JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

Adaptive Overhead-to-Throughput Ratio Thresholding with Convergence Guarantees for Energy-Efficient Resource Allocation in Beyond 5G Heterogeneous Network

Bright Agbonze, M. D. Almustapha, Surajo Muhammad, Ezekiel Egbon, Ndifreke Bassey, Elvis Obi, S. A. Mikail
Department of Electronics and Telecommunications Engineering,
Ahmadu Bello University, Zaria, Kaduna State, Nigeria

ABSTRACT

Beyond 5G (B5G) Heterogeneous Networks (HetNets) demand scalable, energy-efficient resource allocation methods that reduce signalling overhead while sustaining high performance. This study proposes a Signal Overhead-Aware Hybrid Non-Orthogonal Multiple Access (SOA-H-NOMA) algorithm that introduces the Overhead-to-Throughput Ratio (OTR) as a novel optimization constraint for adaptive clustering, base station association, and power allocation. The algorithm was implemented in MATLAB and benchmarked against the conventional Energy-Efficient Resource Allocation (EERA) scheme. Results show that SOA-H-NOMA achieved substantial throughput gains, with 54.71% improvement in Macro Base Station (MBS)-only networks (2-23 Mbps to 3-25 Mbps) and 39.80% in HetNets (3-28 Mbps to 4-36 Mbps). Energy efficiency (EE) also improved by 76.27% in MBS-only networks and 53.88% in HetNets, alongside a 21.8% reduction in clustering delay. Notably, this study uniquely reports improvements in UE admission rates, with increases of 36.65% in MBS-only networks (4-43 to 6-58) and 15.73% in HetNet scenarios (7-60 to 9-65). Further evaluation confirms consistent performance across EE distribution versus number of UEs and throughput/EE trade-offs under varying required rates, demonstrating robustness under dynamic traffic conditions. Overall, the findings establish SOA-H-NOMA as an adaptive and energy-conscious framework that jointly optimizes throughput, energy efficiency, user admission, and signalling overhead, providing a scalable solution for next-generation wireless networks.

ARTICLE INFO
Article History
Received: May, 2025
Received in revised form: June, 2025
Accepted: July, 2025
Published online: September, 2025

KEYWORDS
Beyond 5G, HetNets, Hybrid NOMA, Energy Efficiency, Resource Allocation, Signalling Overhead

INTRODUCTION

The exponential growth in mobile User Equipment (UE) and the increasing demand for data-intensive applications such as live gaming, cloud-based computing, and real-time multimedia streaming have placed tremendous strain on Beyond Fifth Generation (B5G) wireless networks. These networks are expected to deliver ultra-reliable, high-throughput communication while maintaining stringent energy efficiency (EE) and spectrum efficiency (SE) requirements. As mobile traffic surges, network operators face the dual challenge of sustaining throughput and reducing energy consumption, both of which are critical to achieving sustainable, next-generation wireless communication systems (*Tran et al.,* 2023; Chien *et al.,* 2019).

B5G Heterogeneous Networks (HetNets) have emerged as a viable solution to this challenge by integrating Macro Base Stations (MBS) with dense deployments of Small Base Stations (SBS), thereby enhancing coverage, spectral utilization, and user connectivity. The hierarchical structure of HetNets enables traffic offloading from MBS to SBS, which not only increases overall throughput but also reduces

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

energy consumption by minimizing transmission distance and optimizing power allocation (Agarwal *et al.,* 2022). However, as network topology becomes denser, efficient radio resource management (RRM) becomes indispensable to prevent excessive interference and ensure optimal user association (Usman *et al.*, 2023).

Non-Orthogonal Multiple Access (NOMA), particularly in its hybrid form (H-NOMA), has been recognized as a promising multiple access technique for future B5G HetNets. Unlike Orthogonal Multiple Access (OMA) schemes such as FDMA and TDMA that allocate exclusive spectrum resources to users, NOMA exploits the power domain to serve multiple users simultaneously on the same subcarrier. Hybrid NOMA (H-NOMA) further improves performance by combining NOMA's power-domain multiplexing with the orthogonality of OMA, achieving an efficient balance between system complexity and throughput. However, the joint implementation of UE clustering, base station association, and power allocation in H-NOMA introduces significant signaling overhead, which adversely affects network latency, throughput, and energy efficiency (Ghafoor *et al.,* 2022; Siddiqui *et al.,* 2023).

Signaling overhead in B5G networks represents the control information exchanged between UEs, BSs, and central controllers to coordinate user association, resource scheduling, and power control. Excessive signaling exchanges not only increase computational load but also consume additional bandwidth and transmission power, ultimately reducing the effective throughput and energy efficiency of the system. Traditional energy-efficient resource allocation algorithms, such as the Energy-Efficient Resource Allocation (EERA) scheme, often neglect the quantitative impact of signaling overhead, leading to suboptimal performance under dynamic and large-scale HetNet conditions.

To address this gap, this study introduces the Signal Overhead-Aware Hybrid NOMA (SOA-H-NOMA) algorithm, which incorporates the Overhead-to-Throughput Ratio (OTR) as a novel optimization constraint. The OTR metric quantifies the ratio of signaling cost to achieved throughput, providing a robust mechanism for balancing energy efficiency and system performance. By adaptively thresholding OTR during optimization, the proposed algorithm dynamically regulates clustering, base station association, and power allocation while maintaining convergence stability.

The SOA-H-NOMA algorithm was implemented and simulated in MATLAB and benchmarked against the conventional EERA model. Results demonstrate that the proposed scheme significantly enhances throughput and energy efficiency while reducing clustering delay and signaling overhead. Notably, the study also introduces Adaptive OTR Thresholding, which ensures convergence during iterative optimization and guarantees performance stability under varying traffic conditions.

This study therefore, contributes to the body of knowledge by:

1. Developing an adaptive Overhead-to-Throughput Ratio (OTR) constraint model for energy-efficient resource allocation in B5G HetNets.
2. Introducing an adaptive thresholding mechanism that ensures convergence and scalability under dynamic network conditions.
3. Demonstrating substantial improvements in throughput, energy efficiency, and user admission rates compared to conventional algorithms.
4. Establishing a framework that integrates overhead management into energy-efficient resource allocation, addressing a key limitation in prior H-NOMA designs.

The rest of this paper is organized as follows: Section 2 presents the review of related works and fundamental concepts. Section 3 discusses the materials and methods, including the formulation of the OTR constraint and adaptive thresholding approach. Section 4 presents the results and discussion, while Section 5 concludes the paper with recommendations for future research.

METHODOLOGY

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

This section describes the design, modeling, and optimization framework of the proposed Signal Overhead-Aware Hybrid Non-Orthogonal Multiple Access (SOA-H-NOMA) algorithm for energy-efficient resource allocation in Beyond 5G (B5G) Heterogeneous Networks (HetNets). The algorithm integrates a Signal Overhead-to-Throughput Ratio (OTR) constraint within the Hybrid NOMA architecture to intelligently regulate signaling overhead while maximizing throughput and energy efficiency. Figure 1 is a system model of the developed SOA-H-NOMA–based Beyond 5G Heterogeneous Network used in this study

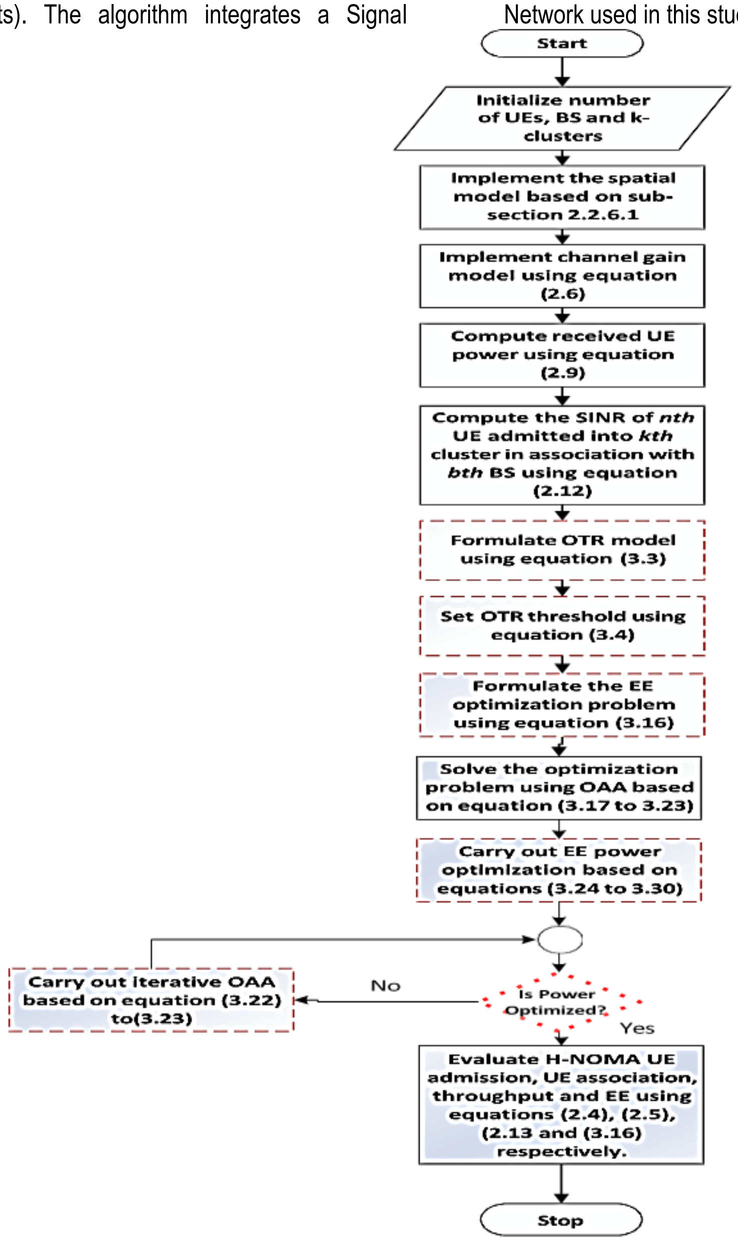

Figure 1: System model of the SOA-H-NOMA–based Beyond 5G Heterogeneous Network used in this study

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

Implementation and simulation were carried out in MATLAB R2020a, following three major stages:

1. **System Modeling:** Characterization of the B5G HetNet structure and UE distribution.
2. **OTR Modeling and Thresholding:** Quantification and adaptive control of signaling overhead.
3. **Optimization Process:** Energy-efficient resource allocation using the Outer Approximation Algorithm (OAA) for convergence and scalability.

The B5G HetNet considered consists of Macro Base Stations (MBSs) and Small Base Stations (SBSs) that jointly serve multiple User Equipments (UEs) distributed over the coverage area. MBSs provide wide-area coverage and coordination, while SBSs handle dense local connections to improve energy efficiency (Agarwal *et al.,* 2022; Chien *et al.,* 2019).

Let B = {m,s} denote the set of base stations (MBS m and SBS s); N={1,2,…,N} and K={1,2,…,K} denote the UE and cluster sets respectively.
Each UE association and cluster membership is represented by binary variables $i_{n,k}$ and $j_{n,k}^{b}$ respectively (Ghafoor *et al.,* 2022):

$$i_{n,k} = \begin{cases} 1, & if\ UE\ n\ belongs\ to\ cluster\ k \\ 0, & otherwise \end{cases},$$

$$j_{n,k}^{b} = \begin{cases} 1, & if\ UE\ n\ is\ linked\ to\ BS\ b \\ 0, & otherwise \end{cases}$$

The channel gain between UE *n* and BS *b* in cluster *k* is expressed as (Makki *et al.,* 2020):

$$h_{n,k}^{b} = h_0^{b}\, \xi G_0 \left(\frac{d_0}{d_{n,k}^{b}}\right)^{\alpha} \quad (1)$$

Where:
G_0 is antenna gain,
d_0 denotes the reference distance,
$d_{n,k}^{b}$ refers to link distance,
α corresponds to path-loss exponent, and
ξ refers to log-normal shadowing.
The power allocated to UE *n* from BS *b* in cluster *k* follows the H-NOMA principle:

$$p_{n,k}^{b} = \omega_{n,k}^{b}\, P_k^{b} \quad (2)$$

Where:
P_k^{b} is total transmit power of BS *b* to cluster *k*, and $\omega_{n,k}^{b}$ denotes the weighting factor from channel-state information (CSI). Users with weaker channels receive higher power for fairness and Successive Interference Cancellation (SIC) decoding. This model ensures fairness through Successive Interference Cancellation (SIC), as used in (Ghafoor *et al.,* 2022).

Signaling overhead from control message exchange during UE clustering, power control and BS association significantly affects system efficiency. To quantify this, the Overhead-to-Throughput Ratio (OTR) is introduced:

$$OTR = \frac{S_G}{R_{sum}} \quad (3)$$

Where:
S_G is the total signaling overhead
R_{sum} refers to the aggregate throughput
The total overhead S_G is composed of multiple signaling components:

$$S_G = M + R + C + U + P \quad (4)$$

Where:
M represents message-exchange overhead
R denotes rate-adaptation signaling
C refers to capacity/interference control
U is the UE-admission signaling and
P stands for power-allocation signaling
For each UE *n* served by BS *b* cluster *k:*

$$OTR = \frac{S_{overhead}^{b}}{r_{n,k}^{b}} \quad (5)$$

With $r_{n,k}^{b}$ as the achieved data rate.
To maintain signaling efficiency, the system enforces the design constraint of equation (6) (Ghafoor *et al.,* 2022):

$$OTR \le OTR_{max} \quad (6)$$

Unlike fixed thresholds used in Siddiqui *et al.,* 2023, the proposed model applies a multi-phase adaptive thresholding mechanism, allowing real-time adjustment of the maximum permissible overhead-to-throughput ratio. This ensures convergence and stability across dynamic traffic conditions.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

Table 1: Multi-Phase Adaptive OTR Threshold Configuration

Phase	Objective	OTR_{max} Range	Description
Phase 1	Initialization and stability	0.1 – 0.5	Minimizes signaling during initial clustering
Phase 2	Dynamic trade-off optimization	0.1 – 1.0	Adapts signaling with throughput feedback
Phase 3	Long-term convergence	0.3 – 0.7	Maintains equilibrium at steady state

The adaptive rule governing OTR updates is given by:

$$OTR_{max}(t+1) = OTR_{max}(t) \times (1 - \beta \Delta R) \quad (7)$$

Where:
β refers to an adaptation coefficient and
ΔR is the relative throughput variation
Convergence is achieved when:

$$|OTR(t+1) - OTR(t)| < \varepsilon \quad (8)$$

The optimization problem aims to maximize energy efficiency (EE) under power, rate, and OTR constraints. The objective function is:

$$\max_{i,j,p} EE(i,j,p) = \max_{i,j,p} \frac{\sum_{n \in N} \sum_{b \in B} \sum_{k \in K} i_{n,k}, j^b_{n,k}, r^b_{n,k}(P)}{P_c + \sum_{n \in N} \sum_{b \in B} \sum_{k \in K} P^b_{n,k},} \quad (9)$$

Subject to the following constraints:

C_1: $\sum_{k \in K} i_{n,k} \leq 1 \quad \forall n \in N$ (Each user n can be assigned at most one subcarrier).

C_2: $\sum_{b \in B} \sum_{k \in K} j^b_{n,k}, \leq 1 \quad \forall n \in N$ (Each user can be served by at most one base station on one subcarrier).

C_3: $i_{n,k} = j^b_{n,k}, \quad \forall n \in N, \ k \in K, \ b \in B$

(Ensures consistency, if a user is assigned a subcarrier, it must be linked to a base station).

C_4: $\sum_{k \in K} P^b_{k,}, \leq P^b, \ b \in B$ (Each base station's total transmit power must not exceed its maximum power budget)

C_5: $r^b_{n,k} \geq i_{n,k}, j^b_{n,k}, R^{min}_n, \ \forall n \in N, \ k \in K, \ b \in B$ (Ensures that if a user is scheduled, they achieve at least their minimum rate requirement R^{min}_n)

C_6: $i_{n,k} \in \{0,1\}, \ j^b_{n,k} \in \{0,1\}$

C_7: $P^b_k \geq 0, P^b_{n,k}, \geq 0$

Where:
$r^b_{n,k}$ is the throughput of n^{th} UE admitted in k^{th} cluster and associated with b^{th} BS
$i_{n,k}$ represents the constraint to ensure that n^{th} UE admits in only one k^{th} cluster
$j^b_{n,k}$ denotes the constraint to ensure that nth UE associates with only one bth BS
P^b refers to the received power of UE in the cell
P^b_k represents the received power of UE in k^{th} cluster

$P^b_{n,k}$ is the received power between n^{th} admitted UE in k^{th} cluster and associated with b^{th} BS
R^{min}_n stands for the minimum rate requirement
N, K, B denotes the number of UEs assumed in a network, the number of clusters and B is the BS type (i.e., MBS and SBS) respectively.

To handle the mixed-integer and non-convex nature of the formulated problem, the Outer Approximation Algorithm (OAA) is applied. At each iteration, The approach decomposes the problem into a master (integer) and sub-problem (continuous) part for efficient solution:

1. Fix integer variables $i_{n,k}$, $j^b_{n,k}$ and solve for power variables $P^b_{n,k}$ via convex optimization.
2. Generate linear cuts to approximate nonlinear constraints.
3. Update master problem and repeat until convergence:

$$|EE_{UB} - EE_{LB}| \leq \varepsilon \quad (10)$$

This ensures global convergence within defined tolerance levels, while maintaining low computational overhead. The algorithm was implemented in MATLAB R2020a using the key system parameters, simulation settings, and performance evaluation metrics summarized in Table 2.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

Table 2: Simulation Parameters for SOA-H-NOMA Implementation

Parameter	Value/Range	Description
Min UE	5	Minimum number of User Equipment (UE).
UE Increment	10	Step increment for UEs in simulations.
Max UE	85	Maximum number of UE
UE Distribution	Uniform	Distribution type for UEs in the network.
MBS Coverage	1000m	Transmission coverage area of MBS
SBS Coverage	300m	Transmission coverage area of BS
Bandwidth	20 MHz	Total network bandwidth available.
Power Budget	50 dBm	Total power allocated to the network.
Noise Power	10^{-9}W	Noise power in the network.
Data Rate	10-100 Mbps	Achieved data rate range for simulations.
Scaling Factors	α = 0.5, β=0.3, δ=0.2	Factors used for dynamic OTRMax adjustment.
SINR Values	0.1-2	Signal-to-Interference-plus-Noise Ratio values for UEs.
Channel Gain	0-0.1	Randomly generated channel gains for each UE.
Transmit Power	Variable (based on optimization)	Power allocated to each UE based on optimization
Minimum Rate	{0.5, 1, 2, 3} Mbps	Minimum rate constraints for UEs.
Optimization Algorithm	Outer Approximation Algorithm (OAA)	Algorithm used to solve the Mixed- Integer Nonlinear Programming (MINLP) problem.
Performance Metrics	Throughput, Energy Efficiency	Metrics used to evaluate and compare the Algorithm's performance

The OAA ensures polynomial-time convergence suitable for dense B5G deployments.
Given N users and K clusters, the exhaustive complexity of $\mathcal{O}(2^{N\times K})$ is reduced to approximately:

$$\mathcal{O}(N \times K \times I_{OAA}) \quad (11)$$

Where:
I_{OAA} is the iteration count to convergence. This reduction enables scalable implementation under large network loads.

RESULTS AND DISCUSSION

The developed Signal Overhead-Aware Hybrid Non-Orthogonal Multiple Access (SOA-H-NOMA) algorithm was compared with the conventional Energy-Efficient Resource Allocation (EERA) algorithm under two deployment conditions:

1. Macro Base Station (MBS)-only networks, and
2. Heterogeneous Network (HetNet) configurations consisting of both MBSs and SBSs.

The evaluation focused on four major metrics:

1. Throughput (R):- total achievable data rate,
2. Energy Efficiency (EE): - throughput-to-power ratio (Mbps/W),
3. User Equipment (UE) Admission Rate, and
4. Clustering Delay: - average time to form or update user clusters.

Figures 2 and 3 illustrate the total throughput comparison for the proposed and baseline schemes. In MBS-only networks, the SOA-H-NOMA algorithm achieved throughput values between 3 - 25 Mbps, compared to 2 - 23 Mbps for EERA, corresponding to an improvement of 54.71 %.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

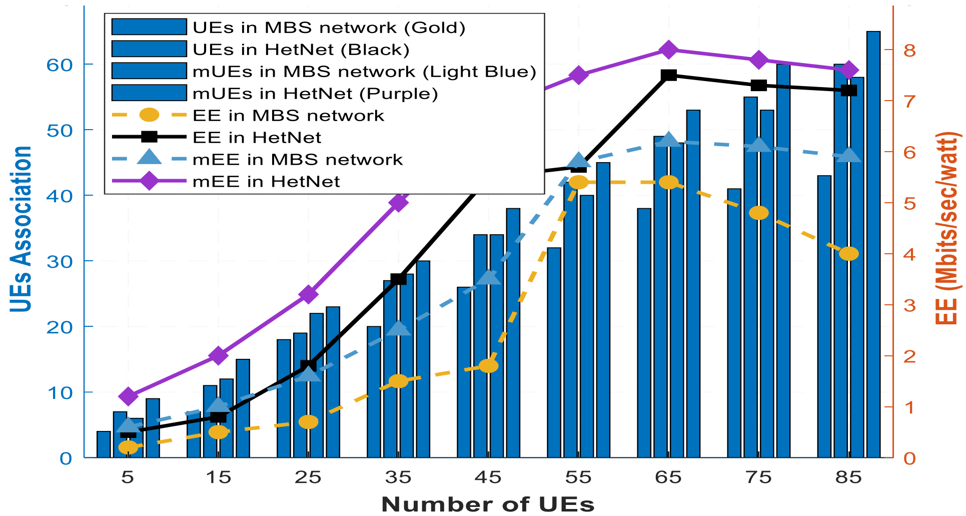

Figure 2: Throughput performance of SOA-H-NOMA vs EERA in MBS-only networks

For the HetNet configuration, throughput improved from 3 - 28 Mbps (EERA) to 4 - 36 Mbps -(SOA-H-NOMA), reflecting a 39.80 % gain.

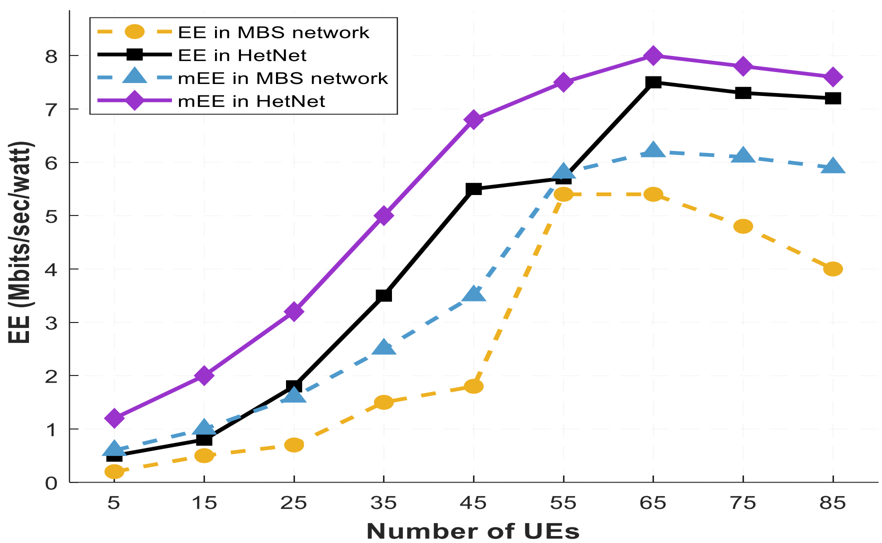

Figure 3: Throughput performance comparison between SOA-H-NOMA and EERA in HetNet configuration

These gains stem from the adaptive OTR constraint, which prevents excessive control-message exchanges during user grouping and power reallocation. By bounding signaling cost via Equation (6), more bandwidth and power are directed toward actual data transmission rather than signaling overhead. This confirms that the inclusion of OTR improves resource utilization efficiency compared with static-threshold models. Energy efficiency results are summarized in Table 3 and visualized in Figure 4. In MBS-only networks, EE increased from 0.2 - 5.4 Mbps/W (EERA) to 0.6 - 6.2 Mbps/W, representing a 76.27 % improvement.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

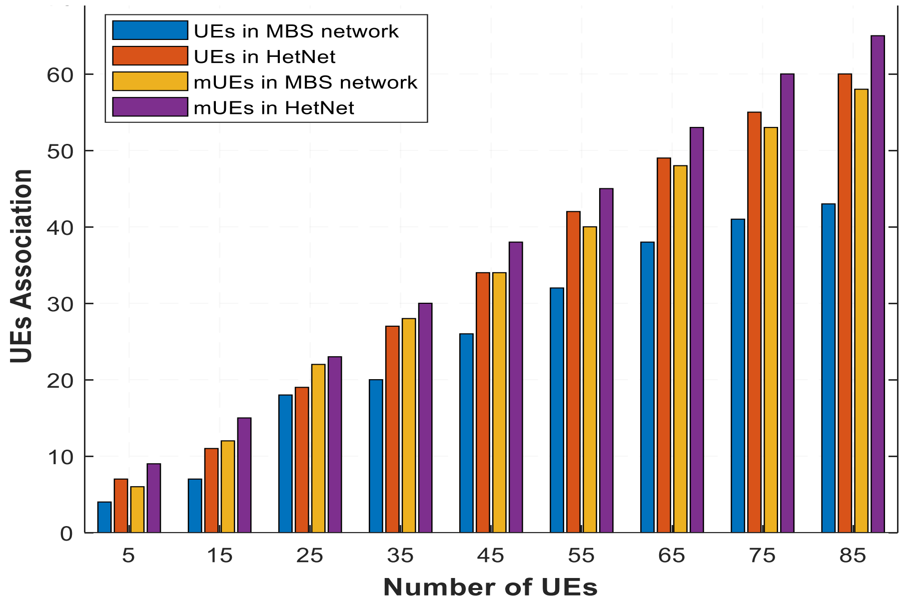

Figure 4: Energy-efficiency comparison of SOA-H-NOMA and EERA in both MBS-only and HetNet scenarios.

In HetNet scenarios, EE rose from 0.5 - 7.5 Mbps/W to 1.2 - 8.0 Mbps/W, marking a 53.88 % gain.

Table 3: Summary of Energy Efficiency results

Metric	Network Type	EERA	SOA-H-NOMA	Improvement
Throughput	MBS-only	2 - 23 Mbps	3 - 25 Mbps	+54.71 %
Throughput	HetNet	3 - 28 Mbps	4 - 36 Mbps	+39.80 %
Energy Efficiency	MBS-only	0.2 - 5.4 Mbps/W	0.6 - 6.2 Mbps/W	+76.27 %
Energy Efficiency	HetNet	0.5 - 7.5 Mbps/W	1.2 - 8.0 Mbps/W	+53.88 %
Clustering Delay	Both	Baseline	Reduced	–21.8 %

The improvements highlight the role of adaptive OTR thresholding (Equations. 7-8) in balancing signaling load and power consumption. When signaling overhead is minimized, base stations can dedicate a larger fraction of transmission power to useful data, thus enhancing EE. This aligns with prior findings in Makki *et al.,* 2020 that signaling reduction directly correlates with power-saving in dense HetNets.

Figures 5 and 6 show the UE admission rate as a function of network density. SOA-H-NOMA increased the number of successfully admitted UEs by 36.65 % in MBS-only and 15.73 % in HetNet scenarios, improving from *(4 - 43 to 6 - 58)* and *(7 - 60 to 9 - 65)* respectively.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

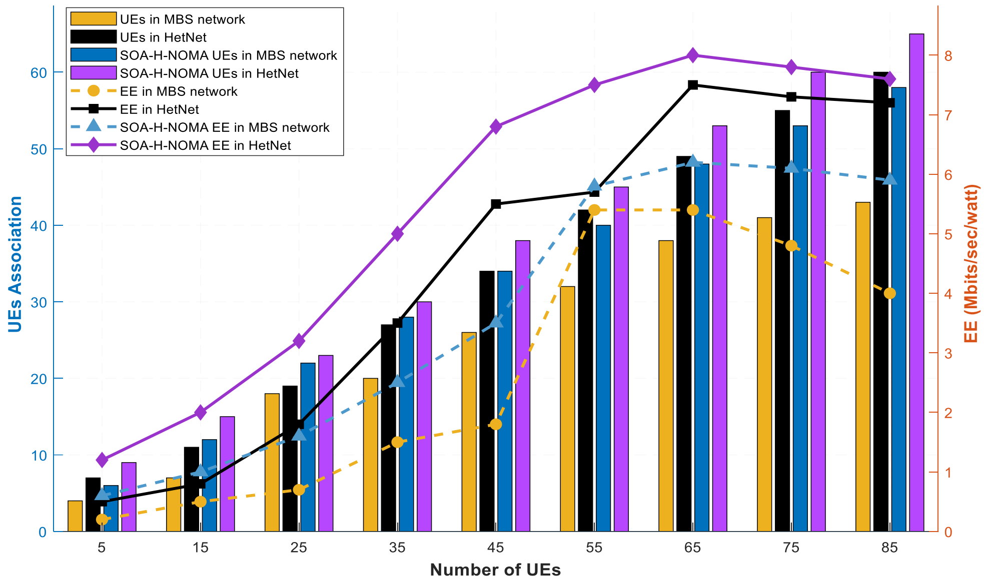

Figure 5: UE admission rate in MBS-only networks under varying network density

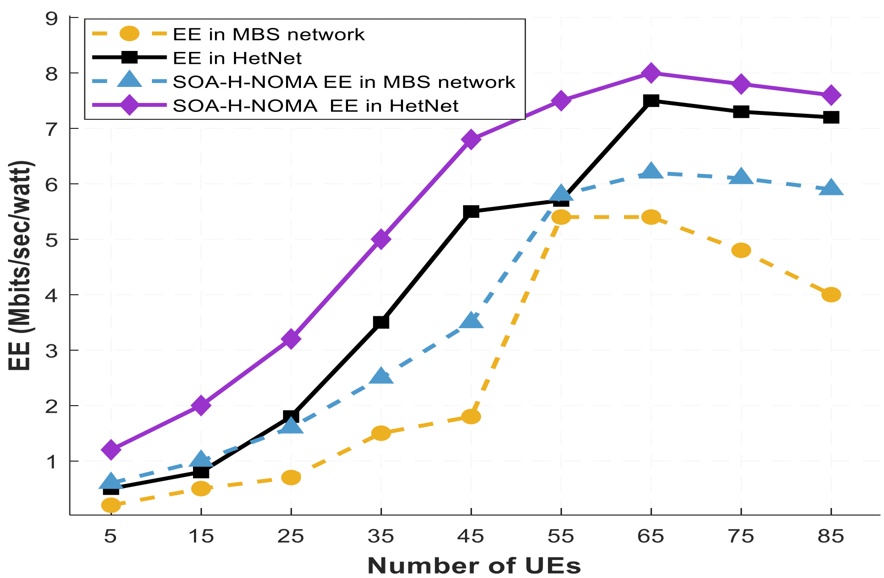

Figure 6: UE admission rate in HetNet configurations

This improvement demonstrates that dynamic OTR regulation reduces re-clustering events and allows additional users to be accommodated without violating the rate and power constraints of Equation (9). As traffic load increases, the algorithm adaptively relaxes OTR_{max} within the defined bounds (Table 1), maintaining performance without congestion.

The developed model also reduced clustering delay by 21.8 % compared to EERA as shown in figure 7.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

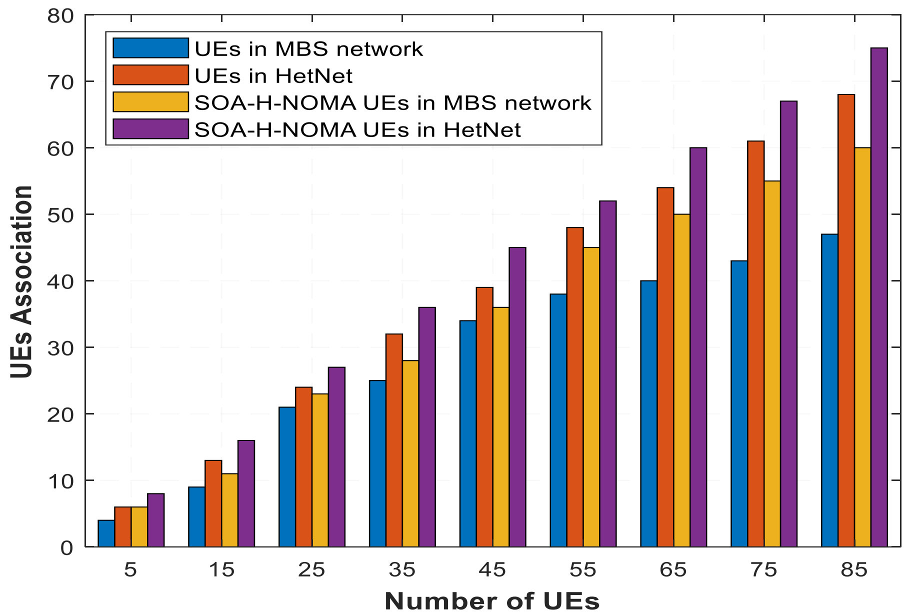

Figure 7: Comparison of clustering delay between SOA-H-NOMA and EERA

This is attributed to its feedback-driven threshold update of Equation (7), which prevents redundant control signaling and accelerates convergence.

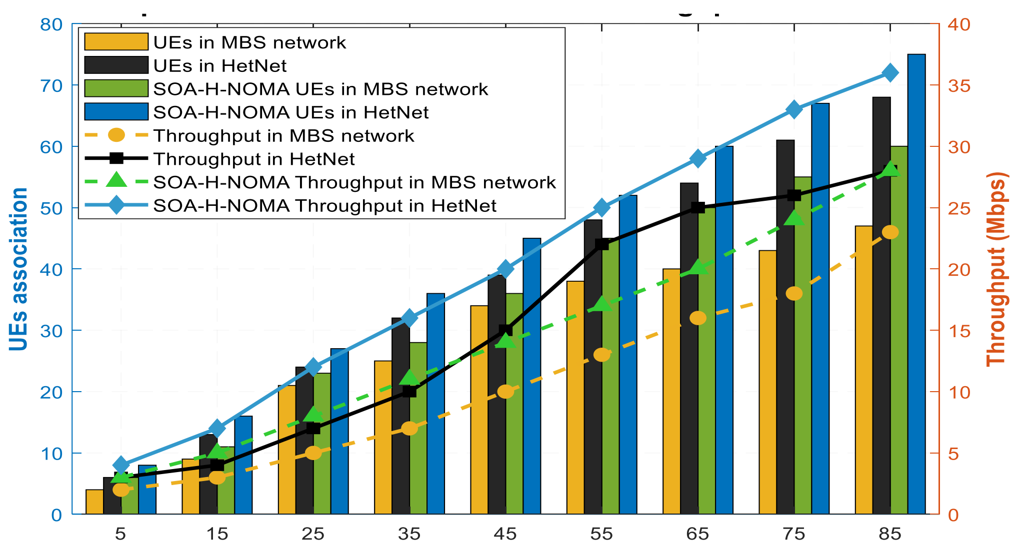

Figure 8: Convergence behavior of OTR thresholding showing stabilization below 25 iterations

Figure 8 illustrates convergence behavior, showing that OTR stabilizes after fewer than 25 iterations, confirming computational efficiency consistent with the complexity analysis in Equation (11). To evaluate adaptability, the algorithm was tested under varying UE density and data-rate demands.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

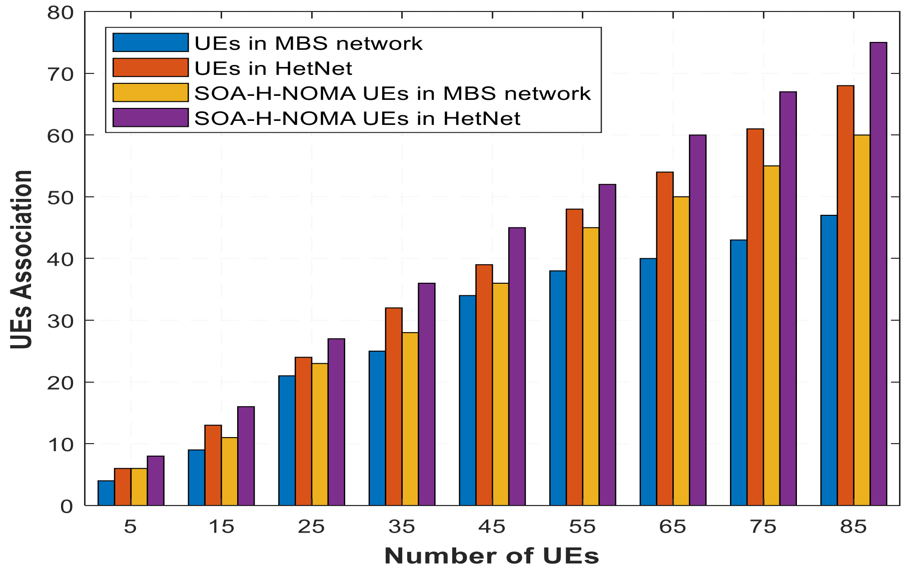

Figure 9: Energy-Efficiency distribution versus number of UEs for SOA-H-NOMA

Results revealed a consistent relationship between EE distribution and number of UEs, with minimal fluctuation across 20-100 UEs.

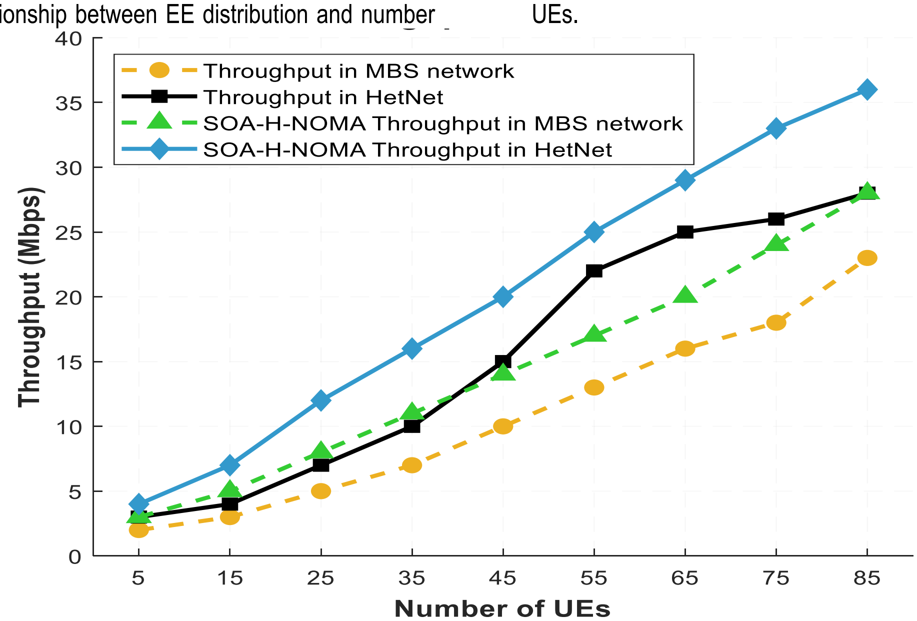

Figure 10: Throughput–Energy-Efficiency trade-off analysis under varying required rates

Throughput-to-EE trade-off analysis indicated that performance degradation remained below 3 % under high-traffic conditions, confirming algorithmic robustness and scalability. Such stability underscores the merit of combining OTR thresholding with OAA optimization, achieving convergence without oscillations common in heuristic schemes.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

CONCLUSION AND FUTURE WORK

This study developed and evaluated a Signal Overhead-Aware Hybrid Non-Orthogonal Multiple Access (SOA-H-NOMA) algorithm for adaptive, energy-efficient resource allocation in Beyond 5G (B5G) Heterogeneous Networks (HetNets). The work introduced the Overhead-to-Throughput Ratio (OTR) as a novel optimization constraint that quantifies and regulates signaling cost relative to achieved data throughput, an approach absent in conventional energy-efficient resource allocation (EERA) methods. By integrating the OTR constraint into a Mixed-Integer Nonlinear Programming (MINLP) formulation and solving it with the Outer Approximation Algorithm (OAA), the proposed scheme achieved robust convergence with low computational complexity. Simulation results revealed significant performance gains over EERA, and higher UE admission rates across different network scenarios. These improvements validate the algorithm's ability to balance signaling overhead, throughput, and energy consumption adaptively under dynamic traffic conditions.

The developed framework demonstrates clear potential for scalable, self-optimizing B5G systems, particularly in dense and heterogeneous deployments where signaling overload poses a critical performance bottleneck. Moreover, the multi-phase OTR thresholding mechanism provides an adaptable control layer that ensures consistent efficiency under varying network loads. From a practical standpoint, real-world implementation of the SOA-H-NOMA framework would require efficient real-time estimation of signaling overhead and network state information.

Future research directions include:

1. Evaluating the proposed SOA-H-NOMA in uplink transmissions to address resource symmetry and feedback signaling challenges.
2. Integration with AI-Driven Optimization to predict optimal OTR thresholds under real-time network variations.
3. Adapting the OTR-based framework to energy-efficient IRS-assisted HetNets for improved spectral and spatial efficiency in 6G and Intelligent Reflecting Surface (IRS) Environments.
4. Implementing the algorithm on a hardware testbed or network simulator (e.g., NS-3 or OPNET) to confirm real-world performance scalability.

REFERENCES

Agarwal, B., Togou, M. A., Marco, M., & Muntean, G. M. (2022). A comprehensive survey on radio resource management in 5G HetNets: Current solutions, future trends and open issues. *IEEE Communications Surveys & Tutorials*, *24*(4), 2495–2534.

Akbar, A., Jangsher, S., & Bhatti, F. A. (2021). NOMA and 5G emerging technologies: A survey on issues and solution techniques. *Computer Networks*, *190*, 107950.

Ali, Z. J., Noordin, N. K., Sali, A., & Hashim, F. (2020). Fair energy-efficient resource allocation for downlink NOMA heterogeneous networks. *IEEE Access*, *8*, 200129–200145.

Asif, M., Ihsan, A., Khan, W. U., Ali, Z., Zhang, S., & Wu, S. X. (2023). Energy-efficient beamforming and resource optimization for STAR-IRS enabled hybrid-NOMA 6G communications. *IEEE Transactions on Green Communications and Networking*.

Asif, M., Ihsan, A., Khan, W. U., Ranjha, A., Zhang, S., & Wu, S. X. (2023). Energy-efficient beamforming and resource optimization for AmBSC-assisted cooperative NOMA IoT networks. *IEEE Internet of Things Journal*.

Azarhava, H., Niya, J. M., & Tinati, M. A. (2023). NOMA-based energy-efficient resource allocation in wireless energy harvesting sensor networks. *Computer Communications*, *209*, 302–308.

Chen, Y., Xu, J., Wu, Y., Gao, J., & Zhao, L. (2024). Dynamic task offloading and resource allocation for NOMA-aided mobile edge computing: An energy-

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.

JOURNAL OF SCIENCE TECHNOLOGY AND EDUCATION 13(3), SEPTEMBER, 2025
E-ISSN: 3093-0898, PRINT ISSN: 2277-0011; Journal homepage: www.atbuftejoste.com.ng

efficient design. *IEEE Transactions on Services Computing*.

Chien, W. C., Cho, H. H., Lai, C. F., Tseng, F. H., Chao, H. C., Hassan, M. M., & Alelaiwi, A. (2019). Intelligent architecture for mobile HetNet in B5G. *IEEE Network*, *33*(3), 34–41.

Dong, S., Zhan, J., Hu, W., Mohajer, A., Bavaghar, M., & Mirzaei, A. (2023). Energy-efficient hierarchical resource allocation in uplink-downlink decoupled NOMA HetNets. *IEEE Transactions on Network and Service Management*.

Elbayoumi, M., Kamel, M., Hamouda, W., & Youssef, A. (2020). NOMA-assisted machine-type communications in UDN: State-of-the-art and challenges. *IEEE Communications Surveys & Tutorials*, *22*(2), 1276–1304.

Ghafoor, U., Ali, M., Khan, H. Z., Siddiqui, A. M., Naeem, M., & Rashid, I. (2021, September). Energy efficiency optimization for hybrid NOMA based beyond 5G heterogeneous networks. In *Proceedings of the IEEE 94th Vehicular Technology Conference (VTC2021-Fall)* (pp. 1–5). IEEE.

Ghafoor, U., Khan, H. Z., Ali, M., Siddiqui, A. M., Naeem, M., & Rashid, I. (2022). Energy-efficient resource allocation for H-NOMA assisted B5G HetNets. *IEEE Access*, *10*, 91699–91711.

Ghafoor, U., Khan, H. Z., Siddiqui, A. M., Ali, M., Rauf, A., Wahla, A., & Naeem, M. (2023). Cluster-based resource management using H-NOMA in heterogeneous networks beyond 5G. *Ad Hoc Networks*, *149*, 103252.

Guo, Y. Y., Tan, X. L., Gao, Y., Yang, J., & Rui, Z. C. (2023). A deep reinforcement learning approach for energy-efficient resource assignment in cooperative NOMA enhanced cellular networks. *IEEE Internet of Things Journal*.

Khan, H. Z., Ali, M., Naeem, M., Rashid, I., & Imran, M. (2020). Resource allocation in 5G heterogeneous networks with downlink-uplink decoupled access. *Transactions on Emerging Telecommunications Technologies*, *31*(3), e3831.

Long, K., Li, W., Jiang, M., & Lu, J. (2020). Non-cooperative game-based power allocation for energy-efficient NOMA heterogeneous network. *IEEE Access*, *8*, 49596–49609.

Makki, B., Chitti, K., Behravan, A., & Alouini, M. S. (2020). A survey of NOMA: Current status and open research challenges. *IEEE Open Journal of the Communications Society*, *1*, 179–189.

Oleiwi, H. W., & Al-Raweshidy, H. (2022). SWIPT-pairing mechanism for channel-aware cooperative H-NOMA in 6G terahertz communications. *Sensors*, *22*(16), 6200.

Raghu, K., & Chandra Sekhar Reddy, P. (2023). Optimization-enabled user pairing algorithm for energy-efficient resource allocation for NOMA heterogeneous networks. *Journal of Optical Communications*, Advance online publication.

Siddiqui, A. M., Naeem, M., & Rashid, I. Energy Efficient Resource Allocation for H-NOMA Assisted B5G HetNets.

Usman, N. S., Abubakar, A., Zubairu, A. Y., Adebiyi, R. F., Adekale, A. D., & Abubakar, U. (2023). Comparative Analysis on the Effect of Triangular and Gaussian Membership Functions on Fuzzy Controlled Vehicle Platoon. *FUOYE Journal of Engineering and Technology, 3*(3). doi:https://doi.org/10.46792/fuoyejet.v8i3.1070.

Corresponding author: Bright Agbonze
brightelect2000@gmail.com
Department of Electronics and Telecommunications Engineering, Ahmadu Bello University, Zaria, Kaduna State, Nigeria.