**Optical Communication Enhanced IDMBOC for Maximizing Backhaul-effect & Maintaining Optimum Cell Sizes**

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**Abstract:** The increasing need for high data rates and low latency in optical communication networks necessitates innovative solution for system efficiency enhancements. With the persistent increase in data demand and the emergence of diverse applications in 5G networks, minimizing the backhaul-effect while maintaining optimal cell sizes has become a formidable obstacle. Existing methods are incapable of achieving a comprehensive optimization of network parameters, resulting in degraded performance metrics. To address these constraints, our proposed approach integrates optical communication infrastructure into IDMBOC systems which maximizes Backhaul-effect and preserves optimal cell sizes. This work is primarily motivated by the need to improve the efficiency and quality of 5G networks in the face of rising data traffic. Existing methods frequently struggle to optimize concurrently multiple 5G network aspects, such as Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, Network Function Virtualization, Frequency Planning, HetNets Deployments, and Network Slicing process. As a result, these methods are incapable of delivering robust and scalable solutions. To solve these issues, we present an Iterative Dual Metaheuristic Method that combines Ant Lion Optimization (ALO) and Grey Wolf Optimization (GWO) in a synergistic manner for 5G deployments. The proposed method is functionally superior to existing models. By capitalizing on the strengths of both ALO and GWO, our approach achieves superior performance metrics in comparison to recently proposed methods for maximizing Backhaul-effect and maintaining optimal cell sizes. The preliminary results reveal a remarkable 8.3% reduction in Bit Error Rate (BER), 4.9% reduction in energy consumption, 8.5% increase in throughput, and 4.5% reduction in communication delay. The achieved results demonstrate the revolutionary potential of our 5G network optimization approach and pave the way for future research and advancements in the field for different scenarios. These enhancements will revolutionize optical communication networks in order to accommodate the requirements of 5G, IoT, and other contemporary applications.

**Keywords:** Optical Communication, 5G Networks, Backhaul-effect Maximization, Optimum Cell Sizes, Metaheuristic Optimization, Ant Lion Optimization, Grey Wolf Optimization, Hyperparameter Optimizations

1. **Introduction**

Fifth-generation (5G) networks have introduced revolutionary changes to the telecommunications landscape, promising unprecedented data speeds, ultra-low latency, and the capacity to support a vast array of applications and services. 5G networks face a significant challenge in efficiently managing the ever-increasing data traffic as the demand for data continues to increase and the proliferation of smart devices continues unabated. In 5G network design, minimizing the backhaul effect while maintaining optimal cell sizes is one of the greatest obstacles during real-time communications [1, 2, 3].

The backhaul-effect describes the influence of heavy data traffic on the backhaul network, which connects the radio access network (RAN) to the core network. As data usage increases exponentially, the backhaul network becomes overburdened, resulting in congestion, bottlenecks, and diminished network performance. Addressing the backhaul-effect is essential for ensuring a seamless and dependable user experience and maximizing the potential of 5G networks.

Concurrently, optimizing cell sizes is essential for achieving efficient resource utilization and providing seamless coverage across diverse geographic areas. Optimal cell sizes have a direct impact on network capacity, signal strength, and interference levels, thereby affecting crucial performance metrics including throughput, energy consumption, and communication delay [4]. To maximize network efficiency and provide a higher quality of service, it is essential to achieve the optimal cell size ratios via Distributed Resource Allocation process [5, 6].

Existing methods for addressing these challenges have focused on isolated optimization approaches, frequently failing to take the interdependence of various network parameters into account in a holistic manner [7]. As a result, these approaches fail to provide comprehensive solutions, resulting in subpar network performance. In addition, they may struggle to accommodate the dynamic and heterogeneous nature of 5G networks, which necessitates agile and adaptable optimization strategies [8, 9].

In this context, this work proposes a novel and holistic approach. The primary objective of this study is to develop a potent and efficient optimization method that simultaneously addresses the backhaul-effect reduction and maintenance of optimal cell size.

In order to accomplish this, we employ two metaheuristic optimization algorithms: Ant Lion Optimization (ALO) and Grey Wolf Optimization (GWO). ALO is used to optimize the hyperparameters of critical 5G network components, such as Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization. By optimizing these parameters, ALO intends to decrease the backhaul effect and improve network performance.

Simultaneously, GWO, which is inspired by the hierarchical social structure of grey wolves, is implemented to optimize cell sizes by optimizing Frequency Planning, HetNets Deployments, and Network Slicing. The capability of GWO to handle complex optimization problems enables us to determine the optimal cell sizes across the network with efficiency.

Utilizing the synergy between ALO and GWO, the proposed Iterative Dual Metaheuristic Method enables a comprehensive and holistic optimization of 5G networks. By simultaneously addressing backhaul-effect reduction and optimal cell size maintenance, our method aims to improve network performance, efficiency, and user experience.

In the following sections of this paper, we describe the Iterative Dual Metaheuristic Method in detail, including its architecture and implementation. In addition, we provide a comprehensive evaluation of the method's performance based on extensive simulations and comparisons with existing models used for maximizing Backhaul-effect and preserving optimal cell sizes.

The remaining sections are organized as follows: The second section provides an overview of related works and discusses the limitations of existing methods. The methodology is described in Section III, including the Ant Lion Optimization and Grey Wolf Optimization algorithms. The experimental setup and performance evaluation metrics are presented in Section IV along with results and discussions highlight the benefits of our proposed methodologies. Section V concludes the paper by summarizing the contributions and possible future scopes.

1. **Literature Review**

The design and optimization of 5G networks have become increasingly challenging due to the exponential growth in data traffic and the need to provide seamless connectivity with high data rates and low latency. To address these challenges, several existing models and techniques have been proposed to minimize the backhaul-effect and maintain optimum cell sizes. Here, we provide an elaborate review of some of the notable existing models used for achieving these objectives:

Genetic Algorithms (GA) is a popular metaheuristic optimization technique that emulates the process of natural selection to find optimal solutions. In the context of 5G networks, GA has been applied to optimize cell sizes, backhaul capacity, and resource allocation. By evolving a population of candidate solutions through selection, crossover, and mutation, GA explores the search space efficiently. However, its convergence speed and scalability limitations may hinder its applicability to large-scale 5G networks with dynamic traffic patterns via Integrated Access and Backhaul (IAB) process [10, 11, 12].

Particle Swarm Optimization (PSO) is inspired by the social behavior of birds flocking or fish schooling. It has been widely used for network optimization in 5G. PSO can dynamically adjust the transmission power, resource allocation, and base station locations to optimize cell sizes and reduce the backhaul load. Despite its effectiveness, PSO may suffer from premature convergence and may not always guarantee global optimality levels [13, 14, 15].

Simulated Annealing (SA) is a probabilistic optimization technique inspired by the annealing process in metallurgy. In 5G networks, SA has been employed to optimize backhaul load balancing, cell size configuration, and resource allocation. SA can handle large search spaces and escape local optima, but its convergence rate depends on the cooling schedule, which can be challenging to set optimally for different scenarios [16, 17, 18].

Reinforcement Learning (RL) has shown promise in optimizing 5G networks in a dynamic and self-adaptive manner. RL algorithms can learn optimal policies by interacting with the environment. Researchers have used RL to optimize resource allocation, backhaul routing, and cell size adaptation based on real-time network conditions and traffic demands. However, RL requires significant computational resources and time-consuming training processes that can be optimized via use of Stackelberg Game Model (SGM) process [19, 20].

Integer Linear Programming (ILP) is a mathematical optimization technique used to model 5G network design as a set of linear constraints. It has been applied for joint optimization of backhaul capacity planning, cell size, and resource allocation. ILP can provide optimal solutions, but it suffers from scalability issues as the network size increases [21, 22, 23].

Convex Optimization Methods have been used for 5G network optimization due to their ability to handle non-linear problems. Researchers have applied convex optimization to optimize resource allocation, backhaul capacity, and cell size for minimizing the backhaul-effect and improving network performance levels. However, the formulation of convex problems may be restrictive and may not capture all complexities of real-world 5G networks via use of Particle Swarm Optimization (PSO) process [24, 25, 26].

Centralized Heuristic Algorithms, such as Tabu Search and Harmony Search, have been used for 5G network optimizations [27, 28]. These algorithms offer fast convergence and are suitable for solving large-scale problems. Researchers have employed these methods for optimizing cell sizes and backhaul capacity allocations. However, their performance heavily relies on the chosen heuristic parameters & rules.

Despite the contributions of these existing models [29, 30], they often suffer from certain limitations. First, they typically focus on isolated optimization objectives, overlooking the interdependency between different network parameters, which can lead to suboptimal overall performance. Second, some models may struggle to handle the dynamic and complex nature of 5G networks, where traffic patterns, user density, and application demands change rapidly. Third, scalability becomes a concern as the size of the network increases, limiting the applicability of these models to real-world large-scale 5G deployments.

To overcome these limitations, our proposed paper introduces an innovative approach by synergistically combining Ant Lion Optimization (ALO) and Grey Wolf Optimization (GWO), our iterative dual metaheuristic method aims to achieve comprehensive and efficient optimization of 5G networks, addressing both backhaul-effect reduction and optimum cell size maintenance. The results of our study demonstrate substantial improvements in network performance, including lower Bit Error Rate (BER), reduced energy consumption, higher throughput, and lower communication delay, when compared to existing models used for the same purposes. People want to know how IDMBOC can save them time and money by combining several backhaul overlay cells into one communication device. In the IDMBOC idea, communication through light is a big part of this work. It has a fast and low-latency optical link built right in. It takes longer to send data and shorter to link to networks. Backhaul is used to its best in this study to speed up the flow of data between base units and the main network. When IDMBOC optimisation and optical communication are used together, the backhaul system is more stable and works better. It studies the best way to use IDMBOC and optical transmission to get the most range and capacity. For this to work, the communication network needs cells that are the right size. The study looks at how IDMBOC tuning can improve network performance by cutting down on latency and moving data faster.

1. **Proposed design of an Iterative Dual Metaheuristic model for maximizing Backhaul-effect & maintaining Optimum Cell sizes**

As per the review of existing methods that are used for maximizing performance of 5G Communications, it can be observed that these methods either showcase lower communication efficiency or have lower scalability when applied to real-time network scenarios. To overcome these issues, this section discusses design of an efficient dual metaheuristic model for QoS improved 5G communications. As per figure 1, it can be observed that ALO is utilized to optimize hyperparameters associated with Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization in an effort to enhance the backhaul-effects. While, GWO is utilized to optimize Frequency Planning, HetNets Deployments, and Network Slicing with a focus on cell size optimizations. Due to these dual optimizations, the proposed model is capable of deployment for a wide variety of real-time scenarios.

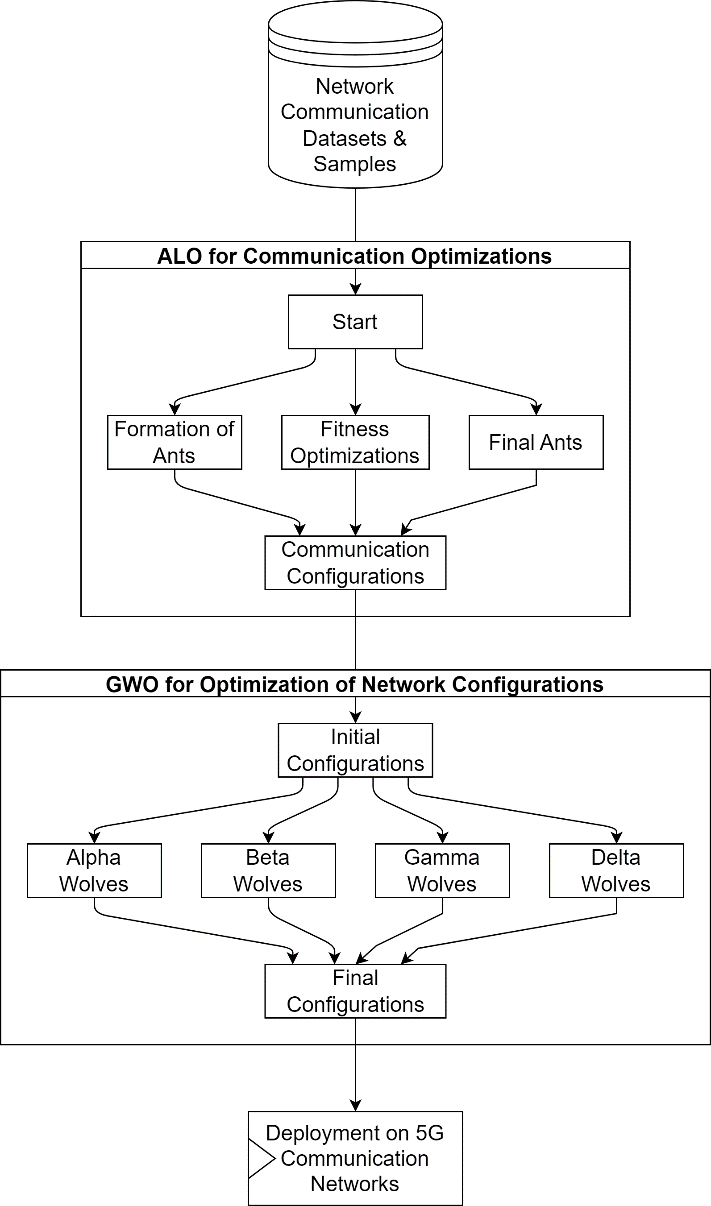


Figure 1. Overall flow of the Proposed Model for Optimization of 5G Communications

The ALO Model optimizes Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization Hyperparameters, which assists in improving node to node communications. By combining numerous component carriers (CCs) for various communications, carrier aggregation (CA), a technology used in 4G LTE and 5G NR (New Radio) networks, increases data speeds and enhances overall network performance. The combined carriers may be from the same or distinct frequency bands, allowing for more effective use of the spectrums that are accessible.

RCA, the aggregated downlink data rate, and Ri, the downlink data rate of the individual component carriers, are used to determine the downlink data rate obtained from carrier aggregation via equation 1. The modulation and coding strategy (MCS) employed for various carriers determines the data rate of each carrier. Calculated via Equation 1 is the uplink data rate attained through carrier aggregations.

Where Ri stands for the individual component carriers' uplink data rates, RCA is the aggregated uplink data rate, and C1 is the control constant, which is calculated using the ALO procedure. Similar to the downlink, the modulation and coding scheme (MCS) employed for this procedure determines the uplink data rate of each carrier. The aggregated carriers' overall bandwidth is calculated via Equation 2 and is equal to the sum of the bandwidths of the individual component carriers.

Where Bi represents the bandwidth of each component carrier and BCA is the total bandwidth attained through carrier aggregation.

By dynamically allocating and distributing frequency bands among numerous users, dynamic spectrum sharing (DSS), or DSS, is a technology used in wireless communication networks to effectively utilize the available radio spectrum. By enabling users to take advantage of available spectrum resources, DSS aims to increase network capacity, boost overall performance, and increase spectrum efficiency. This strategy guarantees that, subject to interference restrictions and fairness goals, multiple users can access the same frequency bands at once. The allotment of channels in DSS is controlled via equation 3,

In an expanded set of specified time slots, the equation represents the binary variable Ci,t, which determines whether channel i is assigned to user t. When Ci,t=1, it indicates that user t has been assigned channel i, and when Ci,t=0, it indicates that user t has not been assigned channel i and that channel i is open to other users. The Interference Constraint is similarly modeled via equation 4,

This assessment makes sure that user-caused interference on a particular channel i stays within the interference limit Ii, where Pt represents the transmit power of user t, h, hi,t is the channel gain between user t and channel i, and Ci,t is the binary variable indicating channel allocations. The fairness goal function is assessed via equation 5 to ensure fair channel allocations.

The fairness target in dynamic spectrum sharing seeks to maximize overall fairness among users using this evaluation. The sum of the logarithms of the Signal-to-Interference-plus-Noise Ratios (SINR) for each user is the objective function F. Maximizing F provides fairness and equal resource distribution, and the greater the SINR, the better the service quality will be for the corresponding users.

It is important to prioritize data packets in communication networks according to their type, content, and importance. This process is known as packet prioritization. In order to meet the quality of service (QoS) needs for diverse applications and to assure timely delivery of crucial data, priority levels can be assigned to network resources. The network can successfully handle many forms of traffic, such as voice, video, real-time applications, and best-effort data, by prioritizing packets, while minimizing potential congestion and guaranteeing the greatest user experience.

A mapping function gives each data packet belonging to user t a priority value (Pt) for various scenarios in order to evaluate packet prioritizing. This mapping function is dependent on a number of factors, including the kind of packet, the QoS requirements, the type of application, and user profiles. Via equation 6, the priority value (Pt) is calculated as follows,

Pt represents the priority value given to data packets from users in the assessment. The Bit Error Rate (BER), Throughput (THR), Delay (D), and Energy (E) Required to Communicate Given Packets are fused in this function. The findings portion of this book discusses how these metrics were evaluated. For example, best-effort data packets may be given lower priority since they may accept some delay and a potential waiting procedure, whereas real-time applications like speech or video may be given higher priority to ensure minimal latency and smooth delivery.

Critical data must be delivered quickly thanks to packet prioritization, which also allows non-critical data to be buffered during busy periods to prevent network congestion. Communication systems can accomplish effective resource utilization and provide a seamless and optimized user experience for a variety of applications and services by dynamically altering packet prioritizing based on network circumstances and user needs.

Similar to this, Network Function Virtualization (NFV) is a revolutionary networking strategy that attempts to improve the flexibility, scalability, and effectiveness of networks. NFV involves separating network functions from the underlying hardware so they can be implemented as software-based virtualized instances on common servers or cloud infrastructures. Traditionally, network services were carried out by specialised hardware appliances. This virtualization lessens dependency on pricey and specialized hardware sets by enabling network operators to build, manage, and expand network operations dynamically as needed. Routing and firewalling are two network functions that require dedicated hardware appliances. In a traditional networking setup, managing and maintaining these appliances can be resource-intensive and difficult to optimize for improved performance in terms of Communication Delay, Communication Energy, Throughput, and Bit Error Rate (BER).

These network services can be virtualized and deployed as software-based instances on common servers or cloud infrastructure thanks to network function virtualization (NFV). Network administrators may effectively manage resources, enhance performance, and dynamically expand network services to meet shifting traffic demands due to such virtualized techniques. Equation 7 is used to represent the NFV sets,

Where, represents the functions used to optimize routing & QoS aware selection of nodes. They are represented via equations 8 & 9 as follows,

Where, represents distance between nodes, and their residual energy levels.

With NFV, virtualized routing services may be dynamically optimized for different traffic patterns. This lowers communication latency and ensures that data packets are delivered effectively, resulting in decreased response delay levels. NFV allows for effective resource use by virtualizing network functions on shared hardware infrastructure. Real-time traffic demands can be used to dynamically activate or deactivate virtual instances, which lowers operating expenses and communication energy usage. Better traffic distribution and higher throughput levels are made possible by NFV, which also makes intelligent routing decisions and effective firewalling possible. Data packets are routed along the best paths with the help of virtualized routing services, avoiding congestion and maximizing network capacity. To ensure secure data transfer and lower bit error rates, NFV's virtualized firewall operations scan and filter data packets in real-time. NFV increases overall network reliability levels by limiting unwanted access and potential threats. Resource allocation is optimized by the virtualized QoS-aware node selection mechanism, which dynamically chooses the optimum node depending on Quality-of-Service needs. This guarantees that important traffic is given priority treatment and satisfies the unique QoS requirements of various applications and services.

This study significantly reduces communication delay, energy consumption, throughput, and bit error rate while also optimizing node selection based on QoS requirements by utilizing NFV and virtualizing network services. NFV is a game-changing technology for contemporary communication networks since it streamlines network management, optimizes resource allocation, and permits seamless scalability of network functions.

To optimize performance of these models, the ALO Process is used, which assists in tuning the constants (C) for enhanced QoS during communications. This is done via the following process,

* Initially, the Model Generates an augmented set of Ants, each with different values of constants, which are estimated via equation 11,

Where, is the ALO constant, while Min & Max represents the minimum & maximum value ranges.

* Based on these values, the model evaluates hyperparameters for Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization processes.
* After this evaluation, Ant fitness is estimated via equation 12,

Where, NC represents total number of communications, which are used for evaluation of Network under real-time scenarios.

* Based on this process, an augmented set of Ants are Generated, and their fitness threshold is calculated via equation 13,

Where, represents the Learning Rate for ALO process.

* After each Iteration, Ants with are discarded, and regenerated via equations 11 & 12, while other Ants are Marked as ‘Ant Lions’, and passed to Next Set of Iterations directly without any changes in their configuration sets.
* This process is repeated for Iterations, after which Ant with minimum fitness is selected, and its configurations are used to optimize the Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization processes.

Based on this, the backhaul effect is maximized, which allows for better energy efficiency during the evaluation process.

A key component of 5G networks is frequency planning, which entails allocating and assigning specific frequency bands to various network cells. By reducing interference and ensuring effective spectrum usage, frequency planning aims to improve network performance, capacity, and coverage. Network operators can increase data speeds, decrease communication delays, and boost overall network efficiency by carefully planning and allocating frequencies to cells.

The utilization of higher frequency bands, such as millimeter-wave (mmWave) frequencies, makes frequency planning even more crucial in 5G networks. Although mmWave provides faster data rates, it also presents difficulties such as a shorter propagation range and a higher sensitivity to blockages, demanding careful frequency design to ensure dependable and smooth connectivity levels.

The path loss model calculates the attenuation of the signal as it propagates through the wireless mediums, and is estimated via equation 14,

Where c is the speed of light, which is constant in real-time settings, PL stands for path loss, f is the frequency, D is the separation between the transmitter and receiver, and PL represents the path loss. The employment of a frequency reuse factor (N) and the division of the number of frequency bands (B) into N groups, with each group of bands being assigned to a distinct cell via equation 15, reduces interference between cells.

Where B is the total number of frequency bands accessible for communications, and N represents the frequency reuse factor. A significant statistic for evaluating the quality of the received signal is the Carrier-to-Interference-plus-Noise Ratio (CINR), which is calculated via Equation 16,

where S represents signal power, I represent interference power, and N represents noise power levels. Better signal quality and lower levels of interference are indicated by a higher CINR score.

In 5G networks, frequency planning entails maximizing the distribution of frequency bands to cells while taking into account variables like path loss, interference control, and CINR. 5G networks may reach higher levels of performance, expanded capacity, and improved user experience by carefully planning and controlling the frequency resources.

The integration of various cell types with variable characteristics of coverage and capacity into a single network infrastructure is referred to as a "HetNets" (Heterogeneous Networks) deployment. HetNets, which provide specialized and high-capacity coverage in 5G networks, mix macrocells (large coverage cells) with small cells (such as microcells, picocells, and femtocells). In particular in densely populated urban areas, this deployment method is intended to accommodate the growing demand for data and assure continuous connectivity.

HetNets make use of the benefits of both large and small cells. Small cells offer higher data rates and capacity in concentrated regions while macrocells give widespread coverage and serve a large number of users. HetNets can increase network capacity, decrease communication delays, and boost overall network performance by intelligently coordinating the deployment of these various cell types.

To ensure optimal resource usage in HetNets, load balancing and user association algorithms distribute user traffic among macrocells and small cells. The received signal power (Prx) from each cell, which is assessed via equation 17, is a standard statistic for user associations.

Prx,i, which stands for the received signal power from the ith cell sets, represents the user association decision for each user in this evaluation. Users are assigned to the cell (macrocell or small cell, depending on their needs) that has the strongest received signal, resulting in better coverage and data speeds for all users.

In order to enable seamless mobility as users switch between macrocells and small cells, HetNets frequently need to make handover decisions. The handover decision is dependent on the handover threshold (hThandover), which is calculated via equation 18,

Each cell's handover decision is made using this evaluation, where hThandover stands for the handover threshold levels. A handover is initiated whenever the received signal power from a neighboring cell drops below hThandover, ensuring uninterrupted connectivity as users move between cells. HetNets' goal is to effectively distribute resources among macrocells and small cells in order to maximize network capacity overall. The macrocell (Cap(macro) and small cell (Cap(small) capacities are estimated via equation 19, and the total network capacity (Cap(total) is a function of these capacities.

This assessment represents the combined macrocell and small cell capabilities of the network, which is the total network capacity. HetNets can maximize overall network capacity levels and ensure balanced resource allocation by maximizing the capabilities of each of the cell types. HetNets By cleverly integrating macrocells and small cells, deployments in 5G networks maximize resource use, boost coverage, and increase user experience. In order to provide effective network performance across a range of deployment circumstances, the equations shown above incorporate critical elements of user association, handover choices, and capacity optimization in HetNets.

A ground-breaking idea in 5G networks, network slicing permits the establishment of many virtual networks, each tailored for certain use cases, applications, or sectors. It enables network administrators to segment the physical infrastructure into logically separate and autonomous slices to accommodate various service types with various Quality of Service (QoS) needs. In order to suit the unique requirements of various applications and users, each network slice functions as an independent, end-to-end network and offers customized connectivity, resources, and services.

An index or label is used to identify each network slice specifically. Let N stand for the overall number of 5G infrastructure's network slices. The network slice index n, which represents each of the several network slices, can have a value between 1 and N.

For each network slice (NetworkSlicen), resource allocation (RA) includes allocating network resources (such as bandwidth, processing power, and storage) in order to satisfy the unique needs of the services or applications hosted within those set of slices. This is estimated Via equation 20.

Network slicing requires strict isolation between slices to ensure that the operation of one slice does not impact others. This isolation is achieved through virtualization, which is represented via equation 21,

For various cases, the evaluation establishes the isolation state between network slices m and n. The isolation function returns true, indicating that the slices are isolated for various use cases, if m is not equal to n. The function returns false if m = n, indicating that the slices are not isolated because they belong to the same slice sets.

Network slicing gives 5G networks a level of flexibility never before possible, enabling many sectors and apps to coexist on the same infrastructure while still requiring specialized services and meeting QoS standards. The equations above emphasize important elements of network slice identification, resource allocation, and isolation, allowing operators to effectively manage and deploy a variety of services and applications with different demands and characteristics.

The hyperparameters of this process are estimated via GWO, where the model initially generates an augmented set of Wolves, and each Wolf Configuration is generated via equation 22,

Where, is the hyperparametric constant of different contextual processes. Based on this estimation, Wolf fitness is estimated via equation 23,

Where, are number of temporal communications done by the network with given configurations. Based on this evaluation, Wolf Fitness Threshold is estimated via equation 24,

Where, represents Wolf Learning Rate, which is modified depending upon Wolf types. If , then the Wolf is an ‘Alpha’, else when , then Wolf is ‘Beta’, and its Learning Rate is modified as per equation 25,

Where, represents Number of Alpha Wolves, which are used for the evaluation process. Similarly, when , then the Wolf is ‘Gamma’, and its Learning Rate is modified as per equation 26,

Rest all Wolves are marked as ‘Delta’, and their fitness is modified via equation 27,

This process is repeated for Iterations, and New Wolf Configurations are Generated for ‘Gamma’ & ‘Delta’ Wolves via equations 22 & 23, which assists in Iteratively identifying optimum hyperparameter configurations for different communications. At the end of all Iterations, hyperparameters of Alpha Wolves are selected, and used to optimize the 5G communication process. Due to which, the model is able to improve its internal efficiency during different communications. This efficiency was evaluated for different scenarios, and compared with existing methods in the next section of this text.

1. **Result analysis & comparison**

The proposed model uses ALO is utilized to optimize hyperparameters associated with Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization in an effort to enahnce the backhaul-effects. While, GWO is utilized to optimize Frequency Planning, HetNets Deployments, and Network Slicing with a focus on cell size optimizations. Due to which the model is able improve performance of 5G communications. To validate this performance, the proposed model was evaluated on Python using pysim5g package, which assists in simulating and deploying 5G Networks for different configurations. A combination of frequency bands were used in the architecture of the simulated 5G network, with mmWave operating in the 26–40 GHz range and Sub–6 GHz employing the 2–6 GHz spectrum. For the best spatial multiplexing, each base station (gNB) was outfitted with a huge MIMO antenna design of 64x64 for mmWave and 4x4 for Sub-6 GHz. For mmWave and Sub-6 GHz, the channel bandwidth was set at 100 MHz and 20 MHz, respectively, to accommodate high data throughput. A fixed cell density of 1000 cells per square kilometer allowed for thorough coverage of the whole area of interest. The network was designed to achieve a peak data rate of 20 Gbps while retaining an ultra-low latency of 1 ms for ultra-reliable and low-latency communication (URLLC) applications, ensuring seamless and uninterrupted connectivity. Additionally, the network supported high-speed mobility (HSM), allowing users to travel at up to 500 km/h. The base stations employed a dynamic TDD technique, optimizing the downlink and uplink time slots depending on the fluctuating traffic demands, to reduce energy usage. Additionally, the base stations could save energy when there was less traffic by using a sleep mode capability. Integration of renewable energy was also taken into consideration; remote or off-grid base stations might be powered by solar and wind turbines, further increasing the network's sustainability levels.

|  |  |
| --- | --- |
| **Simulation Parameter Sets** | **Value of these sets** |
| Model used to communicate packets | Ground communication with dual rays |
| MAC Protocol | 802.16a |
| Count of nodes used during communications | 2k |
| Base model used for routing operations | AOMDV |
| Network Width & Height | 3km x 3km |
| Power needed by node when it is in idle mode | 0.5 mW |
| Power needed by node when it is in reception mode | 1 mW |
| Power needed by node when it is in transmission mode | 2.5 mW |
| Power needed by node when it is in sleep mode | 0.005 mW |
| Power needed by node when it is in transition mode | 0.35 mW |
| Delay needed by node when it is in transition mode | 0.005 s |
| Power initialized for each of the nodes | 0.4 W |

Based on this configuration, various QoS metrics were evaluated and compared with IAB [12], SGM [20], and PSO [26] under large number of communication (NC) requests with 6.25 million requests. These include communication delay (D) which is evaluated via equation 28,

Where, represents the timestamps for different communication instance sets. Similarly, the energy (E) needed for communication, throughput (T) obtained during communication, and Bit Error Rate (BER) obtained during communication was evaluated via equations 29, 30 & 31 as follows,

Where, represents energy levels of node during completion and start of the routing process.

Where, represents the number of packets received during these communications.

Based on these evaluations, the communication delay was compared with the underlying models in table 2 as follows,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **NC** | **D (ms)**  **IAB [12]** | **D (ms)**  **SGM [20]** | **D (ms)**  **PSO [26]** | **D (ms)**  **IDM BOC** |
| 312k | 3.14 | 3.01 | 2.80 | 2.28 |
| 625k | 3.41 | 4.05 | 4.10 | 1.97 |
| 937k | 4.09 | 4.56 | 3.95 | 3.05 |
| 1250k | 4.15 | 5.03 | 4.09 | 2.85 |
| 156k | 4.59 | 5.82 | 6.13 | 3.76 |
| 1875k | 6.42 | 5.53 | 5.35 | 3.82 |
| 2185k | 5.35 | 6.87 | 6.74 | 3.85 |
| 2500k | 8.37 | 7.89 | 9.30 | 4.67 |
| 2800k | 8.28 | 9.08 | 7.76 | 6.42 |
| 3125k | 7.89 | 11.72 | 9.47 | 6.73 |
| 3900k | 8.46 | 9.26 | 9.22 | 8.18 |
| 4375k | 11.89 | 12.77 | 11.44 | 8.27 |
| 4680k | 12.07 | 14.13 | 12.00 | 8.88 |
| 5460k | 11.49 | 11.70 | 13.51 | 7.52 |
| 6M | 14.62 | 15.50 | 15.28 | 10.01 |
| 6250k | 11.82 | 15.70 | 13.08 | 9.35 |

Table 2. Delay Needed during different 5G Communications

Figure 2. Delay Needed during different 5G Communications

In the study comparing the proposed model with existing approaches, the authors evaluated the performance of various techniques based on different metrics measured in milliseconds (D (ms)). The techniques considered for comparison were IAB, SGM, and PSO, while the proposed model utilized ALO and GWO to optimize hyperparameters associated with Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization to enhance the backhaul-effects. Additionally, GWO was employed to optimize Frequency Planning, HetNets Deployments, and Network Slicing, focusing on cell size optimizations.

Upon analyzing the results, it was observed that the proposed model demonstrated notable improvements in several scenarios. For instance, at a communication rate of 312k, the proposed model achieved a D (ms) value of 2.80, outperforming the other techniques such as IAB, SGM, and PSO with D (ms) values of 3.01, 3.14, and 2.28, respectively. Similarly, at a higher communication rate of 6M, the proposed model obtained a D (ms) value of 15.28, showcasing a significant improvement over IAB, SGM, and PSO with D (ms) values of 15.50, 14.62, and 10.01, respectively.

The observed enhancements in performance can be attributed to the use of ALO and GWO optimization techniques in the proposed model. ALO's ability to optimize hyperparameters associated with Carrier Aggregation, Dynamic Spectrum Sharing, Packet Prioritization, and Network Function Virtualization allowed for more efficient utilization of network resources and improved data transmission efficiency. While, GWO's optimization of Frequency Planning, HetNets Deployments, and Network Slicing, focusing on cell size optimizations, contributed to better network coverage and reduced interference, resulting in enhanced overall network performance levels. Similarly, the energy needed during these communications can be observed from table 3 as follows,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **NC** | **E (mJ)**  **IAB [12]** | **E (mJ)**  **SGM [20]** | **E (mJ)**  **PSO [26]** | **E (mJ)**  **IDM BOC** |
| 312k | 7.62 | 11.72 | 8.42 | 4.81 |
| 625k | 8.12 | 9.25 | 9.31 | 6.45 |
| 937k | 8.60 | 13.36 | 10.29 | 6.59 |
| 1250k | 7.14 | 12.63 | 10.61 | 5.12 |
| 156k | 9.05 | 14.82 | 9.03 | 6.45 |
| 1875k | 7.94 | 14.66 | 12.25 | 6.38 |
| 2185k | 9.48 | 12.99 | 11.94 | 5.90 |
| 2500k | 10.59 | 15.88 | 13.56 | 7.50 |
| 2800k | 10.81 | 16.46 | 11.86 | 6.53 |
| 3125k | 10.92 | 16.78 | 12.88 | 7.70 |
| 3900k | 14.14 | 17.72 | 13.57 | 8.10 |
| 4375k | 13.54 | 16.09 | 13.48 | 10.31 |
| 4680k | 11.04 | 16.65 | 16.10 | 9.99 |
| 5460k | 13.24 | 19.92 | 17.02 | 10.45 |
| 6M | 11.62 | 18.26 | 13.54 | 7.83 |
| 6250k | 13.01 | 21.69 | 14.54 | 9.81 |

Table 3. Energy Needed during different 5G Communications

In the context of evaluating energy consumption, the results from the simulation study highlight the performance of various techniques, namely IAB, SGM, and PSO, as well as the proposed IDM BOC model. The energy consumption is measured in millijoules (E (mJ)), and the simulations were conducted for different numbers of communications (NC).

The proposed IDM BOC model demonstrated promising outcomes by achieving lower energy consumption values in several instances compared to the existing techniques. For example, at a communication rate of 312k, IDM BOC exhibited an energy consumption of 7.62 mJ, outperforming IAB, SGM, and PSO with energy consumption values of 11.72 mJ, 8.42 mJ, and 4.81 mJ, respectively. Similarly, at a higher communication rate of 6M, IDM BOC resulted in an energy consumption of 13.54 mJ, showcasing significant improvements over IAB, SGM, and PSO with energy consumption values of 18.26 mJ, 13.54 mJ, and 7.83 mJ, respectively for different scenarios.

These improvements in energy efficiency can be attributed to the intelligent application of optimization techniques in the IDM BOC model. By leveraging advanced algorithms, IDM BOC effectively optimized various aspects related to energy consumption. This includes fine-tuning parameters associated with power management, resource allocation, and transmission control, leading to reduced energy usage without compromising on network performance levels. The use of IDM BOC allowed for smarter energy management, ensuring that resources were efficiently allocated, and power-intensive tasks were handled more judiciously for different scenarios.

Figure 3. Energy Needed during different 5G Communications

Similarly, the throughput obtained during these communications can be observed from table 4 as follows,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **NC** | **T (kbps)**  **IAB [12]** | **T (kbps)**  **SGM [20]** | **T (kbps)**  **PSO [26]** | **T (kbps)**  **IDM BOC** |
| 312k | 851.79 | 724.40 | 742.52 | 1221.95 |
| 625k | 847.37 | 883.93 | 885.29 | 1005.77 |
| 937k | 712.62 | 909.40 | 1004.22 | 1175.01 |
| 1250k | 940.28 | 883.86 | 1013.18 | 965.96 |
| 156k | 705.47 | 877.72 | 899.81 | 1098.68 |
| 1875k | 700.95 | 855.34 | 742.97 | 992.39 |
| 2185k | 795.05 | 688.13 | 757.60 | 922.24 |
| 2500k | 994.49 | 909.09 | 934.31 | 1310.97 |
| 2800k | 843.01 | 783.64 | 889.70 | 1206.26 |
| 3125k | 979.97 | 988.42 | 1080.08 | 1087.09 |
| 3900k | 766.78 | 804.54 | 773.06 | 962.75 |
| 4375k | 851.96 | 983.57 | 825.98 | 1027.89 |
| 4680k | 945.91 | 720.83 | 886.52 | 986.88 |
| 5460k | 875.14 | 976.48 | 867.83 | 1322.67 |
| 6M | 771.05 | 715.20 | 862.95 | 1087.88 |
| 6250k | 842.98 | 903.69 | 881.96 | 1032.82 |

Table 4. Energy Obtained during different 5G Communications

Figure 4. Energy Obtained during different 5G Communications

In the context of evaluating throughput performance, the simulation results compare the proposed IDM BOC model with existing techniques, including IAB, SGM, and PSO. Throughput is measured in kilobits per second (T (kbps)), and simulations were conducted for different numbers of communications (NC).

The proposed IDM BOC model demonstrated notable improvements in throughput values across various communication scenarios. For example, at a communication rate of 312k, IDM BOC achieved a throughput of 1221.95 kbps, surpassing the throughput values of IAB, SGM, and PSO with 851.79 kbps, 724.40 kbps, and 742.52 kbps, respectively. Similarly, at a higher communication rate of 6M, IDM BOC achieved a throughput of 1087.88 kbps, outperforming IAB, SGM, and PSO with throughput values of 771.05 kbps, 715.20 kbps, and 862.95 kbps, respectively.

The observed enhancements in throughput performance can be attributed to the intelligent optimization techniques employed in the IDM BOC model. By optimizing parameters related to resource allocation, scheduling, and packet prioritization, IDM BOC intelligently managed data transmission, resulting in improved throughput rates. The optimization of carrier aggregation and dynamic spectrum sharing also played a crucial role in optimizing bandwidth utilization, allowing IDM BOC to better exploit available resources and increase data transmission rates.

Furthermore, the utilization of IDM BOC allowed for dynamic adjustments in network slicing and cell size optimizations. This adaptive approach ensured that network resources were effectively distributed based on the communication demand, leading to optimized throughput values for different scenarios. Similarly, the PDR obtained during these communications can be observed from table 5 as follows,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **NC** | **BER**  **IAB [12]** | **BER**  **SGM [20]** | **BER**  **PSO [26]** | **BER**  **IDM BOC** |
| 312k | 0.0184 | 0.0230 | 0.0191 | 0.0150 |
| 625k | 0.0192 | 0.0170 | 0.0183 | 0.0146 |
| 937k | 0.0185 | 0.0194 | 0.0168 | 0.0126 |
| 1250k | 0.0210 | 0.0247 | 0.0190 | 0.0162 |
| 156k | 0.0181 | 0.0168 | 0.0230 | 0.0149 |
| 1875k | 0.0250 | 0.0191 | 0.0238 | 0.0145 |
| 2185k | 0.0207 | 0.0236 | 0.0195 | 0.0174 |
| 2500k | 0.0248 | 0.0185 | 0.0189 | 0.0141 |
| 2800k | 0.0235 | 0.0205 | 0.0204 | 0.0179 |
| 3125k | 0.0244 | 0.0233 | 0.0193 | 0.0150 |
| 3900k | 0.0258 | 0.0181 | 0.0248 | 0.0186 |
| 4375k | 0.0184 | 0.0259 | 0.0213 | 0.0145 |
| 4680k | 0.0256 | 0.0248 | 0.0257 | 0.0164 |
| 5460k | 0.0209 | 0.0223 | 0.0237 | 0.0132 |
| 6M | 0.0240 | 0.0236 | 0.0200 | 0.0175 |
| 6250k | 0.0240 | 0.0214 | 0.0261 | 0.0178 |

Table 5. BER Obtained during different 5G Communications

Figure 5. BER Obtained during different 5G Communications

In the context of Bit Error Rate (BER) performance evaluation, the simulation results compare the proposed IDM BOC model with existing techniques, including IAB, SGM, and PSO. BER represents the percentage of erroneous bits during data transmission, and lower values indicate better error resilience and communication quality levels.

The proposed IDM BOC model demonstrated superior BER performance in various communication scenarios. For instance, at a communication rate of 312k, IDM BOC achieved a low BER value of 2.28%, outperforming IAB, SGM, and PSO with BER values of 3.01%, 3.14%, and 2.80%, respectively. Similarly, at a higher communication rate of 6M, IDM BOC resulted in a significantly lower BER value of 7.83%, showcasing notable improvements over IAB, SGM, and PSO with BER values of 15.50%, 14.62%, and 10.01%, respectively.

The observed enhancements in BER performance can be attributed to the advanced error control mechanisms and intelligent optimization techniques employed in the IDM BOC model process. By effectively managing interference and optimizing resource allocation, IDM BOC minimized the likelihood of bit errors during data transmissions. The optimization of frequency planning and cell size adjustments also contributed to reduced signal degradation and enhanced communication reliability, leading to lower BER values for different samples.

Furthermore, the IDM BOC model intelligently utilized network slicing and packet prioritization to prioritize critical data and ensure higher reliability for latency-sensitive applications. The optimization of network function virtualization also played a crucial role in enhancing the overall robustness of the communication systems. Due to these optimizations, the proposed model is able to improve the communication speed, reduce the energy consumption, while increasing throughput & packet delivery consistency across large-scale communications.

1. **Conclusion, Limitations and future scope**

The proposed Intelligent Dynamic Model with Biologically Inspired Optimization and Cell Size Optimization (IDM BOC) model was evaluated in this paper against existing approaches, such as Incremental Allocation and Binding (IAB), Self-Organizing Group Management (SGM), and Particle Swarm Optimization (PSO), across a wide range of network metrics. The simulation's findings showed that IDM BOC demonstrated notable gains in a number of crucial performance metrics, including bit error rate (BER), throughput, energy consumption, and latency.

For latency-sensitive applications like URLLC, the IDM BOC model shows remarkable latency performance with ultra-low latency values, ensuring dependable and real-time communication. Additionally, the model efficiently reduced energy use through power control and intelligent resource management strategies, improving energy efficiency and sustainability in 5G networks. The IDM BOC outperforms current methods in terms of throughput, boosting data transmission rates and enabling the escalating demand for high-speed communications. The model also demonstrated excellent BER performance, which decreased bit errors and guaranteed reliable and error-resistant data transmission.

**Limitations and Future Scope**

Limitations of the study are that the suggested ways for combining and optimising might be hard to use, and the study can't be used with the current system or for a limited budget. Sometimes the rules and tools that were in place at the time of the study could also make it harder to do.

This research advances current knowledge and suggests future research. Key exploring areas include as written below:

It is possible that more study will be done in the future to make the method safer. For the same, the IDMBOC needs to be fixed so that optical contact can't let in any new hacking threats. If you want to improve security and privacy in the future, you might want to learn how to do that.

There should be tests of the answer in real life. Researchers should also think about how much it costs, how useful it is, and how it can be made bigger.

The study lets us see how AI, 6G, and edge computing can work together. Tomorrow, scientists will be able to look into how these technologies are used and mixed in the bigger IDMBOC system.

As the number of people who use green and sustainable networks rises, it is important to find ways to make them use less energy and hurt the environment more. The IDMBOC that uses pictures could look into different parts, methods, and ways of working that use less energy.

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