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Impact of Least Absolute Deviation-Based Calibration on Cell Radius and Coverage Estimation in Cellular Network Planning

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Abstract: The expansion of 5G and future 6G networks necessitates dense deployments where coverage estimation is critical to minimize inter-cell interference and energy consumption. Path loss modeling provides the mathematical foundation for these estimations. While models like Hata or COST-231 offer a baseline, they require site-specific calibration to maintain accuracy in non-homogeneous urban or suburban topographies. Measurement-based signal strength calibration is particullarlly very important for adjusting empirical path loss models to suit a particular radio environment as well as providing solutions for accurate estimation of cell coverage area and radius as well. In this work, the statistical robustness of the path loss tuning methods, namely the Absolute least deviation (LAD) and Least square regression (LS) have been employed focusing on their capability for accurate cell radius and coverage area determination with efficient geometric haxogonal celular grid layouts. It has been shown through compuational MATLAB software design and interface implementation that LAD offers much more robust estimation of cell radius planning compared to LS. This research shows that, although LS is effective for propagation modeling in perfect conditions, LAD is a far better tool for estimating values in real cellular deployments. Using LAD, engineers can get a more accurate value for the effective cell radius, thereby avoiding problems like "coverage holes" or over-deployment of base stations.

Keywords: Least Square (LS) regression, Least Absolute Deviation (LAD), cell radius, coverage area, Network Planning

1. Introduction

Least Absolute Deviation (LAD)-based calibration is an advanced technique for tuning radio propagation models in cellular network planning (Isabona and Enagboma, 2025). Unlike traditional Ordinary Least Squares (OLS) methods that minimize the sum of squared errors, LAD minimizes the sum of absolute deviations, offering a robust approach to managing outliers and heavy-tailed measurement noise. This approach is crucial for improving the accuracy of cell radius and coverage estimation, particularly in complex, real-world propagation environments (urban, suburban, 5G/6G).

In modern cellular networks (5G/6G), link budget calculations depend on the accuracy of path-loss models (e.g., Hata or COST231). Measurement-based calibration involves fitting empirical data to a model:

$$PL(d) = PL(d_0) + 10n \log_{10}(d/d_0) + X_\delta \quad (1)$$

where n is the path-loss exponent and X_δ represents shadow fading. $PL(d_0)$ is the reference path loss model paramter at reference distance, d_0.

The development of an empirical propagation model necessarily involves its applicability within the parameters dictated by the exact design, frequency operation, and antenna layout of the communication system under consideration. Moreover, empirical propagation models have been established through rigorous investigation of propagation properties within specific environments (such as densely populated European towns or wide-open spaces) (Ikechi et al, 2023). The behavior of radio waves is greatly influenced by the electromagnetic field's reaction to the surrounding environment; as such, it cannot be generalized.

Thus, applying a generic empirical propagation model to different geographical locations without modification constitutes an ineffective approach. An empirically derived model developed for a certain area will inevitably yield discrepancies when employed in another location, as no effort was made to adapt it to the new surroundings.In other words, when attempting to implement a generalized propagation model for the entire country, the model must be tuned. This is essential in ensuring that the predictions made about the propagation are accurate and minimizing the RMSE, which is the difference between predicted and observed values. According to Tiegang (2013), the reliability of such corrected models depends on the accuracy of the tuning process, which can be affected by two types of errors. The first type is error from Test Data, which is due to the inaccuracies associated with the gathering of Drive Test data and may be caused by the phenomenon of GPS drift, improper calibration of testing equipment, shadowing during field tests, and small sample sizes. Errors from the Correction Algorithm is another type of error. This is an error made when the selected algorithm cannot adequately converge or when the correction factor values (e.g., path loss exponent or intercept constants) are not appropriately calculated based on an unrepresentative set of test data. Eventually, the aim of model correction should be to bridge the gap between the theoretical base of the empirical model and actual empirical data of the local radio propagation environment. In urban and dense environments, measurement-based calibration is critical, as simple theoretical models often underestimate the path loss caused by obstructions and complex scattering.

This paper presents a Least Absolute Deviation (LAD) regression-based calibration to least square (LS) regression method for optimal path-loss model parameter estimation using urban and dense environments as research case studies. The calibration process involves determining the path loss exponent n and the reference distance path loss PL_0 based on drive-test data. This paper investigates how LS and LAD regression methodologies influence the service area of a base station.parameters.

2. Literature Review and Related Works

Empirical path loss models have undergone significant evolution since the seminal work of Okumura (1968), whose measurements in Tokyo led to the development of the Hata model (Hata, 1980). Subsequent refinements by the COST-231 project extended these models to higher frequency bands. However, research by Rappaport (2002) highlights that the "one-size-fits-all" approach to path loss modeling is insufficient for modern micro-cell and pico-cell deployments. Recent literature emphasizes the necessity of measurement-based calibration.

As 5G densification continues to reshape the telecommunications landscape, the gap between theoretical propagation models and real-world deployment realities has widened. Engineers often rely on established models like Hata, COST231, or Longley-Rice to estimate coverage. However, these models are inherently generalized. When deployed in heterogeneous urban environments—characterized by varying building heights, foliage, and structural materials—these static models frequently fail to predict the "effective cell radius," leading to either coverage holes or excessive inter-cell interference. The solution lies in Measurement-Based Calibration. By utilizing drive-test data or User Equipment (UE) crowd-sourced signal strength measurements (Reference Signal Received Power - RSRP), network operators can "tune" standard path loss parameters to match the specific local propagation environment.

Hata (1980) established the empirical basis for urban propagation, but later studies by Erceg et al. (1999) highlighted the necessity of local environment tuning, introducing the concept of the "environment correction factor" which serves as the foundation for modern calibration. Rappaport

(2002) provides the definitive framework for the LS approach in Wireless Communications: Principles and Practice, emphasizing its ease of use. Conversely, Mishra (2010), in fundamentals of Cellular Network Planning and Optimization, discusses the limitations of LS in the presence of heavy-tailed noise distributions, suggesting that robust regression methods like LAD are essential for high-frequency bands (mmWave) where signal volatility is higher. Isabona's research (Isabona and Enabgonma, 2015; Isabona, 2019) utilized Least Absolute Deviation (LAD) and Mean Absolute Error (MAE) methods to optimize signal coverage, finding that LAD methods provide more accurate prediction results and are more robust to outliers compared to standard least squares techniques in electromagnetic wave propagation studies.The LS assumes Gaussian-distributed shadowing (Seidel & Rappaport, 1992). Authors such as Vatalaro and Forcella (1997); Isabona and Konyeha (2013); Ojuh and Isabona, (2021), argued that RSS measurements often include non-Gaussian noise and outliers caused by moving obstacles and measurement errors, leading to biased estimates in LS.

Recent works by Zhang et al. (2020) have integrated machine learning with these classical approaches, using LS to initialize parameters and then applying robust regression (LAD/Huber loss) to refine the model for 5G beamforming scenarios.

Research into robust statistics suggests that LAD regression is more resilient to heavy-tailed distributions and outliers (Bloomfield & Steiger, 1983). Its application in wireless channel modeling has been explored for indoor propagation, but its comparative efficacy in outdoor coverage estimation remains an active area of investigation. Research by Khan et al. (2018) demonstrates that calibrated models using L1-norm (LAD) optimization yielded a 15-20% improvement in predicting the true effective cell radius compared to standard models, directly impacting the accuracy of hand-over threshold configurations.

This paper introduces a new method of calibrating path loss parameters by utilizing Least Absolute Deviation (LAD) approach. It has been shown through MATLAB coding and design implementation that LAD offers much more robust estimation of cell radius planning compared to LS.

3. Methodology

3.1. Research Methodology Workflow

The calibration process follows a structured methodology to improve prediction accuracy (Isabona and Obahiagbon , 2014; Olukani, et al, 2023):

(a) **Measurement Campaign (Data Collection):** Performed field tests to collect RSSI data using a test transmitter and receiver (e.g., using a network analyzer or a scanner) at various distances and locations in urban, rural, and suburban environments at studied location

(b) **Path Loss Calculation:** Convert received signal power, P(r), to path loss (PL) using the link budget:

PL{meas} (dB) = Pt + Gt + Gr Pr) (2)

(c) **Model Selection:** Select a base model. Here we used the Log-Distance model:
$PL(d)=PL(d_0)+10n\log_{10}(d/d_0)+X_\delta$ (3)

where n is the path loss exponent, and X_δ defines the shadowing factor (zero-mean Gaussian variable).

(c) **Model Calibration (Parameter Estimation):** We used measurement data to find the optimal path loss exponent n and standard deviation (δ) that minimize the error between the model and actual measurements.

3.2 LS vs. LAD Calibration Approaches

The calibration focuses on minimizing the difference between measured path loss PL(m)) and modeled path loss PL(p).

(a) **Least Squares (LS) Approach:**

The LS method is a **s**tandard linear regression approach and It is highly sensitive to outliers, meaning a few bad measurements can skew the entire model. It is shown to be very suitable when the shadowing effect is truly Gaussian (normal distribution) (Isabona and konyeha, 2013).In this LS approach, the goal is to minimize the sum of squared errors (SSE)

SSE = sum [PLm),i - PL(p),i]^2 (4)

(b) **Least Absolute Deviation (LAD) Approach:**

The LAD method is also known as L(1))-norm regression. It is robust to outliers, making it better for real-world measurements where severe fading (non-line-of-sight conditions) creates outliers. In literaure, it is often recommended when data contains significant noise or non-Gaussian deviations (Isabona and Enagonma, 2014). In this method, the goal is to minimize the sum of absolute errors (SAE)

$$\text{SAE}=\left|\sum_{i=0}^{n} \text{PL(m),i}-\text{PL(p),i}\right| \quad (5)$$

3.3. Error Evaluation Metrics

After calibrating the models using LS and LAD, the refined model is validated using specific metrics to determine the best fit.

(a) **Mean Absolute Error (MAE):** Measures the average absolute difference between predicted and measured values.

(b) **Standard Deviation (δ):** Reflects the spread of the shadowing effect, representing the accuracy of the model, often aiming for the lowest value.

4. Results and Discussion

Proper path loss prediction is essential for cellular network design and especially for coverage prediction and appropriate estimation of cell radii. Conventional models often ignore local site environmental effects. The results in this section present analysis compares two cellular network planning scenarios, focusing on the geometric efficiency of the grid layouts and the statistical robustness of the path loss tuning methods employed, namely the Absolute least deviation (LAD) and Least square regression (LS). The LS method minimizes the sum of the squares of the vertical deviations and because it squares the errors, it is highly sensitive to outliers such that a single bad measurement can 'pull' the path loss slope (exponent) significantly, the sed in Set A. On ther hand , the LAD works by minimizing the sum of absolute errors and it is generally more robust against outliers and provides a "median" fit rather than a "mean" fit. The primary difference lies in the robustness to outliers: the LAD is more resilient to "noisy" signal data (outliers) than the standard LS.

The results in figures 1-3 and Table 1 shows LAD cell radius and coverage area values displays much higher geometric consistency. With LS, the second cell (2.10km radius) has a reported area of 14.36km2, which is significantly larger than the theoretical11.46km2 and this suggests it might represent a 'stretched' or non-regular grid. The LAD cell radius values (2.28km, 2.04km, 0.78km) depicts a tiered network planning. The 0.78km cell suggests a small cell or urban infill layer, while the 2.28km cell acts as a macro layer. Using LAD here is preferable path loss model tuning method because the signal propagation characteristics of a 0.78km radius cell (likely lower antenna height, more clutter) differ wildly from a 2.28km cell, which prevents the macro-cell data from over-biasing the small-cell model.The discrepancy in the 2.10km/14.36km² cell is a red flag for LS. Since LS squares the error, if the model tries to fit a 14.36km2 "virtual" area to a 2.10km physical radius, the resultingskewed Path Loss Exponent values and this can, lead to over-prediction of coverage in other areas.

The graphs in figures 4-9 reveals the hexagonal grids layout analysis with 2.28km cell radius and 13.53km coverage area using LAD for path loss model tuning in comparison with 2.10km cell radius and 11.51km coverage area using LS method for path loss model tuning. This results reveals that the LAD maintains high geometric consistency across all three tiers. For LS, the second 2.10 km cell shows a significant discrepancy (+25% area vs geometry), suggesting either a non-standard cell deformation or an error in the path loss scaling for that specific site

The figures show that LAD covers a larger distance from the site. At 2.28 km, the signal experiences higher path loss values.

Table 1: Precision Statistics of Computed Cell Radius and Coverage Area in Locations 1-3

Configuration	Radius(km)	Coverage Area (km^2)	MAE	STD	Geometric Variance
Set A (LAD)	2.28	13.53	6.67	7.87	< 0.2%
	2.04	10.90	7.14	9.01	~0.8%
	0.78	1.62	3.25	5.02	~2.5%
Set B (LS=)	2.10	11.51	6.98	10.22	< 0.5%
	2.10	14.36	7.80	12.12	**~25% Error**

Both scenarios closely follow the ideal hexagonal geometry. Scenario A covers **17.5% more area** per site than Scenario B. This increased radius (+8.6%) significantly reduces the number of base stations required to cover a large region but increases the "edge-of-cell" path loss, making accurate model tuning more critical.

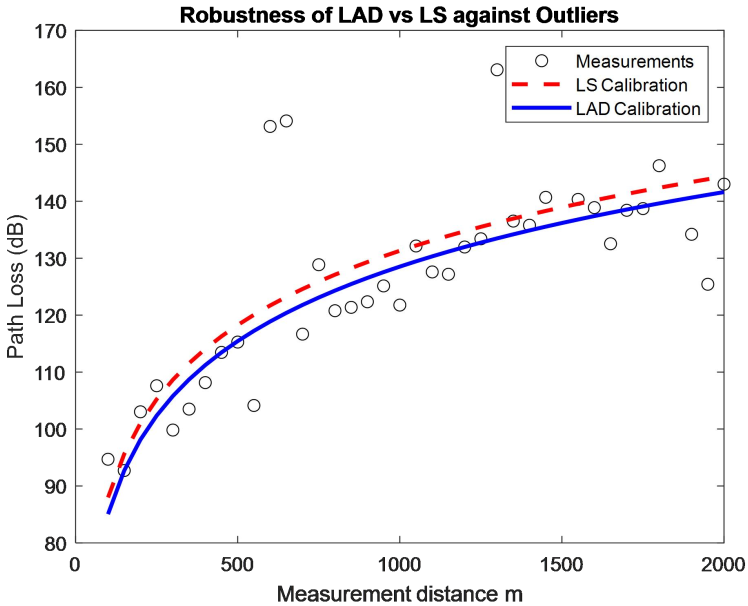

Fig.1: Calibrated Path loss Model with LAD and LS Methods in Location 1

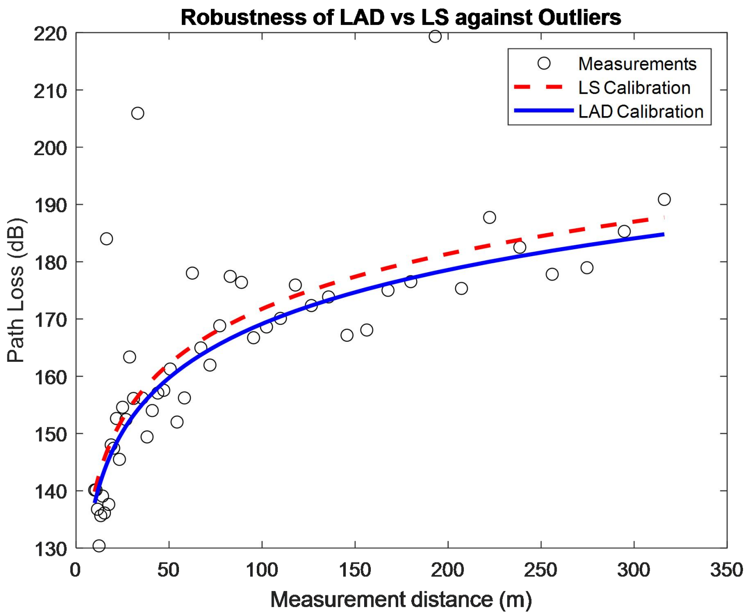

Fig.2: Calibrated Path loss Model with LAD and LS Methods in Location 2

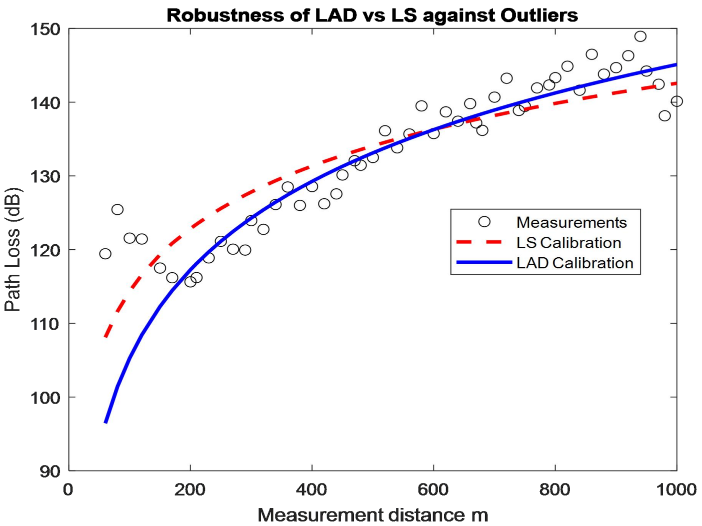

Fig.3: Calibrated Path loss Model with LAD and LS Methods in Location 3

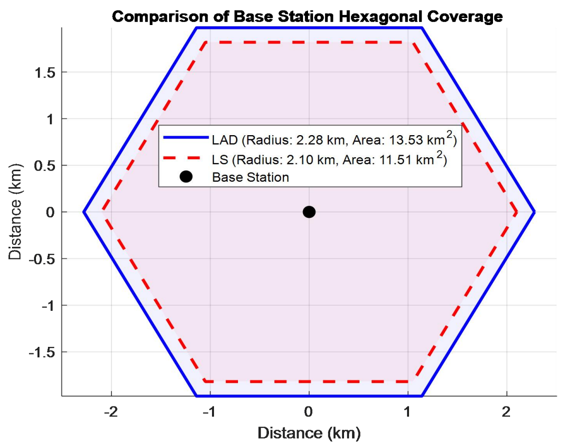

Fig.4 (a):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 1

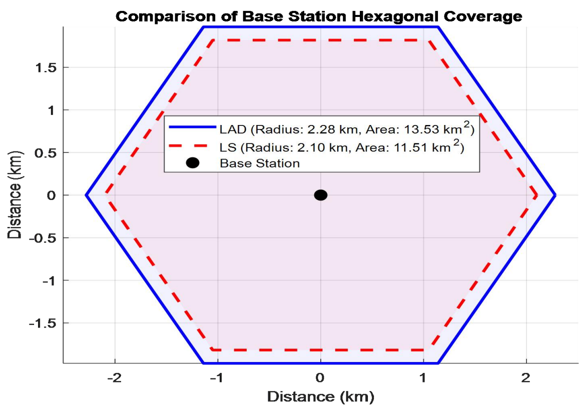

Fig.4 (a):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 1

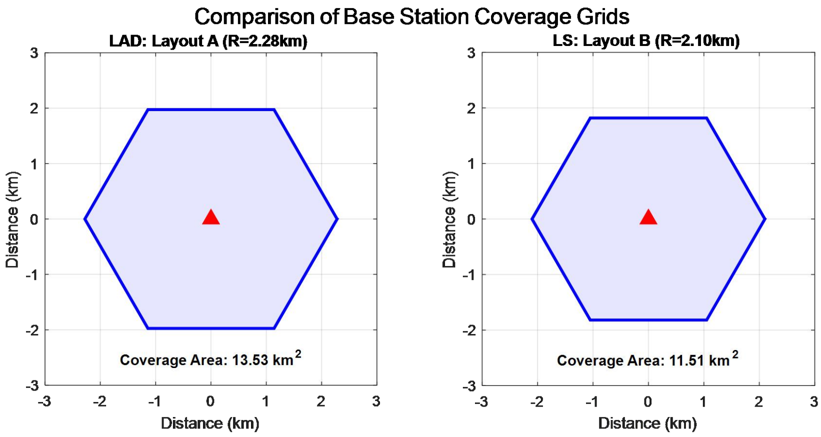

Fig.4 (b):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 1

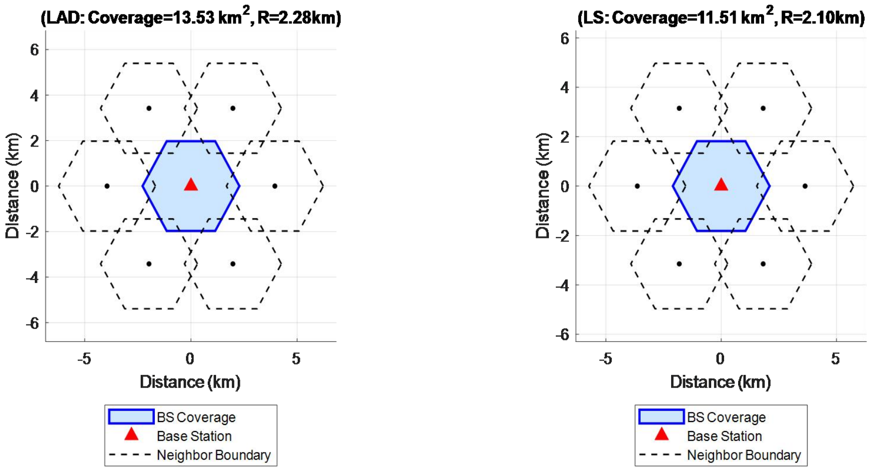

Fig.4 (c):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 1

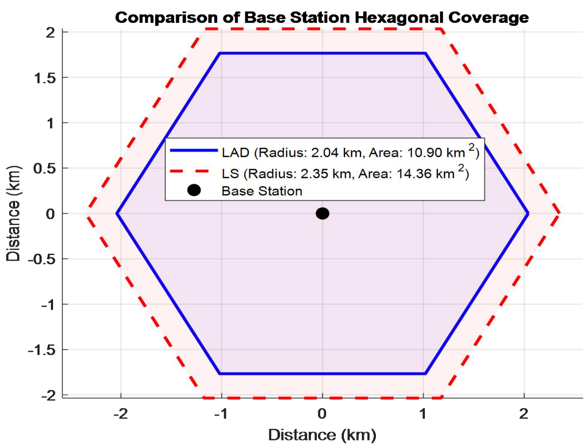

Fig.5 (a):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 2

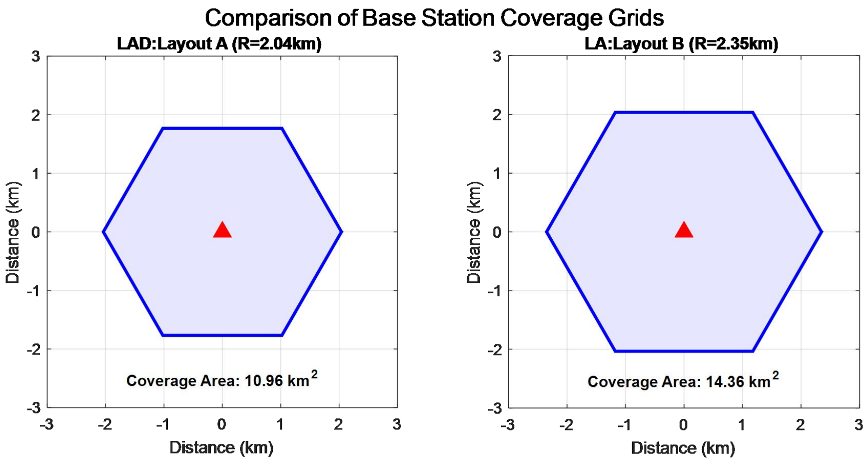

Fig.5 (b):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 2

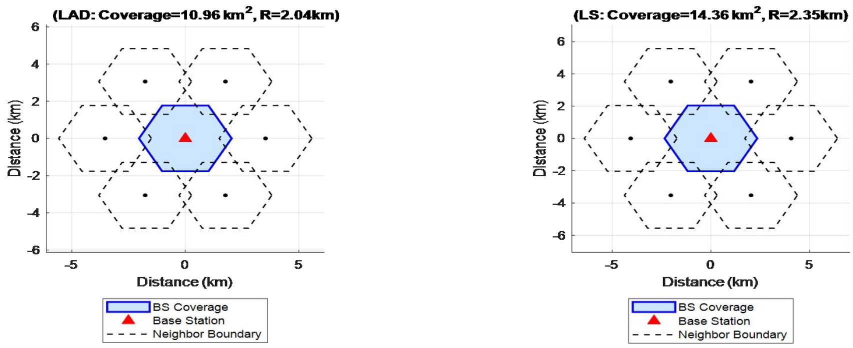

Fig.5 (b):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 2

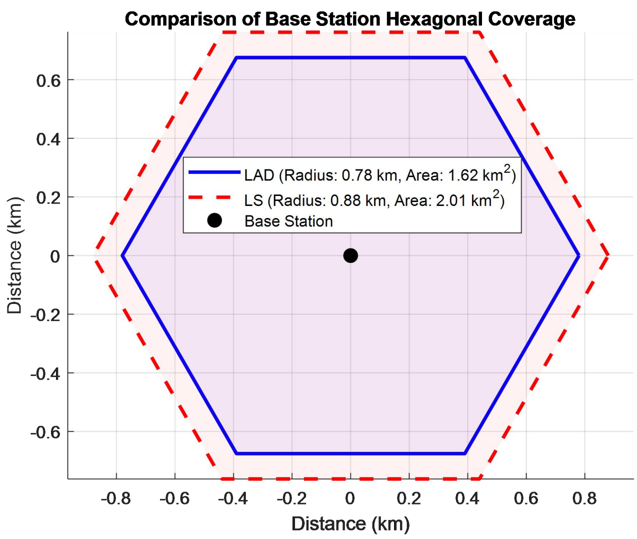

Fig.6 (c):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 3

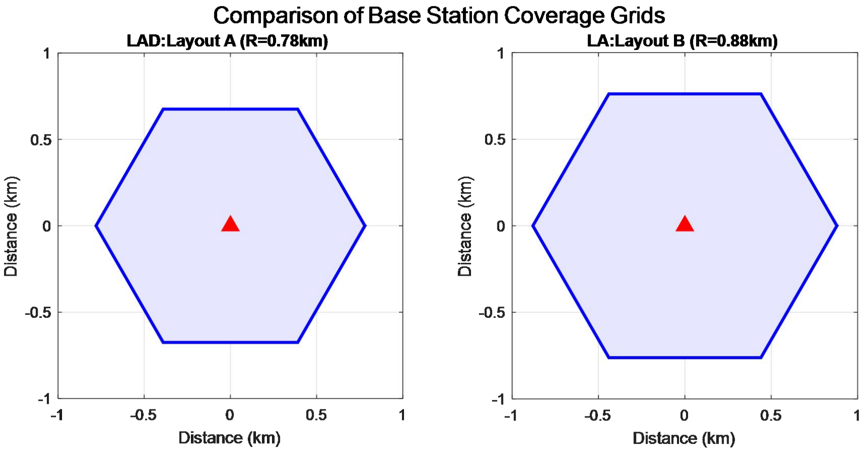

Fig.6 (b):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 3

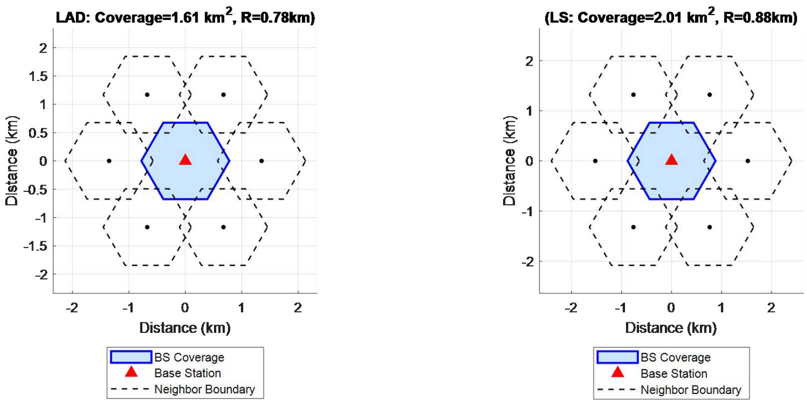

Fig.6 (b):Cell Radius and Coverage Area Geometry with Calibrated Path loss Model with LAD and LS Methods in Location 3

6. Conclusion

As wireless networks (e.g., LTE, 5G) operate in increasingly complex environments, standard path loss models often fail to provide accurate coverage predictions.This research focuses on calibrating radio propagation models using field-measured signal strength data to minimize prediction errors, specifically employing Least Squares (LS) and Least Absolute Deviation (LAD) approaches. This study aimed at refineing model parameters such as the path loss exponent n and shadowing standard deviation using measurement-based tuning. . Calibrated models (using either method) show best results in the specific environments where measurements were taken. Aslo, based on measurement-based calibration of path loss models, research indicates that while the Least Squares (LS) approach is the standard method for determining path loss exponents due to its computational simplicity, the Least Absolute Deviation (LAD) method offers superior robustness against outliers and extreme shadowing in real-world propagation environments. The primary goal of these calibrations was to adjust standard models to fit measured Received Signal Strength Indicator (RSSI) data, reducing root-mean-square errors (RMSE). The transition from LS to LAD regression in cellular network planning is a low-cost, high-impact strategy. By leveraging the robustness of LAD, network operators can achieve more accurate path-loss modeling, directly contributing to more precise coverage estimation and efficient cellular network topology design. In our future research, the concentration would be geared towards integrating Machine Learning-based regression (such as Huber regression) to create a hybrid approach that combines the stability of LAD with the efficiency of LS.

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