Lora in a campus: Outdoor Environment Accurate Modelling Based on Particle Swarm Optimization at 435MHz

Ali S. Kurji ¹, Aseel H. Al-Nakkash ², Osama Abbas Hussein ³

1 Middle Technical University/Computer Technical Engineering, Bagdad, Iraq.
2 Middle Technical University/Computer Technical Engineering, Bagdad, Iraq.
3 Middle Technical University/Computer Technical Engineering, Bagdad, Iraq.
Email: ali.alrubaie@mtu.edu.iq; Assel_Alnakkash@mtu.edu.iq; osama.abbas@mtu.edu.iq.

Abstract. Path Loss (PL) models are an essential factor affecting the network design and its operation. With different environmental conditions, interpreting the PL characteristics in an open environment is a complex problem. In this work, the propagation of LoRa technology in a campus is investigated in order to propose an accurate PL model. The measurements are taken place in two outdoor regions of the Electrical Engineering Technical College in Baghdad, Iraq. Measured field data correlates with global propagation models, demonstrating that ERICSON model results after an evaluation are likely to produce positive results. Different environment conditions make the global PL models difficult to generalize, yield some errors between the measured and estimated PL. For addressing this downside, Particle Swarm Optimization (PSO) has been based to develop the model parameters, hence matching the model to reality. The ERICSON model’s parameters have been improved to the best fit with measured data, and the lowest Root Mean Square Error (RMSE) is gained equals to 3.7168dB and 5.4030dB for the two adopted regions.

Keywords— Path loss, LoRa, Propagation models, PSO, Outdoor Environment.

1. Introduction

Everything that has to be communicated between two points in the universe inevitably has to go through the medium of electromagnetic waves which are affected by environmental phenomena (e.g., reflection, diffraction, and scattering). The design of any communication system depends on the accurate determination of signal propagation. This may be based on the mathematical formula that represents the interaction between signal propagation with these phenomena and referred to as the propagation model or path loss model [1].

Prediction of the signal power loss beside the propagation path significantly affects the network planning phase and later during the network operation phase. Determining the path loss helps the network engineer to determine whether a signal strength or coverage will diminish in a given location, which is an important metric to evaluate the network performance [2]. The variety and complex details of each network environment make the prediction of signal behaviour through its propagation a hard task. The researchers all over the world share their experiences and investigate different methods that overcome this problem. The propagation of electromagnetic waves in the medium is a physical simulation of the signal behaviour through it traveling through that medium [3]. Multiple parameterizations will influence the path loss model, for example, reflection, dispersion, diffraction, and climate. Moreover, height differences between the transmitter and the receiver also have an impact on signal strength. In general,
global existing paradigms that can be used to model signal purification are classified into empirical, statistical, and deterministic models [4]. Deterministic models are the accurate model to find the propagation path losses since it is based on Maxwell’s equations along with reflection and diffraction laws. However, these models are complex and required a high computational process. On the other side, statistical models use probability analyses by finding the probability density function, while the empirical models are mathematical formulas verified from the analyses of field data measurement for different environments. These models are easy to compute with an acceptable error [5]. Accordingly, some deterministic models are adopted to be investigated in this research as in the next section.

Wireless network's coverage efficiency is essentially contingent upon how accurately the adopted PL model materializes the signal propagation in the real environment. In other words, the coverage reliability of a wireless network depends on the accuracy of the adopted propagation model. Hence network engineers seek to find the most fitted existed global models to their real environment at the cost of some acceptable error [6]. Other researchers work on reducing such error by modifying these models, which is usually verified using optimization algorithms. In optimization, the measured data from the field measurement are used to fine-tune the propagation model parameters used in the network design [7]. Below are some researchers works in the literature and related to this work objective.

In [8], five 900 MHz mobile transmitters were used to measure path loss in this study. The measured signal strength data is used to determine the real signal loss due to its propagation. Three commonly prediction models are discussed: Cost-231 Hata, SUI and ECC-33. The Cost-231 Hata model is found to be the most suitable model. Least Squares algorithm is used to improve the predictive accuracy. The initial offset and slope of the Cost-231 model is examined for tuning, and new model parameters are computed. It is evaluated using mean square error, RMSE, standard deviation, and relative error. The estimated error values are computed as well as the predictions. The findings show that the Cost-231 and its tuned version have the least errors comparing to other models.

In [9], a comparison of empirical models (Egli, Hata, SUI and Lee) to the measured PL is conducted. The results show that, COST Hata 231 model outperformed the others. Alternatively, the COST-231 Hata model is developed for estimation PL in the rural and suburban terrain by optimizing its parameters based on reducing the RMSE.

The authors in [10] determine the best fitted propagation model to the adopted environment (Tarak suburban in Indonesia). The measurement result for GSM 900 MHz propagation is compared with different empirical model based on (RMSE) to make a fair decision. COST-231 Hata model is proved to be the most fitted model to the adopted environment. Moreover, the authors optimized the model parameter to reduce RMSE to 6.98 dB.

For a 5G mobile network, the researchers evaluate several propagation models in terms of PL. The evaluation is based on comparing the simulation results of these models with the measured data. It is concluded that Ericsson produced the least difference results [11].

In [12], empirical PL models were tested in the rural and suburban environment of Batna in Indonesian with measured data obtained through the derive test results for mobile communication network. RMSE criterion was used to compare various empirical path loss models. The conclusion states that a COST-231 Hata is more closely approximates the data. Furthermore, COST 231 model parameters were found to more match the measured environment by tuning them through three algorithms which provides optimal values for modelling the adopted environment PL while yielding the lowest (RMSE).

In [13], test models for calculating the PL in suburban and urban areas were evaluated. The model chosen was analyzed to evaluate the performance of the current 2G and 3G mobile networks operating in Baghdad, Iraq. A drive and walk test was used to collect field measurement data. The comparison
results of the simulated and calculated data demonstrate that Cost231-Hata model is the most appropriate propagation model for the 2G and 3G networks case study.

The objective of this paper is to develop a more precise mathematical model for the new technology “LoRa” signal propagation in the adopted environment located at Electrical Engineering Technical College in Baghdad, Iraq. This is a continuation of an integrated project that aims to build a network with LoRa technology for Internet of things applications. Modelling the propagation of LoRa signal in the campus environment is considered as the platform for design and implementing IoT applications. Two contributions are introduced in this work: first; find the best fitted PL model with the adopted case study environment. In this context, four global and most widely used mathematical propagation models were examined, Ericsson, Egli, Okumura Model, and Cost 231Hata Model. Based on the comparisons results between the measured data versus predicted data from simulation, the RMSE is determined and hence the most suitable model is recognized. Secondly, employing a particle swarm optimization algorithm (PSO) algorithm to develop more realistic signal propagation model for future effective applications.

The rest of the paper can be organized as follows: Outdoor propagation models are covered in Section 2, and the PSO algorithm is presented in Section 3. Configuration of an empirical test are discussed in section 4, while conclusion points are illustrated in section 5.

2. Global Deterministic PL Models

2.1. COST-231 Hata Model

"COST 231 was an extension of the Hata model" The European Co-operative for Science and Technology (COST)" that was expanded to be applied in the frequency range 150 MHz to 1500 MHz, and for a distance in the range of 20 km. It is based on four variables to predict the radio propagation loss: frequency, transmitter and receiver antenna height, and distance. Cost model can be used to obtain the PL in three different terrains: urban, suburban, and agricultural [14]. PL in an urban area is calculated using the following equations:

\[ PL_{db} = 33.46 + 33.9(f) - 13.82 \log(hb) - a(hm) + [44.9 - 6.55 \log(hb)] \log(d) \]  
\[ a(hm) = [1.11 \log(f) - 0.7]hm - [1.56 \log(f) - 0.8] \]  

Where, \( g(f) \) is defined by [16]:

\[ g(f) = 44.49 \log(10(f)) - 4.78(\log(10(f)))^2 \]  

where:

- \( f \): Frequency in MHz, \( hb \): height of transmitting antenna in meter, \( hr \): height of the receiver antenna in meter.

2.2. Ericsson Model

The network design engineers used a program developed by the Ericsson company called the Ericsson model to estimate the PL, the path loss is given by the following equations [15].

\[ PL = a0 + a1 \log(10(d)) + a2 \log(10(hb)) + a3 \log(10(hb)) \log(10(d)) - 3.2(\log(10(11.75hr)^2)) + g(f) \]  

Where, \( g(f) \) is defined by [16]:

\[ g(f) = 44.49 \log(10(f)) - 4.78(\log(10(f)))^2 \]  

...
2.3. Egli Model
Egli is an empirical model, where PL can be calculated according to the following [17]:
\[
PL = 20 \log(f_c) + 40 \log(d) - 20 \log(h_{te}) + \begin{cases} 
76.3 - 10 \log(h_{re}) & h_{re} \leq 10m \\
85.9 - 20 \log(h_{re}) & h_{re} > 10m 
\end{cases}
\]
(7)

\(h_{te}\) = height of antenna for base station (m), \(h_{re}\) = height of antenna for mobile station (m), 
d= distance from the base station antenna in (km), \(f_c\) = Transmit frequency in (MHz).

2.4. Okumura Model
The Okumura model was designed on the analyses of collecting field data in Tokoy. It is considered as an excellent urban modelling paradigm that is used in dense buildings areas, like Tokyo. While resolving the urban issues, the city is classified as big cities and medium-sized cities. Okumura provides correction factors taking into account more sub-urban and rural environments. Moreover, Okumura model predict path loss in the range of 3 GHz. The path loss equation is [18]:
\[
PL(dB) = L_f + A_{mn}(f, d) - G(h_{te}) - G(h_{re}) - G_{AREA}
\]
(8)

Where,
\(PL\): Central tendency path loss [dB]
\(L_f\): Free space path loss [dB]
\(A_{mn}(f, d)\): Median attenuation relative to free space [dB]
\(G(h_{te})\): Base station antenna height gain factor [dB]
\(G(h_{re})\): Mobile station antenna height gain factor [dB]
\(G_{AREA}\): Gain due to type of environment [dB]
\(f\): Frequency [MHz]
d: transmitter and receiver separation [Km].

3. Particle Swarm Optimization (PSO) algorithm
Kennedy and Eberhart proposed (PSO) in 1995 as a population-based algorithm for solving global optimization problems. By leveraging the collective experience of unsophisticated people, PSO has the potential to identify optimal global points. In the quest space, the PSO algorithm employs a particle population and determine the position of any particle using its location \((x_i)\) and velocity \((v_i)\) [19]:
\[
\rightarrow x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id}), \rightarrow v_i = (v_{i1}, v_{i2}, v_{i3}, \ldots, v_{id})
\]

To determine the optimal solution, any particle modifies its search path according to two parameters: 
\(x_d\) = optimal possible place for a given particle.
\(x_g\) = the best position (global pest) of the entire swarm.
PSO looks for the optimum solution by changing the velocity and location of each particle iteratively according to the following equations:
\[
\begin{align*}
    x_i(t + 1) &= x_i(t) + v_i(t + 1) \\
    v_i(t + 1) &= w \cdot v_i(t) + c_1 p_1 (x_i(t) - x_i(t)) + c_2 p_2 (x_g(t) - x_i(t))
\end{align*}
\]
(9) (10)

Where:
\(t\) = denotes the iteration in the evolutionary space, \(w\) = is the weight of the inertia, \(c_1\) and \(c_2\) = are constants of scaling, \(p_1\) & \(p_2\) random vectors are distributed between \([0, 1]\)

4. Configuration of an Empirical Test
The objective of this work is to predict LoRa signal propagation materialized by measuring signal strength in an outdoor campus environment. The walking tests are conducted in two regions, A and B,
of Electrical Engineering Technical College in Baghdad, Iraq as shown in ‘figure 1’. The distance is 60 meters between the transmitter and the receiver, where 50 samples of Received Signal Strength Indicator (RSSI) are collected for each two meters. LoRa set up parameters for both transmitter and receiver are illustrated in table 2.

Table 2. Measurement setup parameters.

| NO | Name of label                  | Value |
|----|--------------------------------|-------|
| 1  | Frequency (MHz)                | 435   |
| 2  | Channel Bandwidth (KHz)        | 500   |
| 3  | Transmission of power (dBm)    | 5     |
| 4  | Transmit For the antenna gain (dBi) | 5     |
| 5  | Receive For the antenna gain (dBi) | 5     |
| 6  | Tx height of antenna (m)       | 1.5   |
| 7  | Rx height of antenna (m)       | 1.5   |
To determine the most fitted empirical propagation model, a comparison is computed between global models with the measured field data based on RMSE as calculated by equation (11).

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_{i}(predicted) - P_{i}(measured))^2}
\] (11)

Where:

- \(n\) = total number of measured PL value in meters,
- \(P_{i}(predicted)\) = the predicted PL value per meter,
- \(P_{i}(measured)\) = the measured PL value per meter.

4.1 Results and Discussion

The results of the abovementioned two steps are presented and discussed in the next sections

4.1.1 Step one: Determine the appropriate Prediction Models

In this step, four global propagation models discussed in section 2 have been simulated and compared with the measured field data from the case study. ERICSON model shows better in urban environment performance after evaluating the results. The relation between the expected PL and the measured PL for both regions A, B are presented in ‘figure 2-3’.

![Figure 2](image)

**Figure 2.** Comparison of the measured and calculated path loss for region A.
Table 3 reveals that the ERICSON model gains the lowest RMSE compared to others for both regions (A, B). Also, it can be noticed that the minimum RMSE is achieved in region (B) equals to 19.78489182dB, and for regain (A) equals to 21.16805776dB.

| Prediction Models         | RMSE for area (A) | RMSE for area (B) |
|---------------------------|-------------------|-------------------|
| Ericsson Model            | 21.16805776       | 19.78489182       |
| Egli Model                | 32.73482308       | 28.71975295       |
| COST-231 Hata Model       | 22.50026163       | 25.32690829       |
| Okumura-Hata Model        | 96.52118971       | 101.2507922       |

**4.1.2 Step two: Optimizing ERICSON Model**

Because the environmental details differ essentially, it is not possible to generalize the PL formula and prediction models for all regions. This downside can be overcome by adjusting the model parameters to approach the real adopted environment more precisely. Hence, in this step PSO algorithm is based to tune Ericson model in order to reduce the RMSE with the measured PL. The comparison results between measured PL and estimated PL obtained by the optimized ERICSON model are seen in ‘figure 4-5’. The optimized parameters are illustrated in the table (4-5) for region A and B, respectively.
Figure 4. Comparison of path losses between ERICSON and optimized ERICSON for region A

Table 4. Results of optimal values for modified ERICSON parameters in region A

| Parameters | Optimizing Ericson | Generally Ericson |
|------------|--------------------|-------------------|
| A0         | 48.9709            | 36.2              |
| A1         | 28.4465            | 30.2              |
| A2         | 19.484             | 12.0              |
| RMSE       | 3.7168             | 21.16805776       |

Figure 5. Comparison of path losses between ERICSON and optimized ERICSON for region B.

Table 5. Results of optimal values for modified ERICSON parameters in region B

| Parameters | Optimizing Ericson | Generally Ericson |
|------------|--------------------|-------------------|
| A0         | 67.0949            | 36.2              |
It can be noticed that RMSE is reduced by 85% and 73% from its initial value obtained in step one for region A and B respectively based on optimized Ericson model.

5. CONCLUSION
The objective of this work is to evaluate LoRa signal behavior through its propagation in a real campus environment case study. Prediction of LoRa signal PL resultant from this work will be based for further IoT application implementation. Accordingly, four global deterministic PL models are adopted and compared with the field data measured by walk test in two regions (A and B) in the Electrical Engineering Technical College in Baghdad, Iraq. Since PL models differ in their applicability over different environmental and terrain conditions, RMSE is based to assess the most appropriated model for the real case study. It is found that the ERICSON model give the best performance after evaluating the results, with RMSE of 21.16805776dB and 19.78489182dB for two regions (A and B), respectively. In order to gain better result and more accurate modeling, ERICSON model is being modified using PSO algorithm for tuning the adopted model parameters. The optimized model obtains a better PL prediction which reduces RMSE to 3.7168dB and 5.4030dB for A and B regions, respectively.

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