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Research Article

Path Loss and Error Statistics Analysis in 5G mmWave Wireless Networks Using Particle Swarm Optimization

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ABSTRACT

In wireless communication systems, accurate path loss estimation is one of the major concerns. This study evaluates and estimates path loss in an urban microenvironment using various path loss models, with a focus on optimizing these models to better represent real-world propagation. In this study, we considered particle swarm optimization algorithm to identify the optimized path loss models in the LOS and NLOS scenarios. The analytically calculated path loss is compared with the optimized values, and estimated the error statistics, are used to evaluate each model's performance. Simulation results demonstrate that particle swarm optimization algorithm significantly reduces path loss compared to analytical estimated. The 3GPP-SC model in the LOS scenario, optimized with PSO, achieved minimized error statistics of 3.85, 1.96, and 1.47. In the NLOS scenario, the 5GCM-OS model shows minimized error statistics of 7.84, 2.80, and 1.9. Therefore, in an urban environment, 3GPP-SC and 5GCM-OS models are considered as the optimized path models in LOS and NLOS scenarios to enhance the network performance.

Keywords: 5G, Error Statistics, Millimeter Wave frequency, Particle Swarm Optimization, Path Loss.

INTRODUCTION

As digital technology becomes more prevalent in daily life, high-speed internet connectivity is becoming necessary rather than optional. Signal propagation models are vital for providing sufficient and dependable signal levels in wireless networks, which is necessary for wireless users to obtain high-quality service [1], [2], [3]. Path loss prediction models to optimize system parameters, and to provide accurate path loss (PL) is a crucial component of wireless network architecture. These optimized parameters of wireless networks enhance the throughput, spectral efficiency, coverage area, handover strategies, and quality of service (QoS) [4], [5], [6].

The weakening of signals during their transmission over wireless channels between the transmitter and the receiver is known to as path loss. It is inevitable because of electromagnetic propagation phenomena that can be precisely described and characterized, including diffraction, refraction, and scattering [7], [8]. For accurate wireless communication system design, PL models are essential. To estimate PL across various frequency bands and settings, a variety of PL models have been created and used [9], [10], [11], [12]. However, PL models that works well in one environment might not work well in another.

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Various strategies are used in the literature to reduce PL by optimizing network parameters and enhancing network efficiency. In [13], the authors proposed a genetic algorithm (GA) to improve network efficiency by optimizing the nodes in an IoT network. Additionally, mixed integer linear programming was employed to enhance network performance and throughput by replacing nodes. The communication path loss was minimized using the dynamic optimal formation control (DOFC) algorithm [14]. Simulation and experimental results confirmed that the proposed algorithm effectively reduced communication PL. In Nigeria, the propagation PL characteristics of the global system for mobile communication were analyzed [15]. A received signal strength indicator was used to measure signal strength at various distances from the cell, estimating the PL exponent and characteristics. An average PL exponent of 3.2 was identified from the measurements. Therefore, optimizing path loss is crucial for improving signal strength and enhancing network performance.

An optimization algorithm called particle swarm optimization (PSO) is considered as one of the best optimization techniques for enhancing network performance, selecting the best path, and locating the base station. The PSO and antlion optimization algorithms have been considered to improve the localization accuracy of wireless sensor networks [16]. The authors observed that their proposed algorithm reduced the localization error compared to the existing localization methods. In wireless networks, the location of small cell base stations (BS) is a major concern. In [17], the authors considered the PSO and K-means algorithm to identify the best position of the BSs. The proposed method enhanced the network performance by reducing packet loss and latency. The vehicular ad-hoc network performance has been improved using the PSO with a quality-of-service routing algorithm [18]. This method enhanced the packet drop, delay, and delivery rate.

Therefore, the PSO algorithm is used to improve the 5G wireless network performance by minimizing the path loss in the urban microenvironment (UMi). In this paper, we considered the various PL models to estimate the PL analytically and compared the same with PSO. The optimal PL model, which provides minimized PL and error statistics has to be identified in various scenarios. This is the structure of the remainder of the paper: Section II provides the path loss models, Section III explains the particle swarm optimization algorithm, Section IV provides the results and discussions, and Section V provides the conclusions and future scope.

PATH LOSS MODELS

Accurate design, deployment, and comparison of wireless networks rely on precise wireless channel models to effectively simulate signal propagation. In this study, we examined four path loss models widely adopted by leading organizations: (i) the 5G Channel Model (5GCM), (ii) the 3rd Generation Partnership Project (3GPP) model, (iii) the Mobile and Wireless Communication Enablers for the Twenty-Twenty Information Society (METIS) model, and (iv) the millimeter-wave-based mobile radio access networks or 5G integrated communication (mmMAGIC) model [19], [20].

The path loss in these models is influenced by factors such as the distance between the path difference, the carrier frequency, and the surrounding environmental conditions. We focus on small cells in an Urban Micro (UMi) environment under various scenarios to estimate PL and error statistics. Table 1 summarizes the UMi PL models and their parameters, including shadow fading, carrier frequency, distance, and antenna heights. In the UMi environment, the propagation path is categorized into street canyon (SC) and open square (OS). In Table 1, R_{3D} is the 3-dimensional distance and is calculated as

$$R_{3D} = \sqrt{R^2 + (h_1 - h_2)^2} \quad (1)$$

where R represents the path difference and in meters, h_1 and h_2 are the transmitter and receiver antenna heights in meters, f is the carrier frequency in GHz, and d_{BP} is the breakpoint distance and is given as

In 3GPP-SC model

$$d_{BP} = 4h_{1e}h_{2e}f/c \quad (2)$$

In METIS model

$$d_{BP} = 0.87 * exp\left(\frac{-log_{10}(f)}{0.65}\right) * \frac{4h_{1e}h_{2e}f}{c} \quad (3)$$

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where h_{1e} and h_{2e} are the effective heights $h_{1e}=h_1-1$, and $h_{2e}=h_2-1$, and $c=3*10^8$ m/s. The offset path loss at free space is given as

$$PL_0(dB) = -1.38 * log_{10}(f) + 3.34 \quad (4)$$

PARTICLE SWARM OPTIMIZATION

In wireless communication systems, the quality of service, efficiency, and coverage can be improved through optimization techniques, an iterative process that compares several options to find the optimal one. This method contains various steps: (i) identifying the design parameters, (ii) defining the equality and inequality constraints, and (iii) developing a mathematical model to optimize the design problem [21].

Table 1: UMI Path Loss Models

Model	PL [dB]	Shadow Fading [dB]	Parameters
5GCM-SC LOS	$PL = 32.4 + 20log_{10}(R_{3D}) + 20log_{10}(f)$	σ = 3.76	6GHz<f<100GHz
5GCM-SC NLOS	CI Model: $PL = 32.4 + 31.7log_{10}(R_{3D}) + 20log_{10}(f)$ ABG Model: $PL = 22.4 + 35.3log_{10}(R_{3D}) + 21.3(f)$	σ = 8.09 σ = 7.82	6GHz<f<100GHz
5GCM-OS LOS	$PL = 32.4 + 18.5log_{10}(R_{3D}) + 20log_{10}(f)$	σ = 4.2	6GHz<f<100GHz
5GCM-OS NLOS	CI Model: $PL = 32.4 + 28.9(R_{3D}) + 20log_{10}(f)$ ABG Model: $PL = 3.66 + 41.4log_{10}(R_{3D}) + 24.3(f)$	σ = 7.1 σ = 7.0	6GHz<f<100GHz
3GPP-SC LOS	$PL - LOS = \begin{cases} PL_1, 10m \le R \le d_{BP} \\ PL_2, d_{BP} \le R \le 5Km \end{cases}$ $PL_1 = 32.4 + 21\log_{10}(R_{3D}) + 20log_{10}(f)$ $PL_2 = 32.4 + 21\log_{10}(R_{3D}) + 20\log_{10} f - 9.5\log_{10}(d_{BP})^2 + (h_1 - h_2)^2$ Where d_{BP} is a break point distance, which is given by eq (1).	σ = 4.0	0.5GHz<f<100GHz 1.5m≤h_2≤22.5m h_1≤10m
3GPP-SC NLOS	$PL = \max(PL - LOS, PL - NLOS)$ $PL - NLOS = 22.4 + 35.3log_{10}(R_{3D}) + 21.3log_{10}(f) - 0.3(h_2 - 1.5)$	σ = 7.82	0.5GHz<f<100GHz 10m≤R≤5000m 1.5m≤h_2≤22.5m h_1≤10m
METIS-SC LOS	$PL - LOS = \begin{cases} PL_1, 10m \le R \le d_{BP1} \\ PL_2, d_{BP1} \le R \le 500m \end{cases}$ $PL_1 = 28 + 22\log_{10}(R_{3D}) + 20log_{10}(f) + PL_0$ $PL_2 = 7.8 + 40\log_{10}(R_{3D}) + 20\log_{10} f - 18\log_{10}(h_1h_2) + PL_1(d_{BP})$ Where d_{BP1} and PL_0 are given by eq (2) and eq (3).	σ = 3.1	0.8GHz<f<60GHz 1.5m≤h_2≤22.5m h_1≤10m
METIS-SC NLOS	$PL = \max(PL - LOS, PL - NLOS)$ $PL - NLOS = 23.15 + 36.7log_{10}(R_{3D}) + 26log_{10}(f) - 0.3(h_2)$	σ = 4.0	0.45GHz<f<6GHz 10m≤R≤2000m 1.5m≤h_2≤22.5m h_1≤10m
mmMAGIC-SC LOS	$PL = 32.9 + 19.2log_{10}(R_{3D}) + 20.8log_{10}(f)$	σ = 2.0	6GHz<f<100GHz

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mmMAGIC-SC NLOS	$PL = 31.0 + 45log_{10}(R_{3D}) + 20log_{10}(f)$	σ = 7.82	6GHz<f<100GHz

The PSO algorithm is a search-based technique that iteratively adjusts the population to detect the optimal solution for a given problem. Fig. 1 presents the flowchart of the PSO algorithm. In this algorithm, initially, the number of iterations, cognitive (C_1) and social (C_2) parameters, and initial weight (W) are to be determined. The next step is to determine the objective function based on the PL model and determine the particle position and velocity based on the path difference and carrier frequency. Finally, the best position and PL as an initial value from the objective function are estimated, and the best path loss for a global position out of all particle positions is determined. This procedure should be repeated for the number of iterations or until convergence

criteria are met. The particle position and velocity are estimated as [22], [23]

$$New_{Velocity} = W * Old_{Velocity} + C_1 * rand() * (Personal\ Best\ Position - Current\ Position) + C_2 * (Global\ Best\ Position - Current\ Position) \quad (5)$$

The particle's position is updated using the new velocity, using eq (1) as

$$New_{Position} = Current_{Position} - New_{Velocity} \quad (6)$$

The obtained global best position and path loss provide the minimized path loss. In this paper, we considered 50 iterations, 50 particles, C_1=C_2=1.49445, W=0.729, 1m≤D≤1000m, and 1GHz≤f≤100GHz to estimate the best position, velocity, and path loss.

In this study, we aim to compare the analytical PL of an urban microenvironment using various path models with PSO and to identify the best PL model in multiple scenarios using PSO algorithms.

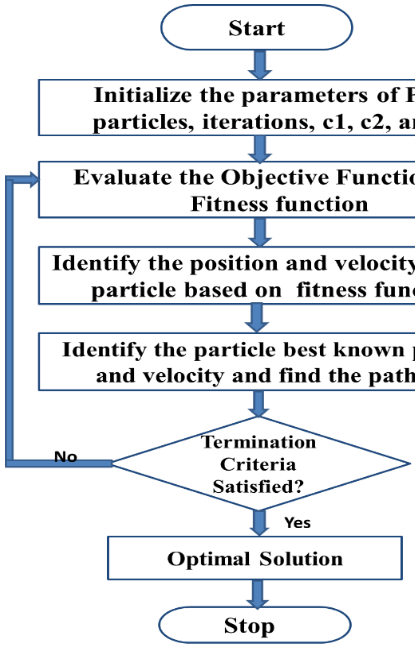

Fig 1: Particle Swarm Optimization Flowchart

RESULTS AND DISCUSSIONS

In this section, we considered PL identification using PL models mentioned in Table 1. The PL is identified analytically and compared using the particle swarm optimization algorithm using MATLAB software. The basic parameters for calculating the path loss are h_1=10 meters, h_2=20 meters, path difference R=1-1000 meters, and operating frequency f=1-100 GHz.

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Path loss with path difference at an operating frequency of 20 GHz, 60 GHz, and 100 GHz, which are shown in Figs 2-4. From Fig 2, it is identified that PL increases with both path distance and operating frequency. At f=20 GHz and R=200 meters, the minimum PL of 103 dB is identified in the 5GCM-OS model under the LOS scenario, while the maximum PL of 168 dB is seen in the mmMAGIC-SC model under the NLOS scenario. As the path distance increases, the PL also rises i.e., at R=1000 meters, the PL in the 5GCM-OS LOS scenario reaches 119 dB, and in the mmMAGIC-SC NLOS scenario, it increases to 200 dB.

Figure 3 shows an increase in path loss with operating frequency compared to Fig 2. At f=60 GHz and R=200 meters, the 5GCM-OS model under the LOS scenario shows a minimum path loss of 112.3 dB, and at R=1000 meters, the path loss rises to 122.5 dB. In contrast, the mmMAGIC-SC model under the NLOS scenario exhibits a maximum path loss of 179.2 dB at R=200 meters and 208.6 dB at R=1000 meters.

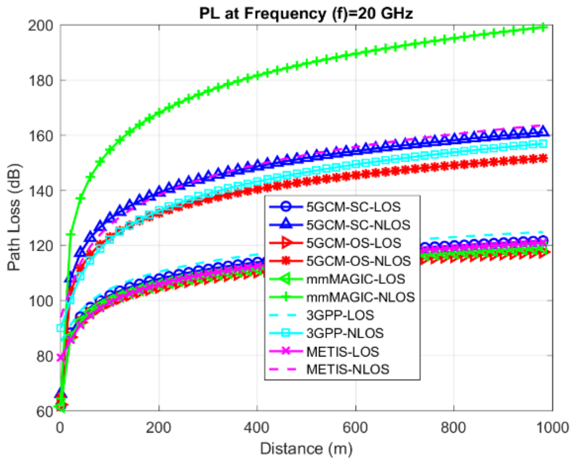

Fig 2: Path loss with Path Difference at 20 GHz

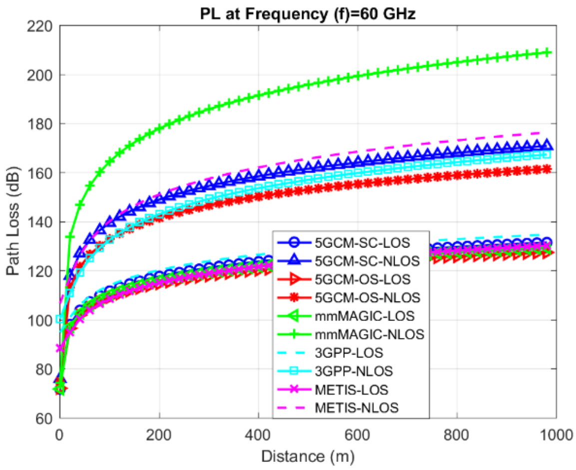

Fig 3: Path loss with Path Difference at 60 GHz

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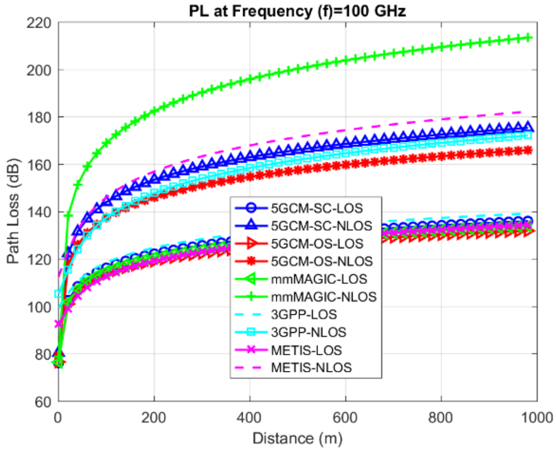

Fig 4: Path loss with Path Difference at 100 GHz

From Fig 4, it is observed that at f=100 GHz and R=200 meters, the 5GCM-OS model under the LOS scenario produces a minimum path loss of 118.3 dB, and at R=1000 meters, the path loss rises to 132.5 dB. In contrast, the mmMAGIC-SC model under the NLOS scenario exhibits a maximum path loss of 181.2 dB at R=200 meters and 214.6 dB at R=1000 meters. Therefore, the increase in carrier frequency increases the PL and this increase is high at the lower path differences compared to the high path differences, which can be observed from Figs 2-4.

In this study, we considered a PSO algorithm to reduce path loss in an urban microenvironment and to identify the optimal PL model. The analytical PL estimation using the PL equations shown in Table 1 and optimal path loss estimation using the PSO algorithm are shown in Figs 5-9.

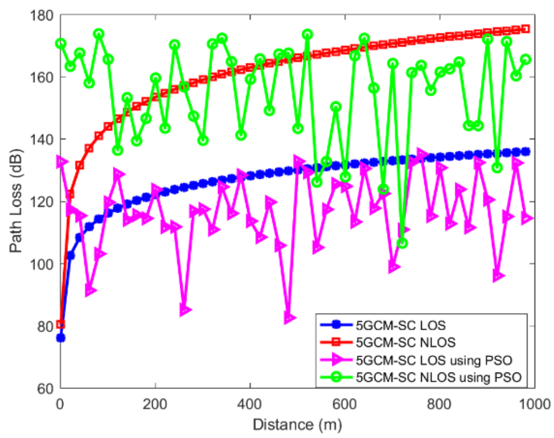

Fig 5: PL Comparison of 5GCM-SC models

Fig. 5 compares the analytical and PSO approaches regarding path loss using the 5GCM-SC model. The figure demonstrates that the PSO algorithm achieves lower path loss than the analytical approach. In the PSO approach, path loss is influenced by the number of iterations; as the iterations increase, path loss decreases. Initially, the path loss is higher with fewer iterations but gradually reduces as the iterations progress. In the LOS scenario, the minimum path loss occurs at a path distance of 435 meters, while in the NLOS scenario, the lowest path loss is observed at 650 meters, which will be considered an optimal path difference in an urban microenvironment using the 5GCM-SC model.

Fig. 6 compares the 5GCM-OS model path loss through analytical and PSO approaches. The optimal path difference in LOS and NLOS scenarios is identified as 800 meters and 270 meters respectively. These optimal values provide the minimum path loss of 87.8 dB, and 108.2 B in LOS and NLOS scenarios.

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Fig. 7 compares the path loss of the 3GPP-SC model using both analytical and PSO approaches. A minimum PL of 82 dB is identified at an optimal distance of 280 meters in the LOS scenario, and 120 dB at 870 meters in the NLOS scenario. These optimal values minimize path loss and enhance signal efficiency in wireless networks.

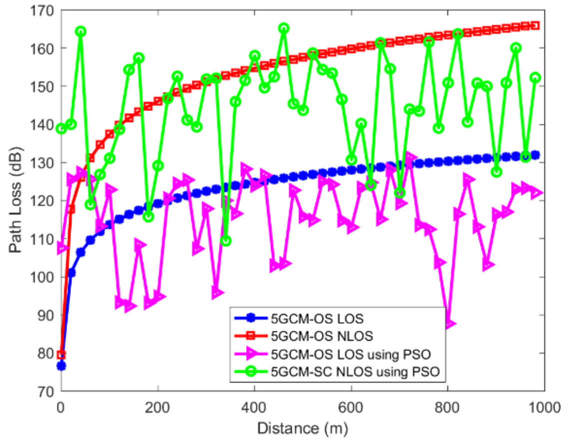

Fig 6: Comparison of Path loss of 5GCM-OS model

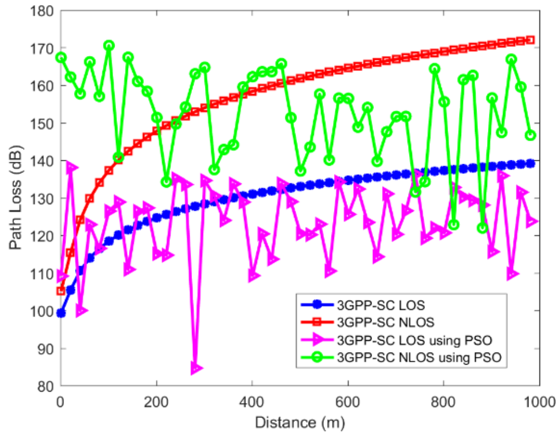

Fig 7: Comparison of Path loss of 3GPP-SC model

Fig. 8 compares the path loss of the METIS-SC model using analytical and PSO approaches. In the LOS scenario, a minimal path loss of 70 dB is observed at an optimal distance of 800 meters, while in the NLOS scenario, it is 74 dB at 490 meters. Similarly, in Fig 9, the mmMAGIC-SC model path loss characteristics are shown. The minimum path loss of 86 dB is observed at an optimal path difference of 460 meters in the LOS scenario and 140 dB at 800 meters in the NLOS scenario.

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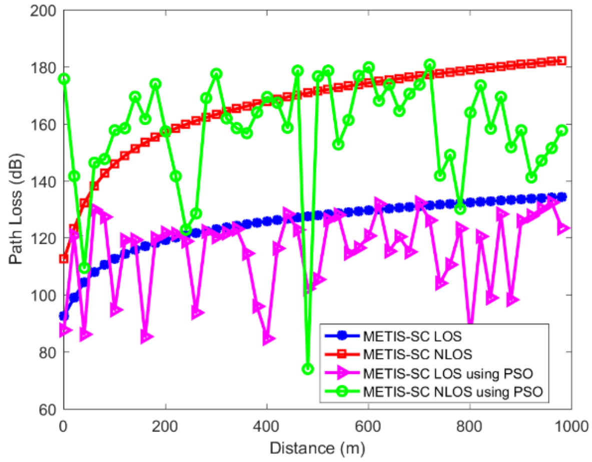

Fig 8: PL Comparison of METIS-SC model

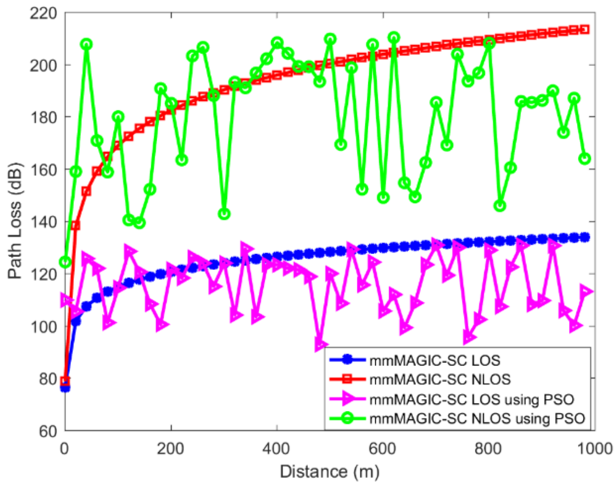

Fig 9: PL Comparison of mmMAGIC-SC Model

Table 2: Path Loss Error Statistics of Various Path Loss Models

Parameter / Model	5GCM-SC LOS	5GCM-SC NLOS	5GCM-OS LOS	5GCM-OS NLOS	3GPP-SC LOS	3GPP-SC NLOS	METIS-SC LOS	METIS-SC NLOS	mmMAGIC-SC LOS	mmMAGIC-SC NLOS
MSE	6.99	12.75	5.15	7.84	3.85	9.97	6.00	12.16	5.71	17.20
RMSE	2.64	3.54	2.67	2.80	1.96	3.16	2.25	3.48	2.40	4.15
SE	1.70	2.2	1.56	1.9	1.47	1.68	2.00	2.08	1.50	3.25

The path loss error measurements such as mean square error (MSE), root MSE (RMSE), and Standard deviation error (SE) are estimated by comparing the analytical path loss with optimized values, which are mentioned in Table 2. From the table, it can be observed that the 3GPP-SC model produces the minimum error statistics in the LOS scenario, while the 5GCM-OS model achieves the same in the NLOS scenario. Consequently, the 3GPP-SC and 5GCM-OS models are identified as the optimal path-loss models for urban microenvironments.

CONCLUSION

In this paper, we considered a 5G wireless network with an urban microenvironment to estimate the path loss in LOS and NLOS scenarios The PL is identified using the multiple PL models and identified the best PL model in LOS and NLOS scenarios. The PSO algorithm is used to estimate the PL and its error measurements of PL models. From the simulation results, we identified the 3GPP-SC as the optimized PL model in LOS scenario and 5GCM-OS model in NLOS scenario as it provides minimized PL in an urban microenvironment. In future, we want to implement the same experimentally in the real world.

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