



### RESEARCH ARTICLE

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## ENHANCING 4G/LTE NETWORK PATH LOSS PREDICTION WITH PSO- GWO HYBRID APPROACH

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### ABSTRACT

In a 4G/LTE network, path loss models are crucial for efficient planning, interference estimation, frequency allocation, and optimization of cell parameters, all essential for the network's overall performance and planning. The Hata, COST231, Egli, and SUI models are among the most widely used in urban and suburban environments. However, these models rely on fixed parameters, which can cause inaccuracies when applied to measured data. This paper uses data collected from the north-central region of Algeria to calculate the path loss for 4G LTE (1800 MHz). The measured path loss is compared with the empirical models mentioned above. The best model for estimating the measured path loss is then optimized using three well-known evolutionary algorithms: Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Covariance Matrix Adaptation Evolution Strategy (CMA-ES). Furthermore, a hybrid optimization model, PSO-GWO, is proposed to improve prediction accuracy. The performance of each optimization method is evaluated using various error metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Standard Deviation (STD), Mean Error (ME), and Mean Absolute Percentage Error (MAPE). Results demonstrate that the hybrid techniques outperform the original Hata and COST231-Hata models, with the PSO-GWO hybrid yielding the lowest RMSE, achieving a significant reduction compared to the traditional models.



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### I. INTRODUCTION

The demand for dependable and efficient wireless communication networks has grown significantly in recent years, particularly in 4G/LTE networks [1],[2]. In the telecommunications industry, path loss refers to the reduction in power density of an electromagnetic wave signal as it propagates from the transmitter to the receiver [3]. Accurate path loss prediction ensures optimal network coverage and service quality. Empirical models are widely used for path loss prediction in various environments [4-8]. However, when applied to measured data, their fixed parameters often lead to inaccuracies. Optimized models utilizing various optimization algorithms should be employed to determine more precise parameters. For predicting radio wave path loss in specific regions, researchers have applied several algorithms to address this limitation to predict path loss across different environments [9-15].

In [10], the authors evaluate multiple empirical propagation models, including COST231 Hata, for estimating path loss in urban and suburban environments. The study analyzes performance variations across different models and underscores the significance of parameter optimization in enhancing prediction accuracy. Paper [11] applies several optimization algorithms, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO), to fine-tune the parameters of the COST231-Hata model, making it more suitable for specific environments or regions. These algorithms minimize the error between the predicted path loss and measured data.

In [12], the authors focus on applying Particle Swarm Optimization (PSO) to reduce path loss in suburban and rural areas for mobile communication networks. Different path loss models calculate the RMSE values between the actual and predicted data. The results indicate that the optimized COST231 model outperforms the other models considered in the study.

In [13], Amel Bouchemha et al. introduced a parametric optimization approach for path loss estimation in a 4G/LTE network, utilizing the Particle Swarm Optimization (PSO) algorithm to enhance network performance. Measurements were conducted in urban area. The proposed PSO-based path loss optimization method demonstrated superior prediction accuracy, achieving lower RMSE values than the analytical method based on empirical path loss models

In [14], comprehensive LTE path loss measurements at 800 MHz and 2600 MHz were conducted in selected urban and suburban areas of Ghana and compared with six widely used propagation models. The refined versions of the Ericsson, SUI, and ECC-33 models developed in this study provide more accurate path loss predictions for Ghanaian environments than traditional propagation models.

In the same context, this paper addresses this issue by examining commonly used empirical propagation models, such as COST231, Hata, SUI, and Egli, based on various parameters, including frequency, distance, and antenna height [16]. The study analyzes predicted and measured path loss in the urban/suburban environment of Médéa, a city in the north-central region of Algeria. Propagation measurements were conducted at a frequency of 1800 MHz. To achieve better accuracy, we employ Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Covariance Matrix Adaptation Evolution Strategy (CMA-ES). Furthermore, a hybrid optimization model, PSO-GWO, is proposed to enhance prediction accuracy.

The rest of the paper is organized as follows: Section II analyzes RF propagation models in LTE/4G networks and the optimization algorithms. Section III presents the experimental setup for data collection, while Section IV discusses the simulation results and their comparisons. Finally, Section V provides concluding remarks.

## II. ANALYSIS OF RF PROPAGATION MODELS IN 4G /LTE NETWORK

### II.1 EGLI MODEL

The Egli prediction model is an empirical model proposed by [17]. It is a simplified approach for estimating radio-wave path loss in areas with irregular topography. Based on real data, the path loss approximation can be formulated as follows:

$$PL = 20 \log(f_c) + 40 \log(d) - 2 \log(h_{te}) + \begin{cases} 76.3 - 10 \log(h_{re}), & h_{re} \leq 10m \\ 85.9 - 20 \log(h_{re}), & h_{re} \geq 10m \end{cases} \quad (1)$$

### II.2 HATA'S MODEL

Initially, this model was developed for urban areas. However, with the addition of correction factors, it can be adapted for suburban areas. For urban and suburban environments, the median path loss equations are expressed as follows:

$$PL(urban)(dB) = 69.55 + 26.16 \log(fc) - 13.82 \log(h_{re}) - a(h_{re}) + (44.9 - \log(h_{te})) \log d \quad (2)$$

For suburban area, it is expressed as

$$PL(suburban)(dB) = PL(urban) - 2[\log(fc/28)]^2 - 5.4 \quad (3)$$

The correction factor ( $a(h_{re})$ ), in Equation (2), differs as a function of the size of the coverage area

$$a(h_{re}) = \begin{cases} 8.29(\log 1.54 h_{re})^2 - 1.1dB \\ \text{for } fc < 300MH \end{cases} \quad (4a)$$

For small and medium areas, it is

$$a(h_{re}) = \begin{cases} 2(\log 115 h_{re})^2 - 4.97dB \\ \text{for } c > 300MHz \end{cases} \quad (4b)$$

In the above equations:  $d$  represents the separation distance between the transmitter and receiver antennas, valid for distances ranging from 1 to 20 km;  $fc$  denotes the operating frequency, which ranges from 150 MHz to 1500 MHz., The transmit antenna height ( $h_{te}$ ) ranges from 30 m to 200 m. The receive antenna height ( $h_{re}$ ) ranges from 1 m to 10 m, as considered in references [18], [19].

### II.3 COST 231 HATA MODEL

The COST 231 model, also known as the PCS extension of the Hata model, is an improved version of the Hata model. It is widely used for predicting path loss in mobile wireless systems. Designed for frequencies ranging from 1500 to 2000 MHz, this model includes adjustments for urban, suburban, and rural (flat) environments [20],[21].

$$PL(d)(dB)=46.3+33.9\log(fc)-13.82\log(h_{te})-a(h_{re})+(44.9-6.55\log(h_{te}))\log(d)+CM \quad (5)$$

CM = 0 dB for medium-sized cities and suburban areas with moderate tree density, or CM = 3 dB for metropolitan centers. The validity range of this model is:

$$\begin{aligned} 1500 \text{ MHz} < f < 2000 \text{ MHz}, \\ 30 \text{ m} < h_{te} < 200 \text{ m}, \\ 1 \text{ m} < h_{re} < 10 \text{ m}, \\ 1 \text{ km} < d < 20 \text{ km}. \end{aligned}$$

## II.4 SUI MODEL

The general path loss expression according to the SUI model is given by [22].

$$PL \text{ (dB)}=A+10\gamma\log_{10}(d/d_0) +X_f + X_h + s \quad (6)$$

Where  $d > d_0$  (with  $d$  in meters) represents the distance between the base station and the receiving antenna, with  $d_0 = 100$  m as the reference distance,  $X_f$  accounts for frequency corrections above 2 GHz. At the same time,  $X_h$  adjusts for the receiver antenna height. Additionally, it compensates for shadowing effects caused by trees and other obstacles along the propagation path. Parameter  $A$  is defined as follows:

$$A = 20\log(4\pi d_0/\lambda) \quad (7)$$

where  $\lambda$  is the wavelength in meters. Path loss exponent  $\gamma$  given by [23].

Where  $h_{te}$  is the base station antenna height in meters, and  $a$ ,  $b$ , and  $c$  are constants that depend on the terrain type.

## II.5 OPTIMIZATION ALGORITHMS

### a. Particle Swarm Optimization (PSO)

The collective behavior of bird flocks inspires PSO and optimizes a function by continuously refining candidate solutions through velocity and position adjustments. The core equations governing PSO are [24]:

$$xi(t+1) = xi(t) + vi(t+1) \quad (8)$$

$$vi(t+1) = wvi(t) + C1\rho1(xli(t) - xi(t)) + C2\rho2(xg(t) - xi(t)) \quad (9)$$

Where.  $\rho1$  and  $\rho2$  are random values uniformly distributed within the range [0, 1].

### b. Grey Wolf Optimizer (GWO)

GWO replicates the leadership hierarchy and hunting strategy of grey wolves. It updates the positions of search agents (wolves) by following the alpha, beta, and delta wolves, who represent the group's top-performing individuals. It was proposed by Mirjalili et al [25].

In this algorithm, wolves are classified into four categories based on their performance:

- Alpha ( $\alpha$ ): The leader of the pack, guiding the hunt and representing the best solution.
- Beta ( $\beta$ ): The second-in-command, assisting the alpha in decision-making.
- Delta ( $\delta$ ): The third rank in the hierarchy, including subordinates and scouts.
- Omega ( $\omega$ ): The lowest-ranked wolves, following the decisions of the higher-ranked ones.

GWO updates the positions of wolves by simulating the three main phases of hunting:

1. Prey Detection: The alpha, beta, and delta wolves lead to the search for the best solution.
2. Encirclement: Wolves adjust their positions based on the leaders' guidance.
3. Final Attack: Convergence occurs as wolves move closer to the prey.

The position update equation is given by:

$$X(t+1) = Xp(t) - A \cdot D \quad (10)$$

### c. Covariance Matrix Adaptation Evolution Strategy

CMA-ES adapts the covariance matrix to generate new candidate solutions with a multivariate Gaussian distribution, which is particularly useful for high-dimensional optimization problems. CMA-ES updates a multivariate probability distribution to generate new solutions dynamically, adapting the covariance matrix over time. This enables efficient search space exploration and facilitates

convergence toward optimal solutions [26]. The main steps of CMA-ES are:

1. Generation of Solutions

At each iteration, a set of solutions is sampled from a multivariate Gaussian distribution defined by a mean vector ( $\mu$ ) and a covariance matrix ( $\Sigma$ ).

2. Evaluation and Selection

The solutions are evaluated based on the objective function; only the best-performing solutions are selected to update the parameters.

3. Parameter Update

The mean vector ( $\mu$ ) is adjusted to move closer to the best solutions; the covariance matrix ( $\Sigma$ ) is adapted to more effectively model the local search space structure.

4. Iteration Until Convergence

The algorithm continues sampling, evaluating, and adapting until a stopping criterion (such as convergence or reaching a maximum number of iterations) and optimal solutions are reached [26].

**d. Hybrid Approaches (PSO-GWO, PSO-CMAES)**

Hybrid models were proposed to enhance optimization performance [27],[28]. In these models, PSO generates an initial solution, which GWO then refines to achieve improved accuracy

**III. EXPERIMENTAL SETUP**

**III.1 DATASET COLLECTION**

To evaluate the performance of this optimization, measurements were conducted in an urban/suburban microcell environment in Médéa, a city in the north-central region of Algeria (Latitude: 36° 15' 51.01" N, Longitude: 2° 45' 14.15" E). The measurements were carried out for three 4G/LTE eNodeBs. eNodeB 1 (No. 26306): Located in the urban area of Ras Bydha (36.26848, 2.750647), eNodeB 2 (No. 26710): Situated in the suburban area of Ramli (36.28003, 2.750035). eNodeB 3 (No. 26748): Found in the urban area of Ras Kalouche (36.27686, 2.74577). Table1 summarizes the eNodeB specifications, including transmission frequencies, transmitted power, and antenna heights.

Table 1: eNodeBs Parameters.

eNodeB	Cell Name	HEIGHT (HBA SOL m)	Power(dBm)	Frequency (MHZ)	MS antenna height (m)
eNB1	26306	20	22	1800	1.5
eNB 2	26710	16	30	1800	1.5
eNB3	26748	24	30	1800	1.5

Source: Authors, (2025).

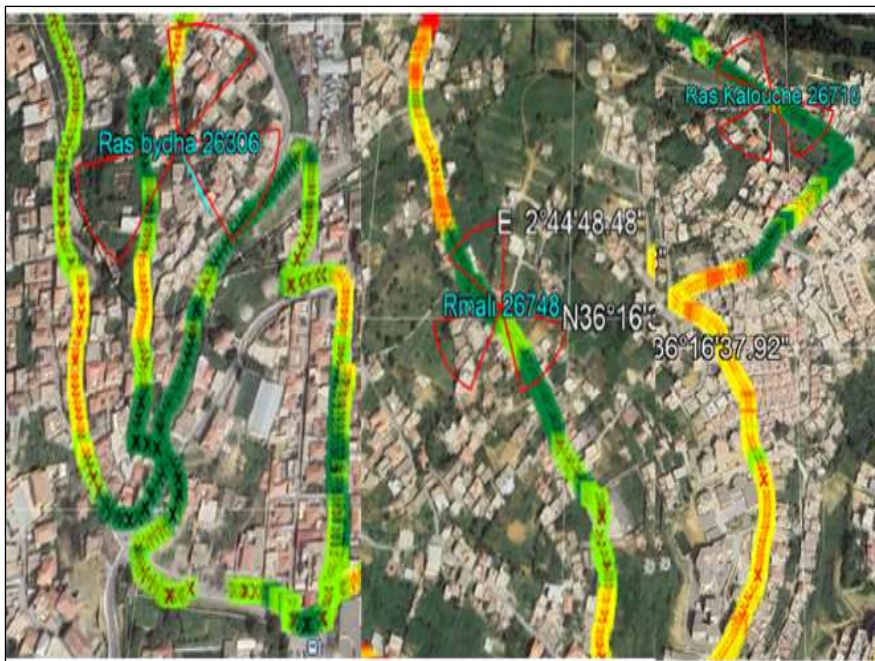


Figure 1: The map of the study area.

Source: Authors, (2025).

Figure 1 illustrates the study area, which provides a top-down view of the measurement routes using Google Maps

### III.2 PERFORMANCE METRICS

The performance of the optimization algorithms is evaluated using the following error metrics:

- **RMSE (Root Mean Square Error)**: Measures the square root of the mean squared errors.
- **MAE (Mean Absolute Error)**: Computes the mean of the absolute errors.
- **STD (Standard Deviation)**: Represents the spread of errors.
- **ME (Mean Error)**: The average of all errors.
- **MAPE (Mean Absolute Percentage Error)**: Measures the percentage error relative to actual values.

## IV. RESULTS AND DISCUSSIONS

### IV.1 COMPARISON WITH PREDICTION MODELS

To evaluate the prediction models, three eNodeBs were compared for predicted and measured path loss. The performance of the empirical models was then assessed against the measured path loss data, as illustrated in Figures 2, 3, and 4.

The forecasting accuracy of these models was quantified using Root Mean Square Error (RMSE), with the results presented in Table 2.

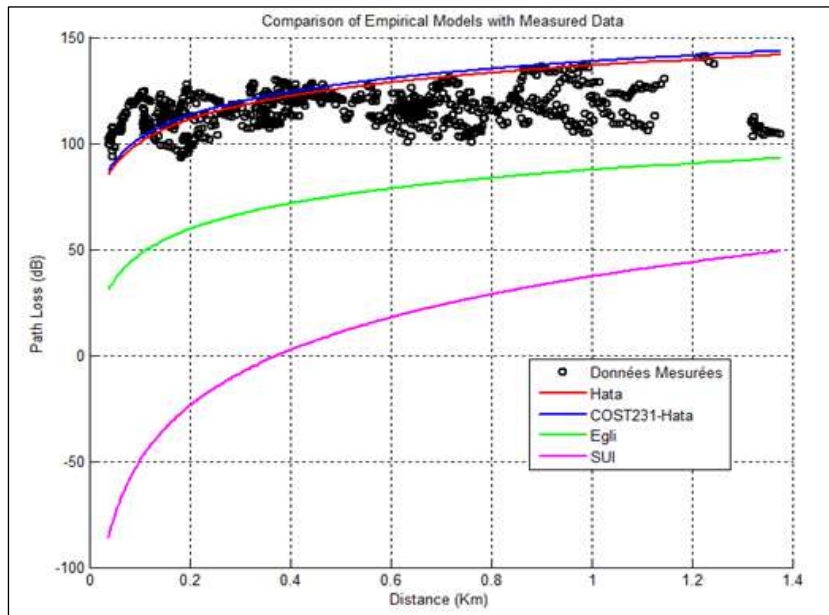


Figure 2: Comparison of Predicted and Measured Path Loss for eNodeB1.  
Source: Authors, (2025)

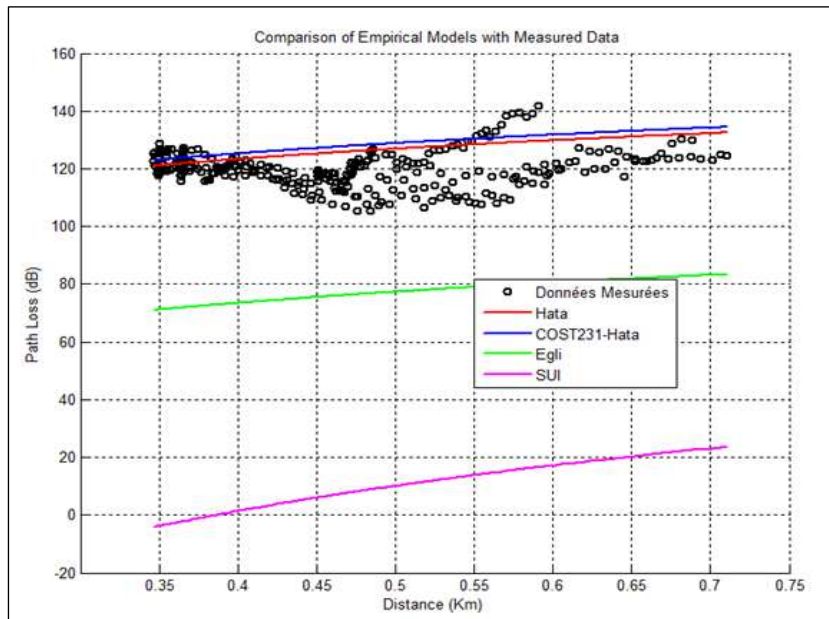


Figure 3: Comparison of Predicted and Measured Path Loss for eNodeB2.  
Source: Authors, (2025).

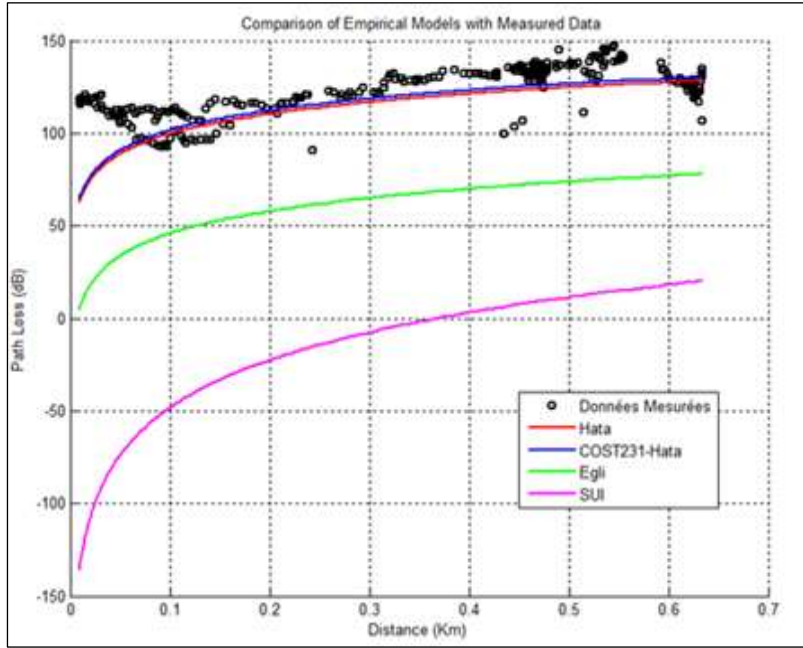


Figure 4: Comparison of Predicted and Measured Path Loss for eNodeB3. Source: Authors, (2025).

Table 2: Performance Comparison of Models Based on RMSE.

Model	eNB1 (urban)	eNB2(urban)	eNB3(suburban)
Hata	14.1231	7.9203	15.9555
COST231-Hata	15.1382	9.1497	14.8317
Egli	45.9474	45.766	63.6113
SUI	115.6488	115.6486	142.0491

Source: Authors, (2025).

According to Table 2, the Hata model demonstrates the best performance for urban coverage areas, as it yields the lowest RMSE compared to other models. In contrast, the COST231-Hata provides the closest match to the measured path loss among all the models for suburban areas. These findings are further validated by Figures 2, 3, and 4.

#### IV.2 OPTIMIZATION PROCESS

The simulation results are presented in the following tables and figures.

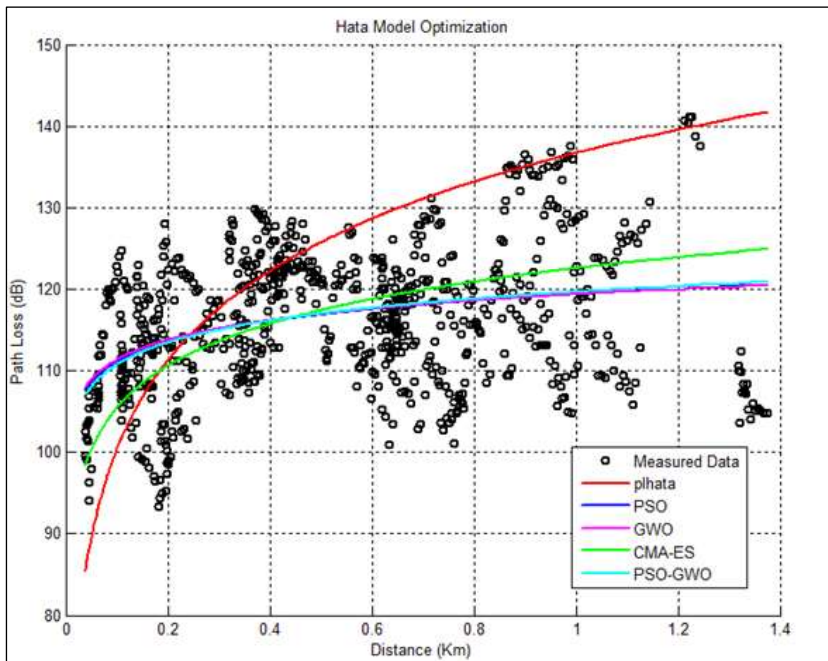


Figure 5: Comparison between the Hata model and optimized models for eNodeB..1 Source: Authors, (2025).

Tables 3 and 4 showcase the optimized Hata model, while Table 5 presents the optimized COST231 model, generated using PSO, CMA-ES, GWO, and PSO-GWO, for eNodeB1, eNodeB2, and eNodeB3, respectively.

Figures 5 and 6 illustrate comparative plots of the optimized Hata model for eNodeB1 and eNodeB2, respectively. while the optimized COST231 model for eNodeB3 is presented in Figure 7.

Through the optimization process of the Hata model, the developed models demonstrated superior prediction accuracy compared to existing models in terms of overall performance, as shown in Tables 3 and 4. This improvement is further highlighted in Figures 5 and 6, illustrating the optimized models' enhanced performance. A similar improvement is observed for the optimized COST231 model, as presented in Table 5 and Figure 7.

An analysis of the three tables reveals that the PSO method achieves the lowest RMSE values in both cases, outperforming CMA-ES and GWO. Furthermore, the RMSE value is further reduced by implementing a hybrid approach combining PSO and GWO, which enhances model accuracy by leveraging the efficiency of both optimization techniques.

Table 3: Measured and tuned models for eNodeB1.

Evaluation parameters	Hata	PSO	CMA-ES	GWO	PSO-GWO
RMSE	14.1231	7.9515	8.4550	7.9541	7.9487
MAE	11.3589	6.4399	6.9206	6.4436	6.4328
STD	12.4622	7.9565	8.4581	7.9590	7.9538
ME	6.6599	-0.038	-0.1975	0.0493	0.0058
MAPE	10.07%	5.57%	6.0050%	5.5819%	5.5701%
Time of Execution	-	0.11 s	0.94 s	0.06 s	0.28 s

Source: Authors, (2025).

Table 4: Measured and tuned models for eNodeB2.

Evaluation parameters	Hata	PSO	CMA-ES	GWO	PSO-GWO
RMSE	7.3318	5.6448	6.2991	5.6512	5.6060
MAE	5.4573	4.1509	4.7119	4.1509	4.0494
STD	6.5528	5.6522	5.7160	5.6584	5.6134
ME	3.3060	-0.0133	-2.6631	0.0560	-0.0004
MAPE	4.6636%	3.4772%	3.8537%	3.4797%	3.3863%
Time of Execution	-	0.14 s	0.86 s	0.08 s	0.26 s

Source: Authors, (2025).

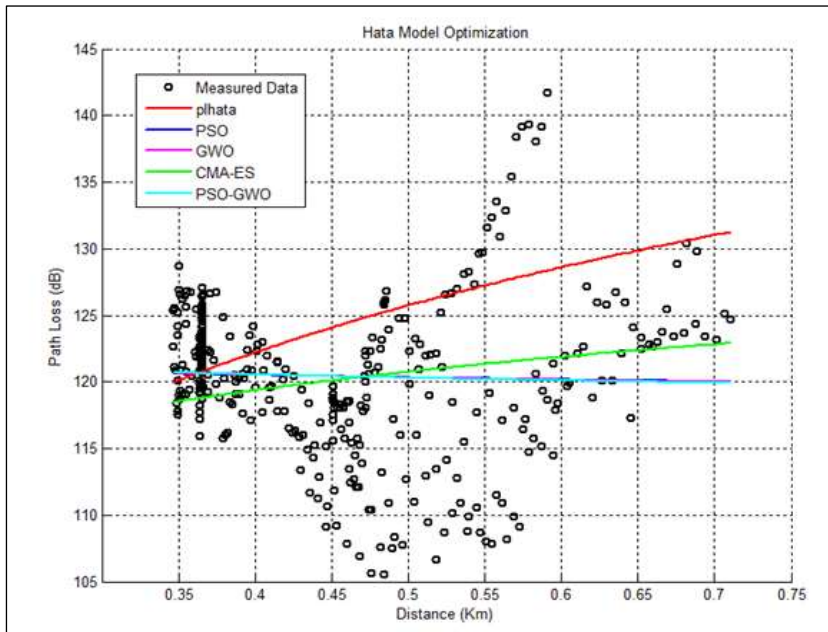


Figure 6: Comparison between the Hata model and optimized models for eNodeB2.

Source: Authors, (2025).

Table 5: Measured and tuned models for eNodeB3.

Evaluation parameters	Cost231	PSO	CMA-ES	GWO	PSO-GWO
RMSE	13.4712	9.9841	10.1101	9.9848	9.9840
MAE	9.4066	7.8136	8.1119	7.8036	7.8221
STD	12.5633	10.0014	10.0479	10.0017	10.0013
ME	-4.9176	0.0131	-1.2662	0.0898	0.0013
MAPE	7.8694%	6.6728%	6.8307%	6.6695%	6.6787%
Time of Execution	-	0.09 s	0.61 s	0.04 s	0.20 s

Source: Authors, (2025).

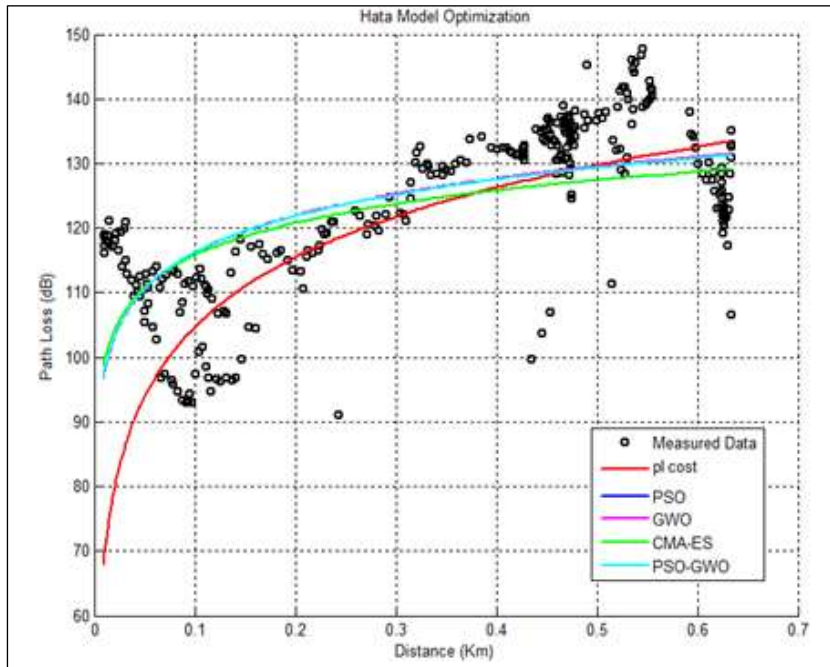


Figure 7: Comparison between the cost231 model and optimized models for eNodeB3.  
Source: Authors, (2025)

## V. CONCLUSIONS

In this paper, various empirical propagation models have been presented and analyzed to evaluate their performance in wireless communication. The tuning models were validated by comparing them with the path loss measurements obtained from three eNodeBs of a 4G/LTE network in Media City, Algeria. Three optimization algorithms were proposed and tested to fine-tune the parameters of the Hata and COST231 models. This study significantly improves path loss prediction accuracy when optimizing the COST231-Hata model for suburban environments and the Hata model for urban environments using PSO, GWO, CMA-ES, and the hybrid PSO-GWO approach. Among the tested methods, the PSO algorithm achieved the best performance. This result was further enhanced by applying the hybrid PSO-GWO approach, suggesting that combining different optimization techniques can yield superior results. Future research will use machine learning models to adapt path loss prediction across diverse environments.

## VI. AUTHOR'S CONTRIBUTION

**Conceptualization:** Messaoud Garah and Nabil Boukhenoufa.

**Methodology:** Messaoud Garah and Nabil Boukhenoufa.

**Investigation:** Messaoud Garah and Nabil Boukhenoufa.

**Discussion of results:** Messaoud Garah and Nabil Boukhenoufa.

**Writing – Original Draft:** Messaoud Garah and Nabil Boukhenoufa.

**Writing – Review and Editing:** Messaoud Garah and Nabil Boukhenoufa.

**Resources:** Messaoud Garah and Nabil Boukhenoufa.

**Supervision:** Messaoud Garah and Nabil Boukhenoufa.

**Approval of the final text:** Messaoud Garah and Nabil Boukhenoufa.

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