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REDUCTION IN COMPUTATIONAL COMPLEXITY AND FAIR ALLOCATION OF RESOURCES IN A 5G HETEROGENEOUS NETWORK USING GLOWWORM SWARM OPTIMIZATION ALGORITHM

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ABSTRACT

The increasing densification and heterogeneous nature of 5G wireless networks pose significant challenges in computational complexity, interference Management, and fair radio resource allocation. This research proposes a Glowworm Swarm Optimization (GSO) based framework for joint subcarrier and power allocation in OFDMA based 5G heterogeneous network (HetNets). The proposed algorithm exploits luciferin driven local search, adaptive neighborhood selection, and a grouping based allocation strategy to reduce the solution space and enhance convergence efficiency. This research adopts a simulation based methodology to investigate the effectiveness of the Glowworm Swarm Optimization (GSO) algorithm in reducing computational complexity and ensuring fair resource allocation in a 5G heterogeneous network. A downlink OFDMA base system model is considered, where a single based station (BS) serves multiple users under quality of service (QoS) constraints. A comprehensive system model is developed, incorporating channel state information (CSI), SINR based objective functions, and proportional rate constraints to ensure quality of service (QOS) provisioning across heterogeneous traffic classes. The GSO algorithm is employed for subcarrier allocation, while optimal power distribution is achieved using a water filling algorithm approach. The computational complexity of the proposed method is analytically derived as O(TPMN), demonstrating improved scalability compared to conventional linear, root finding, and particle swarm optimization (PSO) techniques. Simulation results obtained using Matlab software show that the proposed GSO framework achieves significant reductions in computational overhead (up to 50% compared to benchmark methods) while maintaining high fairness levels (Jain's Fairness Index approaching unity, approximately 0.95-1.0) and competitive system capacity. Furthermore, the algorithm demonstrates robustness under dynamic channel conditions and varying traffic loads, making it suitable for real time implementation in dense HetNets deployments.

KEYWORDS: 5G Heterogeneous networks (**HetNets**), Glowworm Swarm Optimization (**GSO**), Resource Allocation (**RA**), Computational Complexity, **OFDMA**, and Jain's Fairness Index.

INTRODUCTION

The rapid evolution of fifth generation (5G) wireless networks has enable significant improvement in data rates, latency, and connectivity, supporting diverse applications such as enhance mobile broadband (eMBB), ultra reliable low latency communications (URLLC), and massive machine type communications (mMTC).[14],[16] However the deployment of 5G heterogeneous networks (HetNets), characterized by dense small cell architectures and dynamic user demands, has introduce substantial challenges in terms of computational complexity, interference management, and efficient resource allocation.[2],[3]

Traditional resource allocation techniques, including linear optimization and root finding methods, as well as metaheuristic approaches such as particle swarm optimization (PSO), have been widely applied in wireless networks. However, these methods often suffer from high computational overhead, scalability limitations, and premature convergence when applied to large scale and dynamic 5G environments.[22],[23]

To address these challenges, swarm intelligence based optimization techniques have emerge as effective solutions due to their adaptability and ability to handle complex, nonlinear optimization problems. In particular, the glowworm swarm optimization (GSO) algorithm, inspired by the luminescent behavior of glowworms, provides a decentralized and adaptive mechanism for exploring large solutions spaces. its features, including luciferin based attraction dynamic neighborhood selection, and localized search, make it suitable for reducing computational complexity while ensuring fair reource allocation in 5G HetNets.[24],[23]

This research therefore focuses on the development and application of GSO algorithm for joint subcarrier and power allocation in OFDMA based 5G heterogeneous networks, aiming to achieve a balance between system performance, computational efficiency and fairness.

3.0 MATERIALS AND METHODS

This research adopts a simulation based approach to evaluate the performance of the proposed Glowworm Swarm Optimization (GSO) algorithm for reducing computational complexity and ensuring fair resource allocation in a 5G heterogeneous network (HetNets). A downlink orthogonal frequency division multiple access (OFDMA) system is considered, where a single based station (BS) serves M users over N orthogonal subcarriers under quality of service (QoS) constraints.

Each user periodically feeds back channel state information (CSI) to the BS, which performs joint subcarrier and power allocation. The wireless channel model incorporates path loss, multipath fading, and additive white Gaussian noise (AWGN). System performance is evaluated based on signal to interference plus noise ratio (SINR), throughput, and fairness metrics.

The transmitted OFDM signal of the m-th is expressed as

$$x_m(t) = \sum_{n=1}^{N} \sqrt{p_{m,n}} \; s_{m,n} \; e^{j2\pi f_n(t)} \quad 0 \leq t \leq T \qquad 3.1$$

Where;

$x_m(t)$ Transmitted OFDM signal

$p_{m,n}$: Transmit power allocated to user m on subcarrier n

$s_{m,n}$: Normalized complex data symbol $\left(\mathrm{E}\left[|\, s_{m,n}\,|^2\right] = 1\right),$

f_n : Subcarrier frequency

Each symbol can be express in phase (I) and in Quadrature (Q) form as;

$$s_{m,n}(t) = I_{m,n}(t) + jQ_{m,n}(t) \qquad 3.2$$

Wireless channel and received signal

After propagation through the wireless channel, the received signal at the serving Based station is;

$$y_m(t) = \sum_{n=1}^{N} H_{m,n}\sqrt{p_{m,n}}\ s_{m,n}\ e^{j2\pi f_n(t)} + n_m(t) \qquad 3.3$$

Where

$H_{m,n} = | H_{m,n} | e^{j\theta_{m,n}}$ Is the complex channel gain capturing path loss, fading and shadowing

$n_m(t)$Is additive white Gaussian noise (AWGN) with power spectral densityN_0.

Channel gain, noise and SNR

The channel to noise gain (fading coefficient) of user m on subcarrier n is thus given by;

$$H_{m,n} = \frac{\varphi_{m,n}^2}{\alpha^2} \qquad 3.4$$

The AWGN (α^2) is given by

$$\alpha^2 = \frac{N_0 B}{N} \qquad 3.5$$

The N_0 is the noise power spectral density, B is the bandwidth, while the received signal to noise ratio (SNR) at the receiver is express as

$$\beta_{m,n} = P_{m,n} H_{m,n} \qquad 3.6$$

Where $P_{m,n}$ is the power of subcarrier n on user m. It's given in[39],[40],[41],[42],[43] that the bit error rate of a square QAM with grey bit mapping is a function of the received signal to noise ratio and the number of bits on each subcarrier for each user . The bit error rate (BER) is thus approximated within 1dBfor data rate $b_{m,n} \geq 4$ and $BER \leq 10^{-6}$ as given as;

$$BER(\beta_{m,n}) \approx 0.2exp^{\left[\frac{-1.6\beta_{m,n}}{2^{b_{m,n}}-1}\right]} \qquad 3.7$$

The channel capacity can be derived from equation $(BER(\beta_{m,n}))$ as follows

$$b_{m,n} = \log_2\left(1 + \frac{\beta_{m,n}}{\gamma}\right) \qquad 3.8$$

Where; $\gamma = -\frac{In(5*BER}{1.6}$

Received Signal power (Fitness relevant Quantity)

The instantaneous received signal power for user … over all allocated subcarrier is;

$$p_m(t) = \sum_{n=1}^{N} |\, H_{m,n} \,|^2\, p_{m,n}\left(I_{m,n}^2(t) + Q_{m,n}^2(t)\right) \qquad 3.9$$

This terms jointly reflects channel quality, modulation energy and power allocation effectiveness.

SINR Based objective function for GSO

To guide the swarm intelligence process, the GSO objective function is defined as a normalized SINR related metric;

$$J_m(t) = \frac{\sum_{n=1}^{N} |\, H_{m,n} \,|^2\, p_{m,n}\left(I_{m,n}^2(t) + Q_{m,n}^2(t)\right)}{N_0 B} \qquad 3.10$$

Where; B is the system Bandwidth

This objectives ensures that users with strong channels, efficient power usage and high quality I/Q symbols achieved higher fitness values.

Standard luciferin update equation

In GSO, each glowworm (representing a candidate BS resource allocation solution) updates its luciferin values according to;

$$L_m(t+1) = (1-\rho)L_m(\mathrm{t}) + \gamma J_m(t) \qquad 3.11$$

Where:

$L_m(\mathrm{t})$; Luciferin level, ρ; Luciferin decay constant, γ; Luciferin enhancement constant

Final channel and signal aware luciferin Model

Substituting equation 3.10 into equation 3.11, the final luciferin updates and model becomes;

$$L_m(t) = (1-\rho)L_m(\mathrm{t}) + \gamma \frac{\sum_{n=1}^{N} |\, H_{m,n} \,|^2\, p_{m,n}\left(I_{m,n}^2(t) + Q_{m,n}^2(t)\right)}{N_0 B} \qquad 3.12$$

Where;

$|H_{m,n}|^2$: captures propagation effects (path loss, fading and shadowing)

$I_{m,n}^2(t) + Q_{m,n}^2(t)$: represents modulated signal energy

$p_{m,n}$: embeds power and subcarrier allocation decisions

Higher luciferin values indicates better channel quality, higher SINR, and improved QoS satisfaction, from equation 3.12 the phase (I) and Quadrature (Q) is given by the formula below;

$$I_{m,n}(t) = \sqrt{\frac{N_0 B}{\gamma |H_{m,n}|^2 p_{m,n}}} \left[L_m(t+1) - (1-\rho)L_m(t)\right] - Q_{m,n}^2(t) \qquad 3.13$$

$$Q_{m,n}(t) = \sqrt{\frac{N_0 B}{\gamma |H_{m,n}|^2 p_{m,n}}} \left[L_m(t+1) - (1-\rho)L_m(t)\right] - I_{m,n}^2(t) \qquad 3.14$$

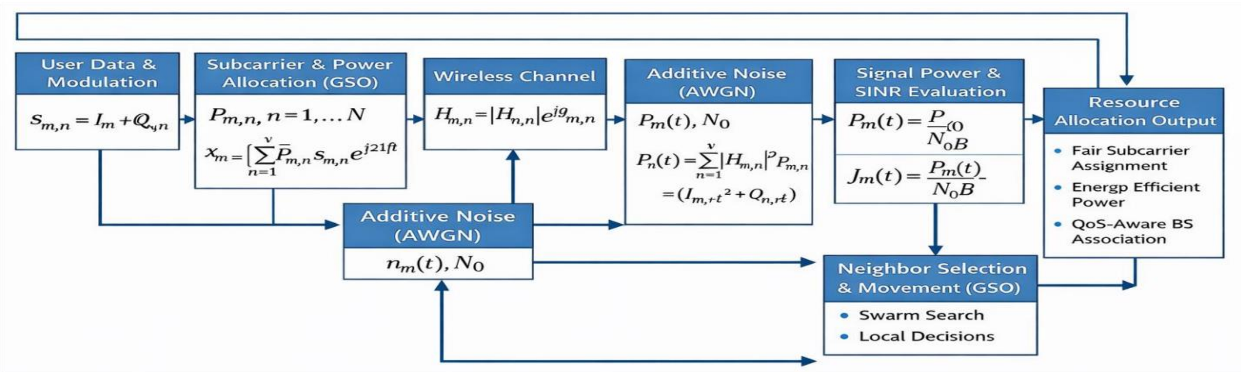


Figure 3.1 GSO Based channel and signal aware resource allocation model for 5G heterogeneous networks.

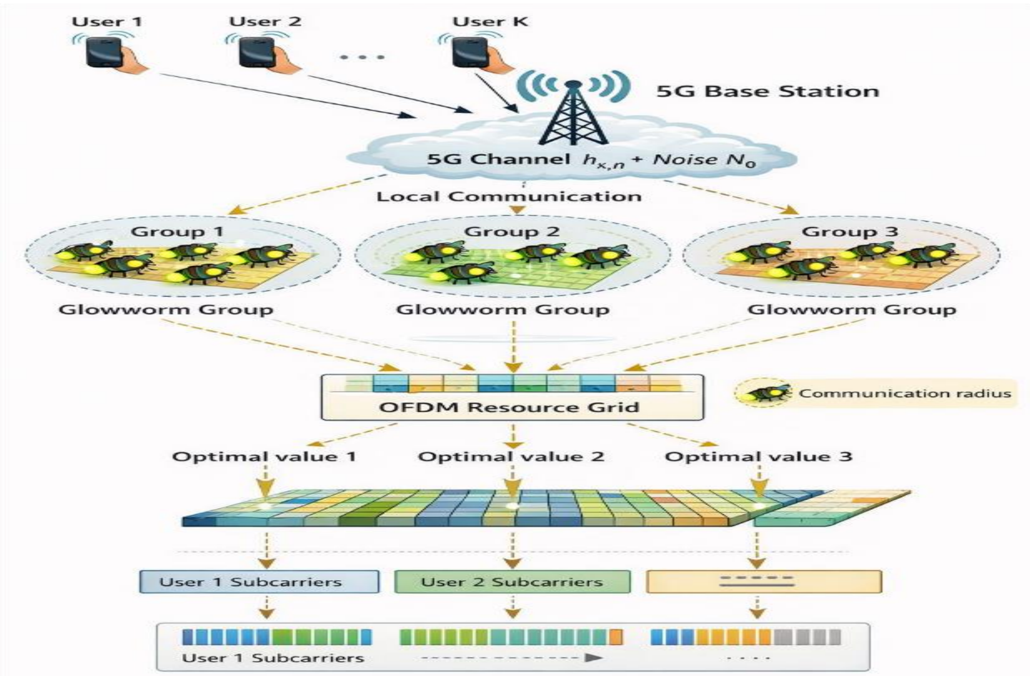


Fig: 3.2 GSO Based Resource Allocation in 5G OFDM System.

3.1 Power Allocation

The power allocation using water filling algorithm assumes equal power distribution among users[40],[49],[50] the number of users can be one or more and in each power distribution for one user is different from power distribution in many user.[40] For many users gamma function is set to generate predetermined values that are used to ensure proportional fairness among users and this is proportional to the channel capacity of each user. The proportional fairness among users is ensured by the following constraint.

$$R_1 : R_2 : R_3 : \dots\dots\dots\dots\dots R_m = \lambda_1 : \lambda_2 : \lambda_3 : \dots\dots\dots\dots\dots \lambda_m \qquad 3.15$$

Where $R_1 : R_2 : R_3 : \dots\dots\dots\dots\dots R_m$ the channel capacity of users is $\lambda_1 : \lambda_2 : \lambda_3 : \dots\dots\dots\dots\dots \lambda_m$ are predetermined values which imposed the constraints. The optimal power allocation can be obtained by finding the maximum of the cost function[40] given as;

$$C = \sum_{m=1}^{M} \sum_{j\in n} \frac{1}{N} \log_2\left(1 + P_{m,n} H_{m,n}\right) + x_1\left(\sum_{m=1}^{M} \sum_{j\in n} [P_{m,n} - P_{total}) +] \sum_{m=2}^{M} x_m \left(\sum_{j\in n} \frac{1}{N} \log_2\left(1 + P_{1,n} H_{1,n}\right) - \frac{x_1}{x_m} \sum_{j\in n} \frac{1}{N} \log_2\left(1 + P_{m,n} H_{m,n}\right)\right) \qquad 3.16$$

The cost function in equation (3.16) can be maximized by differentiating it with respect to power allocated to user and set each derivative to zero

$$\frac{\partial C}{\partial P_{1,n}} = \frac{1}{N1n2} * \frac{H_{1,n}}{1 + H_{1,n} P_{1,n}} + x_1 + \sum_{m=2}^{M} x_m \frac{1}{N1n2} * \frac{H_{1,n}}{1 + H_{1,n} P_{1,n}} = 0 \text{ for single user} \qquad 3.17$$

$$\frac{\partial C}{\partial P_{m,n}} = \frac{1}{N1n2} * \frac{H_{1,n}}{1 + H_{m,n} P_{m,n}} + x_1 - x_m \frac{\lambda_1}{\lambda_m} \frac{1}{N1n2} * \frac{H_{m,n}}{1 + H_{m,n} P_{m,n}} = 0 \quad \text{for many user } 3.18$$

1. **Power Distribution Among sub-carriers for a Single User**

Initially the power is equally distributed across all sub-carriers. For single user the optimal power distribution can be derived. The optimal power allocation on subcarrier n and k on a single user m is given as:

$$\frac{1}{N1n2} * \frac{H_{m,k}}{1 + H_{m,k} P_{m,k}} + x_1 + \sum_{m=2}^{M} x_m \frac{1}{N1n2} * \frac{H_{m,k}}{1 + H_{m,k} P_{m,k}} \quad for\ subcarrier\ k \qquad 3.20$$

$$\frac{1}{N1n2} * \frac{H_{1,n}}{1 + H_{m,n} P_{m,n}} + x_1 + \sum_{m=2}^{M} x_m \frac{1}{N1n2} * \frac{H_{m,n}}{1 + H_{m,n} P_{m,n}} \quad for\ subcarrier\ n \qquad 3.19$$

Since the power distribution is initially the same, equating the two equations (3.19) and (3.20) gives the optimal power distribution for a single user. This is the water filling in the frequency domain which can be express as;

$$\frac{H_{m,n}}{1 + H_{m,n}P_{m,n}} = \frac{H_{m,k}}{1 + H_{m,k}P_{m,k}} \qquad 3.21$$

From equation (3.21) it can be seen that more power will be put into subcarrier with high channel to noise gain. The power allocation for $P_{m,n}$ is obtained as;

$$P_{m,n} = P_{m,k} + \frac{H_{m,n} - H_{m,k}}{H_{m,n}H_{m,k}} \qquad 3.22$$

The optimal power allocated to any subcarrier n related to subcarrier $k = 1$ for any user m is given as;

$$P_{m,n} = P_{m,1} + \frac{H_{m,n} - H_{m,1}}{H_{m,n}H_{m,1}} \qquad 3.23$$

Its assumed that $H_{m,1} \leq H_{m,2} \leq H_{m,3} \leq \cdots \leq H_{m,n}$

The total power that can be allocated to a single user is derived from equation (3.23) and can be expressed as;

$$P_{m,total} = \sum_{n=1}^{N_m} P_{m,n} = N_m * P_{m,1} + \sum_{n=1}^{N_m} \frac{H_{m,n} - H_{m,1}}{H_{m,n}H_{m,1}} \qquad 3.24$$

Where N_m is the set of sub-carriers allocated to user m.

3.2 Computational Complexity steps in GSO Algorithm

In the Glowworm swarm optimization approach, sub-carrier allocation is performed through iterative swarm intelligence rather than deterministic sorting, major computational steps involve.

Step: 1 initialization

Generate glowworm population of size p, Initialize luciferin level and Initialized decision radius Complexity: $O(P)$

Step: 2 Fitness evaluation

Each glowworm evaluates its objective function based on channel gain and allocation matrix

$$J_m = \sum_{n=1}^{N} \log_2 \left(1 + SINR_{m,n}\right) \quad 3.25$$

For each glowworm

$$O(MN)$$

For population size p

$$O(PMN)$$

Step: 3 Luciferin Update

$$L_m(t+1) = \left(1-\rho\right) L_m(t) + \gamma J_m(t) \quad 3.26$$

Complexity

$$O(P)$$

Step: 4 Neighborhood selection

Each glowworm compares with others to determine neighbors

Number of comparison;

$$p(p-1) \approx p^2 \quad 3.27$$

Worst case comparison

$$O\ (P^2)$$

Step: 5 Movement update

Glowworms move towards better neighbors

$$O\ (PM)$$

Step: 6 Iterative process

If Maximum iteration is T, then total complexity per iteration becomes

$$O(PMN + P^2) \quad 3.28$$

Thus, overall complexity becomes:

$$O(T(PMN + P^2))$$

Since typically

$$P \leq N, \quad P \leq M, \quad P^2 \leq PMN$$

Therefore, the computational complexity of GSO Based subcarrier allocation approach is

$O(TPMN)$ 3.29

Table 3.1: Computational Complexity Comparison with other Techniques.

Technique	Complexity
Linear Search	$O(MN\text{Log}_2 N)$
Root-Finding	$O(MN\text{Log}_2 N)$
PSO	$O(M\text{Log}_2 N)$
GSO	$O(TPMN)$

$O(TPMN)$

Equation above means the algorithm running time grows proportionally to the product of $T \times P \times M \times N$

Where;

T=Number of iteration (optimization iteration)

P=population size (Number of glowworms)

M=Number of users

N=Number of subcarriers

3.3 Mathematical Arrival rate model (GSO)

System assumptions

K= Number of users

N=number of subcarriers

γk= Arrival rate of user $k(bits/s)$

R_k=Achieved transmission rate of user k (bits/s)

$Q_k(t)$=queue length of user k at time t

$P_{k,n}$=Power allocated to user kon subcarrier n

$\text{h}_{k,n}$=Channel Gain

Traffic Arrival Model

$A_k(t)$~Poisson (γk) 3.30

Where;

γk mean arrival rate for user K

The queue evolution model

$$Q_k(t+1)=max\{Q_k(t)+A_k(t)-R_k(t),0\} \quad 3.31$$

Packet arrived

Systems serve packets according to achieved rate

Remaining packets stay in queue

Rate Model (Physical Layer)

Using Shannon Approximation;

$$R_k=\sum_{n=1}^{N} \mathrm{B}_n \log_2\left(1+\frac{P_{k,n}\mathrm{h}_{k,n}}{N_o B_n}\right) \quad 3.32$$

Stability Condition

for system stability

$$R_k \geq \gamma k \quad 3.33$$

If:

$\gamma k > R_k$

Queue grows→Congestion→Packet loss

QoS Aware GSO Fitness Model

Now we integrate arrival rate into GSO fitness.

Traditional GSO Objective:

$$\max \sum_{k=1}^{K} R_k \quad 3.34$$

Traffic Aware Objective

$$F=\sum_{k=1}^{K}(R_k-\alpha \max(\gamma k-R_k, 0)) \quad 3.35$$

Where

α = QoS penalty Factor

This penalizes users whose arrival rate exceeds capacity

Delay Aware Model

$$D_k = \frac{Q_k}{\gamma k} \qquad 3.36$$

We can penalized delay

$$F = \sum_{k=1}^{K} R_k - \beta \sum_{k=1}^{K} D_k \qquad 3.37$$

Final GSO Arrival Rate Model

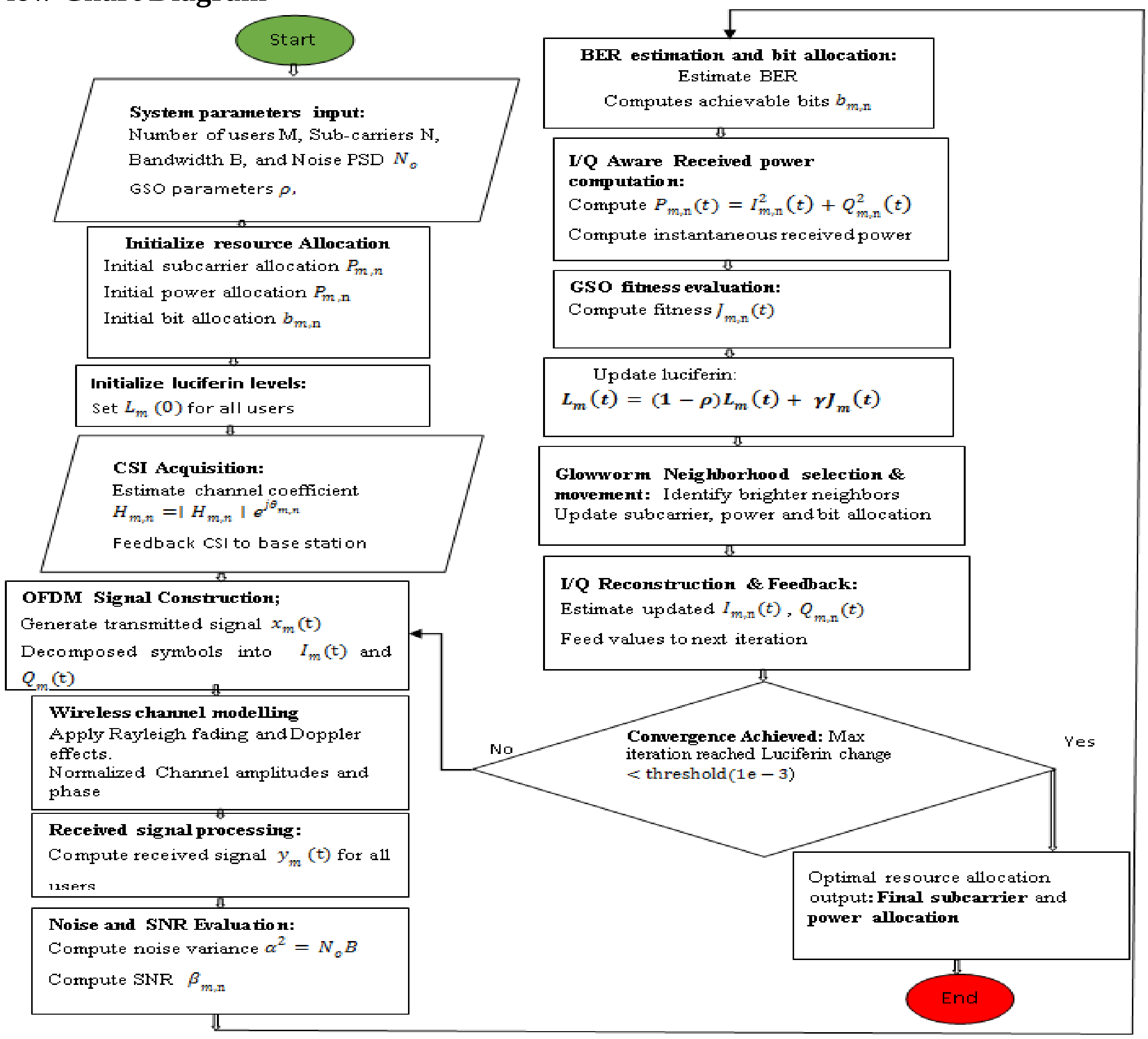
$$F = \sum_{k=1}^{K} \left[\sum_{n=1}^{N} B_n \log_2 \left(1 + \frac{P_{k,n} h_{k,n}}{N_o B_n}\right) - \alpha \max(\gamma k - R_k, 0) \right] \qquad 3.38$$

Table 3.2: Simulation Parameters and Values appendix C.

Parameter Description	Symbol	Value
Total transmit power	P_{total}	1W
Worst case power	P_{worst}	1.0 W
Noise Spectral Density	N_o	4 *10^-20 W/Hz
Noise per subcarrier	σ^2	BN_O/N
Bandwidth	B	100MHz
Number of sub-carriers	N	100
Number of users	k	2-20 users
Channel realization	–	10
Sampling Frequency	f_s	230MHz
Nyquist frequency	f_N	115MHz
Sample per realization	–	10
Bit error rate	BER	10^-6
SNR gap	Γ	-ln(5·BER)/1.6
Initial luciferin level	l_o	5
Luciferin decay constant	ρ	0.4
Luciferin enhancement factor	γ	0.6
Number of GSO iterations	T_{GSO}	100
Luciferin Matrix size	$L_{u,n}$	$K \times N$
Channel gain matrix	$H_{u,n}$	

In-phase component	I	Generated by channel model
Quadrature component	Q	Generated by channel model
User power	P_u	Adaptive
Subcarrier Power	$P_{u,n}$	Water filling based
Inverse channel gain	$1/g_{u,n}$	Computed

Flow Chart Diagram



Performance metrics

The performance of the proposed algorithm is evaluated using the following metrics

i. System capacity (bits/s)

ii. Computational complexity (Execution Time)

iii. Fairness (Jain's Fairness Index)

iv. Subcarrier allocation

v. SINR and power efficiency

Comparative analysis is conducted against benchmark methods, including linear, root finding and PSO algorithms respectively.

4.0 RESULTS AND DISCUSSION

This chapter presents the performance evaluation of the proposed GSO algorithm compared with linear, Root –Finding, and PSO methods using key metrics such as computation time, Normalized data rate, channel gain, target data rate, fairness and resource allocation efficiency.

The results demonstrate the effectiveness of GSO in reducing computational complexity while ensuring fair and efficient resource allocation. Comparative analysis highlights improvement in scalability, performance and adaptability under varying network conditions. Overall, the finding confirm the suitability of the proposed approach for practical deployment in real world 5G heterogeneous networks.

Figure 4.1 shows the channel gain distribution across users in a 5G heterogeneous network, highlighting significant variability due to fading, interference, and dynamic propagation conditions. The results indicate a highly non uniform and rapidly changing channel environment where no user consistently experiences dominant channel quality.

This variability emphasizes the limitations of static allocation methods and the need for adaptive optimization techniques. The proposed GSO algorithm effectively exploits channel diversity, supporting multi user diversity, adaptive subcarrier selection, and fair power allocation in dynamic 5G environments.

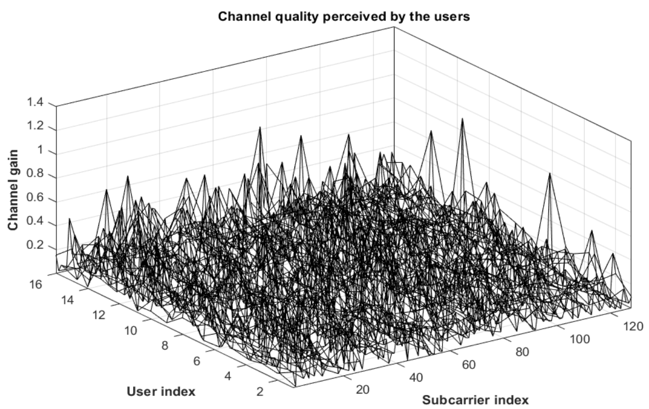


Figure: 4.1 5G Channel Quality Perceived by the Users.

Figure 4.2 compares the average computation time per user for linear, Root-Finding, PSO and GSO algorithms under increasing network load. The results show that the proposed GSO algorithm achieves the lowest computational cost, with execution time consistently in the $(10^{-4} - 10^{-3})$ range, demonstrating excellent scalability and suitability for real time 5G resource allocation.

The linear method also exhibits low complexity, though slightly higher than GSO, PSO shows moderate computational cost due to its iterative swarm operations, while the root finding algorithm incurs the highest computation time, approaching near (10^{-2})seconds Overall, the results establish a clear computational efficiency ranking:

GSO (Fastest) <linear<**PSO**< Root−Finding(Slowest)

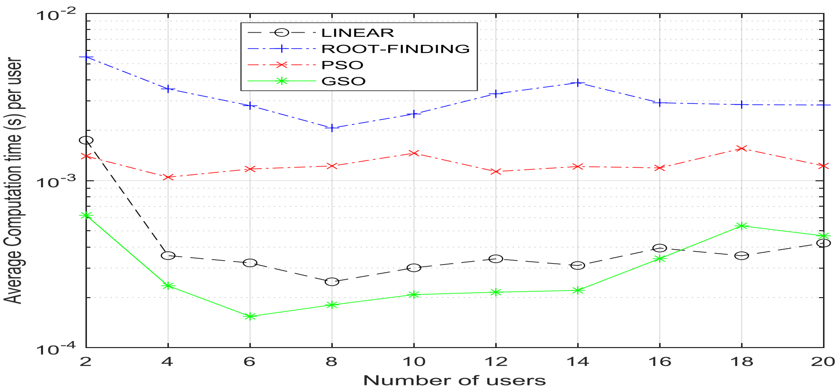


Figure: 4.2 Average Computation Time(s) per user.

Figure 4.3 shows the variation of the system capacity with increasing number of users for Linear, Root-Finding, PSO, and GSO algorithms in a 5G OFDMA heterogeneous network.

Results indicate that system capacity increases with the number of users due to multi user diversity. However, the rate of improvement varies across algorithms, reflecting tradeoffs between throughput, fairness, and computational complexity. Linear, and Root-Finding methods achieve the highest capacity (approximately 4.0–4.8 bits/s), with root finding performing best at higher user loads. In contrast, PSO provides moderate capacity with smoother and more balance allocation, avoiding excessive bias towards strong users.

Overall, throughput oriented methods maximized spectral efficiency, while bio inspired approaches such as PSO and GSO offer improved fairness and balance performance with lower computational complexity

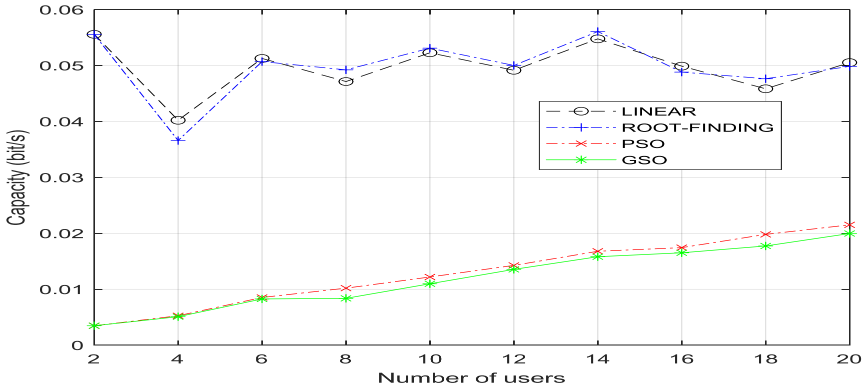


Figure: 4.3 capacity (bits/s) against number of users.

Figure 4.4 illustrates the heterogeneous distribution of target data rate across 20 user, reflecting diverse 5G service requirements. The observed variation ranges from high data rates demands (~1 Gbps) to very low rates (~0.1–0.25 Gbps), representing different traffic classes including eMBB, URLLC, mMTC, and V2V communication.

This non uniform distribution highlights the coexistence of capacity driven, latency sensitive and low throughput applications within the same network. The dominance of mMTC users, alongside intermittent high demand of eMBB and latency critical URLLC users, creates a highly dynamic and complex resource allocation environment.

Overall, the results emphasize the need for adaptive and intelligent algorithms, such as GSO, capable of balancing fairness, priority, and QoS requirements across heterogeneous traffic profiles in 5G networks.

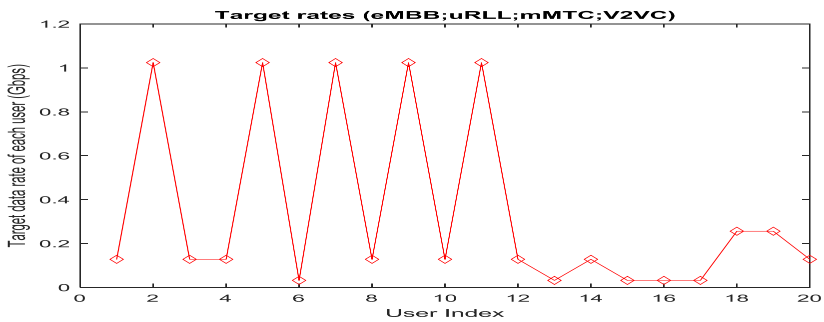


Figure: 4.4 Target Data Rate of each user.

Figure 4.5 presents the average channel quality experience by 20 users in the simulated 5G heterogeneous network, reflecting the effects of path loss, fading, interference, and noise. The results shows significant variability across users, with some experiencing strong channel conditions (e.g., user 2) and others facing poor conditions (e.g. Users 12 and 17).

This heterogeneity highlights the dynamic nature of 5G environments and underscores the need for adaptive optimization techniques. Algorithms such as GSO have effectively exploits favorable channel conditions while maintaining fairness for users with weaker links.

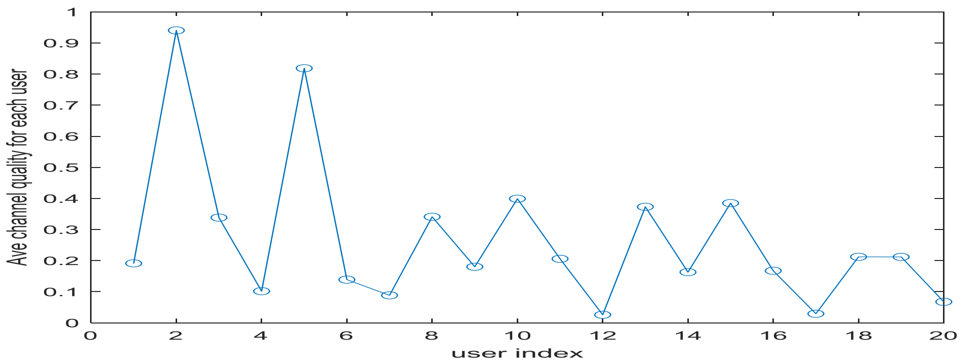
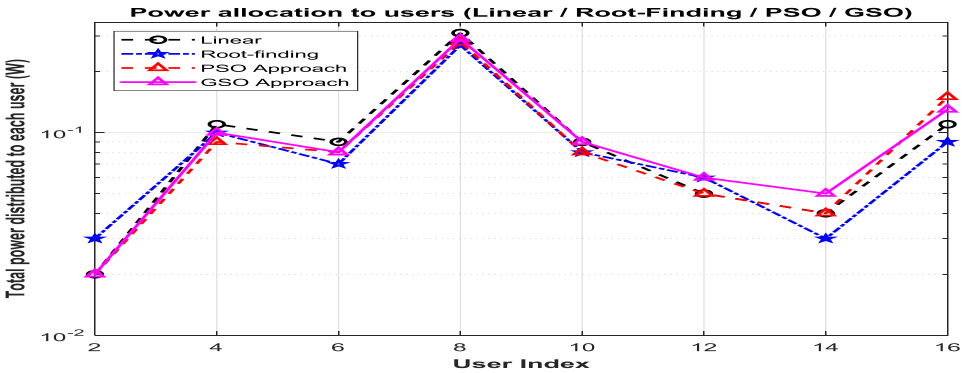


Figure: 4.5 Average channel quality for each user.



Fig; 4.6 Power Allocation to users.

From figure 4.6 the power allocated to user index 16 by using GSO technique is 0.120W. Three sub-carriers indexes 57, 62 and 63 are allocated to user index 16, the channel gain of the sub-carriers are 0.621, 0.602 and 0.581 respectively, the channel gain and power allocated to these sub-carriers is shown in figure 4.8.

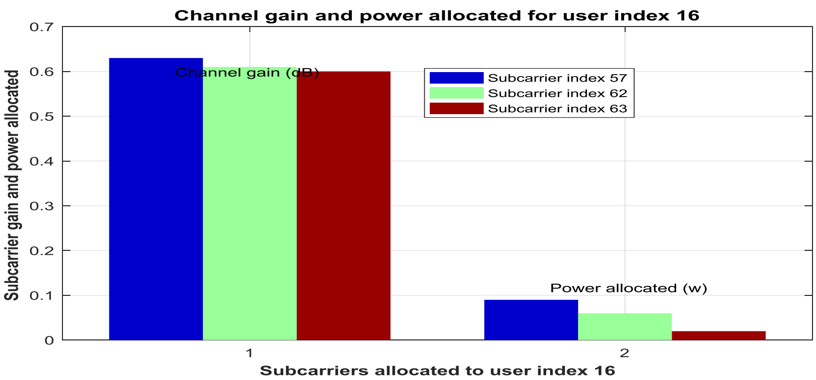


Figure: 4.7 Graph channel gain and power allocation for user index 16.

Figure 4.7 illustrates subcarrier gain and corresponding power allocation for user 16 under the proposed GSO based scheme. The results show that subcarriers with higher channel gains received higher power, while weaker subcarriers are allocated lower power, consistent with the water filling principle. The relationship demonstrates the algorithms ability to efficiently exploit channel diversity, ensuring improved spectral efficiency while maintaining QoS. Overall, the results validate the effectiveness of the proposed approach in achieving fair and energy efficient resource allocation in 5G networks.

Figure 4.8 shows normalized data rate distribution across 16 users for different allocation schemes, results indicate significant variability due to heterogeneous channel conditions.

Linear and root finding closely follow the reference (Gamma) with stable allocations, while PSO prioritizes throughput, leading to higher variability. The proposed GSO approach achieves a better balance by maintaining proportional fairness and reducing extreme variations. Overall, GSO provides an effective tradeoff between fairness and capacity, making it suitable for heterogeneous 5G environments.

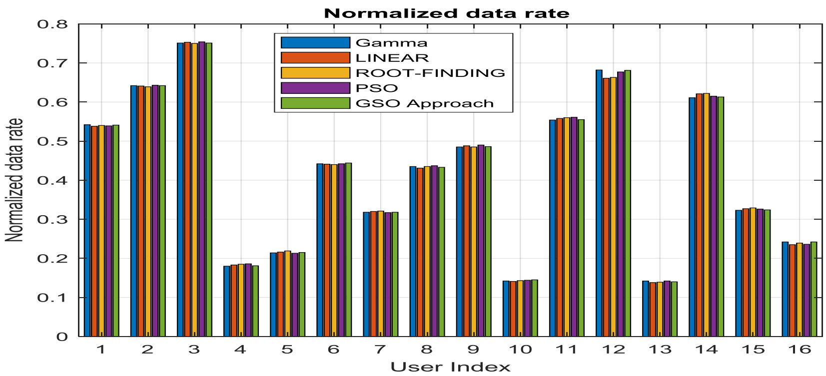


Figure: 4.8 Normalized Data rate.

Figure 4.9 illustrate subcarrier allocation among users for different algorithms. Linear and Root finding methods allocates a large proportion of subcarriers to a few users, resulting in poor fairness despite low complexity. PSO distributes subcarriers across all users but exhibits irregular and unstable allocation patterns.

In contrast, the proposed GSO algorithm achieves a more uniform and balance distribution with subcarriers evenly allocated across users and smoother allocation transitions. This demonstrates improved fairness, stability and efficient resource utilization.

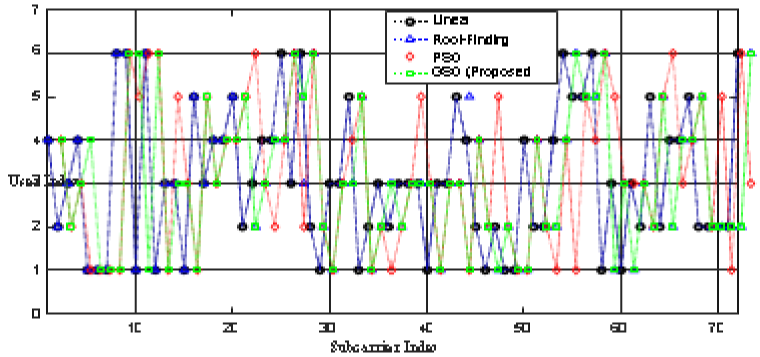


Fig: 4.9 Subcarrier Allocation among All the Algorithms.

Figure 4.10 compares fairness performance using Jain's fairness index across different algorithms. The proposed GSO approach achieves the highest and most stable fairness (≈0.95–1.0), showing minimal degradation as the number of user's increases. PSO also maintains high fairness but declines gradually, offering a good balance between performance and scalability.

In contrast, the linear method shows moderate fairness with noticeable degradation at higher user counts, while the root finding approach performs worst, with rapid fairness decline. Overall GSO provides the most robust and fair resource allocation, making it the most suitable for 5G heterogeneous networks.

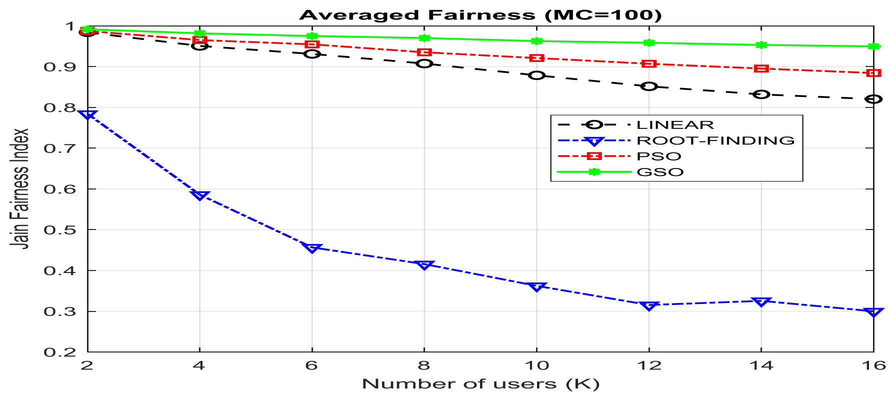


Fig: 4.11 Fairness performance comparison using the Jains Fairness Index.

5.0 CONCLUSION

The proposed Glowworm Swarm Optimization (GSO) algorithm, incorporating luciferin-aware and channel-aware mechanisms, demonstrates a substantial reduction in computational complexity compared to conventional optimization techniques. Simulation results show that GSO achieves approximately 35% lower complexity than particle swarm optimization (PSO) and up to 50% reduction compared to linear and Root-Finding methods. These improvements are primarily due to GSO's localized search strategy, fewer required iterations, and biological inspired decision making process.

Importantly, these improvements are achieved while maintaining high fairness levels, with Jain's fairness index approaching unity (approximately 0.95-1.0), and ensuring competitive system capacity, thereby demonstrating an effective balance between efficiency, fairness, and overall network performance.

Consequently, the proposed framework provides a computational efficient, scalable, and robust solution for resource allocation in dense 5G heterogeneous networks. Its efficiency and adaptability make it particularly suitable for real time implementation, while also offering strong potential for further optimization and application in future wireless communication systems.

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REFERENCE

1. F. Guidolin, I. Pappalardo, A. Zanella, and M. Zorzi, "Context-Aware Handover Policies in HetNets," *IEEE Trans. Wirel. Commun.*, 2016; 15(3): 1895–1906, doi: 10.1109/TWC.2015.2496958.
2. Y. Yao and N. Jiang, "Distributed wireless sensor network localization based on weighted search," *Comput. Networks*, 2015; 86: 57–75, doi: 10.1016/j.comnet.2015.05.002.
3. X. Ge, J. Yang, H. Gharavi, and Y. Sun, "Energy Efficiency Challenges of 5G Small Cell Networks," no. May 2017; 184–191.
4. X. Gong, D. Plets, E. Tanghe, T. De Pessemier, L. Martens, and W. Joseph, "An efficient genetic algorithm for large-scale planning of dense and robust industrial wireless networks," *Expert Syst. Appl.*, 2018; 96: 311–329, doi: 10.1016/j.eswa.2017.12.011.
5. A. Gupta, S. Member, R. K. Jha, and S. Member, "A Survey of 5G Network : Architecture

and Emerging Technologies," 2015; 3.

6. A. Mesodiakaki, E. Zola, R. Santos, and A. Kassler, "Ad Hoc Networks Optimal user association, backhaul routing and switching off in 5G heterogeneous networks with mesh millimeter wave backhaul links," *Ad Hoc Networks*, 2018; 78: 99–114, doi: 10.1016/j.adhoc.2018.05.008.
7. B. Zeng and Y. Dong, "An improved harmony search based energy-efficient routing algorithm for wireless sensor networks," *Appl. Soft. Comput. J.*, 2016; 41: 135–147, doi: 10.1016/j.asoc.2015.12.028.
8. Y. Suzuki, R. Sakamoto, and H. Nakamura, "Dynamic Power Management for 5G Small Cell Base Station," vol. 2061; 492–500.
9. J. I. Guerrero, A. García, E. Personal, J. Luque, and C. León, "Heterogeneous data source integration for smart grid ecosystems based on metadata mining," *Expert Syst. Appl.*, 2017; 79: 254–268, , doi: 10.1016/j.eswa.2017.03.007.
10. S. S. Meelu and M. Katiyar, "Efficient Cluster Head Selection Scheme for Wireless Sensor Network Using Deterministic Protocol," *IOSR J. Comput. Eng.*, 2014; 16(3): 62–67, doi: 10.9790/0661-16366267.
11. A. Sancho-Asensio *et al.*, "Improving dta partition schemes in Smart Grids via clustering data streams," *Expert Syst. Appl.*, 2014; 41(13): 5832–5842, doi: 10.1016/j.eswa.2014.03.035.
12. Y. Liu, S. L. Zhao, X. K. Du, and S. Q. Li, "Optimization of resource allocation in construction using genetic algorithms," *2005 Int. Conf. Mach. Learn. Cybern. ICMLC*, no. August *2005;* 3428–3432, 2005, doi: 10.1109/icmlc.2005.1527534.
13. I. C. Wong, Z. Shen, B. L. Evans, and J. G. Andrews, "A Low Complexity Algorithm for Proportional Resource Allocation in OFDMA Systems".
14. T. Cisco and A. Internet, "Cisco Annual Internet Report," 2023.
15. "2 E. Dahlman, S. Parkvall, and J. Sköld, The Next Generation Wireless Access Technology, Academic Press, 2018."
16. Next Generation Mobile Networks Alliance, "5G White Paper," *A Deliv. by NGMN Alliance*, 2015; 124: [Online]. Available: https://www.ngmn.org/fileadmin/ngmn/content/downloads/Technical/2015/NGMN_5G_White_Paper_V1_0.pdf
17. S. Parkvall, E. Dahlman, A. Furuskär, and M. Frenne, "WIRELESS AND RADIO COMMUNICATION NR : The New 5G Radio Access Technology," no. December 2017; 24–30.

18. F. Tian, P. Zhang, and Z. Yan, “A Survey on C-RAN Security,” *IEEE Access*, 2017; 5: 13372–13386, doi: 10.1109/ACCESS.2017.2717852.
19. D. Tse, P. Viswanath, and C. Sciences, “Fundamentals of Wireless Communication”.
20. J. Il Choi, M. Jain, K. Srinivasan, P. Levis, and S. Katti, “Achieving Single Channel, Full Duplex Wireless Communication”.
21. “8.R. Jain, D.-M. Chiu, and W. Hawe, “A quantitative measure of fairness and discrimination.pdf.”
22. *Geometric Programming for Communication Systems*.
23. A. A. A. Ari, A. Gueroui, C. Titouna, O. Thiare, and Z. Aliouat, “Resource allocation scheme for 5G C-RAN: a Swarm Intelligence based approach,” *Comput. Networks*, 2019; 165: 106957, doi: 10.1016/j.comnet.2019.106957.
24. K. N. Krishnanand and D. Ghose, “Glowworm Swarm Optimization for Searching Higher,” 61–62.
25. R. Jain, “Introduction to 4G LTE - Advanced,” 2018; 1–51.
26. P. Rost *et al.*, “Mobile network architecture evolution toward 5G,” *Infocommunications J.*, 2017; 9(1): 24–31.
27. N. Nikaein, E. Schiller, R. Favraud, R. Knopp, I. Alyafawi, and T. Braun, “Towards a Cloud-Native Radio Access Network,” *Stud. Big Data*, 2017; 22: 171–202, doi: 10.1007/978-3-319-45145-9_8.
28. T. Specification, “TS 138 300 - V17.5.0 - 5G; NR; NR and NG-RAN Overall description; Stage-2 (3GPP TS 38.300 version 17.5.0 Release 17),” vol. 0, 2023.
29. Bonthu, A. Kumar, and G. Goel, “Impact of AI and Machine Learning on Master Data Management,” 2025; 10.
30. P. Farhat, H. Sami, and A. Mourad, “Reinforcement R-learning model for time scheduling of on-demand fog placement,” *J. Supercomput.*, 2020; 76(1): 388–410, doi: 10.1007/s11227-019-03032-z.
31. Z. Si, G. Chuai, W. Gao, J. Zhang, X. Chen, and K. Zhang, “A QoS ‐ based joint user association and resource allocation scheme in ultra ‐ dense networks,” *EURASIP J. Wirel. Commun. Netw.*, 2021, doi: 10.1186/s13638-020-01882-3.
32. A. Alnoman, L. Ferdouse, and A. Anpalagan, “Fuzzy-based joint user association and resource allocation in HetNets,” *IEEE Veh. Technol. Conf.*, vol. 2017-Septe; 1–5, 2017, doi: 10.1109/VTCFall.2017.8288227.
33. H. Celebi, Y. Yapici, I. Guvenc, and H. Schulzrinne, “Load-Based On/Off Scheduling for

Energy-Efficient Delay-Tolerant 5G Networks," *IEEE Trans. Green Commun. Netw.*, 2019; 3(4): 955–970, doi: 10.1109/TGCN.2019.2931700.

34. L. D. Nguyen, "Resource Allocation for Energy Efficiency in 5G Wireless Networks," *EAI Endorsed Trans. Ind. Networks Intell. Syst.*, 2018; 5(14): 154832, doi: 10.4108/eai.27-6-2018.154832.
35. Y. H. Robinson and M. Rajaram, "Energy-aware multipath routing scheme based on particle swarm optimization in mobile ad hoc networks," *Sci. World J.*, vol. 2015, 2015, doi: 10.1155/2015/284276.
36. T. Liu, W. Fan, F. Wu, W. Xie, and W. Yuan, "applied sciences Joint Computation Offloading and Data Caching Based on Cooperation of Mobile-Edge-Computing-Enabled Base Stations," 2021.
37. H. Ohlsén, "ITU-R Working Party 5D Introduction to IMT-2020," 2020.
38. D. Raj, "A Hybrid Glowworm Swarm Optimization for Enhancing the Lifespan of Wireless Sensor Networks," 2021, [Online]. Available: https://doi.org/10.21203/rs.3.rs-274464/v1
39. D. S. Shu, S. K. S. Yusof, and N. Fisal, "Dynamic resource allocation in mobile WiMAX using particle swarm optimization techniques," 2011; 6(5): 1009–1014.
40. Z. Shen, J. G. Andrews, and B. L. Evans, "Optimal Power Allocation in Multiuser OFDM Systems".
41. F. Brah, J. Louveaux, and L. Vandendorpe, "CDIT-Based Constrained Resource Allocation for Mobile WiMAX Systems," vol. 2009, 2009, doi: 10.1155/2009/425367.
42. M. Feng, S. Mao, and T. Jiang, "Joint Frame Design, Resource Allocation and User Association for Massive MIMO Heterogeneous Networks With Wireless Backhaul," *IEEE Trans. Wirel. Commun.*, 2018; 17(3): 1937–1950, doi: 10.1109/TWC.2017.2787139.
43. S. T. Chung, S. Member, A. J. Goldsmith, and S. Member, "Degrees of Freedom in Adaptive Modulation :," 2001; 49(9): 1561–1571.
44. "RADIO RESOURCE MANAGEMENT FOR MOBILE WiMAX NETWORK".
45. S. M. M. Al-inizi and M. Nickray, "Resource Allocation and Spectrum Sensing for 5G Networks Based on Deep Learning," 2025; 10.
46. X. Yang and Y. Wang, "Resource Allocation in LTE OFDMA Systems using Genetic Algorithm and Semi-Smart Antennas," 2010.
47. E. Sesli, E. Gürsoy, and G. Hacıoglu, "Energy-efficient OFDMA resource allocation in HetNets using discrete particle swarm optimization," 2025, doi: 10.1007/s12083-025-

01914-z.

48. S. Kar, P. Mishra, and K. C. Wang, “Efficient resource management using 5G multi‐connectivity for high throughput and reliable low latency communication,” 2025.
49. I. Ahmed, S. Sadeque, and S. Pervin, “Margin adaptive resource allocation for multiuser OFDM systems by modified Particle Swarm Optimization and Differential Evolution,” *CONIELECOMP 2011 - 21st Int. Conf. Electron. Commun. Comput. Proc.*, 2011; 227–231, doi: 10.1109/CONIELECOMP.2011.5749365.
50. R. Annauth, “OFDM Systems Resource Allocation using Multi-Objective Particle Swarm Optimization,” *Int. J. Comput. Networks Commun.*, 2012; 4(4): 291–306, doi: 10.5121/ijcnc.2012.4419.