Signal-to-Noise Ratio Optimization in 5G Network Architectures using the Pelican Optimization Algorithm

*[1]Hammed B. Omodeni, [1]Hammed O. Lasisi, [2]Bolatito F. Aderinkola, and [2]Celestina B. Omodeni
[1]Department of Electrical and Electronics Engineering, Osun State University, Osogbo, Nigeria
[2]Department of Electrical and Electronics Engineering, The Federal Polytechnic, Ede, Osun State, Nigeria
hammed.omodeni@pgc.uniosun.edu.ng|hammed.lasisi@uniosun.edu.ng|fattyade2307@gmail.com

Received: 22-MAY-2025; Reviewed: 26-JUNE-2025; Accepted: 30-JUNE-2025
http://.doi.org/10.4314/fuoyejet.v10i2.17

ORIGINAL RESEARCH

Abstract— Modern fifth-generation mobile networks face significant challenges due to increasingly densely populated locations, which result in limited coverage and lower performance due to congestion, interference bottlenecks, and service quality variations. The introduction and operation of 5G technology presents issues as a viable option for connecting highly populated areas. A unique 5G network structure must be devised to serve highly populated locations, as it will optimize coverage while expanding capacity, as well as improve interference control and service delivery. POA is well-suited for solving complicated optimization issues with more computational efficiency, lowering processing time or resource utilization, and thereby improving complex data management. The performance study revealed that implementing the pelican optimization algorithm enhanced the signal-to-noise ratio over current approaches such as genetic algorithm, PSO, TLBO, and GWO. Modified network architecture for high-density subscribers would be developed using the pelican optimization algorithm, which efficiently explores complex solution spaces, handles multiple objectives, and prevents premature convergence, thereby indicating significant improvement of the signal-to-noise ratio of the modified model, which shows an improvement in the quality of service for high-density subscribers, which is limited to concurrent users of mobile networks. This model's small cell equipment operates at a frequency of 28 GHz with a bandwidth of 700 MHz, supporting 3.5 million concurrent users within the allocated area. The main criterion for evaluating network performance will be user-received power levels.

Keywords— *BS, densely populated area, DSS, high-density subscribers, POA, 5G.*

1 INTRODUCTION

The deployment of fifth-generation (5G) wireless technology opens up new avenues for mobile communication development (Alsharif and Nordin, 2019). Because people in densely populated places utilize enormous volumes of mobile data across connected devices, sound mobile networks are critical (Abrol & Jha, 2018). The construction of a 5G mobile network presents unique obstacles in densely populated locations, yet it is still successful in meeting capacity and performance criteria. The technology delivers rapid data speeds while also providing strong connective features with short response times and accepting a wide range of devices (Attaran & Attaran, 2020). There is widespread agreement on how 5G technology will alter how communication networks operate (Allam & Jones, 2021). A solution must be customized to address deployment and operational issues that arise when employing 5G technology in densely populated subscriber areas (Afolabi et al., 2018).

The Pelican Optimization Algorithm outperformed previous approaches such as the Genetic Algorithm, PSO, TLBO, and GWO in terms of signal-to-noise ratio (Mirjalili et al., 2024).
According to this research study, high-density users in 5G networks require specialized network models to deliver higher coverage and capacity results, as well as interference control and quality of service (QoS). High-density subscriber environments include cities, packed sports stadiums and concerts, and transportation facilities such as airports and train stations (Afolabi et al., 2018; Alnawayseh et al., 2023). Mobile network locations with a large number of users connected at the same time encounter infrastructure overloads, resulting in network difficulties and impaired service performance (Ahad et al. 2019). The urban population expansion and greater use of mobile devices have resulted in an increasing number of high-density subscriber situations in cellular networks (Attaran & Attaran, 2020).

When 5G networks serve densely populated areas, several issues arise (Faramarzi et al., 2022). Serving heavily populated areas presents the most significant challenge to ensuring constant network reach. Implementing this goal entails creating a dense network of base stations as well as identifying ways to pass past signal-blocking barriers (Andrews et al., 2019). Heavy user traffic puts a burden on the network infrastructure,

*Corresponding Author

Section B- ELECTRICAL/ELECTRONICS/COMPUTER ENGINEERING AND RELATED SCIENCES
Can be cited as:
[1]Omodeni H.B., [1]Lasisi H.O., [2]Aderinkola B.F. and [2]Omodeni C.B. (2025). Signal-to-Noise Ratio Optimization in 5G Network Architectures using the Pelican Optimization Algorithm, FUOYE Journal of Engineering and Technology (FUOYE**JET), 10(2), 294-299.**
http://.doi.org/10.4314/fuoyejet.v10i2.17

causing data congestion and sluggish transmission. Multiple base station installations and close users might create interference issues, lowering network performance standards. A densely populated location has wide service quality fluctuations since customers require both basic text messaging and complicated data usage, which includes video streaming. Delivering uniform quality service to all consumers is a significant operational challenge (Alsharif & Nordin, 2019).

The adoption of 5G technology brings new capabilities that show potential solutions to difficulties created by increasing subscriber numbers. 5G's capacity augmentation feature relies on higher bandwidths alongside improved antenna technologies such as Massive MIMO while also providing significant latency reduction (Andrews *et al.*, 2019). Lowering latency enables real-time application support, allowing augmented reality (AR) and virtual reality (VR) to function in crowded events as well as urban locations (Allam & Jones, 2021).

Colorful service demands can be met with 5G network slicing, which produces many virtual networks that operate within a single unified physical architecture (Li et al., 2020). This study investigates the usage of picocells, which provide extensive frequency coverage, to improve 5G networks in order to increase high-density customers. 5G technology introduces Dynamic Spectrum Sharing (DSS) as a key element that optimizes spectrum use, particularly in densely populated locations (Li et al., 2020). The use of 5G technology systems results in a variety of benefits. When there is a high subscriber density, specialized network models are critical because they allow proper usage of 5G capabilities (Afolabi et al., 2018). The model optimizes network resource management while reducing interference and congestion, as well as supporting service/user QoS priority and continuous connection delivery in congested urban areas and events. Researchers have set a goal of developing and testing a 5G mobile network architecture aimed at improving network connection quality in densely populated areas.

2 METHODOLOGY

The pelican optimization algorithm is a population-based algorithm using pelicans as part of the population. In population-based algorithms, each individual in the population represents a potential solution. Every member of the population offers values for the variables in the optimization problem based on where they are in the search space.

A picocell small cell operates at a frequency of 28 GHz from the deployed installation point, which is the optimum chosen site. The design network operates at 28 GHz and has a bandwidth of 100 MHz. A modified network architecture for high-density subscribers was constructed utilizing the pelican optimization algorithm on a 5G network by deploying picocell parameters in Table 1 to achieve optimal user location and coverage radius capabilities, which was implemented in MATLAB.

Mathematical Model of the POA

Initially, population members are randomly initialized based on the lower and higher bounds of Equation (1).

$$x_{i,j} = l_j + rand.(u_j - l_j),\ i = 1, 2, \dots, N,\ j = 1, 2, \dots, m, \quad (1)$$

where

$x_{i,j}$ represents the value of the jth variable indicated by the ith candidate solution.
N is the population's total number of members.
m represents the number of problem variables, and

rand is a random number from [0, 1].
l_j represents the jth lower bound.
and u_j represents the jth upper bound of the problem variables.

In Equation (2), the population matrix is used to identify the individuals of the POA's pelican population. Each row of this matrix represents a proposed solution, while the columns reflect the values of the problem variables.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_1 \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} \cdots x_{1,m} \\ \vdots & \ddots & \vdots \ \ddots \ \vdots \\ x_{i,j} & \cdots & x_{i,j} \cdots x_{i,m} \\ \vdots & \ddots & \vdots \ \ddots \ \vdots \\ x_{N,1} & \cdots & x_{N,j} \cdots \ x_{N,m} \end{bmatrix}_{N \times m} \quad (2)$$

where X represents the pelican population matrix and Xi is the ith pelican.

In the POA, each population member is a pelican, which is a potential answer to the dilemma. As a result, the objective function of the given problem can be evaluated using each candidate solution. In Equation (3), the values for the objective function are calculated using a vector known as the objective function vector.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_1) \\ \vdots \\ F(X_N) \end{bmatrix} \quad (3)$$

where F is the objective function vector and Fi is the objective function value of the ith candidate solution.

$$x_{i,j}^{P_1} = \begin{cases} x_{i,j} + rand.(p_j - |I.x_{i,j}), F_P < F_{i;} \\ x_{i,j} + rand.(x_{i,j} - p_j), \quad else, \end{cases} \quad (4)$$

where

$x_{i,j}^{P_i}$ represent the new status of the ith pelican in the jth dimension based on phase 1.

http://dx.doi.org/10.4314/fuoyejet.v10i2.17 engineering.fuoye.edu.ng/journal

I represent a random number that is equal to one or two.
pj is the location of prey in the jth dimension.
and Fp is its objective function value.

The new position for a pelican is acceptable if the value of the goal function increases in that position. This type of updating, known as effective updating, prevents the algorithm from migrating to suboptimal locations. This process is represented by Equation (5).

$$X_i = \begin{cases} |X_i^{P_1}, & F_i^{P_1} < F_{i;} \\ X_i, & else, \end{cases} \quad (5)$$

where $x_i^{P_i}$ is the new status of the ith pelican and $F_i^{P_i}$ is its objective function value?
From a mathematical standpoint, the method considers the points in the vicinity of the pelican's location to arrive at a better solution. Equation (6) mathematically simulates pelicans' behavior.

$$x_{i,j}^{P_2} = x_{i,j} + R.\left(1 - \frac{t}{T}\right).(2.rand - 1).x_{i,j}, \quad (6)$$

where $x_{i,j}^{P_2}$ represents the new status of the ith pelican in the jth dimension based.

R is a constant, which is equal to 0.2. R(1 - t/T) is the neighborhood radius of xi,j, while t is the iteration counter and T is the maximum number of iterations.

At this phase, effective updating has also been used to accept or reject the new pelican position, which is modeled in Equation (7).

$$X_i = \begin{cases} X_i^{P_2}, & F_i^{P_2} < F_{i;} \\ X_i, & else, \end{cases} \quad (7)$$

where $x_i^{P_2}$ is the new status of the ith pelican and $F_i^{P_2}$ is its objective function value.
The sequence of network design methodology for the modified 5G network is depicted in figure 1.

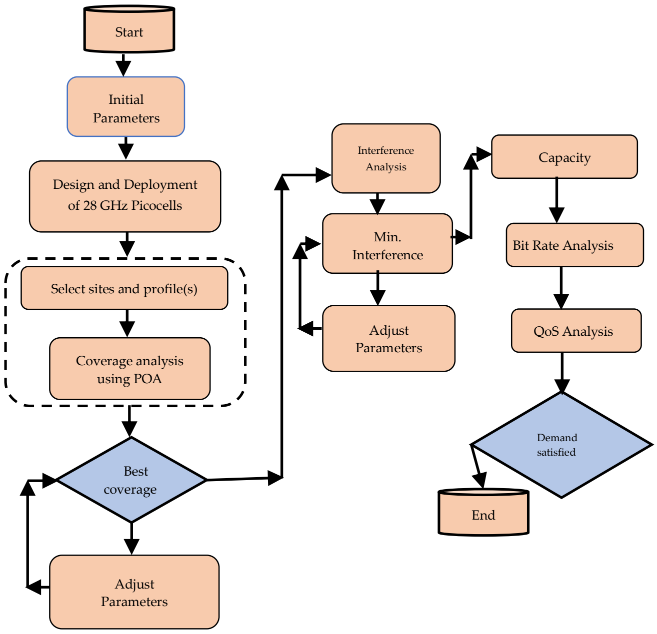


Figure 1. Modified 5G Network Design Methodology

Network Design Parameters

Table 1 shows the parameters used for the network design.

Parameters	Value
Number of users	1–100
Number of antennas at each BS	4
Number of antennas at each user's	1
Bandwidth	10^8 Hz = 100 x 10^6 = 100 MHz
Transmit power of BS	30 dBm
Transmit power of user	23 dBm
Carrier frequency fc	28 x 10^9 = 28 GHz

Algorithm 1.1: Location and radius optimization algorithm

Inputs: User locations and coverage radius

Step 1. Input the optimization problem information.

Step 2. Regulate the POA size of the population (N) and the number of repetitions (T).

Step 3. Initialize the position of locations and radius and calculate the objective function.

Step 4. For t = 1:T

Step 5: Generate the position of the prey using the roulette wheel selection method.

$$\boldsymbol{p_i = rand \leq \frac{f(F_i)}{\sum_{i=1}^{N} f(F_i)}}$$

Step 6. For I = 1:N

Step 7. Phase 1: Moving towards prey (exploration phase).

Step 8. For j = 1:m

Step 9. Calculate the new status of the jth dimension using

$$\boldsymbol{S_{i,j}^{P_1} = \begin{cases} S_{i,j} + rand.(p_j - I.(S_{i,j})), & F_p < F_i \\ S_{i,j} + rand.(S_{i,j} - p_j), & else, \end{cases}}$$

Where $\boldsymbol{S_{i,j}^{P_1}}$ is the new status of the ith location and radius in the jth dimension based on phase 1, I is a random number that is equal to one or two, $\boldsymbol{p_j}$ is the location of prey in the jth dimension, and $\boldsymbol{F_p}$ is its objective function value, F is the objective function vector and F_i is the objective function value of the ith color solution. The parameter I is a number that can be randomly equal to 1 or 2.

Step 10. End.

Step 11. Update the ith population member using

$$S_i^{P_1} = \begin{cases} S_i^{P_1}, & F_i^{P_1} < F_i \\ S_i, & else, \end{cases}$$

Where $S_i^{P_1}$ is the new status of the ith location and radius, and $F_i^{P_1}$ its objective function value is based on phase 1.

Step 12. Phase 2: Winging on the water surface (exploitation phase).

Step 13. For j = 1:m.

Step 14. Calculate the new status of the jth dimension using $S_{i,j}^{P_2} = S_{i,j} + R.\left(1 - \frac{t}{T}\right).(2.rand - 1).S_{i,j}$

Where $S_{i,j}^{P_2}$ is the new status of the ith location and radius in the jth dimension based on phase 2. R is a constant, which is equal to 0.2, $R.\left(1 - \frac{t}{T}\right)$ is the neighborhood radius of $S_{i,j}$, while t is the iteration counter, and T is the maximum number of iterations.

Step 15. End.

Step 16. Update the ith population member using

$$S_i^{P_2} = \begin{cases} S_i^{P_2}, & S_i^{P_2} < F_i \\ S_i, & else, \end{cases}$$

where $S_i^{P_2}$ is the new status of the ith location and radius, and $F_i^{P_2}$ is its objective function value based on phase 2.

Step 17. End.

Step 18. Update best candidate solution.

Step 19. End.

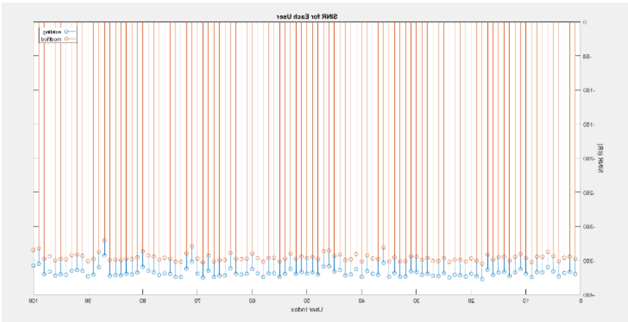
Step 20: Output the best candidate solution obtained by POA.

End

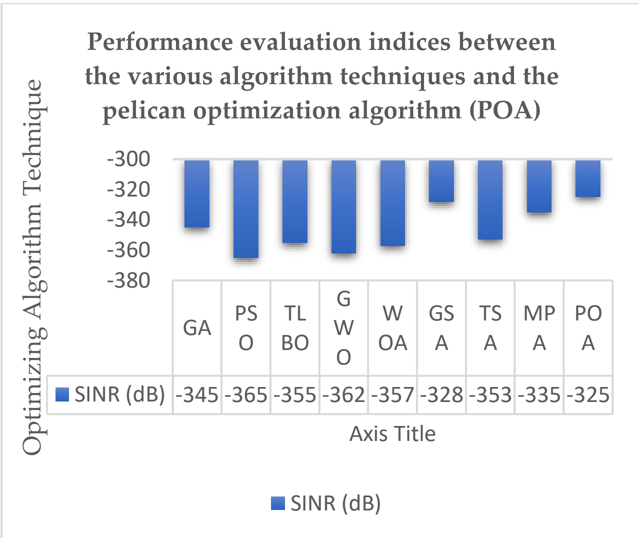
Output: Optimal user locations and coverage radius

3 RESULT AND DISCUSSION

Generated Result



Evaluating the performances of existing signal-to-noise ratio (dB) against modified signal-to-noise ratio (dB)



Performance evaluation indices between the various algorithm techniques and the pelican optimization algorithm (POA)

S/N	Algorithm Technique	Received Power (dBm)	SINR (dB)
1.	Genetic Algorithm (GA)	-345dBm	-345dB

http://dx.doi.org/10.4314/fuoyejet.v10i2.17 engineering.fuoye.edu.ng/journal

2.	Particle Swarm Optimizing (PSO)	-370dBm	-365dB
3.	Teaching Learning Based Optimization (TLBO)	-340dBm	-355dB
4.	Gray Wolf Optimization (GWO)	-360dBm	-362dB
5.	Whale Optimization Algorithm (WOA)	-365dBm	-357dB
6.	Gravitational Search Algorithm (GSA)	-350dBm	-328dB
7.	Tunicate Swarm Algorithm (TSA)	-367dBm	-353dB
8.	Marine Predators Algorithm (MPA)	-350dBm	-335dB
9.	Pelican Optimization Algorithm	-330dBm	-325dB

For signal-to-noise ratio, it was 370 dB for the existing algorithm, but for the modified algorithm, the signal-to-noise ratio is 353 dB.

Therefore, there is significant improvement in the signal-to-noise ratio of the modified model compared to the existing model, which shows that there will be improvement in the quality of service for the high-density subscriber. It potentially improves data rates, enabling more efficient resource allocation and relaxed handover thresholds.

When there is an increase in received power for each user, it enhances the signal quality, reduces interference, and potentially improves data rate, thereby enhancing overall network performance and user experience.

4 CONCLUSION

This study presented a modified 5G network infrastructure architecture specifically designed for dense subscriber areas by implementing the Pelican Optimization Algorithm (POA) for signal power strength and network efficiency improvement. A combination of picocells operating at 28 GHz alongside POA provided optimal user location and coverage radius determination in the proposed model, which produced superior results compared to conventional optimization methods. Performance evaluation demonstrated that the implementation of the Pelican Optimization Algorithm improved the signal-to-noise ratio over the existing methods, which include the Genetic Algorithm, PSO, TLBO, and GWO.

The results clearly show that enhancement in signal-to-noise ratio leads to improvement of signal quality together with reduced interference and better data throughput, which guarantees high-quality service delivery in regions with high population density. The research provides evidence that integrating POA technology into 5G network planning represents an effective solution to combat the ongoing network congestion problems faced in urban environments together with heavy events. Future work will explore multi-objective optimization, edge computing constraints, and deployment in 6G-ready testbeds.

5 REFERENCES

Abrol, A., & Jha, R. K. (2018). Power optimization in 5G networks: A step towards green communication. IEEE Access, 4, 1355–1374. https://doi.org/10.1109/ACCESS.2016.2549641

Afolabi, I., Taleb, T., Samdanis, K., Ksentini, A., & Flinck, H. (2018). Network slicing and softwarization: A survey on principles, enabling technologies, and solutions. IEEE Communications Surveys & Tutorials, 20(3), 2429–2453. https://doi.org/10.1109/COMST.2018.2815638

Ahad, A., Tahir, M., & Yau, K. A. (2019). 5G-based smart healthcare network: Architecture, taxonomy, challenges, and future research directions. IEEE Access, 7, 100747–100762. https://doi.org/10.1109/ACCESS.2019.2930628

Alattar, D., Furlan, R., Grosvald, M., & Al-Matwi, R. (2021). West Bay business district in Doha, State of Qatar: envisioning a vibrant transit-oriented development. Designs, 5(2), 33. https://doi.org/10.3390/designs5020033

Allam, Z., & Jones, D. S. (2021). Future (post-COVID) digital, smart, and sustainable cities in the wake of 6G: Digital twins, immersive realities, and new urban economies. Land Use Policy, 101, 105201. https://doi.org/10.1016/j.landusepol.2020.105201

Alnawayseh, S. E., Khan, T. A., Farooq, U., Zulfiqar, S., Khan, S., & Al-Kassem, A. H. (2023). Research challenges and future facets of cellular computing. In 2023, the International Conference on Business Analytics for Technology and Security (ICBATS). IEEE. https://doi.org/10.1109/ICBATS57792.2023.10111407

Alsharif, M. H., & Nordin, R. (2019). Evolution towards fifth-generation (5G) wireless networks: Current trends and challenges in the deployment of millimeter wave, massive MIMO, and small cells. Telecommunication Systems, 64(4), 617–637. https://doi.org/10.1007/s11235-016-0195-x

Andrea, I., Chrysostomou, C., & Hadjichristofi, G. (2015). Internet of Things: Security Vulnerabilities and Challenges. In 2015 IEEE Symposium on Computers and Communication (ISCC). IEEE. https://doi.org/10.1109/ISCC.2015.7405513

Andrews, J. G., et al. (2014). What will 5G be? IEEE Journal on Selected Areas in Communications, 32(6), 1065–1082. https://doi.org/10.1109/JSAC.2014.2328098

Anonymous. (2018). Review of Chen et al., 2018. Atmospheric Measurement Techniques Discussions. https://doi.org/10.5194/amt-2018-4-rc1

Attaran, M., & Attaran, S. (2020). Digital transformation and economic contributions of 5G networks. International Journal of Enterprise Information Systems, 16(4), 58–79. https://doi.org/10.4018/IJEIS.2020100104

Faramarzi, A., Heidarinejad, M., Stephens, B., & Mirjalili, S. (2022). Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications. Knowledge-Based Systems, 239, 107789. https://doi.org/10.1016/j.knosys.2021.107789

Li, X., Zhao, K., & Liu, H. (2020). Dynamic spectrum sharing for 5G and beyond: Challenges and enablers. IEEE Wireless Communications, 27(4), 96–102. https://doi.org/10.1109/MWC.001.1900495

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. Advances in Engineering Software, 69, 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007