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Modelling and Optimization of Wireless Signal Propagation Path-loss in the Forcados-Ogulagha Maritime Environment of Delta State, Nigeria

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ABSTRACT
The deployment of Long-Term Evolution (LTE) networks in marine environments involves unique challenges owing to the influence of environmental conditions on signal propagation. LTE networks are meant to provide high-speed internet and communication services, which rely largely on precise pathloss modelling. This study model and optimize wireless signal propagation path-loss in the Forcados-Ogulagha maritime environment. A total of eighty base transmission stations were surveyed to measure the signal strength and four maritime locations were selected to represent a typical mixed-path environment.The traditional model was optimized using Decision Tree-Particle Swarm (DT-PSO), Particle Swarm Optimization (PSO), and Random Forest-Particle Swarm (RF-PSO) methods. The results show that certain features, such as measurement distance and temperature, play a crucial role in determining path loss, providing valuable guidance for refining path loss prediction models and optimizing the performance of wireless communication systems. The research further revealed that conventional path loss models showed significant discrepancies compared to actual measurements due to the impact of terrain and topography variations on the model's ability to capture nonlinear and non-stationary path loss factors.

Keywords:
Signal Propagation,
Signal Path-loss,
Wireless Network,
Maritime Environment,
Network deployment.

INTRODUCTION

The loss of power experienced by an electromagnetic wave as it moves from a transmitter to a receiver is known as signal path loss. This reduction is dependent on the transmitted power and is commonly expressed in decibels (dB). Path loss can be caused by a number of variables, including the distance between the transmitter and receiver, the transmission frequency, and the surrounding environment (Faruk et al., 2021). Also, path loss is caused by the interaction of multiple waves that have taken various paths; the different phases of these waves combine, with some waves amplifying the signal while others weaken it. The signal strength at the receiver will depend on the relative strength of the useful signal compared to the strength of the unwanted signals and interference. This network phenomenon occurs when a transmitted signal at a frequency band gets to the receiver after being reflected, refracted, scattered, or diffracted from structures or objects along transmission paths (Xuefei Ji et al., 2020; Igbekele et al., 2020; Zhimwang et al., 2021).

In maritime environments, the sea surface acts as a significant reflective surface, impacting signal propagation and leading to phenomena such as multipath fading and increased pathloss (Parsons, 2000). The variability in sea state can cause fluctuations in signal strength, further complicating pathloss modelling. Additionally, atmospheric conditions such as humidity and temperature gradients can affect signal attenuation and propagation characteristics (Ikeda et al., 2006; Igbekele et al., 2019). Understanding these factors is crucial for optimizing network performance and ensuring reliable communication services (Zhimwang et al., 2023). This study focuses on the Forcados-Ogulagha region, a maritime area in the Niger Delta, known for its complex environmental conditions that significantly influence LTE pathloss (Ogherohwo et al., 2017; Zhimwang et al., 2022).

Previous research has demonstrated that traditional pathloss models, such as the Hata model, may not accurately capture the conditions in maritime settings (Zhimwang et al., 2018; Anaka et al., 2021). These models originally developed for urban and suburban environments, often fall short in accounting for the unique characteristics of maritime environments. Recent advancements in pathloss modelling, including modifications to existing models and the development of new empirical models tailored for maritime environments, are essential for improving prediction accuracy (Wang et al., 2009; Liu et al., 2015; Ogherohwo et al., 2018).
The goal of this study is to develop and validate an optimised path-loss model specifically for the Forcados-Ogulagha maritime environment. By leveraging both empirical data and advanced modelling techniques. Also, the study aims to enhance the accuracy of pathloss predictions and improve LTE network performance in challenging maritime conditions and contribute valuable insights into the optimisation of LTE networks in similar environments, potentially guiding future research and deployment strategies in maritime contexts.
This study is necessary because wireless communication is becoming ever more essential, yet it can be difficult to get dependable connectivity in maritime locations like Forcados-Ogulagha. While signal propagation pathloss in a variety of settings has been the subject of numerous studies, little research has been done expressly on Nigeria's marine environment, especially when it comes to LTE network. This study will enhance a deeper understanding of the complex challenges posed by the heterogeneous nature of this environment and, at the same time, offer potential solutions for telecommunications and other relevant industries in this region. By providing insights into signal propagation pathloss using LTE technology in the Forcados Ogulagha maritime environment and gaining a greater understanding of the relationship between the environmental factors and the propagated signal, Telecom service providers, government agencies (NCC), and maritime industry stakeholders can benefit from the findings to optimize network planning, enhance system design, and improve the overall communication infrastructure in the region.

MATERIALS AND METHODS

Experimental Site and Data Collection

This research was conducted in the Forcados-Ogulagha River and Escravos waters in Delta State, Nigeria. A total of eighty base transmission stations were surveyed to measure the signal strength. Four maritime locations were selected to represent a typical mixed-path environment for the research. These locations are designated as location 1 (Warri-Burutu River), location 2 (Forcados-Ogulagha River), location 3 (Yokri-Ogidigbe River), and location 4 (Escravos-Okerenkoko River). The environments were characterized by linear settlements, freshwater, saltwater, shipyards, islands, and dense mangrove forests.

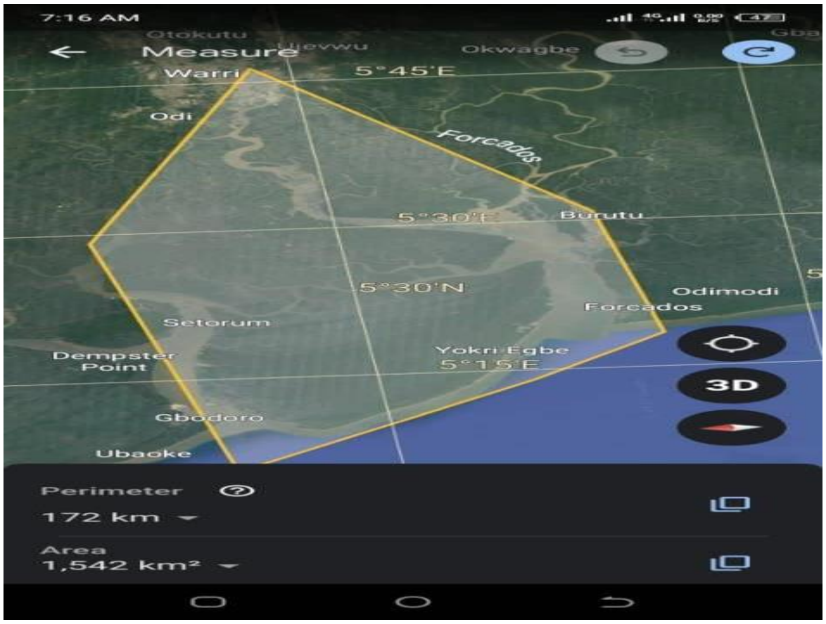

Figure 1: Map of F-O surveyed area

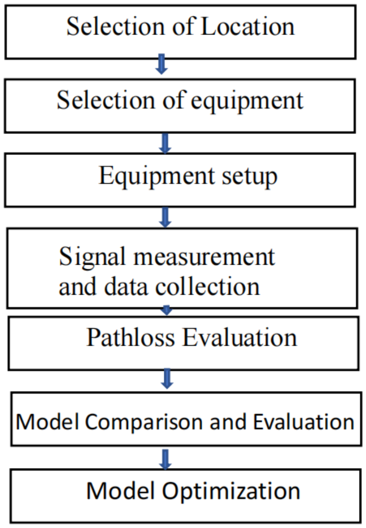

Figure 2: Block Diagram of the Experimental Design

From the measured RSRP, signal loss values were calculated using (Rappaport, 2002; Seybold, 2005):

$$PL(dB) = EIRP(dBm) - RSRP(dBm) \quad (1)$$

where EIRP is the effective isotropic radiated power expressed in the equation below;

$$\text{EIRP} = P_t + G_r + G_t - L_t - L_r \quad (2)$$

where G_r and G_t are the receiver and transmitter antenna gains, L_t and L_r are transmitter and receiver cable losses in dB and P_t is transmitter power. Then equation (1) is expressed as :

$$\text{PL(dB)} = \text{Pt} + \text{Gr} + \text{Gt} - \text{Lt} - \text{Lr(dBm)} - \text{RSRP(dBm)} \quad (3)$$

Optimization of the Preferred Traditional Pathloss Model

The model was optimized using Decision Tree-Particle Swarm (DT-PSO), Particle Swarm Optimization (PSO), and Random Forest-Particle Swarm (RF-PSO) methods. The approach incorporates PSO to enhance the predictions or parameters of the COST231 model. The steps below describe the optimization process for DT-PSO, RF-PSO, and PSO. Each of these steps uses PSO to fine-tune the model's parameters, thereby optimizing the performance of the COST231 model through machine learning, and a MATLAB code was written to represent and generate the results of each step.

RESULTS AND DISCUSSION

To evaluate the accuracy of the predicted results, the performance of the optimized model, PS, and RF-PS for wet and clear air was assessed.

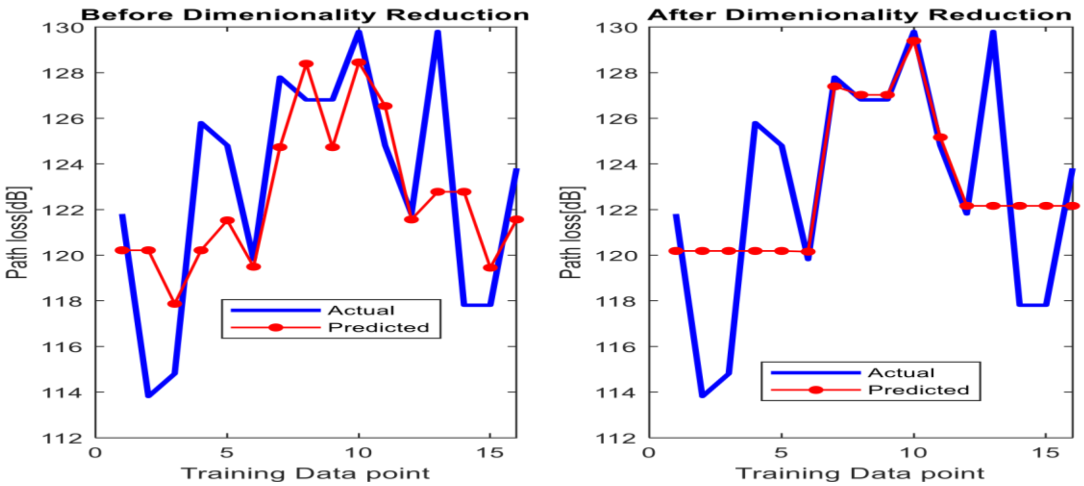

Figure 3: Precision fitting result proposed method with and without path loss dimensioning using collected Clear Air path loss data sample.

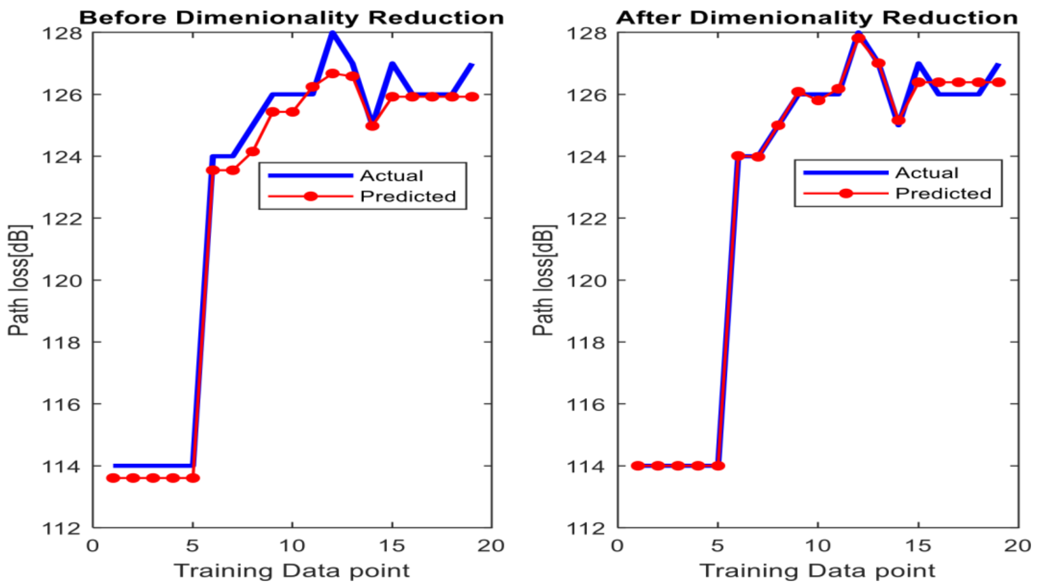

Figure 4: Precision fitting result proposed method with and without path loss dimensioning using collected Wet Air path loss data sample.

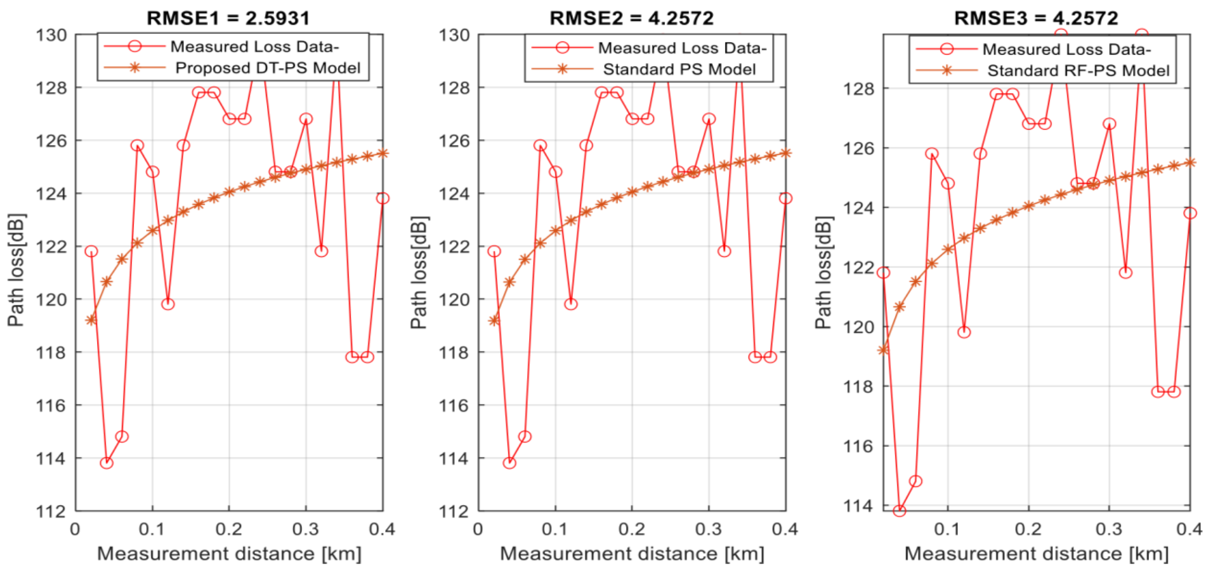

Figure 5: RMSE Path loss prediction fit attained by proposed hybrid DT-PS model compared to standard approaches in location 1 (Morning)

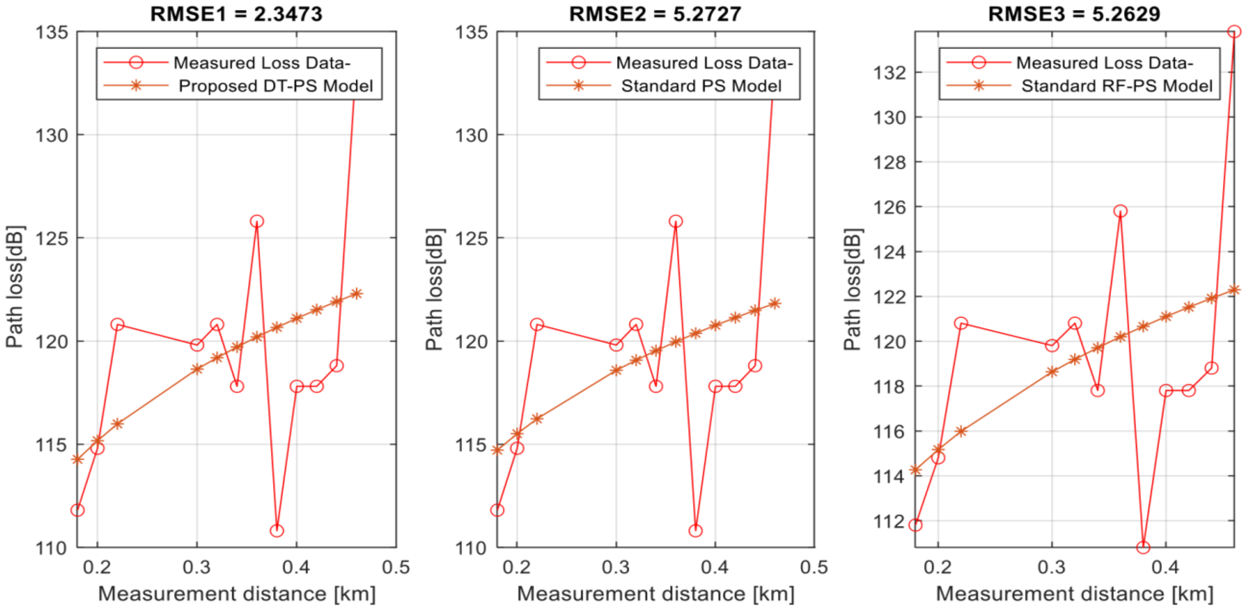

Figure 6: RMSE Path loss prediction fit attained by proposed hybrid DT-PS model compared to standard approaches in location 1 (Afternoon)

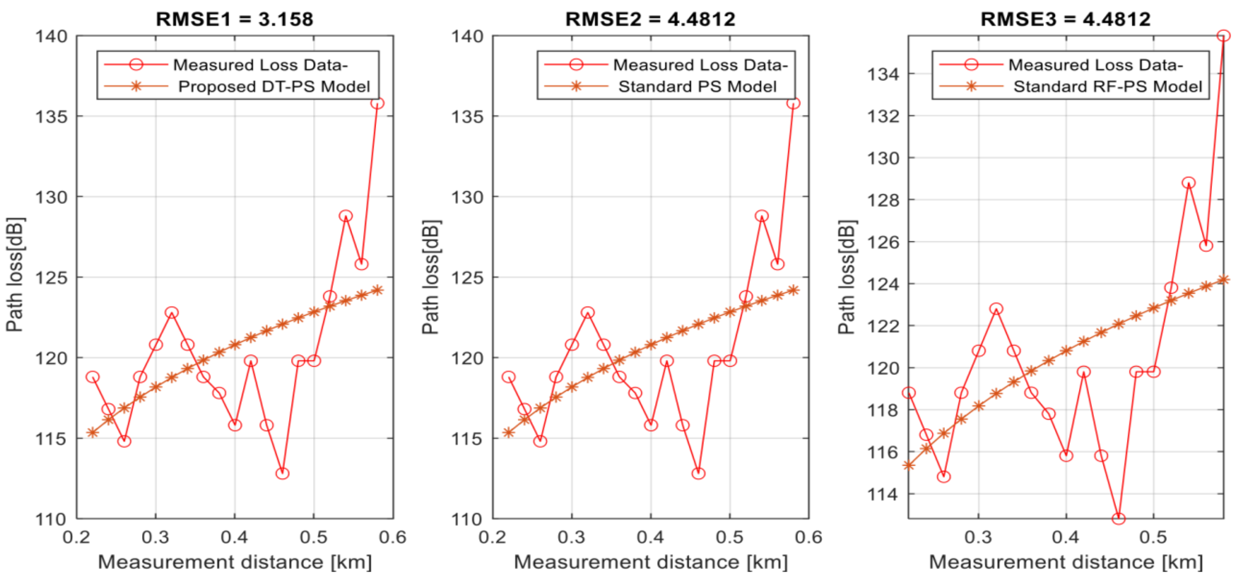

Figure 7: RMSE Path loss prediction fit attained by proposed hybrid DT-PSmodel compared to standard approaches in location 1 (Evening)

The following section examines how using the DT ensemble dimensionality reduction technique along with least square boosting can enhance the efficiency and accuracy of predicted signal path loss data. In Figure 3 and Figure 4, the left side shows the curve without path loss dimensioning, while the right side shows the curves with dimensioning for training and testing based on collected Clear Air and wet season path loss data samples. The graph on the left-hand side shows that the precision fitting results improved when path loss dimensioning was incorporated. It is clear that there is a strong fit between the predicted curve and the measured curve across the training points following the dimensionality reduction and the model's LS-boosting for both seasons. This indicates improved generalization and reduced over fitting of the DT ensemble. However, before dimensionality reduction, the results from the graph for both clear air and wet seasons displayed more variability and noise due to higher complexity. This improvement indicated that the proposed method with path loss dimensioning outperforms the proposed method without path loss dimensioning. This indicated that path loss dimensioning has a significant impact on the accuracy and reliability of the results obtained from the proposed method.

Figures 5 to 7 show the path loss graph against measured distance for the proposed hybrid DT-PS model, PS, and RF-PS model under Clear Air conditions in four different locations at various times of the day. This reveal that the measurement distance and temperature exhibited high relevance, scoring 0.75 and 0.61 for clear air data, and 0.45 and 0.14 for wet air data sets, respectively. It is evident from a closer examination that measurement distance emerged as the most relevant feature, scoring 0.75 and 0.45, followed by temperature with scores of 0.61 and 0.14, respectively. On the other hand, features such as wind, pressure, and humidity were deemed irrelevant. These findings provide valuable guidance for refining path loss prediction models and optimizing the performance of wireless communication systems.

CONCLUSION

The study developed a Regression Decision Tree model to identify and prioritize the most influential factors impacting signal propagation in the study area. This model yielded minimal MSE, signifying the model's optimal generalization capability. The results show that certain features, such as measurement distance and temperature, play a crucial role in determining path loss, providing valuable guidance for refining path loss prediction models and optimizing the performance of wireless communication systems. The research further revealed that conventional path loss models showed significant discrepancies compared to actual measurements, likely due to the impact of terrain and topography variations on the model's ability to capture nonlinear and non-stationary path loss factors. These disparities underscore the necessity for enhanced modeling methods that consider terrain and topographical differences, thus improving the accuracy of path loss prediction in the Forcados-Ogulagha environment.

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