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Path Loss Model Optimization In An Urban Environment Using Genetic Algorithm

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Abstract: An essential requirement for the design of a wireless communication system is the determination of the path loss. This article compares and estimates path loss using urban macro environment path loss models. Path loss model optimization is taken into consideration to represent the real propagation path and to find the optimized path loss model using a genetic algorithm. The analytically measured path loss is contrasted with the optimized path loss values of each model and error statics are used to assess each model's performance. From the results, it can be deduced that the 5GCM LOS and NLOS model generates the mean square error and standard deviation with the lowest values. This model allows to improve the accuracy by 90.30%. The 5G heterogeneous network operators can improve the service quality at millimeter wave frequencies by employing 5GCM path loss model.

***Keywords**: Path Loss Model, 5G networks, Optimization, Genetic Algorithm*

1. Introduction

Due to the widespread adoption of virtual technology in everyday life, high speed internet access is no longer an option but rather a need. Therefore, it is essential that wireless subscribers receive high-quality service. Therefore, signal propagation models are necessary and beneficial for supplying wireless network users with a sufficient and high-quality signal level. Accurate path loss (PL) prediction is a key parameter for designing a wireless network and the prediction models are required to optimize system parameters. These optimized parameters will improve the quality of service (QOS), throughput, spectral efficiency, and coverage area [1-3]. Path loss is the degradation in signal strength when signals travel through wireless channels from the transmitter to the receiver (T-R). Path loss is unavoidable, Since the phenomena of electromagnetic propagation, such as diffraction, refraction, and scattering, can all be precisely described and characterized [4-6].

Path loss models are important to precisely plan a wireless communication network. Several PL models have been developed and used to estimate the propagation loss in various frequency bands and various environments [7-10]. The PL model developed for a particular environment will not be suitable for another environment. There are numerous approaches employed in the literature to optimize empirical path loss models. In [11], the weighted least squares approach, genetic algorithm (GA), and hybrid GA were used to optimize the Cost-231 Hata model, with the hybrid model producing the lowest mean square error (MSE), root mean square error (RMSE), and PL.

The PL of Walfisch Ikegami model was estimated and compared using GA approach, particle swarm optimization (PSO), and grey wolf optimization (GWO) methods [12]. The GWO approach generated the lowest error statistics when comparing the GWO method against the GA and PSO algorithms. The least squares optimization method was utilized to identify the PL of empirical models such as Cost-231, ECC-33, and SUI models, revealing the Cost-231 model as the optimized PL model [13]. The Cost-231 model yielded the lowest PL and error statistics when compared to the other models. Partial derivative optimization method is employed to calculate the optimized PL in a wireless networks. Along with the PL, SINR, BER and total power consumption are estimated and compared with the machine learning based methods [14]. Authors observed that the proposed method achieves better PL compared to the machine learning based methods. In [15], authors proposed K-nearest neighbors and random forest algorithms to determine the PL and delay spread. The obtained PL values are compared with the Cost-231 and Okumura model path loss values, observed that the proposed models produces smaller RMSE.

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Nowadays, wireless communication networks are expected to utilize millimeter wave (mmWave) frequency bands. The underutilized mmWave bands will improve the throughput, coverage capacity, spectral efficiency and quality of service [16-19]. Finding the best placement for 5G base stations (BS) requires careful consideration of PL model analysis at mmWave frequencies. Several mmWave propagation models have been developed by numerous engineers and researchers, including 5GCM, 3GPP, METIS, and mmMAGIC [20,21]. In this article, we focused on the optimization of mmWave PL model by minimizing the propagation loss. We estimated the mean, MSE, RMSE and standard deviation of error (SE) for all PL models. We observed that the 5GCM model generates less PL and error statistics in contrast to alternative PL models. The remainder of the paper is structured as follows. Section II discusses path loss models of an urban environment. In section III, a genetic algorithm is provided. Section IV presents the simulation results and error statistics, while Section V draws conclusions.

2. Path Loss Models

For precise design, comparison, and deployment of wireless networks, the use of wireless channel models becomes imperative to accurately and efficiently simulate signal propagation. The paper discusses the urban macro environment PL models currently utilized by various major organizations, namely: (i) 5GCM (5G channel model), (ii) 3GPP (3rd Generation Partnership Project), and (iii) METIS (mobile and wireless communication enablers for the twenty twenty information society) [20,21]. The PL of these models is dependent on the carrier frequency (f), the environment, and the transmitter-receiver range (R). Urban macro (UMa) environment under line of sight (LOS) and non line of sight (NLOS) scenarios are considered to estimate the PL and error statistics. The UMa PL models, PL, and their parameters, including distance, antenna heights, and shadow fading (σ), are listed in Table I.

A. 5GCM Model

The large-scale CI with respect to distance and ABG models are taken into consideration to calculate the PL in urban macro environment. PL in the frequency range of

6 GHz to 100 GHz is evaluated for these models in both LOS and NLOS scenarios. Table I presents the PL equations for the 5GCM model.

B. 3GPP Model

In this model, (R_{3D}) is calculated based on the distance between transmitter and receiver and antenna heights $h_1 and\ h_2$ and is given by $R_{3D} = \sqrt{R^2 + (h_1 - h_2)^2}$ [19]. In 3GPP LOS scenario, PL is estimated based on break point distance d_{BP} and is estimated as [22-25]

$$d_{BP} = 4h_1 h_2 f * 10^9/c \qquad (1)$$

$$h_{1e} = h_1 - 1.0\ m$$

$$h_{2e} = h_2 - 1.0\ m$$

where c is the velocity of free space at $3 * 10^8$ m/s and h1e and h2e are the effective antenna heights. Utilizing a large-scale ABG model, the PL of an NLOS scenario is estimated [21].

Table 1. Urban Macro Path Loss Models

Model	PL (dB)	σ (dB)	Parameters
5GCM LOS	$PL = 32.4 + 20log_{10}(R_{3D}) + 20log_{10}(f)$	4.1	6<f<100 GHz
5GCM NLOS	CI Model: $PL = 32.4 + 30log_{10}(R_{3D}) + 20log_{10}(f)$ ABG Model: $PL = 19.2 + 34log_{10}(R_{3D}) + 23log_{10}(f)$	6.8 6.5	6<f<100 GHz
3GPP LOS	$PL_{LOS} = \begin{cases} PL_{1,} & 10\ m \le R \le d_{BP} \\ PL_{2,} & d_{BP} \le R \le 5\ Km \end{cases}$ $PL_1 = 28 + 22log_{10}(R_{3D}) + 20log_{10}(f)$ $PL_2 = 28 + 40log_{10}(R_{3D}) + 20log_{10}(f) - 9log_{10}((d_{BP})^2 + (h_1 - h_2)^2)$ Where d_{BP} is given by eq (1)	6	6<f<100 GHz 1.5≤ h_2 <22.5 m $h_1 = 25\ m$

3GPP NLOS	$PL = \max(PL_{LOS}, PL_{NLOS})$ $PL_{NLOS} = 13.54 + 39.08log_{10}(R_{3D}) + 20log_{10}(f) - 0.6(h_2 - 1.5)$	6	0.5<f<100 GHz 1.5≤ h_2 <22.5 m $h_1 = 25\ m$
METIS LOS	$PL_{LOS} = \begin{cases} PL_1, & 10\ m \leq R \leq d_{BP} \\ PL_2, & d_{BP} \leq R \leq 5\ Km \end{cases}$ $PL_1 = 28 + 22log_{10}(R_{3D}) + 20log_{10}(f)$ $PL_2 = 28 + 40log_{10}(R_{3D}) + 20log_{10}(f) - 9log_{10}((d_{BP})^2 + (h_1 - h_2)^2)$ Where d_{BP} is given by eq (1)	4	0.45<f<100 GHz 1.5≤ h_2 <22.5 m $h_1 = 25\ m$
METIS NLOS	$PL = \max(PL_{LOS}, PL_{NLOS})$ $PL_{NLOS} = 161.94 - 7.1log_{10}(w) + 7.5log_{10}(h) - \left(24.37 - 3.7\left(\frac{h}{h_1}\right)^2\right)log_{10}(h_1) + (43.42 - 3.1log_{10}(h_1))(log_{10}(R_{3D}) - 3) + 20log_{10}(f) - 0.6(h_2)$	6	0.45<f<100 GHz 1.5≤ h_2 <22.5 m $h_1 = 25\ m$ w=20 m, h=20 m

C. METIS Model

LOS PL of METIS model depends on break point distance given in eq (1). NLOS PL is estimated based on the large scale ABG model.

These existing PL models are used to optimize the path distance and to minimize the PL in an urban environment in LOS and NLOS scenarios.

3. Genetic Algorithm

Optimization is a process that is carried out repeatedly by comparing numerous solutions to achieve the best outcome, which will enhance the QOS, efficiency and coverage of a wireless communication system. This optimization approach includes various steps: (i) Initially identify the variable design parameters, (ii) Initiate the equality and inequality constraints, and (iii) Finally create a mathematical model to optimize the design problem [26].

The two main categories of optimization methodologies are analytical approach and heuristic approach. Partial derivatives, a linear least squares model, a weighted least squares model, and other analytical approaches are some examples of the mathematical modelling utilized in an analytical approach to optimize design problems. The design problem is optimized using simulations and approximative techniques in the heuristic approach. GA, PSO, GWO, etc., are some examples of heuristic methods [11,12,27].

In this paper, GA is considered to optimize the PL models in an urban macro environment. The process of natural selection serves as the basis for the genetic algorithm, which is an optimization technique. It uses the survival of the fittest concept and is a population based search method [28]. The genetic operators are applied repeatedly to the individual existing population's, which creates new populations to enhance the system performance.

In genetic algorithm, the representation of chromosomes, selection, recombination, mutation, and fitness function evaluation are the primary components, which are shown in the GA flowchart in Fig. 1. Simple GA has been altered to become multi objective GA. Creating the optimal Pareto Front in the objective space is the primary goal of GA, aiming to maximize all fitness functions without negatively affecting any others [29,30].

The step by step procedure of GA is summarised as follows:

- Initially, a counter is initiated to generate the initial

  population.

- At each stage, the algorithm generates a series of new populations by utilizing the individuals that make up the present population.
- Each member of the present population has their fitness value determined, and the raw fitness scores are transformed into a variety of useful values.
- Those from the present population who have lower fitness values are moved to the next one.

A solution that is ideal is produced by these values.

- The crossover and mutation genetic operators are applied to generate children from the parents. These children then replace the current population, forming the next generation.
- The procedure is repeated for many generations and the best solution is identified as the individual with the smallest fitness value.
- Finally, the objective function is optimized by minimizing the fitness value of individuals within the population.

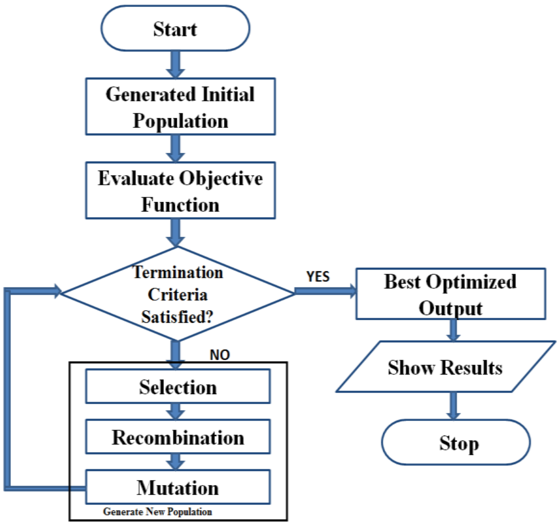


Fig.1: Flowchart of Genetic Algorithm

Therefore, the genetic algorithm efficiently searches for and converges to a global minimum and maximum without the requirement of complex derivative computations.

This optimization process utilized a GA package in MATLAB to achieve its goals. The parameters considered for optimization are the path difference, ranging from 1 to 150 m, and the operating frequency, ranging from 1 to 100 GHz. Therefore, we considered path difference and operating frequency as decision variables in GA. The objective function is determined as the minimization of path loss.

GA tuning is used to optimize the urban PL models and to achieve the desired PL by adjusting population size, mutation rate and selection rate. We carried out several simulations to fine-tune the GA parameters with various combinations of population sizes, mutation rates, and selection rates. Based on the outcomes of these preliminary experiments, we observed that a population size of 100, a mutation rate of 2, and a selection rate of 1 yielded satisfactory results such as enhanced path loss. The optimization process is carried out for a maximum of 50 iterations. In this paper, we compared the traditional MATLAB coding approach with the GA approach for estimating PL in an urban environment.

Initially the counter is initiated to create the initial population, later it is incremented. After, initiating the population, the mutation of the population is carried out and the mating has been performed using the crossover. This process is carried out until the optimize solution for the PL model to be achieved. The optimized and analytical solutions of each model are compared in this paper. The error statics, including MSE, RMSE, and SE, are computed using the optimized and analytically measured values of each path loss model.

4. Results and Discussions

In this article, macro cell PL models are investigated by comparing the analytically measured values and predicted values with genetic algorithm. The optimization toolbox in Matlab is used to implement the GA for the objective functions are specified in Table 1. Path loss is estimated and compared for the four standard models proposed [19] for the LOS and NLOS urban scenarios, which are shown in the Figs. 2-5. These figures demonstrate that the GA produces significantly less path loss compared to the analytically measured values in both LOS and NLOS scenarios. Therefore, the optimization approach improves the performance of PL models.

Error statistics like mean, MSE, RMSE and SE are used to measure the accuracy of the each PL model and to identify the optimized model for the urban macro environment. The analytically measured PL and predicted PL using GA for 5GCM model is noticed in Fig. 2.

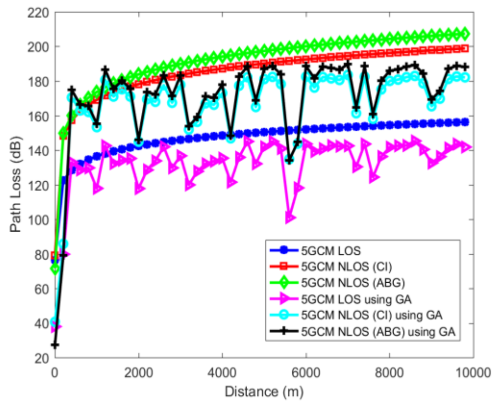


Fig. 2: Path loss comparison using 5GCM model

The path loss estimated by 5GCM CI and ABG models optimized with GA has a better performance compared to the analytically measured 5GCM CI and ABG models in LOS and NLOS scenarios. From this figure, it is observed that the PL raises to a maximum value suddenly for a small path difference i.e., up to 1000 m then it raises slowly for the remaining distance i.e., the PL is more in the near field compared to the far field.

In addition to the 5GCM model, the study also incorporates the 3GPP and METIS models to minimize the PL and to determine the optimized PL model for an urban macro setting. Fig. 3 and 4, shows the comparison of path loss estimated through analytical and optimization approaches of 3GPP and METIS models respectively. These figures distinctly reveal that the optimization approach enhanced the path loss compared to the analytical approach. The minimum, maximum, and mean PL of 5GCM, 3GPP and METIS models are listed in Table 2.

Fig. 3: Path loss comparison using 3GPP model

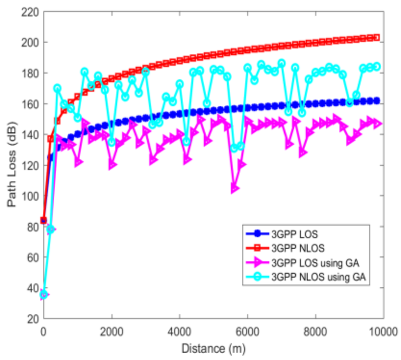
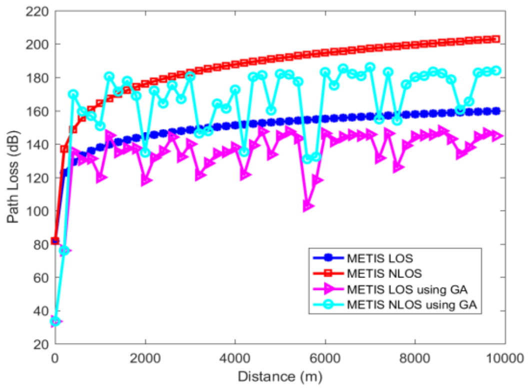


Fig. 4: Path loss comparison using METIS model



Optimized path loss of urban path loss models using CI and ABG models are shown in Fig. 5. From this figure, it is observed that the PL of LOS models is less than the PL of NLOS models because in NLOS scenario the propagation path is obstructed by buildings, trees, advertisement boards, etc., which will cause multipath fading. Therefore, the PL in NLOS scenario is more than the LOS scenario

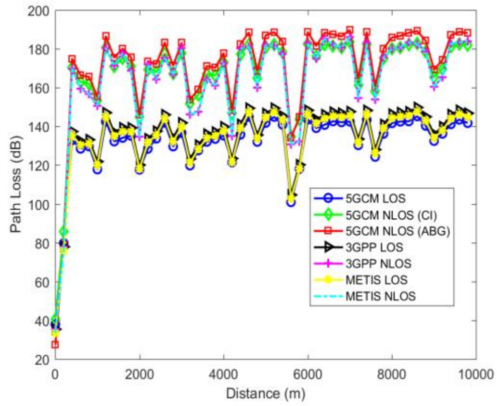


Fig. 5: Comparison of Urban path loss models

the minimum, maximum, and mean PL of LOS and NLOS urban PL models are shown in Table. 2. From this table, it is identified that the minimum, maximum and mean path loss variation between analytically measured and optimization method are more than 35 dB, 10 dB and 15 dB respectively in all models. It shows that the path loss is minimized by using the GA optimization approach. 5GCM NLOS CI model produces minimized path loss and more accuracy i.e., 90.36% compared to 5GCM NLOS ABG model, 3GPP and METIS models. In LOS scenario, 5GCM model produces minimized PL and more accuracy of 89.79% compared to 3GPP and METIS models. Therefore, 5GCM model is considered as an optimized PL model in LOS and NLOS urban environments.

Table. 2: Performance measures of urban path loss models

Path Loss Model	**Analytical Measurements PL (dB)**		**Optimized Measurements PL (dB)**		**Analytical PL (dB)**	**GA PL (dB)**	**Accuracy (%)**
	Min	Max	Min	Max	**Mean**	**Mean**	
5GCM LOS	76.41	156.2	37.95	145.28	146.23	131.65	89.79
5GCM NLOS (CI)	79.11	198.85	40.65	183.52	183.44	166.66	90.36

5GCM NLOS (ABG)	71.6	207.30	27.36	189.75	189.75	170.66	89.37
3GPP LOS	83.7	161.72	35.45	149.77	149.77	135.62	89.61
3GPP NLOS	83.7	202.89	35.45	186.06	186.06	164.70	89.10
METIS LOS	81.7	159.72	33.453	147.77	147.77	133.62	89.47
METIS NLOS	81.7	202.92	3.45	186.09	186.09	164.65	89.08

The error statistics like MSE, RMSE, and SE are measured and listed in Table 3. From this table it is identified that the least error statistics are produced by 5GCM LOS and 5GCM NLOS (CI) model compared to other LOS and NLOS PL models. Therefore, the 5GCM model is considered as an optimized PL model compared to other PL models in LOS and NLOS scenarios in an urban environment. Service providers can use this paradigm to improve the performance of their networks and to provide better signal coverage by reducing the path loss in an urban macro environment.

Table 3. Error statistics of urban path loss models

Path Loss Model	MSE	RMSE	SE
5GCM LOS	6.72	2.6	2.55
5GCM NLOS (CI)	10.71	3.27	3.52
5GCM NLOS (ABG)	13.89	3.27	4.00
3GPP LOS	7.74	2.78	2.74
3GPP NLOS	14.8	3.89	3.85
METIS LOS	7.74	2.78	2.74
METIS NLOS	14.9	3.86	3.9

5. Conclusion

The paper utilized the genetic algorithm to optimize small cell PL models to attain precise path loss. The optimized PL values generated by GA were then compared to the analytically measured path losses. According to the simulation outcomes, the 5GCM model exhibited the lowest PL and error statistics such as MSE, RMSE, and SE, indicating its effectiveness. As a result, the 5GCM model was selected as the optimized PL model for an urban macro-environment. We wish to use PSO and GWO techniques to estimate and compare the PL of urban micro environments in the future.

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