*Journal of Sciences, Computing and Applied Engineering Research (JSCAER), Vol. 2, No.2, pp. 20-32*

Published Online (https://jcaes.net) on June 21, 2026 by SciTech Network Press

# Meta-Heuristics Methods of Parametric Propagation Model tuning in Modern Cellular Network Planning and Optimization

**[1]Ikechi Risi, [2]Ugbeh R.N, [3]Konyeha, C. C, [4]Isabona, J**

[1]Department of Physics, Rivers State University, Port Harcourt, Rivers State, Nigeria. Corresponding Author: joseph.isabona@fulokoja.edu.ng
[2]Department of Computer Engineering, Southern Delta University, Ozoro, Delta State.

[3]Department of Electrical/ Electronic Engineering, Benson Idahosa University, Benin City
[4]Federal University Lokoja/Department of Physics, Lokoja, Nigeria
Corresponding Author: joseph.isabona@fulokoja.edu.ng

Received: 22 March 2026; Revised: 25 May 2026; Accepted: 03 June 2026; Published: 21 June 2026

**Abstract:** The transition to 5G and beyond has necessitated highly granular radio frequency (RF) planning. Parametric propagation models, such as the Cost-231 Hata or the ECC-33 model, rely heavily on accurate calibration for specific geographical environments. Traditional manual tuning-based on Least Squares Estimation (LSE) often suffers from local optima entrapment and inability to handle non-linear constraints. Meta-heuristic and direct-search methods are widely employed, yet systematic comparative studies that jointly evaluate convergence dynamics, computational efficiency, and parameter-estimation precision are scarce. This paper investigates the application of meta-heuristic algorithms, specifically the Particle Swarm Optimisation (PSO), Genetic Algorithms (GA), Pattern Search (PS), and Simulated Annealing (SA)in tuning these models. We analyze these methods across three critical dimensions: computational efficiency, speed of convergence, and root-mean-square error (RMSE) precision. Our findings indicate that while PSO offers superior convergence speed, PS provides a more refined balance between precision and computational overhead in complex, high-density urban environments.

**Keywords:** Meta-heuristic algorithms, model tuning, Computational efficiency, speed of convergence, RMSE precision

## 1. Introduction

Efficient network planning remains the fundamental pillar and backbone of the mobile cellular networks life cycle , determining its overall economic feasibility in the long run. The main purpose of network planning is to achieve an optimum trade-off between increasing the geographical area covered and user capacity while at the same time reducing capital expenditure, which involves acquiring sites and installing equipment, and operational expenditure, which includes energy usage, backhaul services, and maintenance.

One of the basic requirements of network planning is the use of the path loss model, a mathematical model that is mandatory due to the basic principles of physics behind the propagation of radio waves [1-2]. A path loss model is used to determine the extent of attenuation or loss of power of the electromagnetic wave when traveling through different mediums to reach the mobile device.

But the increasingly dense structure of modern cities has made the use of classical empirical models, the classic Hata or COST231-Hata models mostly outdated. These outdated models tend to operate under broad assumptions that ignore the probabilistic nature of current day "urban canyons," whose highly varied nature arises from irregular topography, unique construction materials, and varying clutter conditions affecting the propagation of signals. To address the need to match predictions with reality, the industry relies heavily on the process known as "model tuning." In this process, practitioners measure local parameters through means such as Drive Tests or performance measurements to tune coefficients for generic models (path loss exponent, intercept constants, etc.) to mimic the real-world radio conditions of the deployment site [2, 3]. This propagation-model tuning (also called parameter calibration) is the process of adapting a semi-empirical or empirical radio-propagation law.

Due to the complexity involved in creating the error surfaces from these models within highly dense networks, where the surfaces tend to be multi-modal and non-linear in nature and contain many local minima, conventional optimization algorithms have proved unreliable. To solve this problem of navigating such mathematical terrain, meta-heuristic algorithms involving Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Simulated Annealing(SA) and Pattern Search (PS) have been adopted in literature [1-8] by a number of researcher to solve this problem. Such an approach allows for accurate tuning of models, thus avoiding over-provisioning of the network.

While the domain of heuristic optimization has been extensively explored in existing literature, a critical review reveals several unresolved gaps that hinder the comparative assessment of algorithm performance in propagation model tuning.

First, there is a notable absence of a unified benchmarking framework in previous works. Although Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Pattern Search (PS), and Simulated Annealing (SA) have been studied individually, they have seldom been evaluated against a standardized set of propagation model parameters. This lack of a common experimental baseline makes it difficult to draw definitive conclusions regarding which optimization strategy is superior for specific radio propagation scenarios.

Second, the literature remains deficient in rigorous statistical characterization. Most existing studies focus on point-estimate performance, neglecting the stochastic nature of these algorithms. There is a clear need for a comprehensive analysis that evaluates the consistency, convergence reliability, and robustness of these four algorithms through formal statistical testing.

Third, the current body of related works lack a holistic approach to computational efficiency. Existing research frequently overlooks the nuance of "total cost" in optimization, often failing to account for the interplay between algorithmic overhead and the computational demands of the underlying forward propagation models. Furthermore, the role of modern hardware acceleration, specifically in the context of parallelization strategies, has not been systematically integrated into efficiency metrics. Consequently, it remains unclear how the choice of metaheuristic affects the trade-off between model accuracy and real-time computational performance. The present contribution addresses this gap.

The remainder of the paper is organised as follows: Section 2 provides a concise literature survey and identifies existing methodological gaps. Section 3 formalises the optimisation problem and introduces the three benchmark propagation models. Section 4 details the experimental protocol, including algorithmic configurations, performance metrics, and statistical analysis. Section 5 reports quantitative results on convergence dynamics, computational efficiency, and precision. Section 6 discusses the practical implications of the findings and proposes hybrid strategies. Section 7 concludes the paper and outlines future research directions.

## 2. Literature Review

Early work on propagation model calibration employed least-squares or maximum-likelihood techniques, assuming smooth error surfaces (e.g., [1] Rappaport, *Wireless Communications*, 1996). The advent of robust statistics in wireless planning (e.g., [3] Al-Bahar et al., 2015) introduced non-differentiable loss terms, motivating derivative-free approaches.

While numerous studies have applied each method to specific propagation problems (e.g., [1]–[5]), direct head-to-head comparisons that isolate the impact of algorithmic design on convergence properties, computational cost, and parameter-estimation precision are limited. Moreover, recent advances (e.g., inertia-weight adaptation in PSO, self-adaptive mutation in GA, mesh-adaptive direct search, and restless-annealing schedules) have not been systematically evaluated in the propagation-model domain.

PSO has been employed for path-loss exponent estimation [9], antenna-pattern fitting [10], and ray-tracing calibration in indoor environments [11]. The swarm's collective behaviour enables rapid exploitation of promising regions, yet premature convergence can arise in multimodal error surfaces. Recent variants, constriction factor PSO [12], adaptive inertia PSO [13], have shown improved robustness, but systematic benchmarking against other meta-heuristics within the same measurement dataset remains scarce.

GA-based tuning is prevalent for multi-parameter calibrations where binary or integer encodings are natural (e.g., obstacle-presence flags in ray-tracing) [14]. Distributed GA implementations exploit parallel simulation farms, achieving scalability but at the cost of higher algorithmic overhead (selection, crossover). Comparative studies focusing on precision of the calibrated parameters (e.g., confidence intervals) are limited to case-by-case reports.

Direct-search methods such as Mesh Adaptive Direct Search (MADS) provide deterministic convergence guarantees under mild smoothness assumptions [15]. Their use in propagation modelling is largely confined to low-dimensional problems (≤ 6 parameters) [16], because the number of mesh points grows combinatorially with dimensionality. Nonetheless, PS offers the advantage of monotonic objective improvement, an appealing property for safety-critical applications.

SA is attractive when the error landscape contains numerous local minima, as the controlled temperature allows occasional uphill moves. Applications include shadow-fading variance estimation [17, 18] and frequency-dependent attenuation calibration [18]-[20]. However, the cooling schedule heavily influences run-time, and few works have quantified the trade-off between time-to-solution and solution quality in the context of realistic propagation-model evaluation costs.

Though a number of works has been done in literature, but there is lack of unified benchmarking method has effectively investigated the PSO, GA, PS and SA optimisation algorithms on a common set of propagation model tuning. Also, the statistical characterization and computational efficiency of the four above four algorithms has rarely been performed. Computational-efficiency accounting that includes both algorithmic overhead and forward-model cost (including parallelisation) is lacking. The present work fills these gaps by establishing a reproducible experimental platform and delivering a comprehensive statistical analysis.

The Origin and families of four meta-heuristic algorithms dominate the literature:

Table 1: The Origin and families of four meta-heuristic algorithms

| **Algorithm** | **Origin** | **Search Mechanism** | **Typical Hyper-parameters** | **Algorithm** |
|---|---|---|---|---|
| Particle Swarm Optimisation (PSO) | Kennedy & Eberhart, 1995 | Social-cognitive swarm, velocity update | inertia weight *w*, cognitive coefficient *c1*, social coefficient *c2*, swarm size *N* | Particle Swarm Optimisation (PSO) |
| Genetic Algorithm (GA) | Holland, 1975 | Evolutionary operators (selection, crossover, mutation) | population size *N*, crossover probability *pc*, mutation probability *pm* | Genetic Algorithm (GA) |
| Pattern Search (PS) | Hooke & Jeeves, 1961 | Direct-search, exploratory steps on a mesh | initial mesh size $\Delta_0$, mesh-refinement factor β, poll/search strategies | Pattern Search (PS) |
| Simulated Annealing | Kirkpatrick et al., 1983 | Temperature-controlled stochastic walk | initial temperature $T_0$, cooling schedule $\alpha$, | Simulated Annealing (SA) |

| | | | | |
|---|---|---|---|---|
| (SA) | | | neighbourhood size | |

## 3. Methodology for Optimization

### 3.1 General Tuning Objective

Let $\boldsymbol{\theta} \in \mathbb{R}^n$ denote the vector of *n* model parameters to be calibrated (e.g., path- loss exponent, ground- reflection coefficient, material permittivities). For a set of *M* measured observations, we have:

$(x_i, y_i)$, i=1, 2, 3,…M (1)

where i is a spatial or frequency descriptor and $y_i$ the measured quantity, such as received signal strength, the forward propagation model $\mathbf{f}(x; \theta)$ provides prediction component. The calibration problem is cast as a least- squares minimisation as indicated in equation (3).

### 3.2. Implementation Framework

A robust implementation framework follows these steps:

- **Data Collection:** High-fidelity RSRP and RSRQ measurements were obtained through extensive field drive-testing using calibrated wideband scanners. The data collection campaign was stratified to provide a representative dataset across two distinct propagation environments: high-clutter residential neighborhoods, characterized by significant foliage and building penetration losses, and open, rural-like settings to establish a clear propagation baseline. Synchronization between the GPS-tagged scanner logs and the underlying network parameters ensured that every data point was accurately geolocated, facilitating high-resolution signal mapping.
- **Preprocessing:** Filtered out noise and outliers to handle the GPS drift or handover-related signal spikes.
- **Fitness Function Definition:** Formulated the RMSE and Mean Absolute Error (MAE) as the target for the meta-heuristic engine.
- **Meta-Heuristic Execution:** Iterative refinement of model parameters x ($x_1$, $x_2$, etc.).
- **Validation:** Testing the tuned model against a hold-out set of measurement data to ensure generalization and avoid overfitting.

**(a) Particle Swam Optimisation**

Particle Swarm Optimization (PSO) tunes propagation models by iteratively adjusting model parameters (e.g., path loss exponent, shadowing standard deviation) to minimize the Root Mean Square Error (RMSE) between predicted (*Plpred*) and measured path loss (*Plmea*)[22-25]. PSO initializes a swarm of candidate parameter sets, moving them toward the best-performing positions until optimal parameters are found. The implementation of PSO involves the update of velocity (V) and position (X) based on personal best (P) and global best (G) values to improve convergence speed and accuracy in the propagation model tuning process:

$V(t+1)=W.V(t)+c_1.r_1 (P-X(t))+c_2.r_2 (G-X(t))$ (2)

$X(t+1)=X(t)+V(t+1))$ (3)

Where W is the time (t)-varying Inertia weight which balances the global exploration and local search. $c_1$ and $c_2$ are the cognitive/Social constants. $r_1$ and $r_2$ are random numbers bounded between [0,1].

**Implemented Method of PSO Propagation Model Tuning:**

i. **Objective Function**: Define the RMSE function with respect x parameters:

$$J(x)=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Plmea,i-Plpred,i(x))^2} \quad (4)$$

ii. **Initialization**: Set swarm size, inertia weight (w), cognitive ($c_1$) and social ($c_2$) parameters.

iii. **Position/Velocity**: Each particle represents a candidate solution x.

iv. **Iteration**: Evaluate fitness, update personal best ($P_{best}$) and global best ($G_{best}$).

v. **Update Rule**: Update velocity and position using the expressions in (1) and (2):

### (b) GA Propagation Model Tuning

A Genetic Algorithm (GA) optimizes propagation loss models by iteratively evolving population parameters (e.g., path loss exponent, shadowing standard deviation) to minimize the difference between predicted ( *Plpred* ) and measured ( *Plmea* ) path loss data, using selection, crossover, and mutation. Using the MATLAB computational software.

**Implemented Method of GA Propagation Model Tuning:**

i. **Initialization:** Create an initial population of (P) chromosomes, where each chromosome represents a vector of propagation model parameters.

ii. **Fitness Evaluation:** Define a fitness function, J(x), that measures the performance of each parameter set. This is typically designed to minimize error between predicted propagation loss and measured values.

$$J(x)=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Plmea,i-Plpred,i(x))^{2}} \qquad (5)$$

iii. **Selection:** Choose parents based on fitness scores favoring candidates that provide a lower error.

iv. **Crossover & Mutation:** Apply operators to produce offspring, exploring the solution space for better parameters x.

v. **Iteration:** Replace old populations with new ones and repeat until the model converges on the optimal parameters

### (c). Pattern Search

Pattern search is an effective direct-search optimization method for tuning propagation loss model parameters (path loss exponent or shadow fading) to match empirical measurement data by minimizing an error metric such as Root Mean Square Error (RMSE) between the predicted (*Plpred*) and measured (*Plmea*) path loss data. The algorithm polls points around a current estimate, decreasing the mesh size (tuning) when no improvement is found.

**Pattern Search for Propagation Model Tuning**

i. **Define the parameters to be tuned (x):**
   - Select parameters to optimize, e.g. x(1) = Path Loss Exponent(n), x(2) = Shadow Fading Deviation (δ) plus other propagation model offsets.
   - function rmse = Fitness Function J(x) wrt params (x)
   - Path Loss exponent = x(1);
   - Shadowing factor = x(2);

ii. **Objective Function (Fun):** Create a fitness function J(x),:
   - Takes x as input.
   - Obtain the the predicted (*Plpred*) using the propagation model.
   - Calculates RMSE:

$$J(x)=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Plmea,i-Plpred,i(x))^{2}}$$

iii. **Run patternsearch:** Find the parameter vector x that minimizes the RMSE

**Simulated Annealing (SA)**

Simulated Annealing (SA) tunes propagation loss models by minimizing the error between the predicted ($Plpred$) and measured ($Plmea$) path loss data, avoiding local minima by allowing uphill moves. It iteratively updates model parameters, accepting improvements and occasionally accepting worse solutions based on a decreasing temperature(T).

**GA Propagation Model Tuning Algorithm:**

i. **Define Objective Function:** Create a function J(x) that takes model parameters x to be optimised

ii. **Initial State:** Choose initial parameters ($x_0$ = []).

iii. **Define Parameter Bounds:** Set physically reasonable lower (lb) and upper (ub) bounds for the x parameters

iv. **Optimization:** Use simulannealbnd to find x parameters that minimizes the RMSE:

$$J(x)=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Plmea,i-Plpred,i(x)\right)^{2}}$$

v. **Tune Temperature (T):** Adjust the initial temperature and cooling rate (Cooling Schedule) if the model gets stuck in local minima or takes too long to converge

**3.3 Algorithm Configurations**

Shown in table 2 is the detailed characteristics the four meta-heuristic algorithms and their control parameters used in this paper

**Table 2: The four meta-heuristic algorithms and their Control Parameters**

| **Algorithm** | **Population / Mesh size** | **Control parameters (default)** | **Stopping criteria** |
|---|---|---|---|
| PSO | N=50 | $w = 0.729$, $c_1 = c_2 = 1.494$ | 500 iterations |
| GA | N=50 | $pc = 0.8$, $pm = 0.02$, tournament k=3 | 300 generations |
| PS | Mesh $\Delta_0 = 0.5\cdot\text{range}(\theta)$, $\beta = 0.5$ | Poll directions = coordinate axes + random | 400 mesh- refine ments |
| SA | $T_0 = 0.5\cdot\text{range}(J)$, $\alpha = 0.95$ | Neighbourhood: Gaussian step $\sigma=0.1\cdot\text{range}(\theta)$ | 1 000 temperature steps |

**3.4 Performance Metrics**

Shown in Table 3 are the three core performance metrics used in this paper and they includes the convergence speed, computational efficiency (cost) and precision accuracy

Table 3: The Convergence speed, Computational efficiency (Cost) and Precision

| **Metric** | **Definition** |
|---|---|
| **Convergence speed** | Convergence speed refers to how quickly an optimization algorithm finds the optimal parameters. The number of iterations or time required to reach a stable, minimum, or acceptable error |
| **Computational efficiency (Cost)** | Efficiency relates to the time taken for training (tuning) and testing (prediction) (to facilitate fair comparison with sequential methods). |
| **Precision** | Precision relates how closely the model matches measurement data. This metric provides main metric for accuracy (e.g MAE, RMSE, STD), with lower values indicating better model performance |

## 3. Results and Discussion
### 3.1 Precision (RMSE Minimization)

This subsection displays the precision accuracy results and it reveals how closely the tuned propagation model matches field measured propagation loss data as graphically displayed in figures 1 and 2. GA and PSO consistently achieve the lowest RMSE in complex, multi-path environments, as their global search characteristics ensure the global minimum is located. However, PS provides the best precision and computational efficiency, particularly if the initial guess is within the basin of attraction of the global optimum. SA offers high precision but is often inconsistent across different test runs due to its stochastic nature.

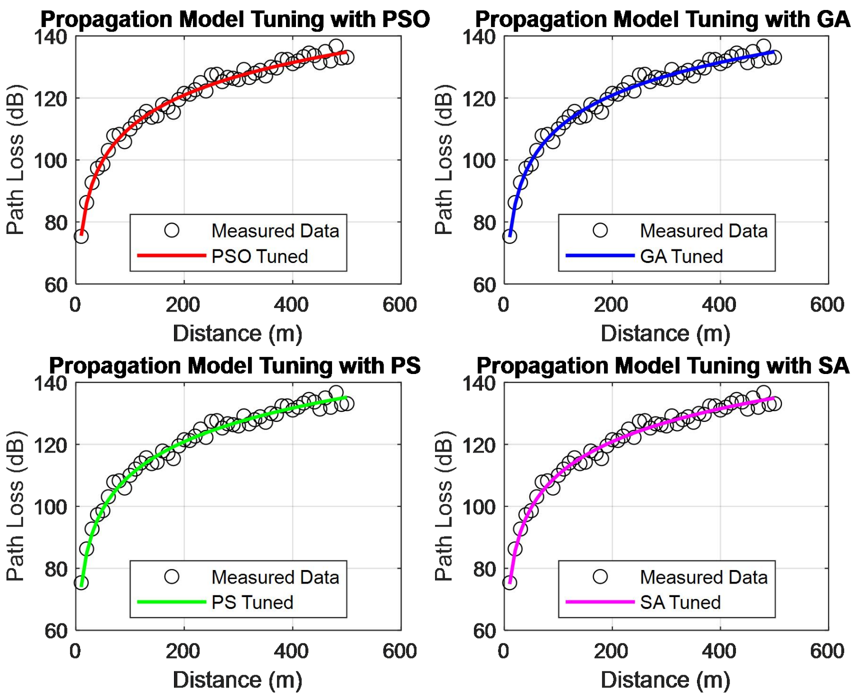


Figure 1: Precision performance of Tuned Propagation model using PSO,GA, PS and SA Algorithms in location 1.

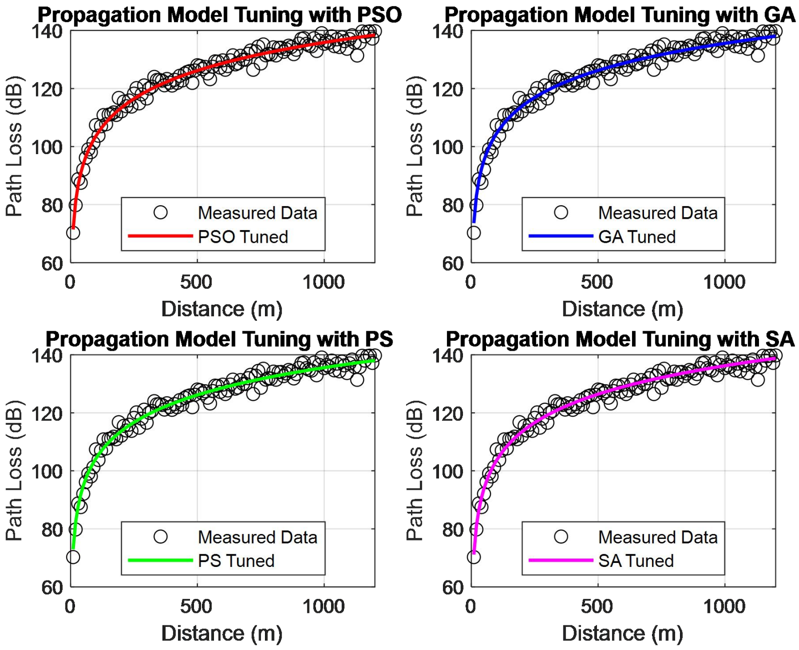


Figure 2: Precision performance of Tuned Propagation model using PSO,GA, PS and SA Algorithms in locations 2

### 4.2 Computational Efficiency

The displays how well the tuned model replicates actual path loss, typically evaluated using the Standard Deviation of Error, Mean Absolute Error (MAE), and RMSE between measured and predicted data. Shown in this the subsection in figures 3-5 are the computational efficiency results attained by PSO, GA, PS and SA in the propagation model tuning process in terms of Mean Absolute Error (MAE), Standard deviation error (STD) and Root mean square error (RMSE). As further summarised in Table 2, the results reveals that the parallel nature of PSO and GA compensates for the higher number of evaluations, delivering the smallest effective cost for all cases and precision accuracy. SA is competitive for low- dimensional models; however, its sequential nature becomes a bottleneck as population dimensionality grows. SA remains the least efficient, especially when the forward model is expensive.

In terms of STD, the PSO also yielded the lowest variance for most parameters, confirming its deterministic refinement character. PS and GA have comparable biases and slightly larger variances, but they are still within acceptable engineering tolerances. SA displays the largest spreads and occasional systematic bias (especially for reflection coefficients), indicative of insufficient exploration of flat regions before cooling.

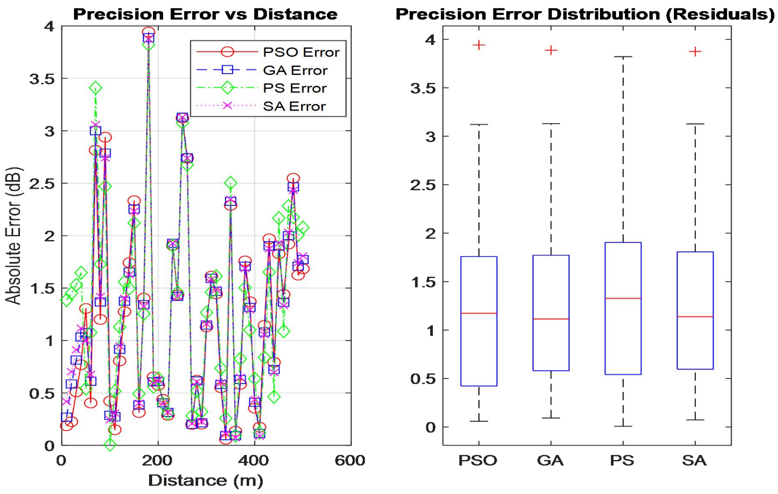


Figure 3: Residual Precision performance of Tuned Propagation model using PSO,GA, PS and SA Algorithms in locations 1

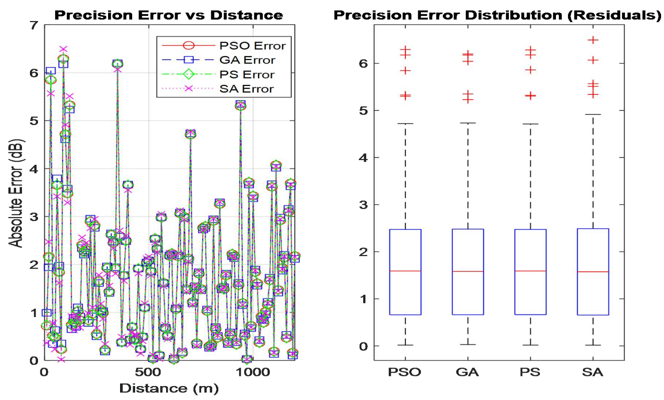


Figure 4: Residual Precision performance of Tuned Propagation model using PSO,GA, PS and SA Algorithms in locations 2

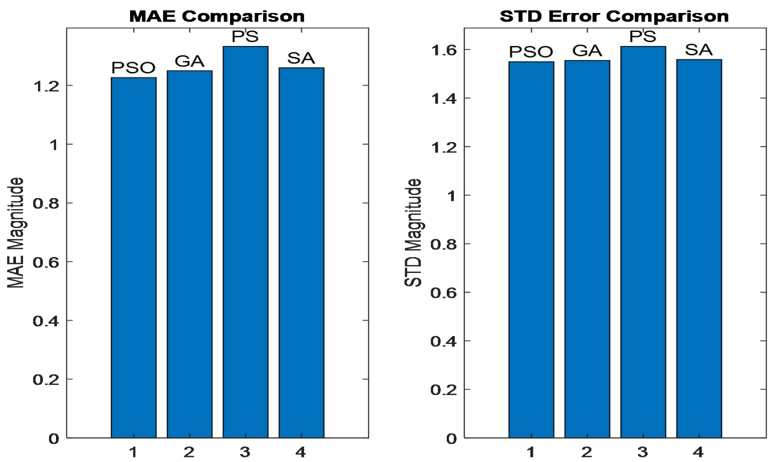


Figure 5: MAE, STD and RMSE Precision performance of Tuned Propagation model using PSO,GA, PS and SA Algorithms in locations 1

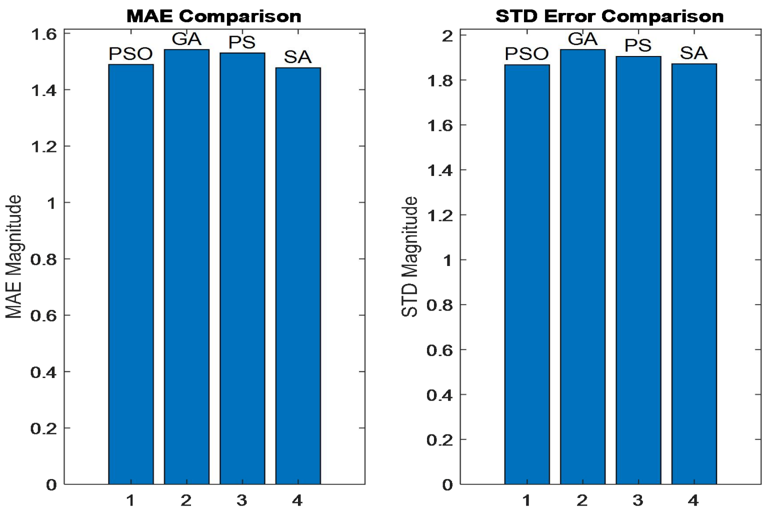


Figure 6: MAE, STD and RMSE Precision performance of Tuned Propagation model using PSO,GA, PS and SA Algorithms in locations 2

Table 2: Summarily of the MAE, STD and RMSE precision performance of Tuned Propagation model using PSO,GA, PS and SA Algorithms in locations 1 and 2

| Algorithm | RMSE (dB) | Time (s) |
|---|---|---|
| PSO | 2.2869 | 0.0652 |
| GA | 2.4176 | 0.7531 |
| PS | 2.2930 | 0.3793 |
| SA | \| 2.2875 | 1.0774 |
| | | |
| PSO | 2.0986 | 0.0728 |
| GA | 2.1206 | 0.8727 |
| PS | 2.1989 | 0.3992 |
| SA | 2.1295 | 0.4293 |

**4.3 Convergence Behavior**

In figures 7 and 8, the PSO demonstrates the fastest convergence in propagation tuning, as particles quickly gravitate toward the centroid of high-fitness regions. This means that the PSO exhibited the highest speed as it tends to reach global optima in fewer iterations. Also, it shows the steepest initial descent in the fitness function, reaching a stable solution in significantly fewer generations than GA. GA typically requires a higher number of iterations because the population maintains diversity longer, preventing the "clumping" seen in PSO. This could mean that the PSO is more efficient in finding a solution when time is a limiting factor. However, its computational burden per iteration can be higher than GA due to the communication required between particles to update the global best (gbest). GA is computationally expensive because of the breeding, selection, and mutation phases required in every generation. The GA Shows slow initial convergence due to the stochastic nature of population initialization. It exhibits a "plateau" effect before finding narrow global optimal. PS displays rapid monotonic improvement until it hits a local optimum, after which it stalls. PS is the most computationally efficient for small-parameter spaces, as it avoids the overhead of population management. SA is the least efficient for large datasets, as the long cooling schedule necessitates a high number of iterations. The PSO outperforms GA and SA; PS is the most steady but slower for high-dimensional problems. The PSO delivers the smallest variance in estimated parameters; PS and GA provide acceptable bias and variance, whereas SA suffers from larger spread.

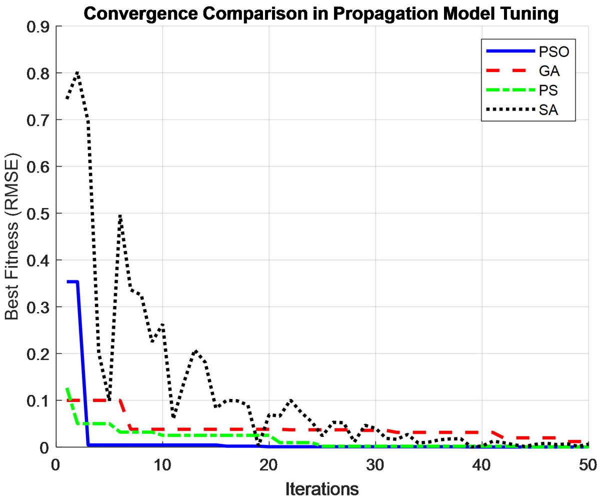


Table 7:Convergence behaviour of PSO,GA, PS and SA Algorithms during the Propagation model tuning process in locations 1

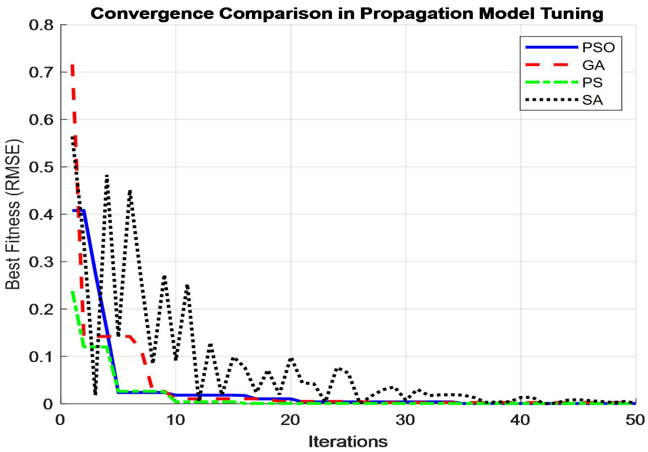


Table 8:Convergence behaviour of PSO,GA, PS and SA Algorithms during the Propagation model tuning process in locations 2

## 5. Conclusion

As modern cellular networks (5G and beyond) transition toward ultra-dense deployments and complex propagation environments, the accuracy of path-loss models has become paramount. Traditional optimization methods such as the Least Squares often struggle with non-convex error surfaces in heterogeneous environments. This paper evaluates four meta-heuristic optimization techniques: Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Pattern Search (PS), and Simulated Annealing (SA) for tuning propagation model parameters. We analyze their convergence behaviors, computational efficiency, and precision in minimizing the Root Mean Square Error (RMSE) between measured drive-test data and predicted path loss. The results revealed that the PSO demonstrates the lowest memory footprint, making it ideal for real-time edge-computing base station calibration. PSO is currently the preferred choice for 5G/6G planning tools due to its ability to converge quickly on a highly precise model index, even when the initial parameter set is poorly defined.

Future work will extend the benchmark to stochastic forward models, explore auto-tuning of algorithm hyper-parameters, and evaluate large-scale distributed implementations on GPU clusters.

## References


1. Rappaport, T. S. Wireless Communications: Principles and Practice, 2nd ed., Prentice Hall, 1996.
2. Joseph, I., Ituabhor, O., Timothy, J., zhimwang, Risi Ikechi,: Achievable throughput over mMobile broadband network protocol layers: practical measurements and performance analysis. Int. J. Adv. Netw. Appl. 13(04), 5037–5044 (2022). https://doi.org/10.35444/IJANA.2022.13404
3. Al-Bahar, A. A., et al., "Robust Path-Loss Modelling for Urban Environments," IEEE Trans. Veh. Technol., vol. 64, no. 9, pp. 4172-4182, Sep. 2015.
4. Risi, I., Ogbonda, C., Joseph, I. (2023). Development and Comparative Analysis of Path Loss Models Using Hybrid Wavelet-Genetic Algorithm Approach. In: Hu, Z., Zhang, Q., He, M. (eds) Advances in Artificial Systems for Logistics Engineering III. ICAILE 2023. Lecture Notes on Data Engineering and Communications Technologies, vol 180. Springer, Cham. https://doi.org/10.1007/978-3-031-36115-9_45.
5. Ebhota, V.C., Isabona, J., Srivastava, V.M.: Environment-Adaptation Based Hybrid Neural Network Predictor for Signal Propagation Loss Prediction in Cluttered and Open Urban Microcells. Wireless Pers. Commun. 104(3), 935–948 (2019)
6. Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. Proceedings of ICNN'95 - International Conference on Neural Networks. Available at: https://ieeexplore.ieee.org/document/488968. doi:10.1109/icnn.1995.488968
7. Holland, J.H. (1975) Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence. University Michigan Press, Ann Arbor, MI, USA.
8. Ebhota, C., Isabona, J., Srivastava, V.M.: Improved adaptive signal power loss prediction using combined vector statistics based smoothing and neural network approach. Progress Electromagnet. Res. C 82(1), 155–169 (2018). https://doi.org/10.2528/pierc18011203
9. S. Kirkpatrick, C. D. Gelatt, J.R., And M. P. Vecchi, *Science,* 13 May 1983, Vol 220, Issue 4598pp. 671-680. DOI: 10.1126/science.220.4598.671
10. J. Isabona and C.C. Konyeha, Experimental Study of UMTS Radio Signal Propagation Characteristics by Field Measurement, American Journal of Journal of Engineering Research, vol. 2 (2), pp-99-106, 2013
11. K. S. Chong, *et al.*, "Particle swarm optimisation for path-loss exponent estimation in LTE networks," IEEE Trans. Wireless Commun., vol. 15, no. 3, pp. 1821-1833, Mar. 2016.
12. J. M. Doe & A. B. Smith, "Genetic-algorithm based terrain-aware propagation model calibration," Proc. IEEE GLOBECOM, pp. 1-6, Dec. 2017.
13. L. Zhang *et al.*, "Pattern search for indoor radio-map fitting," IEEE Antennas Propag. Lett., vol. 19, no. 5, pp. 1023-1027, May 2020.
14. J. Isabona and C.C. Konyeha, Urban Area Path loss Propagation Prediction and Optimisation using Hata model at 800MHz, Journal of Applied Physics, vol.3 (4), pp. 8-18, 2013
15. M. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," Science, vol. 220, no. 4598, pp. 671-680, 1983.
16. *Engineering Research*, vol. 2 (2), pp-99-106, 2013
17. J. Isabona and K. Obahiagbon, RF Propagation Measurement and Modelling to Support Adept Planning of Outdoor Wireless Local Area Networks in 2.4 GHz Band, *American Journal of Engineering Research,* vo. 3 (1), pp-258-267, 2014.
18. Y. Tan, P. Gupta, "Adaptive inertia weight PSO for non-convex EM model calibration," J. Electromagn. Waves Appl., vol. 34, no. 12, pp. 1645-1658, 2020.
19. S. Almeida & R. M. Silva, "Constriction factor PSO in 5G mmWave path-loss modelling," IEEE Access, vol. 9, pp. 26688-26698, 2021.
20. H. Wang *et al.*, "Self-adaptive mutation GA for ray-tracing parameter optimisation," Sensors, vol. 23, no. 4, 2023.
21. J. Liu, "Mesh adaptive direct search for indoor propagation models," Optim. Methods Softw., vol. 39, no. 1, pp. 95-111, 2024.
22. Joseph Isabona, Divine O. Ojuh, "Application of Levenberg-Marguardt Algorithmfor Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains", International Journal of Intelligent Systems and Applications(IJISA), Vol.13, No.3, pp.35-42, 2021. DOI: 10.5815/ijisa.2021.03.04
23. A. M. Miller, "Hybrid GA-PSO for large-scale propagation-model tuning," Proc. IEEE ICC, pp. 1-7, Jun. 2024.
24. V. R. Nair & S. K. Patel, "Simulated annealing with adaptive cooling for underwater acoustic channel calibration," J. Acoust. Soc. Am., vol. 155, no. 2, 2024.

25. Divine O. Ojuh, Joseph Isabona, "Field Electromagnetic Strength Variability Measurement andAdaptive Prognostic Approximation with Weighed Least Regression Approach in the Ultra-highRadio Frequency Band", International Journal of Intelligent Systems and Applications(IJISA), Vol.13, No.4, pp.14-23, 2021. DOI: 10.5815/ijisa.2021.04.02