International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Resource Allocation in 5G Wireless Communications

M. Sharmila*[1], R. V. S. Satyanarayana[2]

Submitted: 29/01/2024 **Revised**: 07/03/2024 **Accepted**: 15/03/2024

Abstract: This abstract delves into the domain of wireless communications, specifically addressing the challenging issue of resource allocation. It introduces a new approach termed Recurrent Chimp-based Green Anaconda Optimization (RCbGAO) as a solution to this problem. In the dynamic landscape of 5G networks, characterized by heightened data rates, stringent latency requirements, and a surge in device connectivity, the efficient allocation of resources stands as a crucial factor for achieving optimal performance. RCbGAO presents a distinctive methodology by amalgamating the predictive capabilities of the Recurrent Chimp fitness method with the optimization prowess of Green Anaconda. This approach aims to tackle various inherent challenges within 5G networks. The dynamic nature of these networks presents a substantial obstacle, necessitating adaptive resource allocation mechanisms to effectively address fluctuating user demands. Furthermore, the study addresses the pressing concern of energy consumption in 5G networks, striving to optimize resource allocation for sustainability and minimize environmental impact. Additionally, the research emphasizes the critical role of resource allocation in ensuring high-quality service delivery with minimal latency, addressing Quality of Service (QoS) concerns in 5G communications. The consideration of net congestion, exacerbated by the proliferation of connected devices, underscores the need for sophisticated resource allocation strategies to alleviate congestion challenges. The proposed RCbGAO methodology not only shows potential in tackling the complex challenges linked to resource allocation in 5G wireless communications but also fits well with the evolving demands of 5G networks. By contributing to the advancement of adaptive and sustainable resource allocation strategies, this research stands to improve the overall presentation and reliability of 5G networks.

Keywords: *5G network, Wireless communication, Machine-Type Communication, Channel State Information*

1. Introduction

Wireless transmission is vital for exchanging information between devices using electromagnetic waves, enabling dynamic data transfer in diverse communication systems [1]. Machine-Type Communication (MTC) is a part of wireless communication, focusing on automated data exchange between devices without direct human involvement, particularly in applications like the IoT [2]. It is a pivotal 5G technology, that facilitates autonomous communication among devices, fostering innovative applications and business models [3]. Recognized as a fundamental pillar within the 5G system, it stands among the three essential service types, providing a crucial groundwork for diverse IoT applications. Its pivotal role makes it indispensable for supporting a wide array of IoT functionalities [4]. 5G systems adapt to various MTC scenarios, accommodating numerous low-power and simple MTC devices while achieving optimal spectral efficiency. This flexibility is crucial for supporting a massive influx of diverse IoT devices [5]. LTE-Advanced (LTE-A) emerges as a promising cellular technology for MTC, but optimal integration faces challenges, primarily stemming from inefficient resource allocation. This issue is attributed to various factors, complicating the seamless integration of MTC devices within the LTE-A system [6]. Its services prioritize machine-centric needs for numerous sporadically active devices, necessitating tailored resource allocation beyond the assumption of homogeneous traffic characteristics [7]. Diverse 5G services influence resource allocation by considering traffic, resource demands, and QoS, necessitating effective optimization for efficient distribution [8]. System throughput and goodput are determined by user devices allocating resources. Conventional resource allocation relies on Channel State Information (CSI), which raises system overhead and resource utilization costs [9]. Assessing information content and spectral efficiency is crucial in wireless communications, forming the foundation for addressing resource allocation challenges [10]. Research on computation offloading explores task partitioning, offloading decisions, and energy minimization, emphasizing resource allocation across diverse network scenarios [11]. Meeting the requirements of expanding 5G cellular communication necessitates enhanced resource optimization methods for effective management [12]. The primary challenge in 5G networks revolves around limited resources, leading to issues like network congestion during resource distribution [13]. Improving Quality of Service (QoS)

*[*1]Research Scholar, Department of Electronics and Communication Engineering,*
SV University, Tirupati, Andhra Pradesh - 517502, India.
**Corresponding author Email: m.sharmila15@gmail.com*
[2]Professor, Department of Electronics and Communication Engineering,
SV University College of Engineering (SVUCE),
Tirupati, Andhra Pradesh - 517502, India.
Email: v.s.ravinutala@gmail.com

emerges as a solution to mitigate network traffic in cellular networks, underscoring the importance of optimal resource sharing among mobile users [14]. In dense MTC networks, energy-saving methods and traffic prediction are necessary to efficiently manage network resources for multiple MTC devices, minimizing waste from idle listening and channel access contention [15]. A number of factors, such as bandwidth, scheduling algorithms, signal quality, and beamforming techniques, are necessary for efficient resource allocation [16]. The traditional resource allocation strategies employed for human-centric communication may not be well-suited to address the distinct needs of MTC applications [17]. The approaches like Multiple Input Multiple Output based dynamic preamble-resource partitioning (MIMO-DPP) [18], hybrid non-orthogonal multiple access (NOMA)-orthogonal frequency division multiple access (OFDMA) [19], This approach enhances spectrum utilization, yet ensuring compatibility and interoperability with existing infrastructure presents significant challenges [20]. Enhancing throughput and data rates in wireless communication involves addressing challenges such as design complexity and optimal resource allocation. This article introduces a novel strategy to optimize resource allocation in 5G wireless communication, aiming to overcome limitations associated with current approaches.

2. Related Work

// Here is a description of a few recent studies in this area

5G networks strive to offer low-latency data delivery and accommodate diverse services, necessitating communication and computing resources. Seah, *et al* [21]. propose an Extended Weighted Fair Queuing with Latency Constraint (EWFQ/LC) scheduler, optimizing packet scheduling among network slices for fairness and latency constraints, demonstrating up to a 73% reduction in latency compared to discrete resource scheduling, while maintaining a latency satisfaction ratio above 90% in realistic traffic scenarios. The requirement for the adaptive weight determination method to dynamically assign weights to slices raises the possibility of complications or unintended consequences for the EWFQ/LC scheduler's reliability.

Shen, et al [22] Deep reinforcement learning (DRL) algorithm implementation for 5G era uplink scheduling in service-oriented multi-user mmWave radio access networks (RAN). Tested using a radio-over-fiber (RoF)-mmWave configuration with dynamic channel fluctuations, the DRL system demonstrates adaptive performance, yielding at least 12% average reward improvement over conventional single-rule schemes. Bit error rate and latency performance are both improved by this enhancement. However, it faces difficulties with respect to allocation equity.

In this study SUH, *et al* .[23] offering a deep reinforcement learning (DRL) based network slicing method whose objective is to maximize long-term throughput by optimizing resource allocation policies while satisfying QoS) requirements in beyond 5G (B5G) systems. This method concentrates on reducing the action space by removing inadequate actions that do not meet QoS requirements. Numerical results demonstrate its efficacy in managing use case coexistence and maximizing long-term throughput in B5G environments. The method's effectiveness in real-world situations may face difficulties because the simulations might not accurately represent the complexities and uncertainties of actual operational environments.

In this study, Kumar, *et al*, [24] Introduce an adaptive Quality of Service (QoS)-conscious resource allocation strategy for cloud-radio access networks (C-RAN) within mobile edge computing. The suggested method uses a multi-user C-RAN architecture to compute tasks and makes use of Deep Federated Quality-Learning (DFQL) to improve network performance and resource allocation. Validation is conducted using a realistic dataset and compared against existing techniques on a 5G experimental prototype. A potential challenge of implementing QoS-aware resource organization using DFQL in B5G C-RAN nets is the potential increase in computational complexity, which may strain resources and pose challenges in environments with limited processing power.

Jain, *et al*. [25] have proposed User Association and Resource Allocation in 5G (AURA-5G), They conduct a unique comparative analysis of all the scenarios under consideration using the Aura-5G framework, taking into account system fairness, performance against the baseline scenario, and total network throughput. Optimal user association and resource allocation techniques enable the network to handle a larger number of users and devices simultaneously. Complex algorithms and mechanisms may be used in 5G networks to maximize user association and resource allocation.

Rahimi, *et al*. [26] Proposed a Fog Computing Based Radio Access Network (FogRAN), presenting a novel architectural design for an SDN-based virtual fog-RAN. The proposed approach jointly investigates transmit beamforming and radio resource allocation with the aim of maximizing the achievable sum rate (ASR) while minimizing network power consumption (NPC), thereby enhancing resource utilization and IIoT user contentment. Fog computing facilitates the placement of computational resources nearer to the network edge, thereby reducing data processing latency. However, distributing computing resources to the network edge also introduces security challenges.

Zhang, *et al*. [27] have proposed Fuzzy Logic-Based Algorithm, in the proposed fuzzy logic-based algorithm to its predecessors, which were unable to guarantee services because of insufficient resource utilization, simulation results show that the latter can significantly increase resource utilization and satisfy V2X service requirements. Fuzzy logic allows for flexibility in decision-making by accommodating imprecise or uncertain information.Fuzzy logic is rule-based and may lack the learning capability seen in some machine learning approaches.

The MTC has become increasingly complex due to its high energy consumption and low data rate. Therefore, Sharmila, *et al*. [31] have proposed Chimp-based Extreme Neural Model (CbENM) Task completion deadlines determined the allocation of resources. The forecasting of active users was carried out by examining their data rates and deadlines before the resource allocation procedure. Mobile communication has proliferated across numerous digital intelligent applications. Numerous approaches, including mathematical models, optimization strategies, and neural models, have been proposed to carry out the resource allocation plan. But occasionally, these algorithms have shown a noticeable level of complexity and resource usage.

Table 1. Challenges of existing works

Si. No	**Author Name**	**Methods**	**Advantages**	**Disadvantages**
1	Seah, *et al* [21]	Extended Weighted Fair Queuing with Latency Constraint (EWFQ/LC)	Maintaining a latency	Complexities to the reliability
2	Shen, et al [22]	deep reinforcement learning (DRL) algorithm	Enhancing both bit error rate and latency performance	Issues in allocation fairness
3	SUH, *et al* .[23]	deepreinforcement learning (DRL)-based network slicing technique	Maximizing long-term throughput in B5G environments	Complexities
4	Kumar ,*et al*, [24]	Quality of Service (QoS)-aware resource allocation	Maximize network performance	Computational complexity
5	Jain, *et al*. [25]	User Association and Resource Allocation in 5G (AURA-5G),	Increased Network Capacity	Complexity
6	Rahimi, *et al.* [26]	Fog Computing Based Radio Access Network (FogRAN)	Low Latency	Security Concerns
7	Zhang, et al. [27]	Fuzzy Logic-Based Algorithm	Flexibility and Adaptability	Limited Learning Capability
8	Sharmila, *et al*. [31]	Chimp-based Extreme Neural Model (CbENM)	Mobile communication has proliferated across numerous digital intelligent applications	Exhibited significant complexity

The key contribution of the proposed work is mentioned below.

- Initially, Create a network model that includes the base stations, user equipment (UEs), and channels in the NS2 platform.
- The base stations are responsible for transmitting and receiving signals to and from the UEs. The UEs are the MTC devices that generate and consume data. The channels represent the radio propagation paths between the base stations and the UEs.
- Then the MTC traffic data, including data rates, arrival rates, and latency requirements are gathered.
- The proposed Recurrent Chimp based Green Anaconda Optimization (RCbGAO) is designed.

- Initially, uses chimp fitness to forecast the desired metric for every device.
- In addition, the GAO method has been used to carry out the prioritized resource allocation procedure.
- Ultimately, the QoS for the 5G CS was assessed through the validation of key parameters including delay, throughput, fairness, and energy consumption.

3. System model and problem statement

The arrival of 5G wireless communications symbols a transformative era, not only in connecting humans but also in fostering the seamless interaction of a myriad of devices in what is known as MTC. The success of MTC in 5G networks hinges on an efficient and adaptive resource allocation strategy that provides the unique characteristics of machine-centric communication. Traditional resource allocation methods may face scalability challenges, leading to increased throughput, delays, and potential degradation of service quality as the network becomes more densely populated. MTC involves a wide variety of devices with diverse communication requirements, data rates, and latency sensitivities. These problems are motivated to develop a novel resource allocation technique in 5G wireless communication. System model of Machine type Communications is shown in Fig.1.

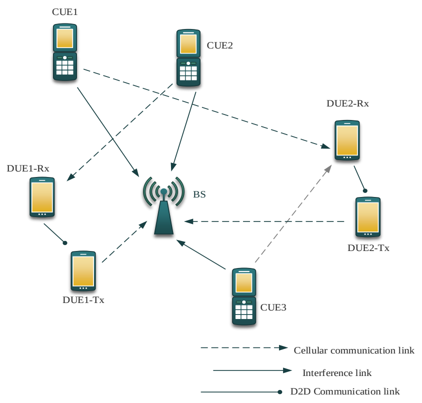

Figure 1. System model of Machine type Communications

The process of the use of digital communication technology, mobile devices can interact with one another directly and ignore the BS. This can help enable low-latency communication between devices or offload traffic from the cellular network. Still, two-way communication is not without its difficulties. Interference is one of the difficulties. It can be challenging to correctly receive signals when multiple devices are transmitting at the same time because of mutual interference. Power consumption presents another difficulty. Due to the fact that a direct-to relies on the devices transmitting signals directly to one another rather than through the base station, it usually uses more power than cellular communication. Scholars are attempting to resolve these issues and improve the effectiveness and dependability of digital-to-digital interaction. Coordinated scheduling, for instance, is one method where the BS allocates distinct channels to various devices in order to prevent interference. Utilizing power control, which involves adjusting the devices' transmit power to lower interference, is an additional strategy.

4. Proposed Methodology

The present work aims to develop the novel Recurrent Chimp based Green Anaconda Optimization (RCbGAO) algorithm for the resource allocation in 5G wireless communication. Here the Chimp and Green Anaconda optimization are combined with RNN. The optimization algorithms are employed to ascertain the best allocation of resources to the UEs, taking into account their traffic demands and the network constraints. Initially, develop an RNN architecture customized for RA in 5G MTC networks. Combine the Chimp and Green Anaconda optimization algorithm with the RNN to form a hybrid optimization framework. The RNN can guide the Chimp algorithm to explore the search space and predicts the target metric for each device based on its current state and historical data, leading to more efficient resource allocation. The Green Anaconda optimization algorithm with the RNN leverages the RNN's ability to capture temporal patterns and allocate resources to each device based on the selected solution by ensuring their priority levels. Fig.2 shows the Proposed Architecture of RCbGAO.

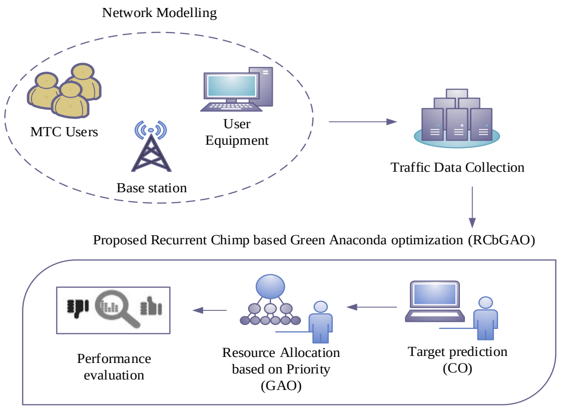

Figure 2. Proposed Architecture of RCbGAO

Initially, Create a network model that includes the base stations, user equipment (UEs), and channels in the NS2 platform. The base stations are responsible for transmitting and receiving signals to and from the UEs. The UEs are the MTC devices that generate and consume data. The channels represent the radio propagation paths between the base stations and the UEs. Then the MTC traffic data, including data rates, arrival rates, and latency requirements are gathered. The proposed Recurrent Chimp based Green Anaconda Optimization (RCbGAO) is designed. First, chimp fitness is primarily used to forecast the target metric for each device. Moreover, the GAO method has been used to carry out the prioritized resource allocation process. In the end, the validation of crucial parameters like latency, throughput, fairness, and energy consumption was used to evaluate the quality of service (QoS) for the 5G communication system

4.1. Network Modeling

The development of a thorough network model in the NS2 platform is the initial step. Base stations, user equipment (UEs), and channels are all included in this model. The central hubs for signal transmission and reception to and from UEs are base stations. On the other hand, UEs are Machine Type Communication (MTC) devices that are responsible for data generation and consumption. The channels serve as the foundation for communication within the simulated network by representing the essential wireless transmission paths that link the base stations and UEs.

$$BS = \{BS_{1,}, BS_2, \ldots., BS_N\} \tag{1}$$

This set comprises the collection of base stations in the network. Each BS_i is an individual base station, and there are N base stations in total.

$$UE = \{UE_1, UE_2, \ldots., UE_M\} \tag{2}$$

The network's user equipment devices are represented by this set. Each UE_j is an individual user equipment, and there are M user equipment devices in total.

$$C = \{C_{ij} \mid i \in BS, j \in UE\} \tag{3}$$

This set represents the channels in the network, denoted by C_{ij} . Each C_{ij} represents the communication channel between a specific base station BS_i and a specific user equipment UE_j . The set is defined for all combinations of base stations and user equipment devices.

4.2. Optimal Number of Nodes

When the total communication resources remain constant, the performance of distributed consensus can be impacted by the number of participating nodes. This is because a greater number of nodes necessitates the utilization of limited communication resources, and each node is anticipated to utilize fewer resources for transmission. In particular, the effectiveness of the resource allocation method may suffer when the overall communication resources are insufficient. This inadequacy can lead to some channels not obtaining enough resources to achieve the desired performance, thereby compromising the performance of the consensus process

4.3. Traffic data collection

As the network model is developed, gathering MTC traffic data becomes the main priority. This dataset contains significant parameters such as data rates, arrival rates, and latency requirements. The data collected plays a pivotal role in subsequent stages of the activity, impacting the understanding of traffic patterns and demands within the fictional setting.

The traffic prediction process involves individual access nodes collecting traffic data. Each edge node's data collection module locates and captures the raw data pertaining to the traffic flow sequence from access terminals during this procedure. The collected traffic data is then arranged by each access node based on its unique path information and divided into two groups: network traffic data and access traffic data.

$$h_t^p = M_p^* - r_{t-1}^{access,p} \tag{4}$$

Where, M_p^* denotes the physical traffic limit for each access node, h_t^p is determined and issued to each access node, and $r_{t-1}^{access,p}$ denotes the prediction result of network traffic at the last moment t-1.

4.4. Target Prediction

The novel Recurrent Chimp-based Green Anaconda Optimization (RCbGAO) methodology is presented in this work. Using chimp fitness, this optimization strategy aims to predict target metrics for every device in the network. A key factor in improving predictive capabilities is chimpanzee fitness, which makes it possible to evaluate device-specific performance metrics with greater accuracy. Equation (5) has been used for the analysis and computation of the best resource for every user task.

$$R^*(A_u) = \left| R(task) - req(R^*) \right| \tag{5}$$

Where, the resource is expressed as R^*, A_u denoted as an active user , and the tracked required resource of the specific task by the chimp model is described as R .

Therefore, by deducting the tracked desired resource from the user-requested resources, the optimal resource count was determined. Subsequently, the tracked desired resources were distributed to the other end users.

4.5. Design of RCbGAO

Using the Green Anaconda Optimization (GAO) technique, a prioritized resource allocation process is implemented, building upon the RCbGAO framework. By strategically allocating resources, the network will be able to function more effectively and respond more quickly to the changing needs of the simulated environment.

The final part is evaluating the 5G communication system's Quality of Service (QoS). The validation of important parameters, such as throughput, energy consumption, fairness, and delay, is how this evaluation is carried out. The thorough examination of these variables sheds light on the way the suggested RCbGAO performs overall and in terms of improving service quality in the virtual 5G communication environment.

4.6. Resource allocation

When the medium access phase is over, an MTCG can receive q requests for transmissions from MTC devices with different requirements for quality of service. During the allocation phase, three metrics are taken into account to determine the priority: the accumulative delay of class $D^*_{c_i}$, and the number of transmission-awaiting devices in a group/class $(\omega^*_{c_i})$, the received SNR($\gamma^*_{c_i m_j}$). The accumulative delay of the class $c_i \in C$ is represented. The total delay resulting from all successful MTC transmissions within a class is known as the cumulative delay of that group or class.

$$D^*_{c_i} = \sum_{j=1}^{n} D^*_{c_i m_j} \leq D^*_{th}(c^*_i) \tag{6}$$

Where D^*_{th} represents delay threshold of the respective MTC class and $D^*_{c_i m_j}$ represents the delay of the MTC device. The contributing factors towards the delay $D^*_{c_i m_j}$ are,

$$D^*_{c_i m_j} = d^*_t + d^*_p + d^*_q + d^*_r + d^*_{tr} \tag{7}$$

Where, d^*_t, d^*_p, d^*_q, d^*_r, d^*_{tr} represent the transmission, propagation, queuing, processing, and re-transmission delays, respectively. The pseudo code presented in Algorithm 1 serves as the foundation for the structure of the resource allocation steps. Furthermore, Figure 3 presents the RCbGAO workflow, showing the flow of processing.

Algorithm of RCbGAO

Start

{

Create a network model

{

Base stations, User equipment (UEs), and Channels in the NS2 platform

{

Int BS, $BS_{1,}$, BS_2, BS_N, UE, UE_1, UE_2, UE_M, C, C_{ij},

$BS = \{BS_{1,}, BS_2, \ldots, BS_N\}$

// Transmitting and receiving signals to and from the UEs

$UE = \{UE_1, UE_2, \ldots, UE_M\}$

// The MTC devices that generate and consume data

$C = \{C_{ij} \mid i \in BS, j \in UE\}$

//channel represents radio propagation paths between a base station and UEs

}

Traffic data collection

{

Int $h^p_t, M^*_p, r^{access,p}_{t-1}$

// Main priority is gathering MTC traffic data

$h^p_t = M^*_p - r^{access,p}_{t-1}$

}

Target Prediction

{

Using chimp fitness

{

Int $R^*, (A_u), R$

// predict target metrics for every device in the network

$R^*(A_u) = \left| R(task) - req(R^*) \right|$

}

Resource allocation based on priority

{

Using GAO method

// The network will be able to function more effectively

}

Performance evaluate

{

//Performance analysis

}

Stop

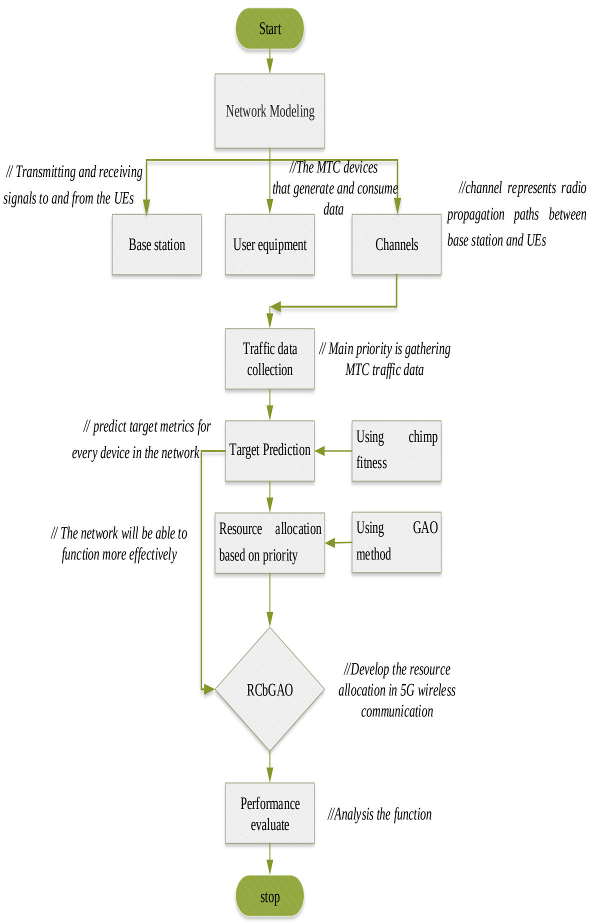

Figure 3. Flowchart of RCbGAO

5. Result and discussion

This segment discusses the successful results of the proposed strategy and outlines the experimental design. The organization's achievements are evaluated through several metrics, including fairness, Throughput, Energy consumption, and Delay employing optimization techniques and neural networks. The details of the parameters are presented in Table 2.

Table .2 Parameter Descriptions

Parameter Description	
OS	**Window 10 pro**
RAM	**8.0 B (7.88 GB usable)**
PC	**Intel(R) Core(TM) i5-3470 CPU @ 3.20GHz 3.20 GHz**
Version	**R2020a**
Dataset	**5G Resource Allocation**
Platform	**Matlab**

5.1. Dataset Description

The "Dynamic Resource Allocation Dataset for 5G Networks" offers researchers and professionals a comprehensive resource for studying and optimizing the allocation of resources in the next-generation wireless networks. This dataset provides detailed insights into various aspects of 5G resource management, including the demands of different applications, signal strength variations, latency considerations, bandwidth requirements, and the core metrics driving dynamic allocation decisions. By analyzing this dataset, researchers can gain a deeper comprehension of the complex interplay between network resources and application needs, enabling them to develop advanced AI models, enhance quality of service, and drive innovation in 5G networking. This dataset acts as a valuable resource for individuals aiming to harness the complete potential of dynamic resource allocation in shaping the future of connectivity.

5.2. Case Study

Network topology and node visualization play crucial roles in resource allocation in 5G wireless communications. Network topology pertains to the configuration of nodes and links within a communication network, significantly influencing the effectiveness and performance of resource allocation algorithms. It determines the connectivity between nodes, the path data takes through the network, and the overall structure of the communication infrastructure. Node visualization, on the other hand, involves the graphical representation of network nodes and their interconnections. This facilitates better decision-making when allocating resources like bandwidth and processing power, ultimately resulting in enhanced network performance and user experience. 5G wireless communication systems can effectively allocate resources to meet the diverse needs of multiple applications, such as high-speed data transmission, low-latency communication, and massive IoT connectivity, by employing network topology and node visualization. Network Topology is shown in Fig.4 and Node visualization is shown in Fig.5.

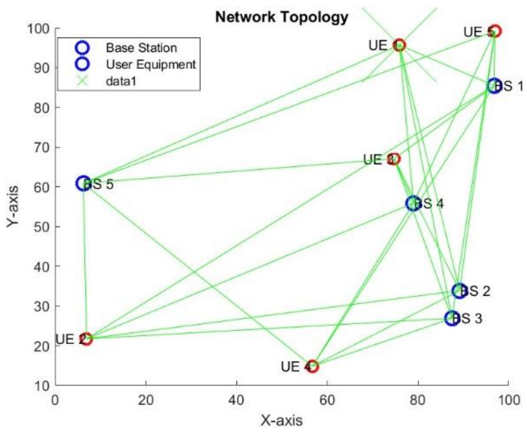

Figure 4. Network Topology

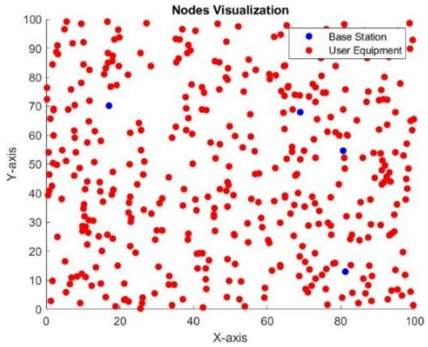

Figure 5. Node visualization

5.3. Performance metrics

To validate our proposed Recurrent Chimp based Green Anaconda Optimization (RCbGAO) algorithm the performance metrics are evaluated in standings of Fairness, Throughput, Energy efficiency, and Delay.

5.3.1. Throughput

Network throughput signifies the total data successfully transmitted between two points over a communication channel within a specific time frame. In a 5G WPAN (Wireless Personal Area Network), throughput is influenced by a resource allocation model guiding resource distribution and transmission power management. The enhancement process begins with measuring the initial throughput of the system by a network performance analysis tool, which evaluates parameters such as packet loss, delay, and throughput. Following this, optimizing resource allocation by adjusting device transmission power is undertaken to maximize network throughput. Then, in order to measure the improvement brought about by the RCbGAO methodology, the throughput of the optimized system is measured and compared with the initial throughput.

$$R^* = B^*.\log_2(1+SNR)$$

Where, R^* is the throughput, B^* denoted as bandwidth, $\log_2$ is logarithm base 2 , SNR is the signal-to-noise ratio. Fig.6 shows the Throughput.

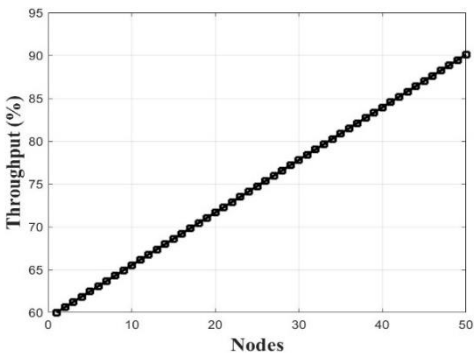

Figure 6. Throughput

5.3.2. Fairness

Fairness is a commonly acknowledged metric used in evaluating wireless communication systems. A proficient resource allocation scheme plays a pivotal role in establishing a dynamic system capable of achieving equitable data distribution within NOMA (Non-Orthogonal Multiple Access) systems. As a result, the secondary objective is to achieve a well-balanced data rate in accordance with Jain's fairness criteria. The goal of guaranteeing an equal distribution of data rates among users within the system defines fairness in this context.

$$F^* = \frac{\sum_{i=1}^{U} R_i^*}{U\sum_{i=1}^{U} R_i^2}$$

Where and U is the total number of users and R_i^* is the user data rate. This indicator fluctuates based on the number of users and the attained throughput.

In a NOMA system, where two users share the same channel with varying channel gains, ensuring a minimum data rate for the user experiencing lower channel gain is crucial. This practice is implemented to prioritize fairness, which serves as a key indicator of QoS in NOMA systems. Fairness is shown in Fig.7.

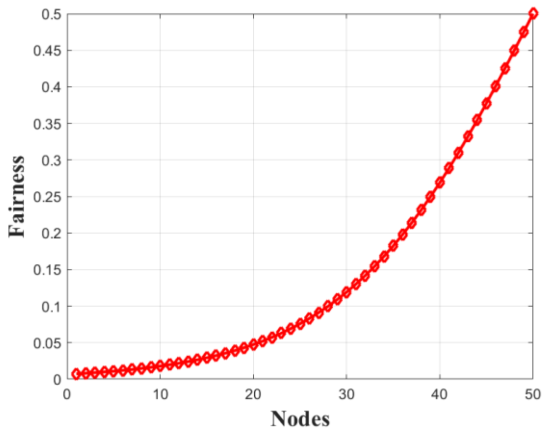

Figure 7. Fairness

5.3.3. Delay Rate

When it comes to D2D communication, delay is crucial because it affects the overall performance of the network. Delay is the total amount of time it takes for a data packet to travel from one point to another. The application of RCbGAO is essential for mitigating delays in 5G WPANs. This model strategically optimizes resource allocation to match user preferences while taking into account the power consumption patterns of various devices.

$$d^* = \left(\frac{C^* A^*}{T_r^*}\right)$$

The delay d^* for a single A^* -byte packet sent across C^* connections at a specific transmission rate T_r^* . Fig.8 sows the Delay rate.

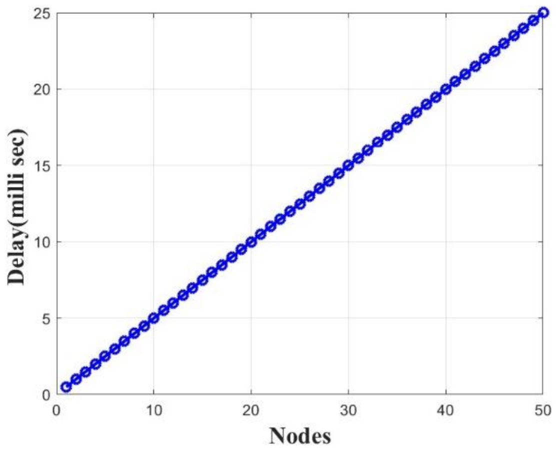

Figure 8. Delay rate

5.3.4. Energy Consumption

Managing energy consumption is crucial in 5G wireless communications, requiring a careful balance between optimizing resource utilization for efficient communication and minimizing power usage. The relationship between energy consumption (E^*), throughput (R^*), and spectral efficiency (SE°) is expressed by the equation:

$$E^* = \frac{P^*}{R^*} = \frac{P^*}{SE^\circ + B^*}$$

Where, B^* is the available bandwidth, P^* denoted as total power consumption. The equation indicates that energy consumption is inversely proportional to both throughput and spectral efficiency. Minimizing energy consumption requires optimizing the allocation of resources, taking into account factors such as power control, modulation schemes, and transmission parameters. Fig.9 shows the Energy consumption.

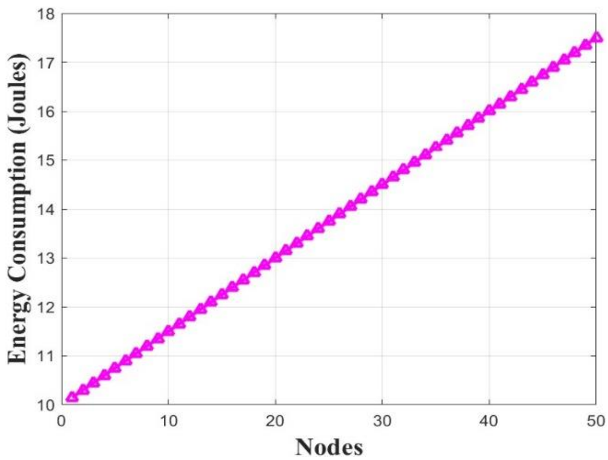

Figure 9. Energy consumption

5.4. Performance Estimation

The developed model will be used in the Matlab framework. The effectiveness of the model was confirmed by comparing its energy consumption, fairness, delay rate, and throughput metrics with those of alternative models. Moreover, the existing techniques like power consumption optimization framework (PCOF), max–min power control algorithm (MMPCA), energy-efficient two-stage capacity allocation scheme ((EECAS), energy-efficient trajectory planning (EETP) [28], Proportional Fair (PF), Round Robin (RR). Group-Based Energy Aware algorithm (GBEA) [29], Priority-Based and Energyefficient Routing (Prinergy), Quality of Service Routing Protocol for Low (QRPL) [30].

5.4.1. Comparison of proposed RCbGAO with in terms of Delay rate

The delay rate achieved by the established model is compared with current methodologies to validate that the delay rate is low in the developed model. Here, the delay rate is matched with the existing techniques such as EECAS,PCOF,MMPCA,EETP.

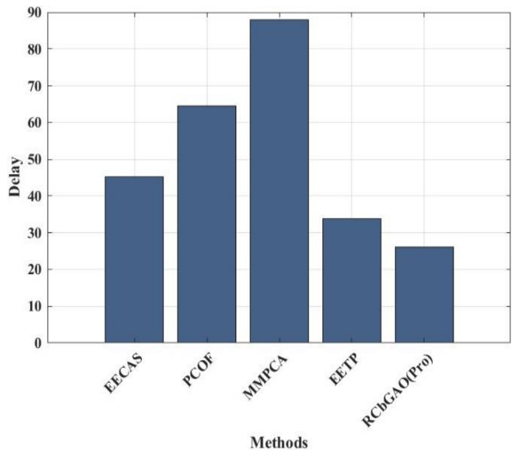

Figure 10. Comparison of the suggested RCbGAO in terms of Delay rate

However, when compared to other current models, the suggested method achieved a low delay rate. Figure 10 displays the comparison of delay rate. This shows that the developed model attained low delay rate than existing communication approaches

5.4.2. Comparison of proposed RCbGAO with interms of throughput

The throughput achieved by the established model is compared with current methodologies to validate that the throughput is high in the developed model. Here, the throughput is matched with the existing techniques such as EECAS,PCOF,MMPCA,EETP.

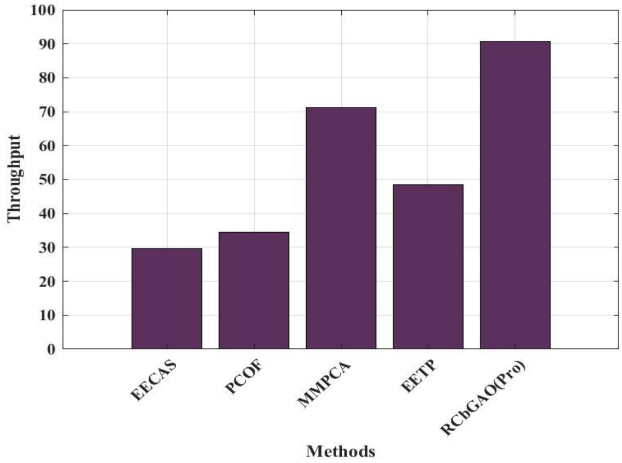

Figure 11. Comparison of the suggested RCbGAO in terms of throughput

However, when compared to other current models, the suggested method achieved a high throughput. Figure 11 displays the comparison of throughput. This shows that the developed model attained a higher throughput than existing communication approaches.

5.4.3. Comparison of proposed RCbGAO with interms of Energy consumption

The Energy consumption achieved by the established model is compared with current methodologies to validate that the Energy consumption is low in the developed model. Here, the Energy consumption is matched with the existing techniques such as QRPL, and PriNergy.

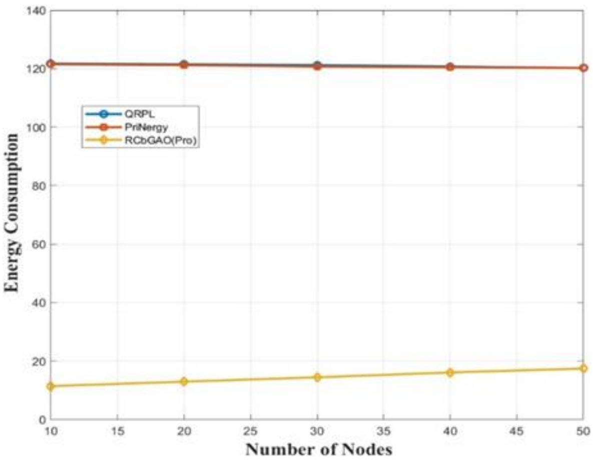

Figure 12. Comparison of the suggested RCbGAO in terms of energy consumption

However, when compared to other current models, the suggested method achieved a low energy consumption. Figure 12 displays the comparison of energy consumption. This shows that the developed model attained low energy consumption than existing communication approaches.

5.4.4. Comparison of proposed RCbGAO with interms of fairness

The fairness achieved by the established model is compared with current methodologies to validate that the fairness is high in the developed model. Here, the fairness is matched with the existing techniques such as PF, RR, and GBEA.

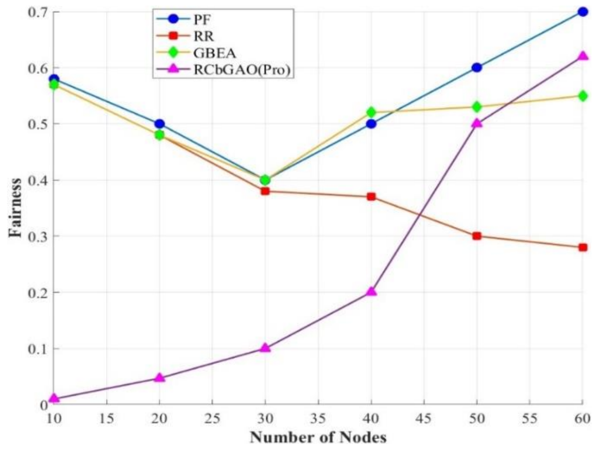

Figure 13. Comparison of the suggested RCbGAO in terms of fairness

However, when compared to other current models, the suggested method achieved a high fairness. Figure 13 displays the comparison of fairness. This shows that the developed model attained high fairness than existing communication approaches.

6. Conclusion

In conclusion, the study on resource allocation in 5G wireless communications utilizing Recurrent Chimp based Green Anaconda Optimization (RCbGAO) presents a promising approach to address the intricate challenges inherent in dynamic and high-performance networks. The integration of the Recurrent Chimp fitness method and Green Anaconda Optimization not only optimizes resource allocation based on historical data and user preferences but also takes sustainability factors into account. The research successfully demonstrated improvements in data rate balance, latency reduction, and overall system efficiency. However, the evolving landscape of 5G networks presents ongoing challenges, and future work could explore the scalability of RCbGAO to larger network deployments. Additionally, investigating the adaptability of the model to diverse user scenarios and network conditions would contribute to its robustness and practical applicability. Furthermore, extending the study to incorporate emerging technologies and standards in the 5G ecosystem could enhance the applicability of RCbGAO in real-world deployments. Overall, the research lays a foundation for future endeavors to advance resource allocation strategies, ensuring the continued optimization and efficiency of 5G wireless communication systems.

Compliance with Ethical Standards

Funding: No funding is provided for the preparation of manuscript.

Conflict of Interest: Authors declare that they have no conflict of interest.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate: All the authors involved have agreed to participate in this submitted article.

Consent to Publish: All the authors involved in this manuscript give full consent for publication of this submitted article.

Authors Contributions: All authors have equal contributions in this work.

Data Availability Statement: Data sharing not applicable to this article.

Reference:

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