A Novel Power Optimization Technique for Sliced 5G Network

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***Abstract*—To reduce power consumption and extend network lifespan, academic and industrial groups have focused on energy-efficiency approaches for Next Generation Networks (NGNs). Fifth-generation (5G) networks offer a large number of services at high data rates, low latency, and massive connectivity. Increasing volumes of heterogeneous traffic from billions of devices, ranging from smartphones to intelligent transport systems, significantly challenge network resource utilization, particularly power consumption. This study targets energy-efficient resource allocation in sliced 5G systems, ensuring service-level guarantees for heterogeneous applications through intelligent optimization. This work proposes a novel hybrid optimization framework for energy-aware resource provisioning in 5G sliced networks using Hybrid Grey Wolf–Tasmanian Devil Optimization (HGWTDO) with a Linear Pattern Search (LPS) refinement technique. While HGWTDO combines the global search ability of Grey Wolf Optimization (GWO) and the exploitation abilities of the Tasmanian Devil Optimizer, the addition of LPS provides accurate local convergence. LPS has been integrated into the proposed solution to enhance optimization results. The solution is augmented with a Classification Tree-based classification that assigns users to their corresponding slices for Mobile Broadband (eMBB), Ultra-Reliable Low Latency Communications (URLLC), and massive Machine-Type Communication (mMTC) based on quality of service (QoS) requirements. The suggested system provides improved power efficiency under QoS constraints and is an intelligent, scalable solution for energy-aware 5G network slicing compared with existing techniques.**

***Index terms*—Particle Swarm Optimization, Ant Colony Optimization, Adaptive Tasmanian Devil Optimization, Linear Pattern Search, Grey Wolf Optimization (GWO), 5th Generation Networks.**

I. INTRODUCTION

Fifth-generation (5G) network deployment is a breakthrough in mobile communications, providing much higher data rates, ultra-low latency, and the capability to support a vast number of connected devices. These features enable a whole variety of future applications, from immersive multimedia broadcasting to autonomous cars, remote operation, and industrial IoT.

Manuscript received November 26, 2025; revised December 16, 2025. Date of publication July 1, 2026. Date of current version July 1, 2026. The associate editor prof. Gordan Šišul has been coordinating the review of this manuscript and approved it for publication.

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Digital Object Identifier (DOI): 10.24138/jcomss-2025-0199

This breakthrough technology brings forth pressing challenges, at the top of which are effective resource management and energy efficiency [1].

Network slicing is one of the key ideas for addressing heterogeneous service requirements in 5G networks. Network slicing enables the development of multiple virtualized, isolated network slices with distinct settings for various use cases, such as enhanced eMBB, URLLC, or mIoT. [2]. Each slice is tailored to its traffic behaviors and QoS demands, and a unified physical infrastructure serves various applications. Though the advantages are immense, provision for such dynamic and heterogeneous slices is highly advanced in terms of resource management and power distribution.

Traditional resource allocation techniques are not intelligent or dynamic enough to meet the increasing performance requirements and energy constraints of 5G networks. Intelligent optimization techniques capable of dynamic adaptation to real-time network scenarios are therefore becoming increasingly popular. One such well-known technique in this context is GWO, which has been shown to have potential for enhancing energy efficiency by simulating leadership-based hunting procedures for resource management in 5G RAN slicing application scenarios [3], [22], [23].

At the same time, rule-based and adaptive heuristic solutions are being crafted to account for fluctuations in traffic load and application demand. The solutions employ feedback-based optimization algorithms that continuously adapt system parameters to changing network conditions. In contrast to traditional static models, these adaptive solutions can provide greater responsiveness and energy savings across a range of use cases. Besides, hybrid metaheuristics combining algorithms such as GWO with other nature-inspired algorithms, such as PSO and ACO, are also being explored to address the nonlinear and multi-objective nature of 5G-dense network resource management.

Developments in Network Function Virtualization (NFV) and Software-Defined Networking (SDN) have added more control and programmability to network infrastructure. These technologies make it easier to offer differentiated, service-aware resource management approaches that promote greater isolation and customization among network slices [3]. Researchers are increasingly seeking quantum-inspired solutions, such as the Variational Quantum Regressor, to address the computational complexity of multi-variable optimization in dense 5G environments [4].

For applications where low latency and high reliability are critical, such as mission-critical and real-time automation, optimization techniques are developed that ensure deterministic behaviour at the cost of higher energy consumption [10]. For these applications, adaptive systems based on Stochastic Petri Nets (SPN) have proven effective for modelling and management of different usage scenarios, providing a probabilistic environment that enables adaptable, scenario-dependent decision-making [8], [16], [17].

Inspired by these breakthroughs, this research presents a new hybrid optimization approach for resource and energy management of sliced 5G networks. The new model seeks to optimize energy efficiency, quality of service guarantees, and resource fairness through adaptive allocation mechanisms that respond to time-varying traffic flows and service requests. By leveraging prediction-aware insight fusion and optimization-guided scheduling, the framework minimizes power consumption without impairing network performance. The results encourage more sustainable and intelligent 5G networks that pave the way for new opportunities to optimize communication systems empowered by future-generation network slicing.

This paper presents a Hybrid Grey Wolf–Tasmanian Devil Optimization (HGWTDO) with an LPS scheme for power-efficient resource allocation in a 5G network. The contributions of this work are highlighted as:

- Development of optimal power allocation for resource allocation in 5G using a hybrid HGWTDO algorithm. The proposed HGWTDO combines the TDO with the traditional GWO algorithm to improve solution diversity, the exploration-exploitation balance, and convergence, thereby enhancing optimal power allocation.
- The LPS scheme is utilized to improve the local convergence and improve the solution diversity of the HGWTDO algorithm for optimal power allocation.
- The effectiveness of the system is evaluated on the DeepSlice dataset based on average power allocation and computation time.

This article is presented as follows: related work is summarized in Section II. Section III emphasizes the proposed methodology. Section IV highlights simulation results and performance analysis. Finally, section V depicts conclusions.

II. Related Work

This section provides a survey of various soft-computing algorithms for resource allocation in 5G. Kulkarni et al. [1] introduced a dynamic resource-allocation approach for 5G Radio Access Network (RAN) slicing using GWO. The primary objective is to reduce power consumption while efficiently allocating resources across slices. The proposed GWO-based strategy achieves a 17.5% improvement in energy efficiency, demonstrating its potential for lightweight optimization. However, the method shows limited capacity to handle complex or high-dimensional resource management problems, underscoring the need for more scalable, robust optimization frameworks.

Y. Azimi et al. [2] investigated the use of deep reinforcement learning (DRL) for energy-efficient resource allocation in 5G RAN slicing. The model focuses on real-time optimization of power and resource blocks, resulting in improved allocation precision in dynamic environments. Nonetheless, the DRL approach suffers from significant drawbacks, including high computational overhead, extended training times, and complexity, which restrict its applicability in time-sensitive and real-time systems. To address architectural flexibility, X. Wang [3] proposes a differentiated resource allocation method using SDN and NFV. Their solution dynamically allocates power and bandwidth resources across network slices, improving both scalability and quality of service compliance. The SDN/NFV-based model leverages programmability to adapt to varying service demands. Pathak et al. [4] employed a Variational Quantum Regressor (VQR) for resource allocation optimization in 5G environments. The study shows that VQR improves predictive accuracy and minimizes Mean Squared Error (MSE) in resource allocation outcomes. Despite the promising results, the approach is constrained by current limitations in quantum hardware availability and computational scalability, especially in large-scale deployments. Hanczewski [5] focused on optimizing bandwidth and power distribution in critical systems within 5G networks through a multi-agent resource management model. Although it demonstrates efficient resource handling, it falls short of addressing slicing-specific requirements. Xie [6] introduced an adaptive algorithm based on Stochastic Petri Nets (SPN) for multi-scenario power service environments. The model dynamically reallocates resources under varying conditions, improving reliability and efficiency. Though effective in general power systems, the solution lacks contextual adaptation for 5G-sliced networks, where latency sensitivity and traffic diversity introduce additional complexity that standard adaptive methods do not fully address.

Lewis and Torczon [7] presented Pattern Search Methods for solving linearly constrained minimization problems. As a derivative-free optimization technique, pattern search is valuable for complex engineering tasks where gradient information may be unreliable or inaccessible. Wang and Lyu [8] presented the Adaptive Tasmanian Devil Optimizer (ATDO), an advanced metaheuristic designed to solve complex global optimization problems. Originally applied to wireless sensor network (WSN) deployment, ATDO dynamically adjusts its exploration and exploitation strategies to enhance convergence and avoid local optima. Its flexibility and scalability make it suitable for broader applications beyond WSNs. Drawing on its adaptive nature, this research integrates ATDO into the 5G slicing context to optimize power consumption. Furthermore, a hybrid model combining ATDO with GWO is proposed to improve energy efficiency while satisfying quality of service constraints across diverse network slices [11], [12], [13].

Shami et al. [9] provide an extensive review of PSO, including its fundamental principles, variants, and hybridization techniques for addressing complex optimization problems. The study reinforces the power of PSO in exploiting nonlinear, multidimensional search spaces while operating in dynamic environments, such as those encountered in wireless networks. But it lacks a specific focus on 5G network slicing and real-time resource allocation with minimized energy consumption. By combining PSO's global search capability with other metaheuristics, improved performance in energy-conscious, slice-specific optimization for 5G networks is attainable [21]. Dorigo and Stützle [10] present a detailed overview of Ant Colony Optimization (ACO), highlighting its evolution and effectiveness in solving complex, multi-objective problems. ACO, inspired by the collective behavior of ants, employs distributed search and probabilistic path selection to explore optimal solutions. Its adaptive and scalable features make it suitable for dynamic environments like 5G networks. In this study, ACO is employed as a benchmark metaheuristic for power-efficient resource allocation in network slices. Its ability to handle nonlinear constraints and optimize under uncertainty contributes to energy-aware, QoS-compliant decision-making in sliced 5G systems [20].

In recent years, various studies have focused on optimizing the outcomes of the power allocation methods. Kulkarni et al. [25] introduced a Deep Actor-Critic RL model (DACRL-NS) for dynamic resource allocation in 5G network slicing. The method learns from real-time network conditions and reallocates resources based on slice quality of service needs, removing slices that fail to meet minimum quality of service requirements. Their approach improved throughput by 8.92% for rate-based slices, 16.36% for latency-based slices, and boosted overall throughput by 17.14%—Fayad and Cinkler [26] aimed to reduce power consumption in 5G mmWave networks. Since exact ILP optimization becomes infeasible at scale, they applied a Genetic Algorithm to find a near-optimal allocation. The GA approach reduced power usage and improved throughput and energy efficiency, achieving savings of 22.34% in residential and 33.12% in office environments. Abuajwa and Mitani [27] used Simulated Annealing (SA) for resource allocation in NOMA-based 5G systems. Because optimal allocation is NP-hard, SA efficiently assigns channels and power levels. Their results showed a 22% gain in energy efficiency and a reduction in computation time, demonstrating SA's suitability for real-time allocation. Al-Zubi et al. [28] proposed a Markov-based analytical model for power allocation in HARQ-enabled MIMO-NOMA networks. They modeled retransmission behavior using a discrete-time Markov chain and introduced two power allocation strategies that minimized outage probability, achieving near-zero outage for specific users. Yadav and Nanivadekar [29] presented a hybrid optimization-based power allocation model to improve energy efficiency in 5G. Using MS-DA, the system converges to optimal power allocation for SISO and MIMO setups, maintaining quality of service while reducing energy consumption. Their method outperformed conventional allocation techniques across different network conditions.

Sampath et al. [30] developed a QoS-aware Deep Q-Network (Q-DQN) power allocation method for uplink 5G heterogeneous networks. Their approach helps IoT devices automatically select the most energy-efficient base station while still meeting quality of service requirements. By learning from real-time network conditions, the Q-DQN model adjusts transmission power to improve energy savings without affecting connectivity to macro base stations. Experimental results showed clear improvements in QoS, network capacity, and energy efficiency, demonstrating that reinforcement learning can effectively balance performance and power consumption. Halabouni et al. [31] proposed a hybrid resource allocation method that combines a Genetic Algorithm and Simulated Annealing (GA-SA) for NOMA-MIMO systems. GA handles user pairing, while SA fine-tunes power allocation to maximize SINR and reduce interference. The hybrid technique reacts dynamically to changes in SINR and avoids getting stuck in local optima—an issue encountered with traditional methods. Tests revealed up to 15% higher throughput and 20% higher SINR than using GA or SA alone. Although power usage increases slightly, the method delivers a 25% gain in throughput efficiency, making it well-suited for high-performance 5G networks.

Various methods have been presented for resource allocation, considering power, delay, and bandwidth optimization, to enhance the QoS of 5G services. However, the efficacy of the algorithms is limited by computational complexity, the inability to handle multi-objective functions, poor solution diversity, and an imbalance in the exploitation-exploration strategy. The poor convergence of optimization algorithms leads to suboptimal and longer resource allocation times in 5G. Thus, this paper provides the HGWTDO with an LPS scheme to enhance convergence, solution diversity, the balance between exploitation and exploration, and to minimize optimization time, thereby improving power allocation in 5G.

III. METHODOLOGY

The optimizer proposed in this research work introduces a hybrid algorithm that combines GWO and TDO, called Hybrid Grey Wolf–Tasmanian Devil Optimization (HGWTDO). This research work focuses on an energy-aware resource allocation scheme designed explicitly for sliced 5G networks. The primary objective is to reduce the overall power consumption while satisfying the individual quality of service demands of each network slice. For data collection, the network is classified into three broad categories —enhanced eMBB, URLLC, or mIoT. using a machine learning algorithm called a classification tree. Each slice is designed to cater to various types of applications. For instance, eMBB enables high-data-rate services such as video streaming, URLLC is tailored for ultra-reliable and low-latency services such as real-time automation control, and mIoT combines an unimaginably massive number of low-power devices such as sensors [3], [14], [15]. By segregating the network into these slices, each user can be allocated resources more appropriately, based on their service demands. This ensures efficient use of available resources and compliance with each slice's quality of service constraints.

A. Formulating the Power Allocation Problem

The core optimization problem is to allocate power among users to minimize the total network power consumption. Let P_i denote the power allocated to the i^{th} user. The fitness function considers allocated power, Packet Delay Budget (PDB), Packet Loss Rate (PLR), and Guaranteed Bit Rate (GBR) as given in equation 1. Power allocation plays a crucial role in 5G by ensuring that users meet strict latency, reliability, and data rate requirements while avoiding unnecessary energy consumption.

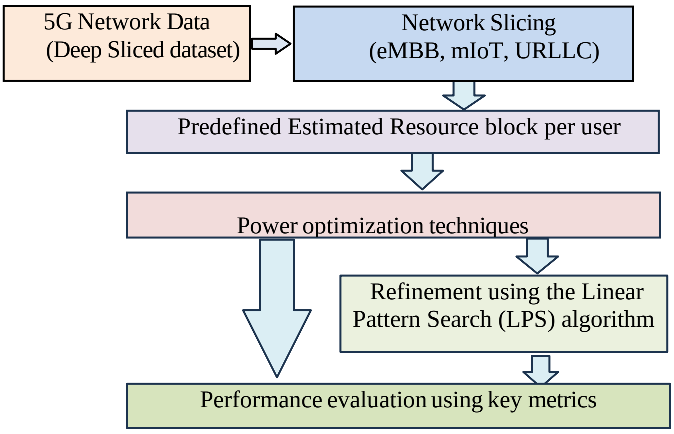

Fig. 1. Proposed workflow diagram

By adapting transmit power based on network conditions and QoS demands, the system can deliver reliable performance during congestion or poor channel conditions. This intelligent power control enables efficient, user-centric, and environmentally sustainable 5G communication.

$$fitness_i = \min\left(w_1 \sum_{i=1}^{N} P_i + w_2 PDB_i + w_3 PLR_i + w_4\,(1/GBR_i)\right) \tag{1}$$

Here, N is the total number of users in the network, PDB signifies packet delay budget, PLR symbolizes packet loss rate, GBR_i stands for guaranteed bit rate of i^{th} device. The weights w_1, w_2, w_3 *and* w_4 are chosen such that $w_1 + w_2 + w_3 + w_4 = 1$. Here, all weights are given equal importance of 0.25. Each power allocation must respect upper and lower bounds that vary by service slice. For instance, users in the eMBB slice may have higher power requirements than those in the mIoT slice. Upon satisfying the above requirement, the power allocated to different slices will be constrained by Equation 2.

$$P_i^{min} \le P_i \le P_i^{max} \tag{2}$$

The power is initially randomly allocated in between 0.25W (P_i^{min}) and 1W (P_i^{max}) for all devices.

B. Metaheuristic HGWTDO Optimization Techniques

To address this optimization problem, several nature-inspired metaheuristic algorithms were studied and compared. These include PSO [9], ACO [10], ATDO [8], and HGWTDO. Each of these algorithms mimics natural phenomena, such as bird flocking in PSO and ant foraging in ACO, to discover optimal or near-optimal solutions in complex environments. HGWTDO learns to adapt to the temperament of each slice and user needs, and iteratively updates candidate solutions until an optimal or suboptimal power allocation is achieved. The flow diagram of the HFWTDO is shown in Figure 2.

Grey wolves have distinct social structures and hierarchies and hunt in groups. The primary stages of hunting grey wolves are as follows: • Tracking, encircling, and intimidating the victim until it becomes stable • Finding, chasing, and surrounding the target • Launching an attack on the target.

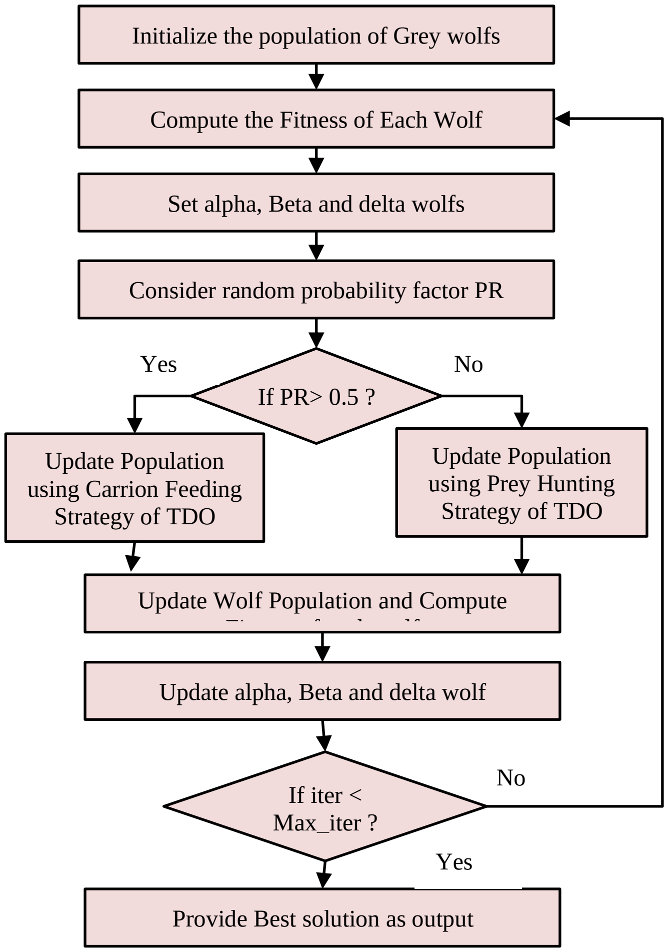

Fig. 2. Flow diagram of HGWTDO algorithm

The prey is represented in equations 3-4 as a swarm of grey wolves that have circled it after searching it.

$$\vec{e} = \left|\vec{o}.\vec{x_p}(i) - \vec{x}(i)\right| \tag{3}$$

$$\vec{x}(i+1) = \vec{x_p}(i) - \vec{b}.\vec{e} \tag{4}$$

where $\vec{z}$ indicates the coefficient vector characterizing the blockage in the hunting channel as wolves approach the prey, and, as equation 5 illustrates, i denotes the current iteration. The prey's $\vec{x_p}$ and the grey wolf's $\vec{x}$ positions are given by equation 6, where $\vec{b}$ is a control parameter and $\vec{e}$ is the coefficient vector that defines the separation between the two wolves.

$$\vec{z} = 2 \times \vec{r_2} \tag{5}$$

$$\vec{b} = 2 \times \vec{l} \times \vec{r_1} - \vec{l} \tag{6}$$

In every iteration, the component $\vec{l}$ declines linearly from 2 to 0, and the arbitrary vectors $\vec{r_1}$ and $\vec{r_2}$ are selected from the interval [0, 1]. The wolves α, β, and δ lead the pack's attacks on their prey after encircling the victim. Of the three wolves, the Alpha is the most favorable choice. Equations 7–13 provide a mathematical depiction of the grey wolf's predatory nature.

$$\vec{e_\alpha} = |\vec{z_1}.\vec{x_\alpha}(i) - \vec{x}(i)| \tag{7}$$

$$\vec{e_\beta} = |\vec{z_2}.\vec{x_\beta}(i) - \vec{x}(i)| \tag{8}$$

$$\vec{e_\delta} = |\vec{z_3}.\vec{x_\delta}(i) - \vec{x}(i)| \tag{9}$$

$$\vec{X_1} = \vec{X_\alpha}(i) - \vec{b_1}.\vec{E_\alpha} \tag{10}$$

$$\vec{X_2} = \vec{X_\beta}(i) - \vec{b_2}.\vec{E_\beta} \tag{11}$$

$$\vec{X_3} = \vec{X_\delta}(i) - \vec{b_3}.\vec{E_\delta} \tag{12}$$

$$\vec{x}(i+1) = \frac{(x_1 + x_2 + x_3)}{3} \tag{13}$$

In the standard GWO, the population is updated using a single exploration-focused strategy, which often overlooks better potential solutions and lacks a balance between exploration and exploitation. To address this, the proposed method integrates GWO with the Tasmanian Devil Optimization (TDO) algorithm to improve population updates. TDO is inspired by the behavior of Tasmanian devils, which are opportunistic feeders. They either hunt prey or consume carrion—each with a 50% chance. In the algorithm, the individual with the highest fitness is considered the best devil and guides the population. Depending on the strategy triggered (hunting or feeding), the population is updated to search widely (exploration) or refine promising solutions (exploitation). This combination helps achieve better balance and improves hyperparameter selection.

1) Feeding on carrion (Exploration phase)

Tasmanian devils sometimes avoid hunting and instead feed on nearby carrion, often left by larger predators. In TDO, these carrions represent positions of other solutions rather than the best individual. The k^{th} The Member is seen as carrion, and TDs primarily focus on it. Using equation 14, the i^{th} demon selects the C_i from the available carrion. A value between 1 and N is selected for the variable k.

$$C_i = T_k \quad i = 1,2,\ldots\ldots,N;\ k = 1,2,\ldots\ldots N; i \neq k \tag{14}$$

After carrion selection, the TD's position is updated using equations 15-16. If the Fitness of the carrion is better, then only the TD moves toward the carrion; otherwise, it moves away.

$$T_{i,j}^{new\_c} = \begin{cases} T_{i,j} + r1 * (C_{i,j} - r2 * T_{i,j}) & \text{if } Fitness_{ci} < Fitness_i \\ T_{i,j} + r1 * (T_{i,j} - C_{i,j}) & \text{otherwise} \end{cases} \tag{15}$$

$$T_i = \begin{cases} T_{i,j}^{new\_c} & \text{if } Fitness_i^{new\_c} < Fitness_i \\ T_i & \text{otherwise} \end{cases} \tag{16}$$

Here, $T_{i,j}^{new\_c}$ stands for the updated Tasmanian devil population after finding carrion, $C_{i,j}$ represents the selected carrion, r1 is the arbitrary number between [0,1], r2 is the arbitarary number (1 or 2), $Fitness_{ci}$ denotes the Fitness of carrion, $Fitness_i$ signifies Fitness of the selected TD for updation and $Fitness_i^{new\_c}$ denotes the Fitness of the updated devil.

2) Feeding on eating Prey (Exploitation phase)

In this phase, the Tasmanian devil (TD) searches for prey, attacks it, and consumes it. It encompasses stages such as searching, attacking, killing, and eating the prey. This phase is similar to finding carrion and eating. The location of the other members, rather than the best member, is assumed as prey. The k^{th} member is considered prey, and the devils target the carrion. The ith TD selects the P_i as prey, as given in equation 17. The value of k is chosen between 1 to N.

$$P_i = T_k \quad i = 1,2,\ldots\ldots,N; k = 1,2,\ldots\ldots N; i \neq k \tag{17}$$

Once the prey is chosen, the devils chase and trap the prey. After prey selection, the TD's position is updated using equations 18 and 19. If the prey's fitness is higher, only the TD travels toward the prey. Else. It travels away from the prey.

$$TD_{i,j}^{new\_p} = \begin{cases} TD_{i,j} + r1 * (P_{i,j} - r2 * TD_{i,j}) & \text{if } Fitness_{pi} < Fitness_i \\ TD_{i,j} + r1 * (TD_{i,j} - P_{i,j}) & \text{otherwise} \end{cases} \tag{18}$$

$$TD_i = \begin{cases} TD_{i,j}^{new\_p} & \text{if } Fitness_i^{new\_p} < Fitness_i \\ TD_i & \text{otherwise} \end{cases} \tag{19}$$

Here, $TD_{i,j}^{new\_p}$ stands for the updated TD population after hunting prey, $C_{i,j}$ Represents the selected prey, r1 is an arbitrary number between [0,1], r2 is an arbitrary number (1 or 2), $Fitness_{ci}$ denotes Fitness of carrion, $Fitness_i$ signifies Fitness of the selected TD for updation and $Fitness_i^{new\_p}$ is the Fitness of an updated TD after hunting prey.

During the second phase of prey chasing and hunting, the TD updates its position within the local search area. The position is updated using equations 20-22 during the chasing process. The new position is accepted if it provides higher Fitness than the previous position.

$$R = 0.01\left(1 - \frac{\text{iter}}{\text{iter\_max}}\right) \tag{20}$$

$$T_{i,j}^{new} = T_{i,j} + (\text{Two} * r1 - 1) * R * T_{i,j} \tag{21}$$

$$T_i = \begin{cases} T_{i,j}^{new} & \text{if } \text{Fitness}_i^{new} < \text{Fitness}_i \\ T_i & \text{otherwise} \end{cases} \tag{22}$$

where R gives the radius of the search space, iter is iteration count, iter_max stands for total iterations, $T_{i,j}^{new}$ is the updated status of the TD while chasing the prey and Fitness_i^{new} is the Fitness of the updated TD position?

C. *Refinement Using Linear Pattern Search*

To enhance the precision of the metaheuristic algorithms, a LPS mechanism was used as a post-optimization step. Unlike stochastic approaches, LPS is a local search method that is derivative-free and deterministic, producing neighbors of a current solution by progressively modifying one variable at a time. A new neighbor is chosen as the new solution if it has a lower total power consumption. Let P_i be the current power of user i, and Δ be the small step size. LPS moves in the direction given by equation 23.

$$P_i \rightarrow P_i + \Delta \tag{23}$$

If the new solution decreases, P_{total} is accepted, the step size is halved and the search continues; otherwise, it is halved and the search continues. This optimization was applied to all algorithms — PSO, ACO, ATDO, and HGWTDO — to ensure equal performance in the comparison and enable each algorithm's solution to be locally optimized without gradients or knowledge of the objective function's shape [12], [18], [19].

D. *Power-Based Evaluation and Validation*

Power consumption is used as the sole optimization criterion for the process. The total power used by all consumers after optimization is compared with the available power budget to determine energy efficiency. The leftover power is determined using equation 24.

$$P_{remaining} = P_{budget} - P_{total\_utilised} \tag{24}$$

This remaining energy is a measure of how much energy each algorithm saves in satisfying slice-specific requirements. By using LPS after each global optimization iteration, each algorithm's solution is translated closer to a local optimum, ensuring that the outcomes reflect both global exploration and local exploitation. The suggested method integrates network slicing with global metaheuristic optimization and local adaptation through LPS. The resulting hybrid method supports effective QoS-conscious, energy-efficient resource provisioning in 5G network environments.

IV. Results and Discussion

This section gives the performance analysis of the listed metaheuristic algorithms for power optimization in a sliced 5G network. The aim is to distribute power optimally across three service slices — eMBB, URLLC, and mIoT — while minimizing total power consumption and meeting QoS demands. Four optimization methods —PSO, ACO, ATDO, and HGWTDO —were used and validated across different user cases. Average dissipated power per slice, total power consumed, and remaining power are also considered crucial performance measures.

A. *Simulation Setup*

The proposed system was simulated in MATLAB. User counts of 30, 50, and 100 were randomly assigned across the three service slices, like eMBB, URLLC, and mIoT. A fixed power budget was distributed among users based on decisions made by each optimization algorithm. To ensure fairness and robustness, all algorithms were run multiple times under identical conditions with different random initializations. The objective was to minimize total power consumption while meeting each slice's QoS requirements, and the minimum/maximum power limits per slice were strictly enforced.

B. *Data Acquisition and Preprocessing*

A 5G service dataset from Kaggle [24] is used to simulate real network demands and includes key QoS factors: Packet Delay Budget (latency), Packet Loss Rate (reliability), and Guaranteed Bit Rate (GBR). These factors represent the ITU/3GPP-defined service categories — URLLC, eMBB, and mIoT. Although simulated, the dataset reflects real 5G performance, making the results reliable and generalizable. Each record contains three features: packet delay budget, packet loss rate, and guaranteed bit rate. Since these values vary widely, they are normalized to a 0–1 scale so each parameter contributes equally during optimization, as defined in Equation 25.

$$x_{\text{norm}} = \frac{(x - x_{\min})}{x_{\max} - x_{\min}} \tag{25}$$

This preprocessing step prepares the data for efficient handling in the later optimization stages.

C. *Discussion of Simulation Scenarios without using LPS*

The system has implemented optimization techniques across 30, 50, and 100-user scenarios. In this section, we run optimization techniques without using the Linear Pattern Search algorithm.

1) *Simulation Results for 30 Users:*

In the simulation involving thirty users, the network was provisioned with a total bandwidth of 100 MHz, a power budget of 50 watts and a time frame of 50 milliseconds. The system throughput was configured at 1000 Mbps to support service-specific demands across the URLLC, eMBB, and mIoT slices. Table I illustrates the performance of four optimization algorithms — PSO, ATDO, HGWTDO, and ACO — for power allocation among three users in a 5G-sliced network supporting URLLC, eMBB, and mIoT services.

TABLE I
AVERAGE POWER ALLOCATION BY ALGORITHMS, INCLUDING SLICES FOR THREE USERS

Algori-thms	Device Type	1st	2nd	3rd	4th	5th	AVG allocated power (w)
PSO	URLLC	25.3	28.4	29.7	28.7	29.9	28.368
	eMBB	13.2	14.6	12.4	13.5	11.7	13.098
	mIoT	1.53	2.34	3.23	2.99	2.55	2.528
	Remaining power	9.9	4.69	4.7	4.89	5.85	
ATDO	URLLC	28.4	24.4	27.6	29.6	27.9	27.566
	eMBB	13.2	14.2	13	14.7	11.5	13.314
	mIoT	4.49	4.47	4.69	4.61	2.37	4.126
	Remaining power	3.99	6.91	4.69	1.13	8.25	
ACO	URLLC	19.4	21.3	18.5	22.8	25.8	21.554
	eMBB	9.15	7.9	11	8.23	11.3	9.518
	mIoT	1.99	4	3.01	3.52	2.79	3.062
	Remaining power	19.5	16.8	17.5	15.5	10.1	
HGWTDO	URLLC	11.5	21.2	7.58	13.7	18.3	14.452
	eMBB	10.2	5	7.32	9.59	10.2	8.458
	mIoT	0.8	4	3.25	4	1.45	2.7
	Remaining power	27.5	19.8	31.9	22.7	20.1	

Table II provides the average allocated power per slice and the overall remaining power, both in watts and as a percentage. Among the algorithms, HGWTDO demonstrates the highest efficiency by allocating the least average power across all slices, as shown in Table 1: 14.45W for URLLC, 8.46W for eMBB, and 2.7W for mIoT, resulting in a significant remaining power of 24.39W, which accounts for 48.78% of the power budget. This indicates its superior ability to balance optimization across service-specific constraints. In comparison, ACO achieves moderately efficient power use with a remaining power of 15.87W (31.73%), while PSO and ATDO perform less efficiently, leaving only 6.006W (12.01%) and 4.994W (9.99%), respectively. Both PSO and ATDO tend to over-allocate power to URLLC.

TABLE II
AVERAGE POWER SAVED BY ALGORITHMS FOR 30 USERS

Algorithms	Initial Power Demand (W)	Remaining power (W)	Final allocated power (w)	Power Saved (%)
PSO	50	6.006	43.99	12.012
ATDO	50	4.994	45	9.988
ACO	50	15.866	34.13	31.732
HGWTDO	50	24.39	25.61	48.78

These results confirm that HGWTDO is the most effective technique in optimizing resource allocation in sliced 5G scenarios, achieving energy conservation without compromising the QoS requirements of each service category.

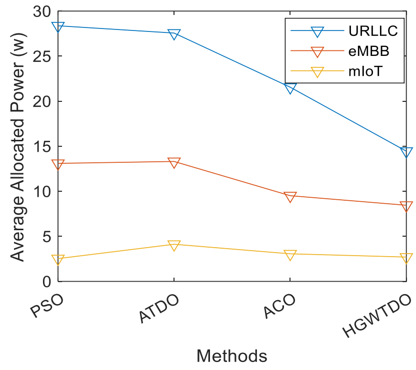

Fig. 3. Power allocation in Watts for 30 users of 3 device types

Figure 3 compares average power allocation across URLLC, eMBB, and mIoT slices for four optimization algorithms: PSO, ATDO, HGWTDO, and ACO. URLLC consistently receives the highest power due to its stringent QoS demands, while mIoT requires the least. Among all methods, HGWTDO achieves the lowest power allocation for each slice, indicating superior efficiency in managing resource constraints. PSO and ATDO allocate more power, particularly to URLLC, showing less effective optimization. ACO performs better than PSO and ATDO but remains less efficient than HGWTDO. Overall, HGWTDO demonstrates the most energy-efficient and slice-aware power allocation strategy.

Figure 4 depicts the average power allocation for the thrirty users using four optimization algorithms across device types: eMBB, mIoT, and URLLC. HGWTDO demonstrates the minimum allocated power required to support its enhanced performance. ACO provides considerable energy savings, while PSO and ATDO provide lower energy conservation. The outcomes indicate that the strength of HGWTDO lies in achieving the lowest power consumption, making it energy-efficient for 5G networks. This verifies that HGWTDO is the most power-conscious solution among the studied optimization methods with 30 user scenarios.

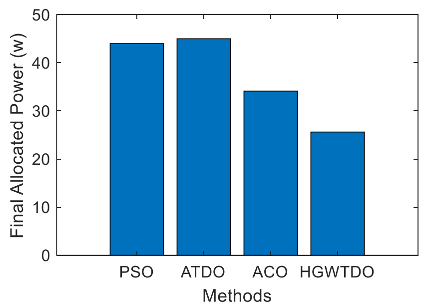

Fig. 4. Average Power allotted by algorithms for 30 users without LPS

2) Simulation Results for 50 Users:

For the 50-user case, the simulation settings were set to a total bandwidth of 100 MHz, a power budget of 50 watts, and a duration of 50 milliseconds. The network throughput was kept at 1000 Mbps to compare the efficiency of power allocation across a larger number of users in all three URLLC, eMBB, and mIoT slices. Table III provides the remaining power results of 50 participants using four optimization algorithms: ATDO, PSO, ACO, and HGWTDO. HGWTDO is the least energy-consuming among them with an average rest power of 22.20 watts, i.e., 44.40% of the budgeted power. It is in proportion to its increased capability of resource allocation, while being less energy-consuming.

TABLE III
THE POWER ALLOCATED TO 50 USERS BY OPTIMIZATION TECHNIQUES

Algorithms	Initial Power Demand (W)	Remaining power (W)	Final allocated power (w)	Power Saved (%)
PSO	50	14.437	35.563	28.874
ATDO	50	13.969	36.031	27.938
HGWTDO	50	22.203	27.797	44.406
ACO	50	14.457	35.543	28.914

ATDO, PSO, and ACO are compared, with average residual power percentages of around 27.94%, 28.87%, and 28.91%, respectively. PSO and ACO differ minimally. The consistently higher residual power across runs indicates that HGWTDO can meet service requirements while consuming less energy. With higher user density, this efficiency is crucial to the network's sustainable operation.

The energy consumption of the three user classes—eMBB, mIoT, and URLLC is seen in Figure 5 for four algorithms. Power consumption by eMBB is as high as 20 W, while mIoT is as low as 3W. The results in Figure 4 demonstrate a fair power allocation in the range 7W to 14W for all three slice types. Meanwhile, PSO offers dynamic power allocation over the range 3W to 20W, demonstrating the effectiveness of resource-allocation algorithms.

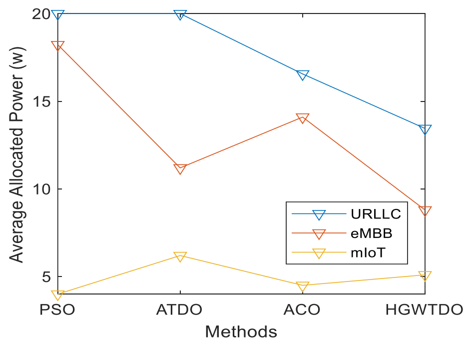

Fig. 5. Power allocation in Watts for 50 users of 3 device types

Figure 6 shows the average power allocation by the four optimization algorithms for 50 users: PSO, ATDO, HGWTDO, and ACO. HGWTDO clearly outperforms the others, achieving the highest remaining power of approximately 44%, indicating superior power efficiency. PSO and ACO perform comparably, each retaining about 29% of the power budget, while ATDO trails slightly. The higher residual power observed in HGWTDO demonstrates its effective power-saving capability while still fulfilling Quality of Service requirements. These findings confirm HGWTDO as the most energy-conscious solution for power allocation in medium-scale 5G network slicing environments.

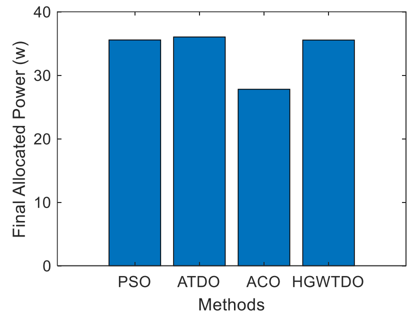

Fig. 6. Average power allotted by algorithms for 50 users without LPS

3) Simulation Results for 100 Users:

For the 100-user scenario, the simulation parameters were set to 100 MHz bandwidth, a 50-watt power budget, and a 50-millisecond duration. The overall network throughput was maintained at 1000 Mbps. This setup is to determine how efficiently power is managed with a larger number of users across all three URLLC, eMBB, and mIoT slices.

TABLE IV
THE POWER ALLOCATED TO 100 USERS BY OPTIMIZATION TECHNIQUES

Algorithms	Initial Power Demand (W)	Remaining power (W)	Final allocated power (w)	Power Saved (%)
PSO	50	2.88	47.12	5.76
ATDO	50	5.1	44.9	10.2
HGWTDO	50	16.55	33.45	33.1
ACO	50	14.6	35.40	29.2

Table IV illustrates the power consumption for the mIoT, URLLC, and eMBB slices for four algorithms—PSO, ATCO, ACO, and HGWTDO—executing for 100 users without a LPS. Above all, HGWTDO demonstrates the lowest overall power consumption (33.45 W) and is the most energy-efficient. Conversely, both PSO and ATDO exhibit the lowest efficiency, with total power values of 47.12 W and 44.9 W, respectively. Both findings clearly indicate the suitability of HGWTDO for reducing power consumption in an unsupervised 5G slicing environment.

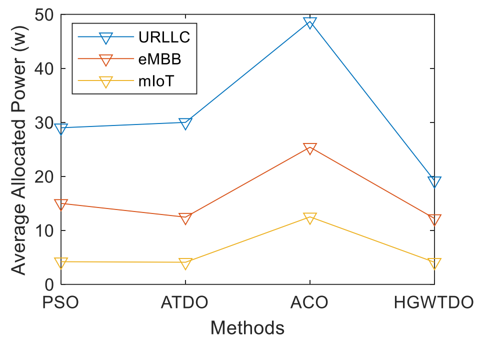

Fig. 7. Power allocation in Watts for 100 users of 3 device types

Figure 7 compares the power consumption of three 5G slices: mIoT, eMBB, and URLLC, for 100 users without LPS. Among the four optimization techniques, HGWTDO consumes the least power across all three slices — eMBB (18.53 W), mIoT (4W), and URLLC (11.36 W), demonstrating its efficiency. ACO, on the other hand, is extremely energy-hungry, especially for eMBB (48.5 W), mIoT (12W), and URLLC (25.5 W), reflecting inefficiency. Thus, HGWTDO is the most energy-efficient option for LPS-less networks at large scale and is best suited for sustainable 5G resource management. The results indicate that HGWTDO achieves the lowest total power usage (33.45 W), confirming its superior efficiency in managing energy resources. PSO, on the other hand, consumes the highest total power (47.12W), making it the least efficient among the compared techniques. This comparison highlights the energy-saving potential of HGWTDO and supports its use in power-aware 5G network resource allocation strategies.

D. Discussion of Simulation Scenarios with LPS

In this section, the authors discuss the implementation of optimization techniques using the Linear Pattern Search approach across 30, 50, and 100-user scenarios.

1) Simulation Results for 30 Users with LPS:

For 30 users, Linear Pattern Search, the simulation was set with a total bandwidth of 100 MHz, a power capacity of 50 watts, and an arrival window of 10 milliseconds. The total throughput was set to 1000 Mbps to test the efficiency of power optimization.

TABLE V
THE POWER ALLOCATED TO 30 USERS BY OPTIMIZATION TECHNIQUES WITH LPS

Algorithms	Initial Power Demand (W)	Remaining power (W)	Final allocated power (w)	Power Saved (%)
PSO	50	32.49	17.51	64.98
ATDO	50	30.01	19.99	60.02
HGWTDO	50	33.31	16.69	66.62
ACO	50	29.2	20.8	58.4

Table V and Fig. 8 compare the power allocation and the percentage power savings of the four listed algorithms with LPS. HGWTDO outperforms other algorithms, achieving 66.62% power savings. Using an iterative table, such as Table 1, for algorithms with LPS, Figure 8 compares power allocation to URLLC, eMBB, and mIoT users. URLLC users with ATDO and eMBB users with ACO performance are identical and are assigned the maximum power. mIoT users are always allocated with minimum power, particularly in HGWTDO, since they demand little data and energy. ACO has the highest allocated power of 20.8W, followed by ATDO and PSO. The power allocated by HGWTDO with LPS is the lowest at 16.69W, indicating that it is the best solution for the 30-user scenario.

2) Simulation Results for 50 Users with LPS:

For 50 users using Linear Pattern Search, the simulation was configured with an aggregate bandwidth of 100 MHz, a power capacity of 50 watts, and an arrival window of 50 milliseconds.

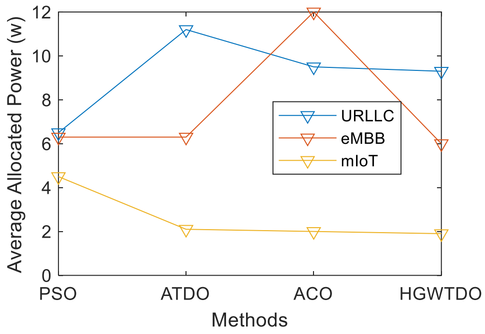

Fig. 8. Allocated power for thirty users by algorithms with LPS

TABLE VI
THE POWER ALLOCATED TO 50 USERS BY OPTIMIZATION TECHNIQUES WITH LPS

Algorithms	Initial Power Demand (W)	Remaining power (W)	Final allocated power (w)	Power Saved (%)
PSO	50	17.5	32.5	35
ATDO	50	17.5	32.5	35
HGWTDO	50	24.84	25.16	49.67
ACO	50	22.75	27.25	45.5

The aggregate throughout was set to a constant of 1000 Mbps for testing power-optimization efficiency across URLLC, eMBB, and mIoT slices. Table VI presents the results of power optimization for 50 users using the four listed algorithms with LPS enhancement. Of these, HGWTDO shows the maximum power saving of 49.67%, yet only 25.16 W of a total 50 W power budget is utilized. ACO then finds only 45.5% of power saving, allocating 27.25 W out of 50W. PSO and ATDO use the same final power level (32.5 W), resulting in a 35% reduction in power. These results indicate that HGWTDO, optimized via LPS, is the optimal solution for power allocation. Therefore, it is a highly suitable candidate for adaptive and power-aware resource allocation in sliced 5G networks.

Figure 9 presents the comparison of power consumption for 50 users with LPS on four optimization algorithms. The result indicates that HGWTDO achieves the lowest power consumption for the URLLC slice (8.37 W) and also competitive efficiency for the eMBB (13.86 W) and mIoT (2.56 W) slices. Alternatively, PSO achieves the highest power consumption for URLLC (15.50 W), indicating inefficiency for ultra-reliable low-latency use cases. The nature of eMBB and mIoT slices is almost linear for the listed algorithms. Generally, HGWTDO offers greater power optimization, particularly in latency-focused applications, and is therefore an appropriate option for energy-efficient resource allocation in sliced 5G networks.

3) Simulation Results for 30 Users with LPS:

For the 100-user scenario, the simulation was configured with a total frequency bandwidth of 100 MHz, a power budget of 50 watts, and a time frame of 50 milliseconds. The overall network throughput was maintained at 1000 Mbps to assess the performance of power allocation strategies under high user density within a sliced 5G environment.

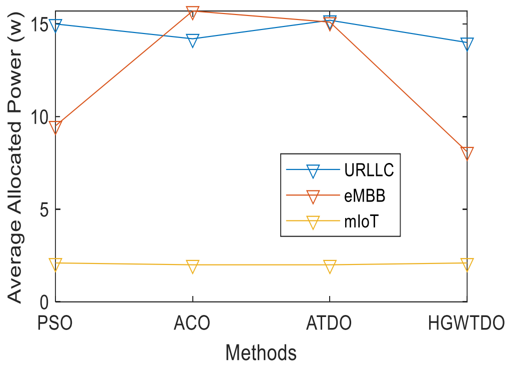

Fig. 9. Allocated power for 50 users by algorithms with LPS

TABLE VII
THE POWER ALLOCATED TO 3 USERS BY OPTIMIZATION TECHNIQUES WITH LPS

Algorithms	Initial Power Demand (W)	Remaining power (W)	Final allocated power (w)	Power Saved (%)
PSO	50	5.99	44.01	11.98
ATDO	50	5.49	44.51	10.98
ACO	50	19.21	30.78	38.43
HGWTDO	50	20.97	29.03	41.94

Table VII shows the results of power optimization for 100 users using four listed algorithms, with LPS support. The best power optimization result was achieved via HGWTDO at 41.94% power saved, followed by ACO at 38.43%. Both approaches reduced the total power allocation by a considerable margin without sacrificing the service demand of each slice—ATDO and PSO saved 10.98% and 11.98%, respectively. Use of LPS also improved the solutions for all algorithms, though HGWTDO benefited more, as its global and local searches were optimized.

For 100 users, the nature of power consumption across all network slices under different algorithms is identical, as given in Fig. 10. Compared to other algorithms, HGWTDO achieves the lowest power consumption across all slices. In particular, HGWTDO decreases power consumption to 16.5 W for eMBB, 9.8 W for URLLC, and 2.7 W for mIoT. On the contrary, PSO is most widely used for eMBB slices and URLLC.

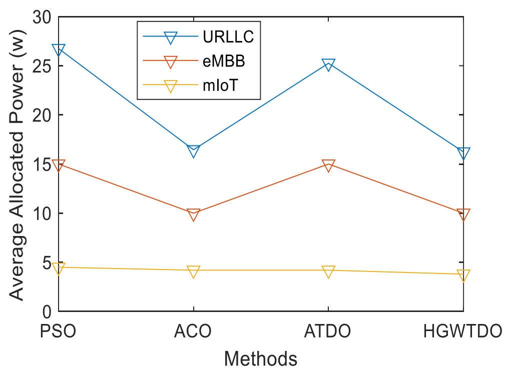

Fig. 10. Allocated power for 100 users by algorithms with LPS.

E. Computation Time Required

In optimization, how fast optimizers converge to a solution is a crucial parameter. The computational time required by each optimizer is analyzed. The computation time of ACO, ATDO, HGWTDO, and PSO for 30, 50, and 100 users with LPS is shown in Figure 11. The HGWTDO needs an average simulation time of 1.116 for 100 users, 0.343 for 50 users, and 0.0267 for 30 users, ensuring the highest power allocation for users than existing techniques. The HGWTDO takes longer to compute, particularly as the number of users increases. PSO is the quickest among all scenarios; however, it provides lower power allocation than HGWTDO. Computation time increases with the number of users, leading to performance and processing speed compromises. In the future, focus can be given to improving HGWTDO's computational time.

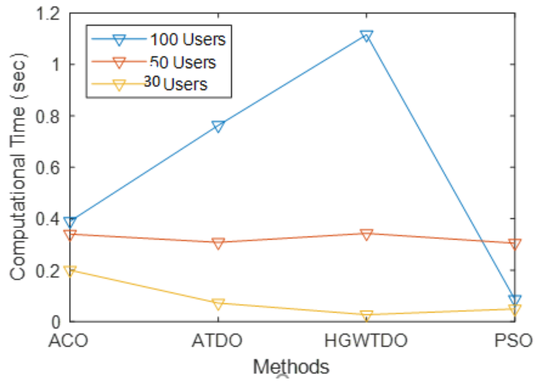

Fig. 11. Computation time required by algorithms with LPS

In all three user scenarios, the HGWTDO algorithm performed best in terms of power efficiency and scalability. Its hybrid structure, which blended global search with structural and adaptive local refinement, enabled it to maintain high residual power.

The HGWTDO has provided a significant boost in the performance of power allocation over traditional techniques. Its performance is limited by the higher computational cost of fusing GWO, TDO, and LPS. The scalability for a higher user count, dynamic network conditions, and slicing constraints is limited. The real-time deployment is a key challenge with strict latency constraints.

V. CONCLUSION AND FUTURE SCOPE

This work proposed an efficient power allocation model for sliced 5G networks by applying various nature-inspired optimization algorithms with LPS. The network was sliced into URLLC, eMBB, and mIoT slices with different quality of service requirements. Simulations were performed using four metaheuristic algorithms such as PSO, ACO, ATDO, and HGWTDO —across three user scenarios (30, 50, and 100 users) to compare their flexibility and energy efficiency. Simulation results reported that HGWTDO performs better than other algorithms in all scenarios. Integrated with LPS, HGWTDO demonstrated greater efficiency, retaining over 42% of the overall power in the 100-user scenario, reflecting scalability and reliability. HGWTDO, while offering superior optimization performance, incurs the highest computational cost, especially as user load increases, indicating a trade-off between efficiency and processing speed. In contrast, PSO and ATDO showed limitations in adapting to dynamic network demands, especially under larger user loads. ACO performed moderately well, yet remained less effective than HGWTDO. Overall, the results confirm HGWTDO with LPS as a highly effective approach.

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