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OPTIMIZATION OF PATH LOSS PREDICTION IN MILLIMETER WAVE COMMUNICATIONS USING POLYNOMIAL REGRESSION MODEL AND GENETIC ALGORITHM

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Summary

Millimeter wave (mmWave) technology have attracted significant interest due to bandwidth availability improvement offering huge amount of spectrum to fifth generation (5G). The shorter wavelength of mmWave signals allows for greater data transmission rates and bandwidth, but it also makes them more susceptible to various forms of attenuation and absorption between the transmitting and the receiving antennas, also referred to as path losses. The path loss model is an important tool in wireless network planning; allowing network planner to optimize the cell towers distribution and meet expected service level requirements. However, each type of path loss propagation model is designed to predict path loss in a particular environment that may be inaccurate in other different environment. Improving the existing models and developing new models are is vital for characterizing the wireless communication channel in both indoor and outdoor environments. This paper presents an efficient and novel path loss model based on polynomial regression analysis for predicting signal strength in millimeter bands. A genetic algorithm is used to optimize the parameters of the polynomial regression model by minimizing the sum of squared errors of the proposed model of path loss. The performance and accuracy of the polynomial regression model are evaluated and compared to both the measured path loss values and those obtained by lognormal shadowing model. The results show the close fit of the polynomial model to the field measurements with significantly lower root mean square error (RMSE) compared to the distance-shadowing model which proves the validity and accuracy of the proposed model.

Keywords: Millimeter Wave, Path Loss, Polynomial Model, Genetic Algorithm, RMSE, Optimization.

1. INTRODUCTION

The rapid increase in mobile data usage has created significant challenges for wireless service providers to overcome one of the worst wireless communications problems, which is the frequency band shortage [1–4]. This dramatic increase necessitates a significant increase in mobile network capacity heavily used in 3G/4G networks (700 MHz to 2.6 GHz). Millimeter-wave technology is a promising solution to the latter problem of limited bandwidth in wireless communications. It is being utilized in fifth generation (5G) mobile networks due to its access to a large amount of available spectrum resource. Millimeter

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wave technology is primarily used for line-of-sight communications due to its fast attenuation [5–7]. As a result, it is well suited for high-speed wireless communication applications, such as wireless backhaul and chip-to-chip communication. Furthermore, this technology has a wide range of potential uses in various fields, including virtual reality, wearable devices, vehicle networks, satellite communications, object imaging, and object tracking [8–11].

Despite the potentiality of millimeter wave technology, it has faced some challenges. Some of these challenges include path loss, high penetration loss, and narrow beamwidth. Other Challenges include atmospheric gases attenuation, precipitation attenuation, scattering effects, multipath, and diffraction in both indoor and outdoor scenarios [12].

The difference in signal strength between the transmitter and the receiver is referred to as path loss. Several models have been proposed for cellular systems operating in different environments, including indoor, outdoor, urban, suburban, and rural settings. Some of these models were derived statistically based on field measurements, while others were developed analytically based on diffraction effects [13]. Each model uses specific parameters to achieve reasonable prediction accuracy, for example Empirical models, require adjusting some parameter according to field strength measurements made in a particular environment, free Space Path Loss (FSPL) model assumes a lossless propagation environment and is based on the inverse square law. It is typically used for line-of-sight (LOS) communications. Okumura-Hata model is an empirical model that is widely used for urban and suburban environments. It takes into account the effect of buildings and other obstacles on the propagation of radio waves [14–16]. COST Hata model, this model is an extension of the Okumura-Hata model is used in urban and suburban environments [17, 18].

Since the terrain conditions vary largely, the path loss prediction models cannot be generalized. This drawback can be overcome by adjusting the model parameters to suit the desired environment. In the last few years, many researchers have applied different algorithms to predict the path loss in theirs environments [19]. The optimized model can provide optimal parameters for radio-wave path-loss predicting in the target area in [20, 21] the Genetic algorithm is used to optimize the appropriate model and to minimize the mean square error between the results obtained using this optimized model and the experimental measurements.

This paper is organized as follows: Section 2 presents log distance and polynomial path loss models. Sections 3 presents the optimization of the polynomial model by global genetic algorithm. Section 4 results are presented and discussed. Finally, Section 5 presents conclusions.

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2. MATERIALS AND METHODS

2.1. Log-distance Pathloss Model

The log-distance is one of the most simplified models, typically used to characterize pathloss in radio communication systems. The average large-scale path loss for an arbitrary T-R separation is expressed as a function of distance [13]:

$$\mathrm{PL}[\mathrm{dB}] = \mathrm{PL}(\mathrm{d}_0) + 10\mathrm{n}\log\left(\frac{\mathrm{d}}{\mathrm{d}_0}\right) . \quad (1)$$

$PL(d_0)$ is the path loss in decibels (dB) at the reference distance ; d_0 calculated using the free-space path loss model, n is the path loss exponent, which indicates the rate at which the path loss increases with distance in different propagation environment.

2. 2. Log Normal Shadowing Model

The actual wireless communication environment is more complex, the received signal is a superposition of reflected, diffracted, and transmitted signals, each with their own attenuation characteristics. This multipath signal is different from the free space signal. In a multipath environment, a mixed model between path loss and shadow fading is commonly used, with the formula [7]:

$$\mathrm{PL}(\mathrm{d})[\mathrm{dB}] = \mathrm{PL}(\mathrm{d}_0) + 10\mathrm{n}\log_{10}\left(\frac{\mathrm{d}}{\mathrm{d}_0}\right) + \mathrm{X}_\sigma , \text{ for } \mathrm{d} \geq \mathrm{d}_0. \quad (2)$$

Where X_σ is Gaussian random variable with zero mean and variance σ^2 depicting the attenuation caused by flat fading.

2. 3. Polynomial Model

The general behavior of path loss in a non-line of sight scenario is nonlinear due to fading. As a result, a linear regression model is no longer suitable for predicting or accurately fitting path loss data. Therefore, we opted for the polynomial regression which is able to fit the data to a curve with a low level of error. The prediction function using a polynomial model can be written as follows:

$$\mathrm{PL}_i = \beta_0 + \beta_1 \mathrm{d}_i + \beta_2 \mathrm{d}_i{}^2 + \ldots + \beta_\mathrm{n} \mathrm{d}_i{}^\mathrm{n} + \varepsilon_i \quad i = (1, 2, \ldots.n) . \quad (3)$$

Where β_0; β_1;…..; β_n are the coefficients to be determined and ε_i is the random error, d_i is the distance between transmitter and receiver. The model can be written as a system of linear equations:

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$$\begin{bmatrix} PL_1 \\ PL_2 \\ PL_3 \\ . \\ . \\ . \\ PL_n \end{bmatrix} = \begin{bmatrix} 1 & d_1 & d^2{}_1 & . & . & . & d^m{}_1 \\ 1 & d_2 & d^2{}_2 & . & . & . & d^m{}_2 \\ 1 & d_3 & d^2{}_3 & . & . & . & d^m{}_3 \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ 1 & d_n & d^2{}_n & . & . & . & d^m{}_n \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ . \\ . \\ . \\ \beta_m \end{bmatrix} + \begin{bmatrix} \varepsilon_0 \\ \varepsilon_1 \\ \varepsilon_2 \\ . \\ . \\ . \\ \varepsilon_m \end{bmatrix}. \tag{4}$$

The system of expression above can be represented using the matrix

$$\mathrm{PL} = \mathrm{X}\beta + \varepsilon . \tag{5}$$

Where $\mathrm{X} = \dfrac{(\sum PL)\left(\sum d^2\right) - (\sum d)(\sum d * PL)}{n\left(\sum d^2\right) - \left(\sum PL\right)^2}$, and $\varepsilon = \dfrac{n(\sum PL * d) - (\sum d)(\sum PL)}{n\left(\sum d^2\right) - \left(\sum PL\right)^2}$.

2.3.1. Optimization Process by Global Genetic Algorithm

The path loss measurement data used in this study was obtained by the New York University Wireless Research Center and published in [15]. The measurements were collected at different heights for both transmission and reception points and provides large-scale channel characterization (path loss) for mmWave transmissions. A total of 63 points were evaluated in this study.

In order to find the optimal parameters of a polynomial regression model, we apply a Global Genetic Algorithm (GGA) optimization approach to calculate the polynomial regression model Parameters. By combining tournament selection, extended arithmetic crossover, and adaptive mutation operations, an optimal solution vector is obtained. The **Fig. 1** describes the flow chart and outlines the main algorithmic steps.

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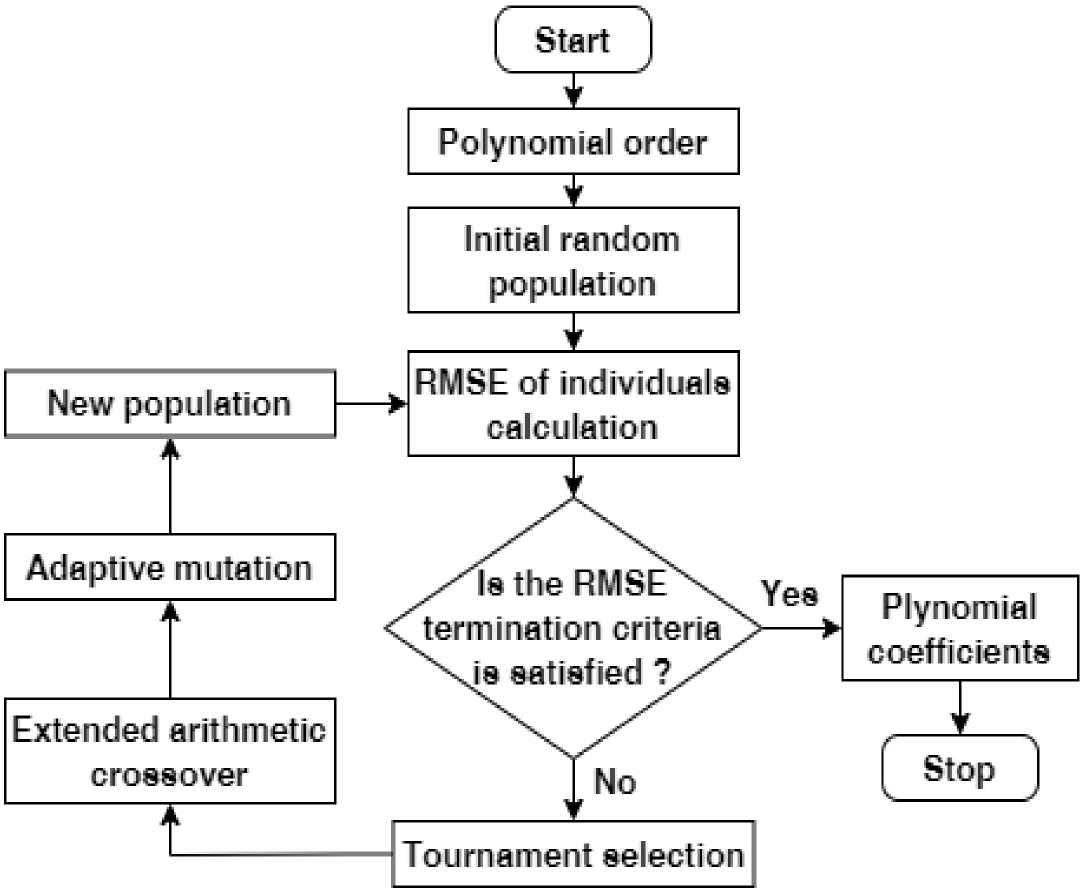

Figure 1: Flowchart of the Global Genetic Algorithm Optimization Process

The fitness function used for evaluation and parameters adjustment is defined by the mean square error (RMSE) as:

$$\mathrm{RMSE} = \sqrt{\sum \frac{\left(P_m - P_r\right)^2}{N}}. \tag{6}$$

Where: P_m is the measured Pathloss (dB); P_r is the predicted Pathloss (dB) and N is the number of measured data points.

3. RESULTS AND DISCUSSION

To study and evaluate prediction models, a comparison in terms of path loss over the distance between the experimental measurements, the model based on the polynomial equation and the log-distance model around a frequency of 73 GHz is shown in **Fig 2**.

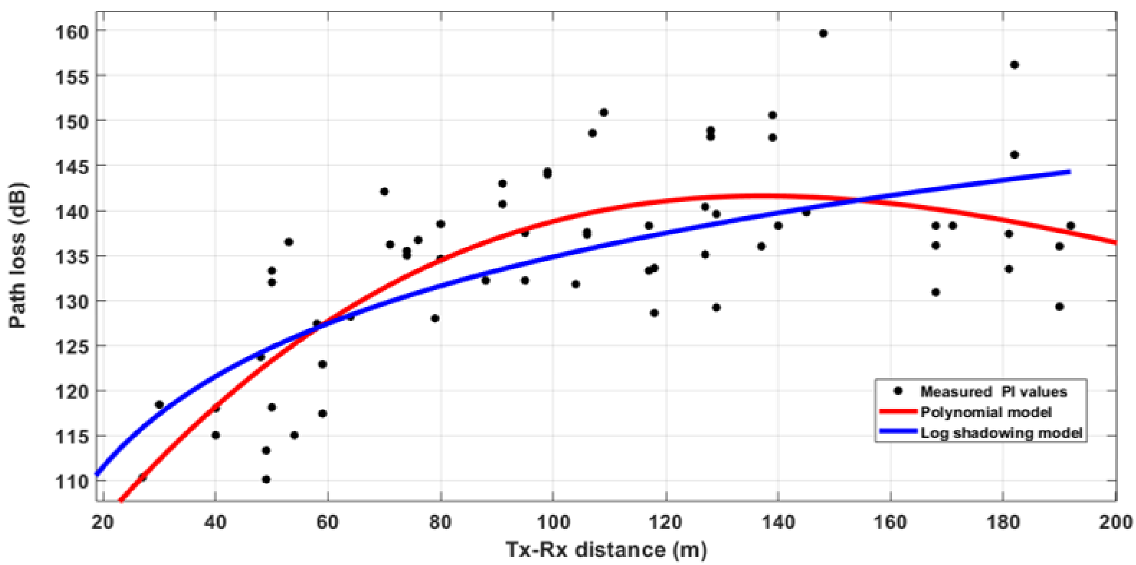

Figure 2: Pathloss versus Distance for Experimental, Log Distance Shadowing and Polynomial Model

To study and analyze the prediction accuracy of these models, the Root Mean Square Error (RMSE) was calculated using the equation 6.

In **Table 1**, we present the values of RMSE for both models: polynomial model and log shadowing model.

Table 1: Result of RMSE

Models	RMSE
Polynomial model	11.93 dB
Log distance model	8.2 dB

The loss in a channel estimated by the polynomial model exhibits a higher RMSE error value than that obtained by the log distance model. In order to improve the polynomial model and reduce the RMSE, we chose the genetic algorithm (GA) to optimize the proposed model using the genetic processes as indicated in **Fig 1**.

In **Table 2**, we present both cubic and quadratic polynomial regression models parameters obtained by genetic algorithm (GA) using experimental data obtained in urban zone at frequency 73 GHz [15].

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Table 2: Result of Optimization by GA

Polynomial models	Parameters of polynomial			
	β_0	β_1	β_2	β_3
Quadratic polynomial model	96.115	0.659	–0.002	0
Cubic polynomial model	90.219	0.874	–0.004	0.000007

To investigate the validity of the proposed model, the path loss propagation values of the polynomial regression with a genetic algorithm optimization and the log-distance shadowing model are calculated and plotted in **Fig. 3**.

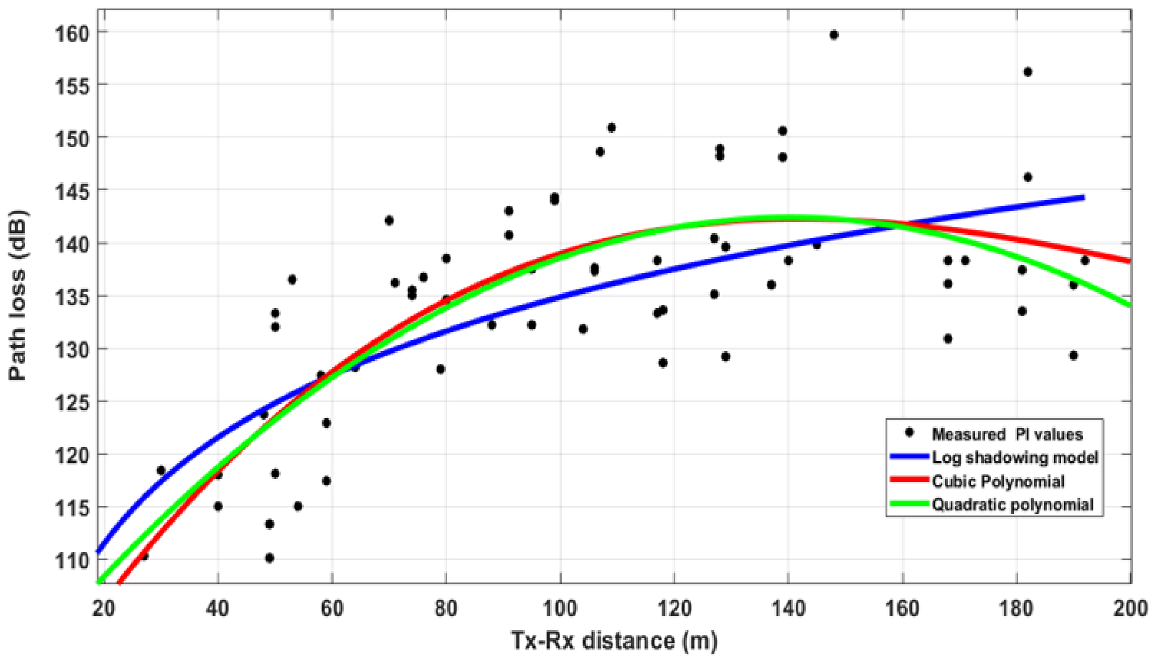

Figure 3: Pathloss versus Distance for Experimental, Log Distance Shadowing and Optimized Polynomial Model

The RMSE of the polynomial model with GA optimization and then RMSE of the log-distance shadowing model both were computed using the experimental data as shown in **Table 2.**

Table 3: RMSE of the predicted models

Models	RMSE
Log distance shadowing	8.2 dB
Quadratic polynomial mode	7.09 dB
Cubic polynomial model	7.06 dB

Fig. 3 depicts the comparison between the quadratic and cubic polynomial models to the experimental result. The plot clearly shows that the polynomial curve fits the data better than the log distance. Additionally, The RMSE was calculated as presented in **Table 3** for both cubic and quadratic polynomial regression models, with values of 7.09 dB and

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7.06 dB, respectively. The log distance RMSE was found to be 8.2 dB, which indicate that the proposed model based on GA is more accurate than the log distance-shadowing model.

4. CONCLUSIONS

This paper presents a novel path loss for non-line of sight transmission in urban zone for millimeter wave communication. The proposed model is based on a polynomial regression. The polynomial parameters were optimized by global genetic algorithm. The obtained results were compared to the log distance-shadowing model and to the measurement data. The obtained result show that the proposed model provides more accuracy compared to the log distance shadowing who exhibits a higher value of RMSE.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data Availability

Manuscript has data included as electronic supplementary material

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