IMPROVING THE PERFORMANCE OF CELLULAR SYSTEM USING OPTIMAL SMALL CELLS DEPLOYMENT TECHNIQUE

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ABSTRACT

Deciding on the most suitable location for cell deployment continues to pose significant challenges for network administrators. Despite the operation of numerous cell sites, customers often experience poor quality of service. A major contributing factor is the inadequate consideration of critical parameters such as population density, terrain characteristics, and interference patterns during the deployment process. This study developed a new cell deployment model using network information collected from areas with diverse terrain characteristics. The data was analyzed and used to train a linear regression model for predicting network performance metrics. The prediction outputs served as the foundation for a smart, decision-based framework for cell deployment. This framework was implemented as a desktop application capable of real-time network testing and cell deployment. The model was developed using MATLAB's regression learner application and integrated with JavaScript programming for seamless functionality.

Keywords: Cell Deployment; Machine Learning; Linear Regression, Pathloss, Data collection, Matlab, quality of service.

1. INTRODUCTION

The main reason behind the invention of mobile phones was to facilitate systematic voice communication in the early 70s. Currently, mobile devices and applications have grown so much that virtually all human activities depend on them. This growth of mobile applications and users has been fuelled by the rapid expansion of supporting technology, which has transformed from the First Generation (1G) to the present-day 5G (Seiamak et al., 2015).

Over the years, network operators have proposed various administrative solutions to improve the quality of service and traffic management for the increased number of subscribers. One such solution identified by Chataut and Aki (2020) was to improve network densification and spectrum capacity to accommodate more carriers simultaneously and increase the number of antennas in a cell. However, Abonyi and Jonathan (2018) argue that the high cost of spectrum and limited number of antennas per cell make this solution inefficient.

Recently, small cell (pico, femto, and micro) deployment has gained research attention due to its advantages over traditional larger cells (macro), such as lower cost, smaller space requirements for installation, and indoor installation feasibility. These small cells are installed to support macro cells and form a heterogeneous cellular network structure, with the potential to address problems arising from increased user traffic in conventional 4G networks. According to Su et al. (2014), cell deployment is a process of planning and implementation of distribution cells so as to provide network coverage and capacity for communication purposes. The strategy or this process of cell deployment can be classified into random deployment and deterministic deployment strategies (Su et al., 2014). Random deployment involves deploying small cell locations randomly within an area, while deterministic deployment positions cells based on predetermined factors (Abonyi and Jonathan, 2016). Both strategies have their advantages and disadvantages, but the use of deterministic strategy provides a better solution to mobile network problems compared to its counterpart. Furthermore, Abonyi and Jonathan (2018), posited that distributed strategies for cell deployment can be categorized into uniformly distributed, cell edge, and user-aware strategies. However, researchers have found that using the user-aware strategy for cell deployment, which considers key network and environmental information to determine the cell deployment location, outperforms the other strategies. However, a limitation of this approach is the inability to localize the best position for cell deployment. Therefore, there is a need for an optimal cell deployment strategy that can determine the best position for smart cell deployment.

Studies have revealed that deploying cells in optimal positions can address issues in mobile heterogeneous networks, such as overload, interference, congestion, poor coverage, and signal strength. In addition, these studies provided various notable solution for cell deployment, however, the complexity of cell deployment problem makes it difficult for one solution in a given environment to be applicable for all environment. Abonyi (2019) develop a novel clustered based two element antenna strategy which considered signal strength information, user clusters, and range information for cell planning and deployment and when validated experimentally considering 30 users, reported 100% accuracy in detecting position for cell deployment over 6Km;

however despite the huge success recorded in the paper, the model may not be applicable to most African environments like Nigeria characterized with terrain such as mountains, valley and hills, as these actor were not mentioned in the work.

This research proposes to develop an optimal cell deployment model considering artificial intelligence techniques and then smart decision-based strategy. The intention is to accurately predict the network information of Milliken Hills, Enugu, Nigeria, considering the complex environmental characteristics. The predicted information will serve as input for a decision-based system, which will assess key parameters such as signal strength, quality, coverage area, and interference to determine the suitability of the area for cell deployment and provide recommendations. Experimental validation and testing in a complex environment will be conducted to ensure the reliability and credibility of the results. The aim of this research is improving the performance of a cellular system using optimal small cells deployment technique. The set out objectives are to;

i. Create a strategic prediction framework for network planning by leveraging machine learning algorithm.
ii. Design an integrated strategic framework for Network Planning and cell deployment (ISPD) that combines the prediction model and decision based framework.
iii. Conduct extensive performance evaluations of the system and validate the results

2. METHODOLOGY

The method used are the exploratory, experimental and simulation. This encompasses several key steps aimed at improving the performance of a cellular system through optimal small cell deployment. An exploratory phase involves conducting a comprehensive literature review to gather relevant knowledge on small cell deployment techniques, performance evaluation methodologies, and cellular system optimization approaches. Following this, an experimental phase involves conducting a site survey test to collect data on various site characteristics that can influence the deployment of small cells, such as population density, terrain, building structures, and existing macro-cellular infrastructure. The selection of Milliken Hills in Coal Camp, Enugu State, Nigeria as the research site underscores the pressing need for cell deployment in the area. Situated amidst hills and mountains, this community faces persistent challenges in providing reliable communication services to its subscribers. The existing geographical features obstruct signal propagation, resulting in subpar network coverage and unreliable connectivity. Based on the gathered data an optimal cell deployment strategy was developed using machine learning and rule-based optimization algorithm, tailored specifically to the requirements of the cellular system under study considering 3GPP LTE (3rd Generation Partnership Project Long-Term Evolution) design standards. Extensive performance evaluations were conducted to assess the impact of the cell deployment technique on the cellular system, encompassing measurements of signal strength, coverage area, data transfer rates, call quality, and overall network capacity. Finally, the results obtained from the deployment were validated and the effectiveness of the optimal small cell deployment technique was evaluated, providing insights into the regions where new cell are required for deployment.

3. Development of a Strategic Prediction Framework for Network Planning Using Machine Learning

The method developed in this work for optimal cell deployment is the machine learning technique. This was adopted out of the other numerous artificial intelligence techniques and traditional approach due to the complexity of the requirements for cell planning and deployment. These complexities were due to the numerous environmental factors within the Milliken Hills such as terrain, hills, vegetation, population density, traffic patterns, and interference levels, so as to effectively predict cell coverage performance. To develop the model for optimal cell deployment, several steps were utilized which are data collection, selection of the machine learning algorithm, training, testing, evaluation, generation of the prediction model for network planning.

3.1 Data collection

Data of network coverage and topological information for Milliken Hills, Coal Camp, Enugu was collected from Airtel Nigeria, specifically tailored to the Airtel cell with serial number 401699. The dataset was generated from a 15days, 40km per 1minute interval drive test conducted on 3rd August, 2021, after the installation of the cell. The instrument used for the data collection is BladeRFxA9 spectrum analyser powered by an external USB3 hub. The calculation for the number of cell to be deployed in the area is determined based on factors such as population density, traffic demand, network capacity requirements, and coverage area. In network dimensioning, capacity sharing is considered, where multiple cells share the available network resources and overall is defined as;

$$Number\ of\ Cells\ Required\ = \left(\frac{Total\ Area}{Coverage\ Area}\right) * \mu \qquad 1.0$$

Where μ is capacity sharing factor and given as 0.7.

The algorithm

1. Initialization:
2. Set parameters of dependent variables (Y): RSRP (< -90 dBm), RSQ (< -10 dB), coverage (1 km²), and interference level (> -100 dBm).
3. Initialize LR (Logistic Regression) cell deployment model.

4. If Output of LR = true:
5. Identify all Y variables and read corresponding values.
6. Check X factors:
7. For each CPD over the target area:
8. Check Population Density (CPD) using Equation 3.4.
9. Check Network Capacity (NCC) of the micro cell using Equation 3.5.
10. Calculate the number of micro cells (NC) needed using Equation 3.7.
11. Assess the suitability of deploying cells based on the coverage area required to meet the capacity demands using cells.
12. Analyze the predicted quality of service metrics (such as RSRP, RSQ, and interference level) obtained from the LR model for the target area.
13. If RSRP < -90 dBm and RSQ < -10 dB and interference level > -100 dBm and coverage area $1km^2$:
14. MsgBox ("Flag the area as potentially suitable for cell deployment.")
15. Compute NC with Equation 3.7 to determine the recommended needed number of cells
16. Else if RSRP < -90 dBm and interference level > -100 dBm:
17. MsgBox ("Flag the area as potentially suitable for cell deployment.")
18. Compute NC with Equation 3.7 to determine the recommended needed number of cells
19. Else if RSQ < -10 dB and interference level > -100 dBm:
20. MsgBox ("Flag the area as potentially suitable for cell deployment.")
21. Compute NC with Equation 3.7 to determine the recommended needed number of cells.
22. Else
23. MsgBox ("Flag the area as good network reception and hence not suitable for cell deployment.")
24. End the algorithm.

The algorithm for cell deployment aims to identify suitable areas for micro cell deployment based on certain conditions and criteria. The initialization phase sets the parameters for dependent variables, such as RSRP (Received Signal Reference Power) being above -90dBm, RSQ (Received Signal Quality) being below -10dB, coverage area of $1km^2$, and interference level above 100dBm. The algorithm then initializes a Logistic Regression (LR) cell deployment model.

If the output of the LR model is true, the algorithm proceeds to identify all variables and read their corresponding values. It then checks various factors, denoted as X. For each calculated population density (CPD) over the target area, the algorithm assesses the suitability of deploying micro cells. This assessment is based on the coverage area required to meet the capacity demands using micro cells and an analysis of predicted quality of service metrics obtained from the LR model. If the conditions are met (RSRP < -90dBm, RSQ < -10dB, interference level > -100dBm, and coverage area), the algorithm flags the area as potentially suitable for micro cell deployment. Similarly, if RSRP is below -90dBm and the interference level is above -100dBm, the area is flagged as potentially suitable. Alternatively, if RSQ is below -10dB and the interference level is above -100dBm, the algorithm computes the recommended number of micro cells needed using Equation 3.7. The figure 3.5 presents the flow chart of the strategic algorithm for cell deployment.

Table 1: Parameters and standards for network information analysis

Parameter	**Description**	**Ideal Value**
Signal Strength (RSRP)	Power level of the received signal from an LTE cell	-70 dBm to -90dBm
Signal Quality (RSRQ)	Quality of the received signal from an LTE cell	-10 dB to -20dB
Coverage	Extent of network coverage area	Maximum coverage possible
Interference Level	Level of interference experienced in the network	-90dBm to -95dBm
Coverage size	The required micro cell coverage	$1km^2$

3.2 The integrated strategic framework for Network Planning and cell deployment (ISPD)

The strategic framework for network planning and cell deployment presents the system integration of the trained LR model and the decision based algorithm for cell deployment at Milliken Hills. The flow chart showed how the test data which contain geographical information of an area considered for the cell deployment, when loaded to the trained LR cell deployment model it was used to predict the quality of service information of the area such as signal strength, signal quality and level of interference. This output is analyzed considering the 3GPP standard in table 3.3 and the algorithm (2) to make a decision if the area is fit for cell deployment or not. The flow chart in figure 3.6 presents the system workflow. Overall the data of the network information collected from the area for consideration are imported to the LR based prediction model which used the dependent variables to predict the independent variables as model in equation 3.3. This was used to predict the network planning information requirements, providing data for RSRP, RSQ, interference and transmitting power. These informations service as input to the decision based model developed considering network capacity, coverage area information, population density of the area and then 3GPP standard for RSRP, RSQ, interference for LTE to then make a decision if the area is suitable for cell deployment or not.

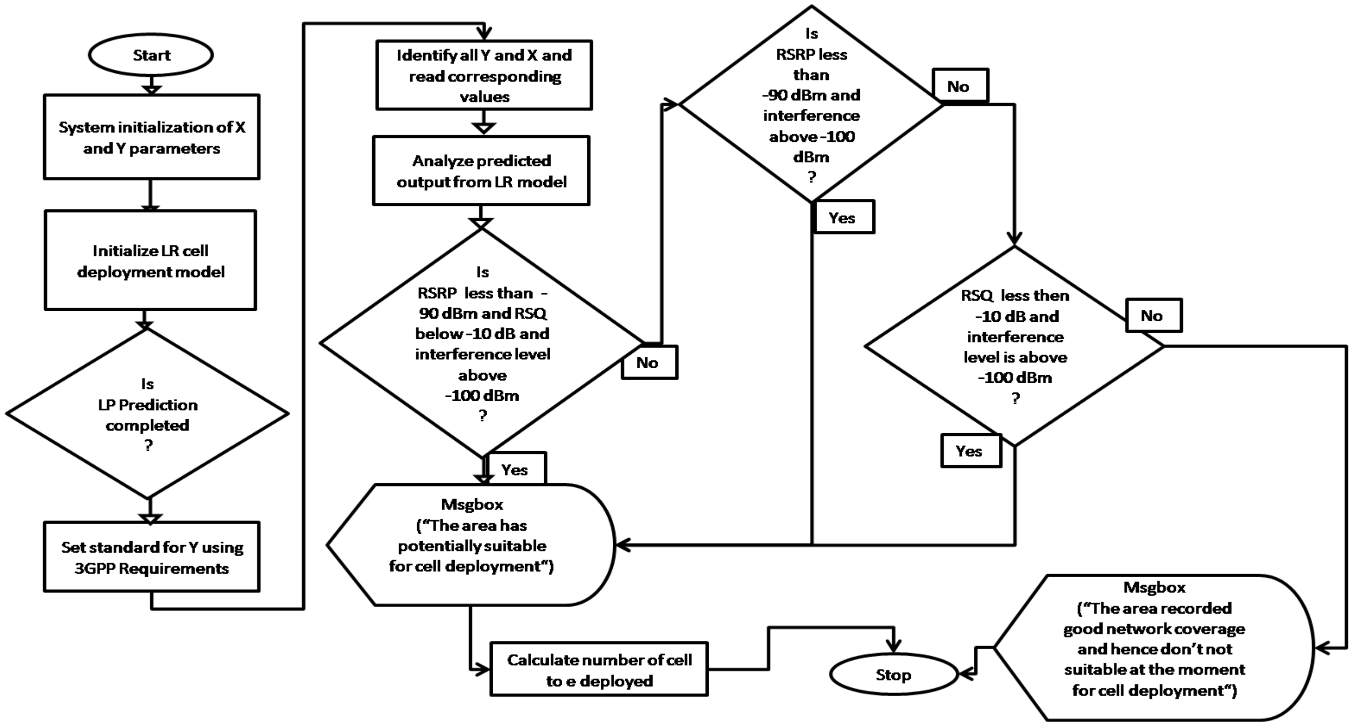

Figure 1: Flowchart of DFPD

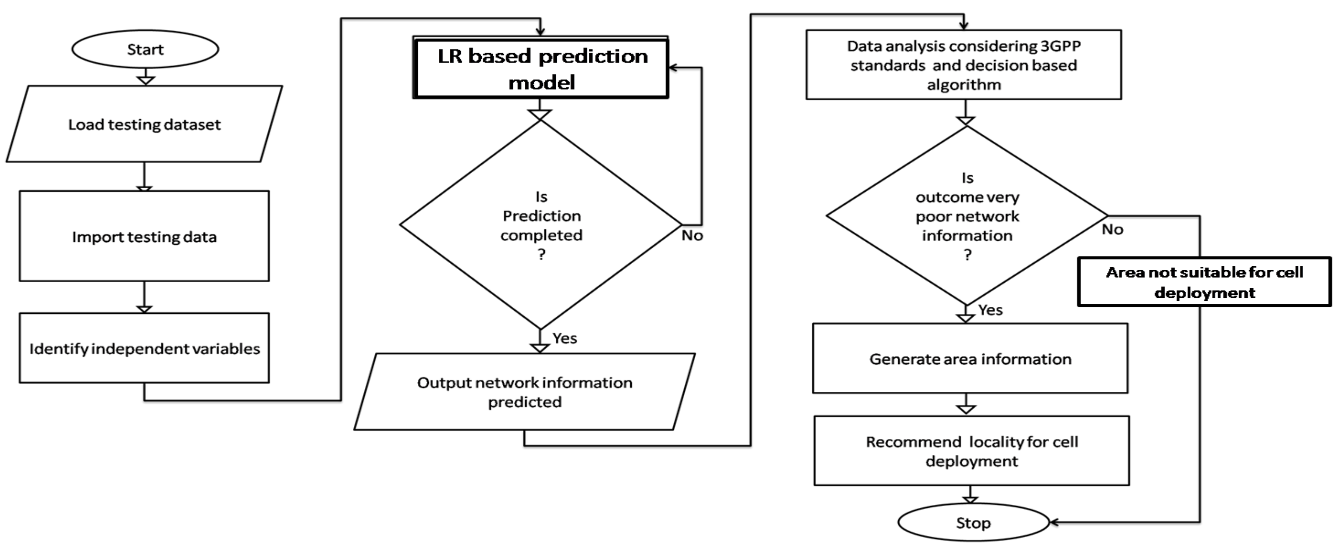

Figure 2: Flow chart of the ISPD

3.3 Implementation of the ISPD

The models and algorithms developed were implemented using Regression App within MATLAB. The process involved a series of steps aimed at ensuring accurate prediction and evaluation of cell deployment suitability.

Initially, data collection was undertaken, focusing on gathering test data that contained pertinent geographical information for the target area. This encompassed factors like terrain characteristics, population density, and other variables impacting cell coverage. The collected data underwent pre-processing techniques to cleanse, normalize, and transform it into a suitable format for subsequent analysis. Next, the pre-trained linear regression (LR) cell deployment model was loaded into the Regression App. This LR model had been previously trained on a labelled dataset, featuring geographical information as input features and quality of service metrics (signal strength, signal quality, interference level) as output. By integrating the LR model into the app, it became primed for generating predictions based on the test data.

Utilizing the loaded LR model, the test data was inputted into the app, enabling the prediction of quality of service information for the target area. Leveraging the provided geographical information, the LR model generated predicted values for signal strength, signal quality, and interference level. These predictions were then extracted from the app for further examination.

The output yielded by the LR model underwent analysis by comparing it against the applicable standards set forth by the 3rd Generation Partnership Project (3GPP). These standards establish acceptable ranges or thresholds for signal strength, signal quality, and interference level. Reference to the 3GPP standards, often presented in tabular form like Table 3.3, facilitated the evaluation of the predicted quality of service values in terms of their adherence to the defined criteria as presented in the algorithm 2.

Based on the analysis of the predicted quality of service values and their alignment with the 3GPP standards, informed decisions were made concerning the suitability of the target area for cell deployment. This decision-making process involved assessing whether the predicted values fell within the acceptable ranges or thresholds specified by the 3GPP standards, guiding determinations of deployment suitability or the need for further considerations and modifications. The table 3.2 presented the criteria used or the data analysis and network planning to determine the area which need network deployment.

Table 2: Criteria for network planning analysis (Isabona and Obahiagbon, 2013)

Criteria	RSRP	RSRQ	Interference
Excellent	≥ -80 dBm	≥ -10 dB	≤ -70 dBm
Very Good	-80 to -90 dBm	-10 to -15	-70 to -80 dBm
Good	-90 to -100 dBm	-15 to -20	-80 to -90 dBm
Fair	< -100 dBm	< -20 dB	≤ -100 dBm

Table 3: Result of drive test performance

Distance (Km)	**Real data**		
	Signal Strength (RSRP) (dBm)	**Signal Quality (RSRQ) (dB)**	**Interference Levels (dBm)**
0.1	-71	-3	-82
0.2	-69	-4	-83
0.3	-68	-5	-80
0.4	-72	-3	-84
0.5	-70	-4	-81
0.6	-71	-3	-82
0.7	-69	-4	-83
0.8	-68	-5	-86
0.9	-72	-3	-84
1.0	-70	-4	-85
1.1	-71	-3	-82
1.2	-69	-4	-83
1.3	-68	-5	-80
1.4	-72	-5	-84
1.5	-70	-6	-85
1.6	-71	-6	-85
1.7	-69	-8	-84
1.8	-86	-7	-86
1.9	-89	-8	-85
2.0	-91	-8	-86
2.1	-88	-9	-88
2.2	-89	-10	-90
2.3	-87	-10	-88
2.4	-88	-9	-91
2.5	-89	-10	-92
2.6	-93	-11	-96

2.7	-94	-12	-97
2.8	-92	-10	-98
2.9	-93	-11	-99
3.0	-94	-12	-100
3.1	-98	-13	-105
3.2	-99	-14	-82
3.3	-97	-13	-83
3.4	-100	-14	-80
3.5	-102	-14	-84
3.6	-105	-16	-81
3.7	-106	-17	-82
3.8	-104	-17	-83
3.9	-105	-16	-86
4.0	-106	-17	-84
Average	-84.625	-8.825	-86.475

The result reported the quality of service performance within the Milliken hills environment, considering RSRP, RSRQ, and interference over 4Km distance from the primary characterized cell radius. The result reported average RSRP at -84.625dBm, RSRQ at -8.825dB and interference of -86.475dBm. Overall these results implied fair quality of service within the area, however better insight on the results was revealed using figure 3.

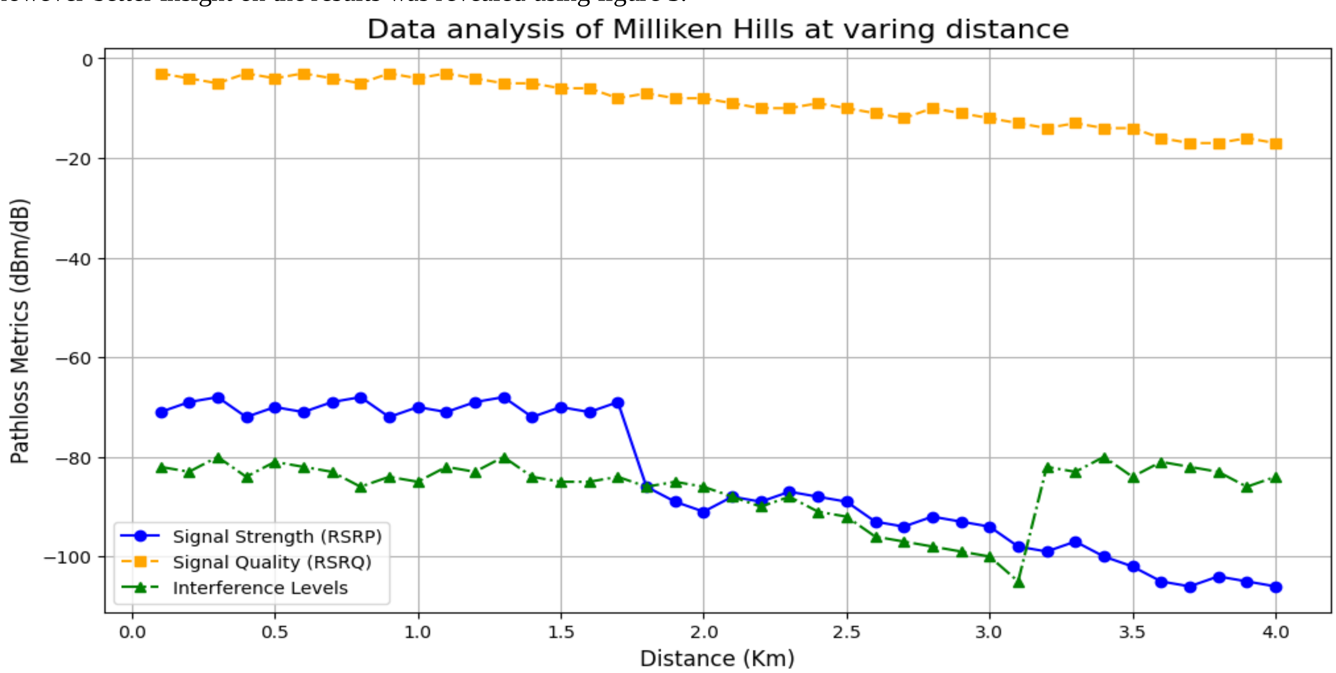

Figure 3: Pathloss result from drive test

The figure 4.3 presents the result of the overall quality of service in the area at various distances in Km. from the result it is of common knowledge that the quality of service degrades as the user deviate from the serving cell. However, notable observation was made after 1.9km, as the signal quality degraded more and also the signal strength and interference. The reason was because at this area, more of high trees, hills, and valley were characterized by the environment, thus resulting to scattering effect, increased multi-path characteristics such as reflection, diffraction, attenuation and increased interference as evident in the graph. This problem continued until after 3.2km, when the interference became greater than -100dB due to the deviation from the coverage range of the interfering cell. At this point, the evidence showed that cell can be deployed in the environment.

3.4 System Validation

To perform the system validation, data was collected, considering 4km of 100meter interval each in an area characterized with diverse environmental topologies, while considering RSRP, RSRQ and interference level. These collected data at various location was input to the software which identified the network information as a dependent variable and then apply the predictor to predict the network condition of the place and then decide if fit for cell deployment. The results are reported in the table 4.4.

Table 4: Result of system validation

Distance (Km)	RSRP (dBm)	RSRQ (dB)	Interference Levels (dBm)	Prediction outcome	Decision
0.1	-72	-3	-82	Excellent	Area not fit for deployment
0.2	-68	-4	-83	Excellent	Area not fit for deployment
0.3	-67	-5	-80	Excellent	Area not fit for deployment
0.4	-71	-3	-84	Excellent	Area not fit for deployment
0.5	-71	-4	-81	Excellent	Area not fit for deployment
0.6	-72	-3	-82	Excellent	Area not fit for deployment
0.7	-68	-4	-83	Excellent	Area not fit for deployment
0.8	-69	-5	-86	Excellent	Area not fit for deployment
0.9	-71	-3	-84	Excellent	Area not fit for deployment
1.0	-71	-4	-85	Excellent	Area not fit for deployment
1.1	-70	-3	-82	Excellent	Area not fit for deployment
1.2	-68	-4	-83	Excellent	Area not fit for deployment
1.3	-67	-5	-80	Excellent	Area not fit for deployment
1.4	-71	-5	-84	Excellent	Area not fit for deployment
1.5	-71	-6	-85	Excellent	Area not fit for deployment
1.6	-72	-6	-85	Excellent	Area not fit for deployment
1.7	-69	-8	-84	Excellent	Area not fit for deployment
1.8	-88	-7	-86	Fair	Area not fit for deployment
1.9	-87	-8	-85	Fair	Area not fit for deployment
2.0	-90	-8	-86	Fair	Area not fit for deployment
2.1	-88	-9	-88	Fair	Area not fit for deployment
2.2	-89	-10	-90	Fair	Area not fit for deployment
2.3	-87	-10	-88	Fair	Area not fit for deployment
2.4	-88	-9	-91	Fair	Area not fit for deployment
2.5	-89	-10	-92	Fair	Area not fit for deployment
2.6	-93	-11	-96	Poor	Area suitable for cell deployment
2.7	-94	-12	-97	Poor	Area suitable for cell deployment
2.8	-92	-10	-98	Poor	Area suitable for cell deployment
2.9	-93	-11	-99	Poor	Area suitable for cell deployment
3.0	-94	-12	-100	Poor	Area suitable for cell deployment
3.1	-98	-13	-105	Poor	Area suitable for cell deployment
3.2	-99	-14	-82	Poor	Area suitable for cell deployment
3.3	-97	-13	-83	Poor	Area suitable for cell deployment

3.4	-100	-14	-80	Poor	Area suitable for cell deployment
3.5	-102	-14	-84	Poor	Area suitable for cell deployment
3.6	-105	-16	-81	Poor	Area suitable for cell deployment
3.7	-106	-17	-82	Poor	Area suitable for cell deployment
3.8	-104	-17	-83	Poor	Area suitable for cell deployment
3.9	-105	-16	-86	Poor	Area suitable for cell deployment
4.0	-106	-17	-84	Poor	Area suitable for cell deployment

The analysis in table 4.4 shows that the network quality is excellent up to a distance of 1.7 km, fair from 1.8 km to 2.5 km, and poor beyond 2.6 km. Based on the criteria of recommending small cell deployment only in areas with poor network quality, small cells should be deployed from a distance of 2.6 km onward.

4. Summary

This research focuses on the application of machine learning algorithm for cell deployment in Nigeria. It begins with the adoption of COST231-Hata and Okumura Hata path loss prediction models to determine network coverage data in a particular area and justify the need for cell deployment. In addition, real-time site survey test was performed to assess the correctness of these models by gathering information about site attributes. The challenge with the data collected is the need for high level expert analysis to be able to make decision on the best place for the cell deployment and due to the tendencies for human error, complexities and time delay, most of the time, the most suitable position for the cell deployment most time are not identified, which justified the need for an automated approach for cell deployment decision. To achieve this, data of an ideal area characterized for cell deployment was collected over 4KM and then applied to train linear regression algorithm to generate a model to predict the quality of service in a particular area. This prediction outcome formed the input to a smart decision based framework which considered other parameters such as interference level, signal strength and then decide if the area is actually suitable for cell deployment. The model developed was integrated as a desktop application using Javascript programming language and then applied for the testing of site for network planning and cell deployment. To conduct extensive performance evaluations o the model and assess its impact for small cell deployment, experimentations were performance using real life test and the results showed that the system was able to predict network information condition of a particular area and then decision if the area is suitable for cell deployment is recommended. The study contributes the following to knowledge;

1. Machine learning model for pathloss prediction was presented using linear regression
2. Smart decision based framework for cell deployment
3. Software application system for network test and cell deployment

5. Conclusion

Over the years, due to the complex geographical terrain in various regions, deciding the best place to install network cell has remained a major issue. This is evident today in many locations, because despite the present of cell in nearby areas, yet customer's still experience poor quality of service and this has remained an issue. To solve this problem, this research explored the application of machine learning algorithms, specifically linear regression for the prediction of network condition in a particular area, then a smart decision framework was developed and integrated the linear regression model to develop a desktop application system for network planning and cell deployment using Matlab and Javascript programming language. The results when tested considering live data of a particular area showed that the linear regression was able to predict the network information of a location correctly using the relationship between the dependent variable which is the test data and then the independent variable which is the trained linear regression predictor. Experimental test using real live data was able to demonstrate the effectiveness of the model in application for cell deployment.

6. Recommendation

The software developed was recommended for adoption by telecommunication companies in Nigeria to help their engineers make more informed decision on the most suitable point for cell deployment. The application is also suggested for student to be applied to characterize network quality in a particular area, network planning and drive test experiments.

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