30], the authors transferred UDs from a congested cell and moved them to a neighbouring cell to address the imbalance between the allocation of traffic demand and network resources. Operator utility and user utility were taken into account for

the handover process in 5G networks using a utility-based mobility load balancing method in [31].

The authors in [32] recommended a unified load-balancing solution for LTE-A/5G HetNets. The system constantly improves HCP configuration for a specific user based on three limited functions: the UE's speed, the signal-to-interference-plus-noise ratio (SINR) of the UE and the number of physical resource blocks (PRBs) per user equipment (UE). A two-step target cell determination technique is employed by the cell load level and RSRP requirements to ensure that users are transferred to low-loaded target cells.

[33] suggested a flexible technique for mobility load balancing in an LTE small-cell network. To detect congested cells and trigger UE offloading from overloaded cells to potential target cells, an adaptive threshold is used.

Multiple RATs were also taken into account in the literature for increasing QoS in diverse cellular networks. A distributed load-balancing approach for heterogeneous networks (HetNets) using multiple radio access technologies was suggested by the authors in [34]. The QoS for users is taken into account by the distributed game-theoretic approach, and a cost function is developed to reflect the cell load state, necessary data rates, and delay restrictions. The suggested technique assigns users to less-loaded cells depending on cost, allowing overcrowded cells to iteratively reduce user cost in a dispersed way.

Based on the above considerations, the load-balancing problem in this paper is solved by call admission control using an artificial intelligent algorithm.

A novel CAC scheme for use in scenarios in which 5G and Satellites RATs coexist.

The proposed mechanism can be used to admit new calls and choose the most suitable RAT dynamically for each session. Adaptability is achieved using the EPSO Algorithm. The proposed framework aimed to evenly distribute the traffic burden among satellite gateway links and base stations (BSs) to achieve load balance, such that no one AP or BS has a higher traffic load than another.

2.1.1 CALL ADMISSION CONTROL IN HETEROGENEOUS WIRELESS NETWORKS

The study of radio resource management (RRM) is important in heterogeneous wireless networks because radio resources are frequently expensive and scarce, making their effective utilisation an ongoing research topic [35].

The effective use of resources in any Radio Access Network (RAN) is due to radio resource management (RRM) solutions. According to [36], one of the resource management techniques that play a significant part in efficiently managing resources is called admission control.

Call admission control 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 [37]. The CAC algorithm decides whether or not to accept an incoming call. Additionally, it determines whether the existing radio access networks are adequate to handle incoming calls [37].

An effective call admission control algorithm aims to maintain the ongoing connections' quality of service (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 [38] within the WiFi access network environment and implemented with Unmanned Aerial Vehicles (UAVs) which connect to a backhaul 5G network. In response to its evaluation of the WiFi 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.

In [39], an Energy Efficient Proposal for IoT CAC in a 5G Network was presented. The technique used CAC modelling for IoT in new radio access 5G networks to reduce energy usage.

A Dynamic Handover Control Parameter for LTE-A/5G Mobile Communications was proposed in [40], 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 (CACA) algorithm is presented in [41] to ensure a smooth transition in 5G networks with a suitable quality of service (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. The authors in [42] presented a flexible resource management and predictive handover algorithm based on the target base station'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 [43] 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.

[44] 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.

[45] 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 in [46]. 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.

The authors in [47] 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 Internet of Things by enabling connected, low-energy gadgets to connect to the network with a suitable quality of service.

A novel vertical handover method based on a multi-attribute and neutral network for heterogeneous integrated networks is presented in [48]. 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.

2.1.2 INTELLIGENT TECHNIQUES 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 artificial intelligence (AI)-related techniques have been used to optimise computer systems in a variety of challenging situations [49].

These techniques may include multidisciplinary machine learning methods, bioinspired algorithms, and fuzzy neural networks. Recursive feedback-based learning and local interactions make these methods very simple [49].

The demand for intelligence has pervaded the future of heterogeneous wireless networks. 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 extremely challenging and difficult to execute as communication networks get more sophisticated [14]. The network must be able to continuously change its strategy to the real environmental conditions to achieve network resource self-management.

Future networks will be able to use artificial intelligence (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 [50].

Modern artificial intelligence techniques are being used in 5G networks to increase their capacity to manage traffic. When a network is overloaded, artificial intelligence can help with decision-making. Thus, artificial intelligence combined with 5G can meet both the anticipated needs and the new technical obstacles [51].

In [52], 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 [53] 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 [54], handover prediction is used to address the issue of providing full mobility in WLAN and LTE heterogeneous networks without degrading the quality of service (QoS). The model relies on inspecting the signal strength between the mobile user and all base stations nearby. 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 [55] 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 [56], it was suggested to use artificial intelligence techniques for energy optimization with multi-sleeping control in 5G heterogeneous networks. This was done by using a reinforcement learning algorithm 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 [57] 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 (MM) approach using reinforcement learning is proposed for small-cellular networks in [58]; 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 [59] presented interference control and handover techniques with reinforcement learning in HetNet to solve the problem of controlling interference between the macro base station (MBS) and the small cell base station (SBS). Each BS learns parameters for the transmission power, activation pattern, and bias to achieve the best network performance in HetNet.

In [60], 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, [61] integrates two Q-learning-based selection techniques (QSS) 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 base stations (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 [62] proposed a novel Clipped Double Q-Learning (CDQL)-based load balancing framework to increase total network throughput and resource block usage; while also improving packet loss ratio, jitter and latency.

In [63], Deep Q-learning is used to handle load balancing in the device-to-device (D2D) communication scenario. In (Jang, S. et al., 2018), the bandwidth adaptation problem in a network is formulated as a partially observable Markov decision process (POMDP).

A distributed optimisation strategy based on multi-agent RL was developed by the authors in [64] 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 (D3QN) method is implemented after the state, action, and reward functions for UEs are defined.

In [65], an online RL-based user association strategy for vehicular networks is presented. [66] investigated an RL-based method to provide power control and rate adaptation in cellular networks. A technique for learning was examined in [67] 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 [68]. 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.

In order to address the problems of better mobility management and handover (HO) and to offer an excellent service for end users' throughput, call dropping probability, handover delay and energy consumption, the authors in [69] examined the application of metaheuristics algorithms like grey wolf optimisation (GWO) and Mayfly optimisation (MFO) techniques.

A new hybrid cuckoo search (CS) and genetic algorithm (GA) that maximises the capacity of heterogeneous wireless networks in terms of lowering latency, increasing throughput, and reducing handover failure probability was proposed in [70]. 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.

[71] 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 [72].

Particle swarm optimization (PSO) is one of the bio-inspired algorithms, It is straightforward in its search for the best solution in the problem area. Particle swarm optimisation (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 [73].

The history optimal information is mostly used by the traditional particle swarm optimisation (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 [74].

In this paper, the EPSO algorithm is suggested to improve the traditional PSO algorithm's optimisation performance. The Enhanced Particle Swarm Optimisation is different from other optimisation methods it does not rely on the gradient or any differential form of the objective and simply requires the objective function [75]. 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 paper.

3.0 PROPOSED SYSTEM MODEL

This section defines the proposed model to be used throughout the paper. Furthermore, the section discusses the metrics as well as the load balancing problem in 5G-Satellite networks.

3.1 NETWORK 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 2 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 $N = \{1, 2, \dots, N\}$. 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 λ is 1(calls/s) and the average call holding time $1/\mu = 100(s)$.

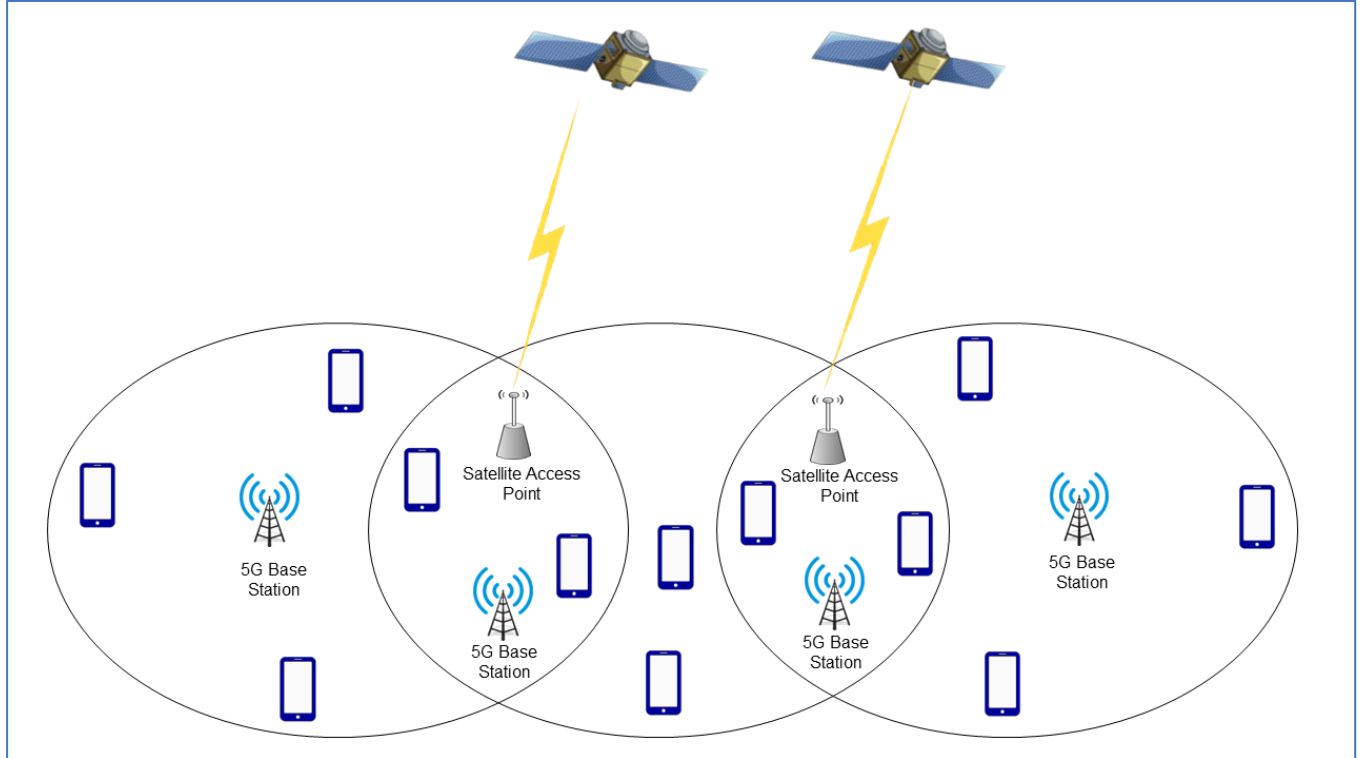


Figure 2: 5G -Satellite Heterogeneous Network Architecture

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 utilizes 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 three network attributes collected by the CAC algorithm (namely signal strength,

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 load and available bandwidth. It then evaluates the defined network status value for each RAT and checks if it is $\leq \eta_{\text{threshold}}$. 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 $\leq \eta_{\text{threshold}}$ 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 shows the algorithm flowchart.

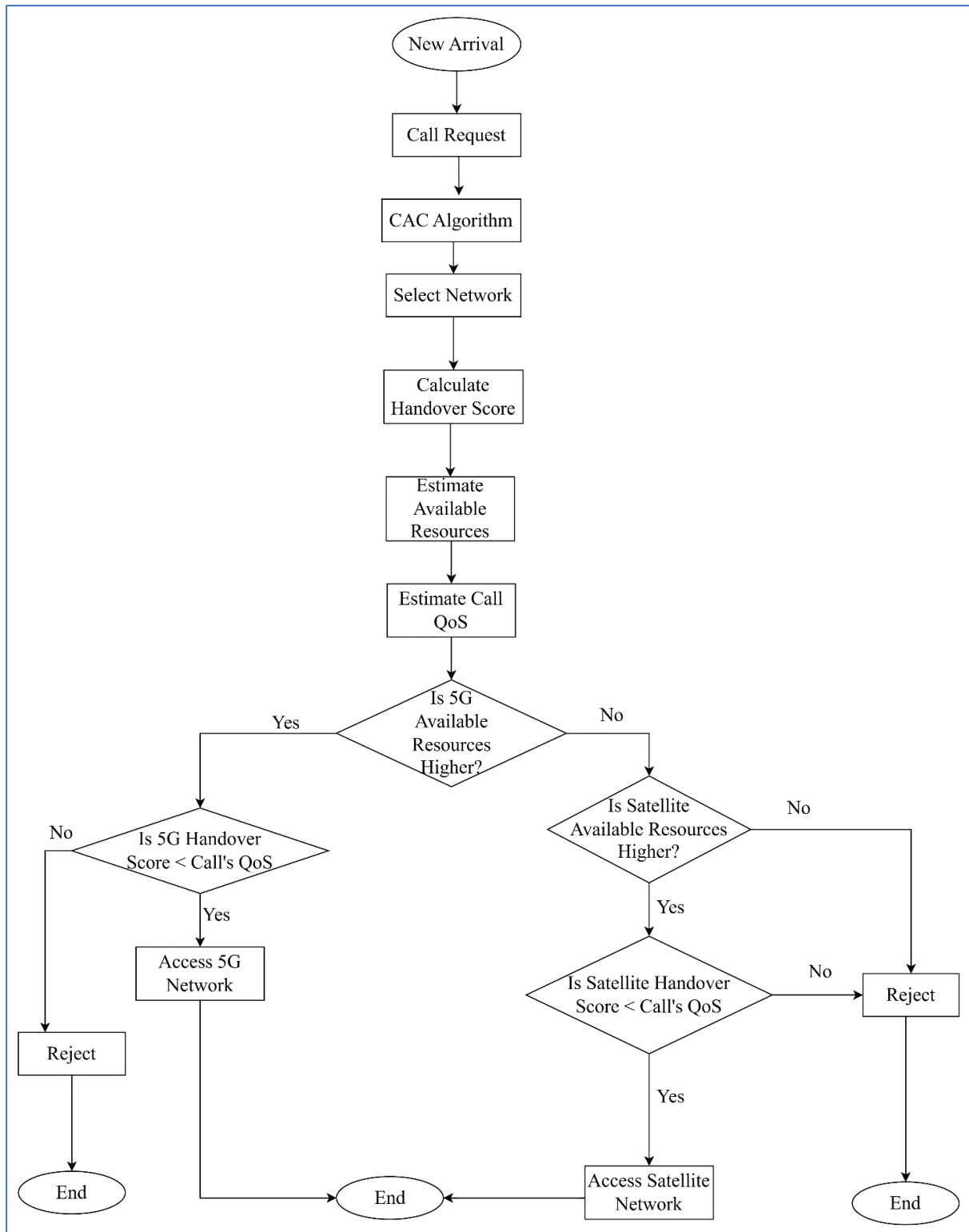


Figure 3: CAC Flow Chart

3.2 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) Call Arrival Process:

It is modelled as a Poisson process, representing the random and independent arrival of calls to the network. The arrival rate 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. This process is vital for estimating future network loads and making admission decisions.

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 3 network information used in this paper; these are also the decision variables: signal strength, 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, the 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: blocking the call, accepting the call in 5G RAT, accept the call in Satellite RAT.

5) 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 to avoid overload due to sudden call influx or handovers.

The handover probability is calculated using the formula below :

Handover Probability = $1 - e^{-(\text{Difference in Signal Strength}) / \text{Handover Threshold}}$
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. This probability influences CAC decisions, making it more conservative if the handover likelihood is high.

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 optimize network performance, resource utilization, and QoS satisfaction while avoiding congestion [36]. It uses a decision rule considering network resources, handover probability, and call QoS.

The rule calculates a handover score and compares it to call QoS:

$\text{handover_score} = \text{handover_probability} * \text{available_resources}$

If handover_score is greater than call_qos , the call is rejected.

Otherwise, the call is admitted.

This decision-making process optimizes call handovers in 5G-Satellite HWNs by considering handover probability and available resources in the target network segment. If the resources are insufficient for the required QoS, the call is rejected; otherwise, it is admitted to the network.

3.3 PROPOSED ALGORITHM

EPSO is a variant of the standard Particle Swarm Optimization (PSO) algorithm that aims to improve its performance and overcome its limitations [75]. 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 optimization 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 [75].

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 space, 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 [76]. The enhancement includes parameter adaptation, hybridization with local search techniques, diversity maintenance, memory mechanisms, adaptive neighbourhood topologies, niching and multi-swarm approaches [77]. The parameters can be dynamically adjusted during the optimization 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, and finance amongst others [76].

It has been tested on various optimization problems and has shown superior performance compared to other algorithms [76]. 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) [75]. EPSO has been used for feature selection of microarray data and has required less processing time to select the optimal features than PSO [78]. EPSO can also be adapted and enhanced in HWNs to optimize various parameters such as network topology, resource allocation, power control, and mobility management [79], [80].

It is a promising solution for CAC in 5G-Satellite HWNs due to these unique features. Previous research often faced challenges in dynamically allocating resources in heterogeneous network environments, especially in scenarios with varying user densities and mobility patterns. EPSO addresses this by employing an adaptive resource allocation strategy that continuously monitors network conditions, such as signal strength, network load, and available bandwidth. By dynamically adjusting resource allocation based on network observations, EPSO ensures efficient utilization of network resources across diverse deployment scenarios, thus enhancing scalability.

Also, many existing algorithms lacked adaptability in optimizing network performance under changing environmental conditions. EPSO overcomes this limitation by employing adaptive optimization criteria that can be tailored to suit different network environments and deployment scenarios. By adjusting optimization criteria based on factors such as user density, mobility patterns, and service demands, EPSO ensures robust performance and adaptability in heterogeneous network environments.

Scalability challenges often arise from uneven distribution of network traffic and congestion in certain network segments. EPSO addresses this by prioritizing load balancing and congestion management within heterogeneous network environments. Through intelligent decision-making and resource allocation, EPSO optimizes network performance by redistributing traffic to alleviate congestion hotspots and ensure equitable resource utilization, thus enhancing scalability.

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 convergence properties make it reliable for optimizing 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 [81]. 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. 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.

Figure 4 shows the proposed algorithm pseudocode

```

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 4: EPSO Algorithm Pseudocode

3.4 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 maximize the throughput of all UDs, maximize fairness and minimize 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.

3.4.1 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, that is 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).

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

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

$$M_i(t) = \frac{r_i(t)_{5g} + r_i(t)_{sat}}{R_i} - (1)$$

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.

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

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

TTN = Total throughput of the network (which includes 5G and Satellite)

TTN =

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

3.4.2 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:

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

3.4.3 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 n 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.

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

where

E = total traffic offered

m = number of resources in the service system

3.4.4 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.

3.4.4.1 QoS constraints

There are three QoS parameters considered in the modelling: Signal Strength, 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 [82]. 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 [82].

In this paper, the threshold for the received signal strength is set at ≤ -80 dbm. If this value is below the predefined threshold RSSI_{th}, 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 ≤ -80 dbm. 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 Load

The amount of data transmitted over a network at any given time is known as the network load. The network load is an essential element in network control, traffic monitoring, and simulation. The quality of service in a particular network is ensured by properly managing the network load. Hence, understanding network load is crucial for a UD to make informed decisions about choosing the best RAT for a call. 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 UD to query the network directly for load information. UDs can interpret these messages and the network's response to assess potential congestion in specific RATs. 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.

C) 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.

3.4.4.2 Activated Services Constraint

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

3.4.4.3 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 =

$$\sum_i \sum_c [x_i^c(t)_{wlan} \left[\frac{r_i(t)_{wlan}}{R_i(t)} \right] + x_i^c(t)_{5g} \left[\frac{r_i(t)_{5g}}{R_i(t)} \right]] - (2)$$

Maximise

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

Minimise

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

4.0 PERFORMANCE EVALUATION

In this section, the performance of the proposed ESPO - CAC framework is evaluated with other two AI algorithms named Artificial Bee and Simulated Annealing. To evaluate performance, a series of tests in various settings are used. The suggested algorithm's performance is evaluated using three key metrics: throughput, call-blocking probability and fairness.

4.1 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 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 a number of 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. The approximated simulation area size is $500 \times 500 m^2$ with BS randomly deployed. In this paper, 100 UEs are considered and the required data rates for each UD were 5 Mbps to 30 Mbps. 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 1.

This paper aims to examine the performance of the intelligent call admission framework using three metrics, namely throughput, call blocking and fairness. The throughput measures the amount of data successfully delivered; It is important to ensure the highest possible throughput rate to maximize network performance. The call-blocking instances show the percentage of calls that are denied access to the network; this is an important factor for real traffic where blocking is unsuitable from the user's point of view.

To prove the validity of the performance of the proposed algorithm, which is based on CAC, it is compared with the two other AI algorithms, Artificial Bee Colony and Simulated Annealing.

Artificial Bee Colony algorithm is an optimization method which relies on the intelligent foraging behaviour of a honey bee swarm and has produced impressive results when used to address several optimisation problems in different industries [83]. The Artificial Bee Colony algorithm only uses conventional control parameters like colony size and maximum cycle number. The Artificial Bee Colony algorithm provides a population-based search method as an optimisation tool [84]. In this process, individuals, known as food positions, are gradually altered by artificial bees. So, the goal of the artificial bees is to find the ones with the best nectar quality and quantity, which also corresponds with the best food source. The Artificial Bee Colony algorithm uses a defined objective function to solve the optimisation problem. The objective function is subject to different variables and constraints. The goal of the algorithm is to maximize or minimise the objective function.

Simulated annealing is a metaheuristic method for evaluating the global optimum of a given function for an optimization problem in a large search space [85]. Numerous optimization problems, including travelling salesman problem, job-shop scheduling, graph partitioning and, protein folding have been successfully tackled by Simulated Annealing. What gives simulated annealing an edge over others is the fact it can bypass local minima and connect to a global minimum [86]. Additionally, it requires little set-up effort and does not need to know the search space beforehand. The problems solved by Simulated Annealing are stated as an objective function of numerous variables, and subject to a number of constraints. The problem requiring optimization is defined first; this involves specifying the function to minimize or maximize.

Table 1: Simulation Parameters

Parameter	Value
Simulation area size	500 x 500 m^2
Confidence Level	95%
Number of runs	30
Number of users	10 – 100
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	3000s

4.2 Scenario and Results

4.2.1 Scenarios

Three simulation scenarios were created. 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).

In the first scenario, single decision variables (signal strength and network load) are considered for call admission control and the impact of these variations on the CAC is investigated. The first scenario shows the capability of the proposed algorithm to

make use of the available network attributes (decision variables) to satisfy the throughput requirement of the applications, as well as maximise fairness and minimise call blocking.

The second scenario is an extension of the first one above. Multiple decision variables (signal strength and network load; signal strength and available bandwidth) are considered for call admission control here and the impact of the complexity of the decision-making on throughput and call blocking is also evaluated.

In the third scenario, the number of users is varied and the impact of this on call blocking and fairness is evaluated. The number of devices is increased from 10 to 100.

4.2.2 Performance Analysis and Results

In order to analyse the performance of the CAC algorithm in the 5G-Satellite heterogeneous network, three scenarios have been simulated. This section examines the effect of the number of users and network information to determine the CAC's effectiveness in improving the performance of the system.

4.2.2.1 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. Figure 5 shows the throughput results under three types of CAC algorithms; EPSO, Artificial Bee and Simulated Annealing when users were admitted using the single-decision and multiple decisions. Figure 5a shows the total throughput result for the call admission scenario based on signal strength. Figure 5b shows the total throughput result for the call admission scenario based on network load. Figure 5c shows the total throughput result for the call admission scenario based on the signal strength and network load. Figure 5d shows the total throughput result for the call admission scenario based on the signal strength and available bandwidth. The objective function of these algorithms is to maximise throughput.

In the single decision scenarios (Figure 5a & Figure 5b), the throughput increases because the networks could accommodate more users. However, with multiple decision scenarios (Figure 5c & Figure 5d), because of the complexity added, it

shows there is a decrease in the total throughput maximised. However, the result shows that the proposed EPSO algorithm always has the highest throughput in all the scenarios.

Tables 2 & 3 also compare the performance of enhanced particles against the performance of Artificial Bee and Simulated Annealing using the absolute percentage difference and relative performance difference. The results show there is a significant increase in the performance of the proposed algorithm compared to the other algorithms. EPSO improvement rate is on average 14% higher than artificial bee; and 17% higher than the simulated annealing algorithm.

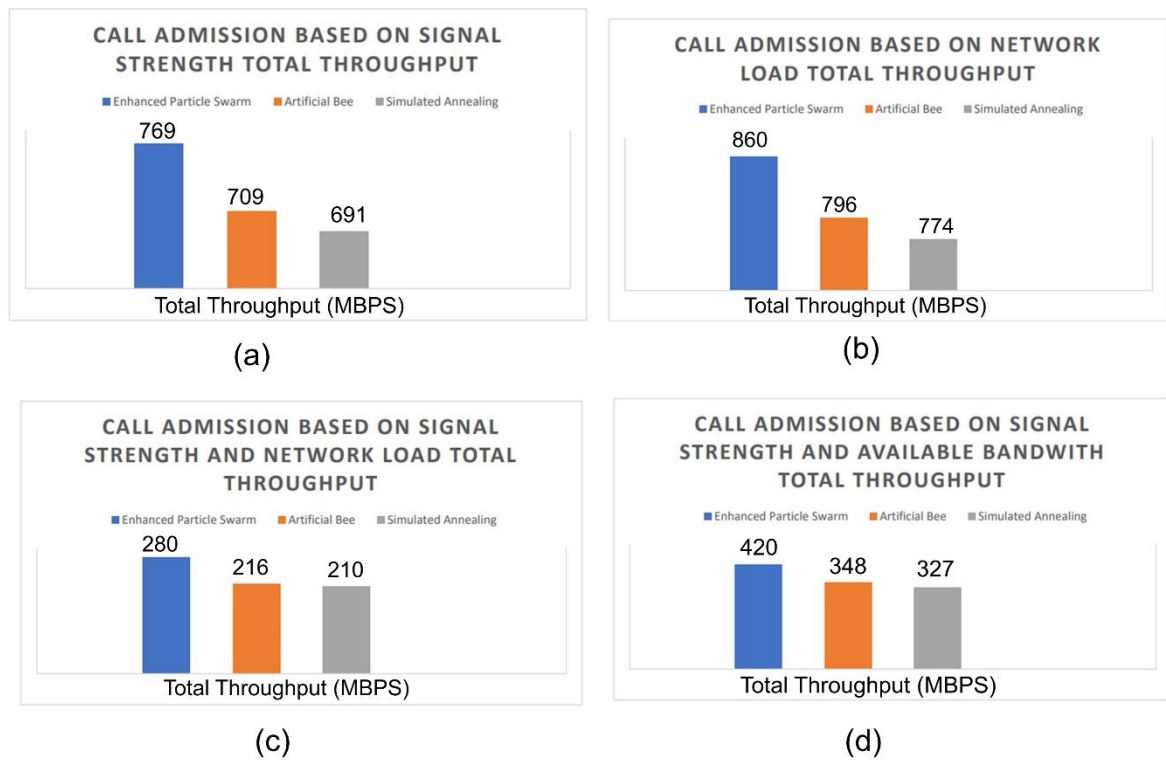


Figure 5: Throughput Result

Table 2: Artificial Bee Colony vs EPSO (CAC Performance Comparison)

Decision Variables	Absolute Difference (%)	Relative Difference (%)
Signal Strength	8%	8%
Network Load	8%	7%
Signal Strength and Network Load	26%	23%
Signal Strength and Available Bandwidth	19%	17%

Table 3: Simulated Annealing vs EPSO (CAC Performance Comparison)

Decision Variables	Absolute Difference (%)	Relative Difference (%)
Signal Strength	11%	10%
Network Load	11%	10%
Signal Strength and Network Load	29%	25%
Signal Strength and Available Bandwidth	25%	22%

4.2.2.2 IMPACT ON CALL BLOCKING

Call Blocking is another important indicator of the scheme. In this section, the impact of call blocking is presented, Figures 6 & 7 show the results of call blocking. The result is evaluated based on the single call admission scenario, and multiple call admission scenario; as well as increasing the number of users from 10 – 100. The objective of the algorithms is to minimise call blocking.

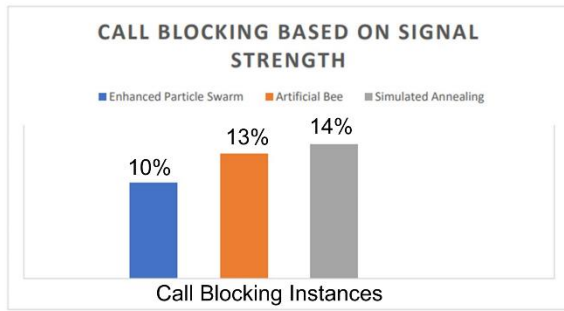
Figure 6 displays the difference among the three algorithms, using a percentage of call-blocking instances. Figure 6a shows the call-blocking result for the call admission scenario based on signal strength. Figure 6b shows the call blocking result for the call admission scenario based on network load. Figure 6c shows the call-blocking result for the call admission scenario based on the signal strength and

network load. Figure 6d shows the call-blocking result for the call admission scenario based on the signal strength and available bandwidth.

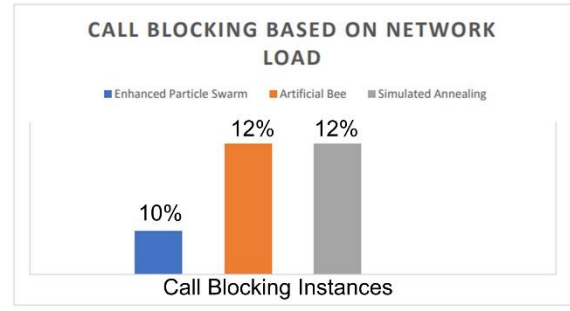
Figure 7 shows the performance of the three algorithms when the number of users is increased. Figure 7a shows the number of calls blocked for the call admission scenario based on signal strength. Figure 7b shows the number of calls blocked for the call admission scenario based on network load. Figure 7c shows the number of calls blocked for the call admission scenario based on the signal strength and network load. Figure 7d shows the number of calls blocked for the call admission scenario based on the signal strength and available bandwidth.

The results show that the number of calls blocked increased when the number of users increased. 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.

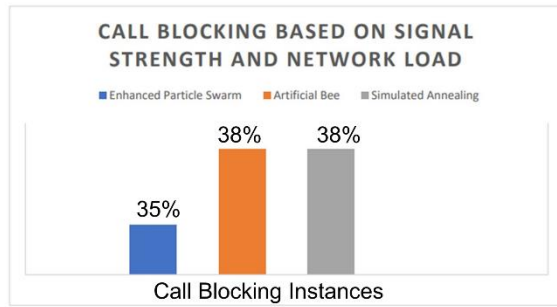
The performance comparison of EPSO against the performance of Artificial Bee and Simulated Annealing using the absolute percentage difference and the relative performance difference is also shown in Tables 4 & 5; the results show there is a significant increase in the performance of the proposed algorithm compared to the other algorithms. EPSO improvement rate is on average 16% higher than artificial bee; and 19% higher than the simulated annealing algorithm.



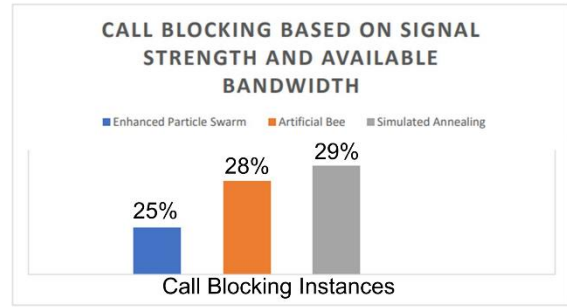
(a)



(b)

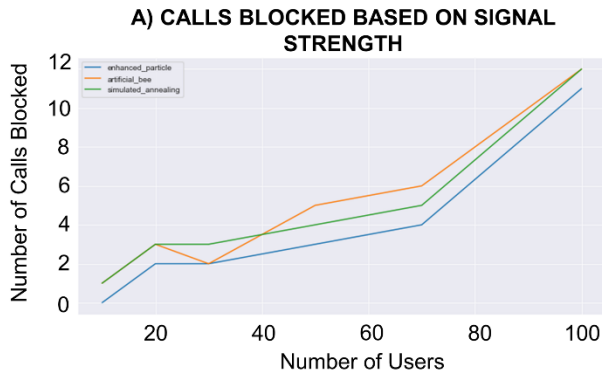


(c)

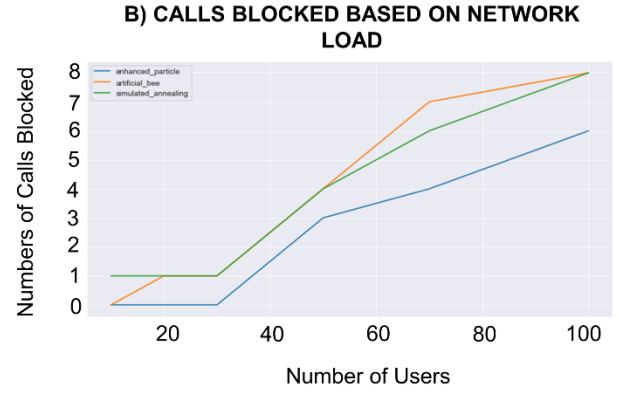


(d)

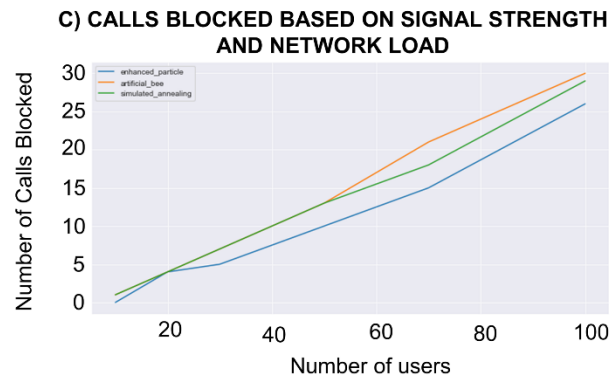
Figure 6: Call Blocking Result



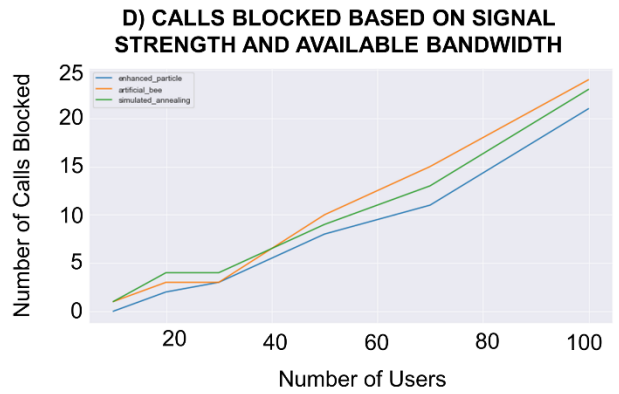
(a)



(b)



(c)



(d)

Figure 7: Number of Calls Blocked Result

Table 3: Artificial Bee Colony vs EPSO (Call Blocking Instances Performance Comparison)

Decision Variables	Absolute Difference (%)	Relative Difference (%)
Signal Strength	26%	30%
Network Load	18%	20%
Signal Strength and Network Load	8%	9%
Signal Strength and Available Bandwidth	11%	12%

Table 4: Simulated Annealing vs EPSO (Call Blocking Instances Performance Comparison)

Decision Variables	Absolute Difference (%)	Relative Difference (%)
Signal Strength	33%	40%
Network Load	18%	20%
Signal Strength and Network Load	8%	9%
Signal Strength and Available Bandwidth	15%	16%

4.2.2.3 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 is to maximize fairness.

Tables 6 & 7 show the fairness computed using Jain's index for the three 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.

Figure 8 shows the fairness performance of the three algorithms when the number of users is increased. Figure 8a shows the fairness result for the call admission scenario based on signal strength. Figure 8b shows the fairness result for the call admission scenario based on the signal strength and network load.

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 the scenarios.

This is a significant improvement in the EPSO performance when compared to the other algorithms; Table 8 - 11 shows the absolute percentage difference and relative percentage difference results.

For the CAC based on the signal strength scenario, the EPSO improvement rate is on average 11% higher than the artificial bee; and 15% higher than the simulated annealing algorithm. For the CAC based on the signal strength and network load scenario, the EPSO improvement rate is on average 15% higher than the artificial bee; and 22% higher than the simulated annealing algorithm.

Table 5: Jain's Index For CAC Based On Signal Strength

No of Users	Enhanced Particles	Artificial Bee	Simulated Annealing
10	1	0.905	0.852
20	1	0.897	0.866
30	1	0.882	0.828
50	1	0.88	0.831
70	1	0.885	0.879
100	1	0.899	0.866

Table 6: Jain's Index For CAC Based On Signal Strength and Network Load

No of Users	Enhanced Particles	Artificial Bee	Simulated Annealing
10	1	1	0.794
20	1	0.951	0.795
30	1	0.803	0.842
50	1	0.763	0.743
70	1	0.819	0.740
100	1	0.827	0.820

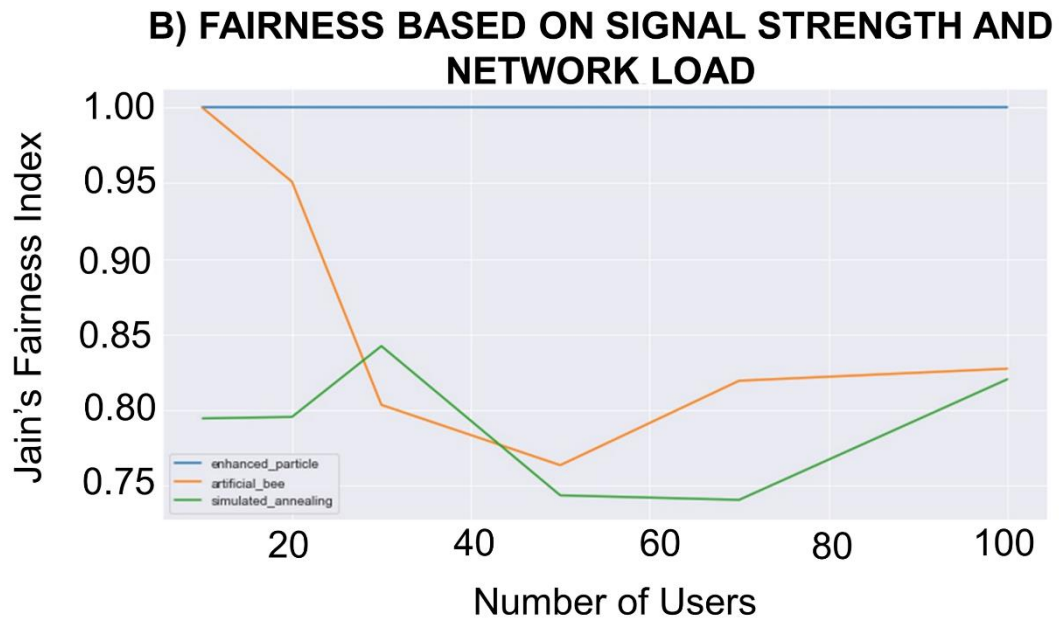
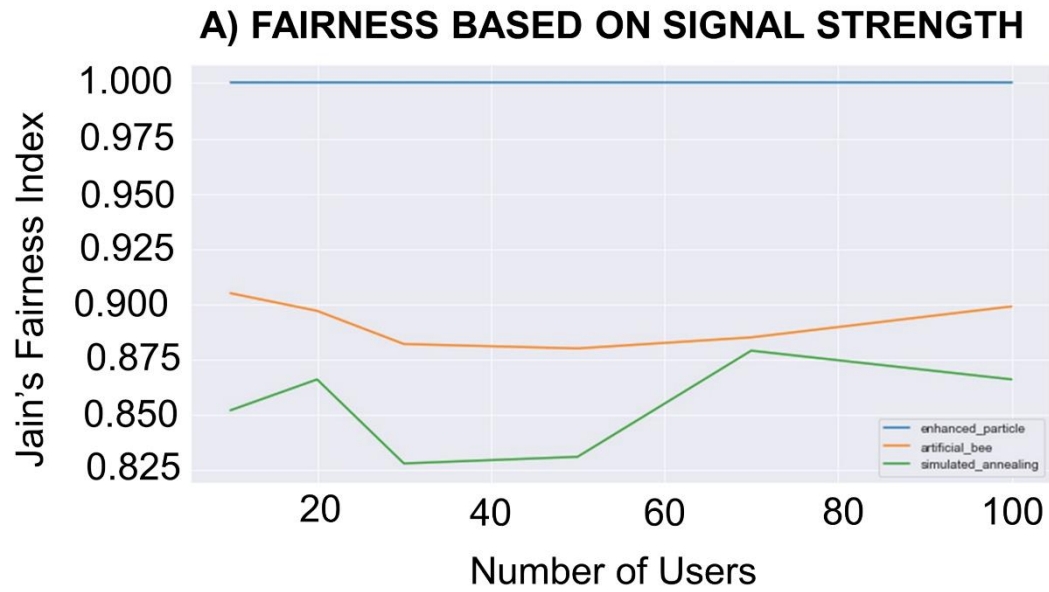


Figure 8: Fairness Result

Table 7: Artificial Bee Colony vs EPSO For Signal Strength (Fairness Performance Comparison)

No of Users	Absolute Difference (%)	Relative Difference (%)
10	10%	10%
20	11%	10%
30	13%	12%
50	13%	12%
70	12%	12%
100	11%	12%

Table 8: Simulated Annealing vs EPSO For Signal Strength (Fairness Performance Comparison)

No of Users	Absolute Difference (%)	Relative Difference (%)
10	16%	15%
20	14%	13%
30	19%	17%
50	18%	17%
70	13%	12%
100	14%	13%

Table 9: Artificial Bee Colony vs EPSO For Signal Strength and Network Load (Fairness Performance Comparison)

No of Users	Absolute Difference (%)	Relative Difference (%)
10	0%	0%
20	5%	5%
30	22%	20%
50	27%	24%
70	20%	18%
100	19%	17%

*Table 10: Simulated Annealing vs EPSO For Signal Strength and Network Load
(Fairness Performance Comparison)*

No of Users	Absolute Difference (%)	Relative Difference
10	23%	21%
20	23%	21%
30	17%	16%
50	29%	26%
70	30%	26%
100	20%	18%

5.0 CONCLUSION

In this paper, the load balancing problem in 5G-Satellite heterogeneous wireless networks is solved by call admission control which aims to guarantee the QoS requirements of services, maximise throughput, maximise fairness and minimise call blocking. An intelligent enhanced particle swarm optimization-based Call Admission Control (CAC) scheme 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 load balancing algorithm was compared with the Artificial Bee Algorithm and Simulated Annealing Algorithm. The proposed scheme provides better results for maximising throughput and fairness and minimizing call blocking.

The research work presented in this paper 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.

Future work can 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.

Future studies can also 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. These algorithms can adapt in real-time to changing network conditions and user behaviour, providing even more efficient resource management.

In addition, energy-efficient communication strategies can be investigated, especially in satellite components, to address the sustainability challenges associated with increased data traffic. Explore energy-efficient transmission protocols and low-power satellite technologies.

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