

Direction-of-Arrival (DOA) Estimation Based on Real Field Measurements and Modified Linear Regression [†]

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Abstract: This study applied modified linear regression in machine learning (ML) to predict the direction of arrival (DoA) in cellular networks using field measurements and radiofrequency parameters. Models were developed from base station data, with preprocessing for pattern identification and formula adjustments to improve the accuracy across angle ranges. Machine learning, tested here as an additional method to traditional techniques, achieved a root mean square error (RMSE) of 3.63 to 17.93, demonstrating enhanced adaptability. While requiring substantial data and computational resources, this approach highlights machine learning's potential as a valuable tool for DoA estimation in cellular networks.

Keywords: DoA; machine learning; cellular network; linear regression; real radio frequency measurements

1. Introduction

Direction-of-arrival (DoA) estimation is a fundamental topic of considerable interest in wireless communications and radar-based applications. In this paper, we propose a new methodology based on real field measurements for acquiring radiofrequency parameters, analyzing the radio infrastructure characteristics of the base station (BS) and employing a machine learning (ML) technique to address the challenges in DoA estimation caused by imperfect arrays. Nowadays, industries are also using traditional methods to detect the DoA, such as those employed in fifth-generation fighter planes, achieving impressive results. Compared to existing methods, the proposed ML approach using linear regression achieves lower complexity. Numerous direction estimation algorithms have been proposed, each with distinct characteristics. Generally, existing DoA estimation methods can be roughly classified into super-resolution methods and Fourier transform (FT)-based methods. Recently, ML and deep learning techniques have been explored for DoA estimation, leveraging multiple signal classification (MUSIC), estimation of signal parameters via rotational invariance techniques (ESPRIT), and signal sparsity in the spatial domain of an antenna array model. Deep learning-based DoA super-resolution methods often use sampled received signals or the covariance matrices of received signals as inputs for feature extraction. In [1], a deep learning-based method is proposed where the input is the covariance matrix and the output is the spectrum from which the DoA is estimated. A sparse loss function is used to train the network. In [2], the study explores the use of deep neural networks (DNNs) for estimating the DoA of wireless signals. Techniques such as batch learning [3] and various optimization strategies are employed during the training phase. The correlation matrix serves as the input to the DNN, and the output represents the probability of an incident wave's presence in each direction. We use the correlation matrix because it is a statistical measure indicating the extent of a linear relationship between two variables, as shown in [4]. This technique is also chosen because it is a common method for



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describing simple relationships without inferring causality, as shown in [5]. Several key parameters are considered in configuring the system, including the antenna structure, signal frequency, signal-to-noise ratio (SNR), the number of signal sources, and the architecture of the deep neural network, which encompasses the number of intermediate layers and units per layer.

The methodology described in [6] utilizes an oversized lens-loaded cavity antenna with reconfigurable mode mechanisms. This includes a computational layer employing ML to optimize the antenna's state. In contrast, this research uses a mobile device to acquire data, which are then processed to develop a DoA estimation model. Fourier transform-based methods have also been proposed, such as in [7], where the short-time Fourier transform and spatial time-frequency distributions (STFD) matrix are used alongside the MUSIC algorithm to estimate source DoAs [8]. The novelty of this research lies in using mobile devices and ML to create reliable models for DoA behavior and prediction.

Instead, it uses real radio frequency measurements from the mobile station (MS), considers radio frequency infrastructure characteristics, and applies ML techniques. The paper is organized as follows. Section 2 reviews the DoA estimation method, Section 3 presents the results, and Section 4 concludes the paper. The key acronyms are listed in Table 1.

Table 1. List of acronyms.

Acronym	Definition
BS_{LAT}	Base Station Latitude
BS_{LON}	Base Station Longitude
M_{LAT}	Mobile Latitude
M_{LON}	Mobile Longitude
RSSI	Received Signal Strength Indicator
$RSSI_{strongest}$	Received Strongest Signal Intensity
RSRQ	Reference Signals Received Power
$RSSN_r$	Reference Signal Signal-to-Noise Ratio
D	Distance
DoA	Direction of Arrival

2. Methodology

The methodology for analyzing terrain in open fields with various obstacles involves a multifaceted approach. Techniques such as adaptive directional time–frequency distributions [9] and multiple screening k-means clustering for multiple sources [10] can be utilized. In this study, we propose using both contemporary measurement tools and advanced computational techniques. Data acquisition is conducted using NetMonitor Pro, Google Maps, Google Earth, and Android-based smartphones, ensuring comprehensive coverage and accurate geospatial referencing. Additionally, ML methodologies implemented in RStudio are employed to develop predictive models, allowing for the extraction of valuable insights from the collected data [11,12].

2.1. Algorithm for DoA Estimation

This algorithm includes the blocks for the DoA estimation process using a ML technique. The process begins with the selection of coverage areas, identifying regions of interest for analysis. Next is the analysis of the existing infrastructure, where the network infrastructure is evaluated and sectorization within the area is established. Following this, measurements are executed by collecting field data with mobile devices, resulting in a dataset of 19,419 measurements. After data collection, data preprocessing takes place to generate additional attributes and estimate the actual DoA from the collected data. The ML technique involves using modified linear regression to generate the DoA model. A critical step is the feedback in the flow diagram, which entails adjusting the model through parameter selection and formula modification until the error is minimized. Finally, the

process concludes with the obtaining of the resulting model, leading to the creation of a final model for each range of angles, as shown in Figure 1.

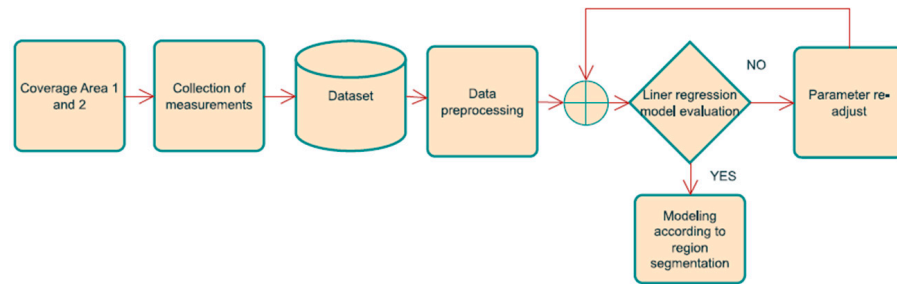


Figure 1. Process flow diagram of DoA Estimation.

The Friis equation (Equation (1)) [13] states that the far-field received signal power depends inversely on the square of the distance between the transmitter and receiver, and it is directly related to the gains of the antennas involved

$$P_{Rx} = \frac{P_{Tx} \cdot G_{Tx} \cdot G_{Rx} \cdot \lambda^2}{(4\pi D)^2} \quad (1)$$

where P_{Rx} is the received power, P_{Tx} is the transmitted power, G_{Tx} and G_{Rx} are the gains of the transmitting and receiving antennas, respectively, λ is the wavelength and D is the distance between the transmitting and receiving antennas. Equation (1) emphasizes the importance of the distance and relative DoA in signal reception, indicating that antenna gains depend on the DoA to optimize the signal strength and accuracy in different directions.

2.2. Data Collection Method

Data were collected in Quito, Ecuador, where a mobile device gathered data from mobile network operator towers. In Coverage Area 1, the measurements followed a circular and radial pattern around the BS, collecting approximately 72 samples at 5° intervals. Three circular measurements were taken in Zone 1, with radial measurements conducted outward from and returning to the BS, and circular measurements made in both the clockwise and counterclockwise directions, as shown in Figure 2a. This systematic approach ensures thorough coverage for accurate analysis of the signal propagation characteristics.

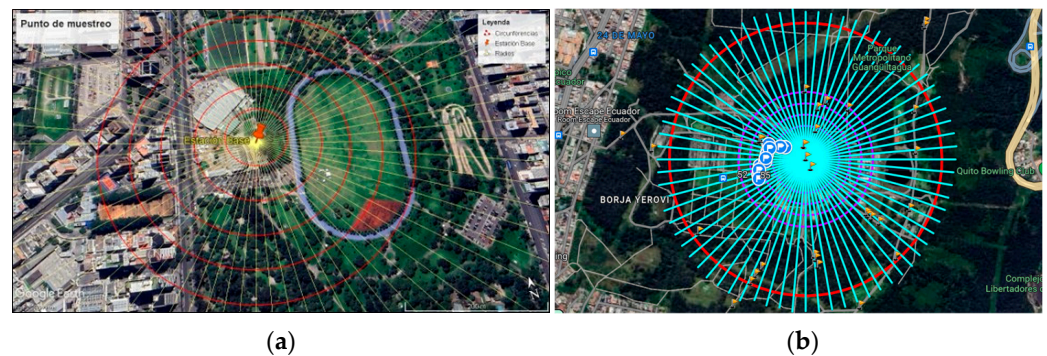


Figure 2. (a) Map of the final radial and circular routes for measurements in Coverage Area 1. (b) Map showing the final radial and circular routes for measurements in Coverage Area 2 (Google Maps).

In Coverage Area 2, radial and circular measurements were also taken every 5 degrees, with two measurements per radial path: one from the BS to the handover point and one back [8].

Circular measurements were taken every 50 m from the BS, selected for its accessibility to ensure efficient data collection. A thorough inspection assessed the actual coverage

area of the selected BS, allowing for segmentation based on the data collection method. Tools like Google Earth Pro version 7.3, Google Maps version 6.2, and Wikiloc version 3.40.10 were used for this purpose. Data were transferred from Wikiloc to Google Earth Pro and then to Google Maps via a KMZ file, guiding the execution of the radial and circular measurements in Coverage Area 2, as shown in Figure 2b.

For the radial measurements, a total of 72 radials resulted in 144 measurements (72 outward and 72 returning). The extent of the circular measurements varied based on the BS's coverage and path accessibility, constrained by factors such as steep slopes, inaccessible wooded areas, dense vegetation, irregular paths, and restricted zones like water treatment facilities.

2.3. Infrastructure Characteristics (Antenna Orientations)

To compare the estimated and actual DoA angles, we calculated the true DoA using Equation (2) with parameters from Table 2. This calculation employs the Haversine formula [14] to determine the distance between the BS and the mobile device (M) based on the latitude and longitude (Figure 3). The angular deviation was then computed using the Pythagorean theorem applied to latitude and longitude variations, with the dotted lines representing the reference axis relative to the BS.

$$\tan(\alpha) = \frac{Dist(\Delta LAT)}{Dist(\Delta LON)} \quad (2)$$

where:

1. *Dist*: is the distance of the variation in longitude or latitude.
2. ΔLAT : latitude variation.
3. ΔLON : longitude variation.

Table 2. Considerations for analyzing the angle of the actual DoA.

Case	Considerations	θ Value
1	$BS_{LAT} < M_{LAT} \wedge BS_{LON} < M_{LON}$	$\theta = 90^\circ - \alpha$
2	$BS_{LAT} > M_{LAT} \wedge BS_{LON} < M_{LON}$	$\theta = 90^\circ + \alpha$
3	$BS_{LAT} > M_{LAT} \wedge BS_{LON} > M_{LON}$	$\theta = 270^\circ - \alpha$
4	$BS_{LAT} < M_{LAT} \wedge BS_{LON} > M_{LON}$	$\theta = 270^\circ + \alpha$

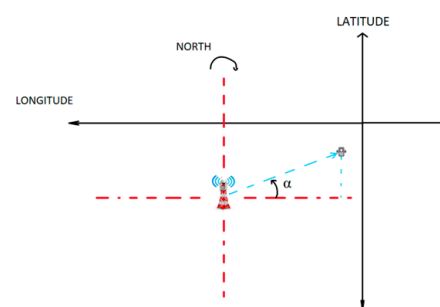


Figure 3. The reference system was positioned at the analyzed BS.

The BS in Coverage Area 1 is approximately 35 m tall and strategically positioned to optimize signal propagation. Its antennas are oriented and divided into five sectors to accommodate the dense urban landscape, ensuring adequate coverage for users in the area. Figure 4a illustrates this sectorization.

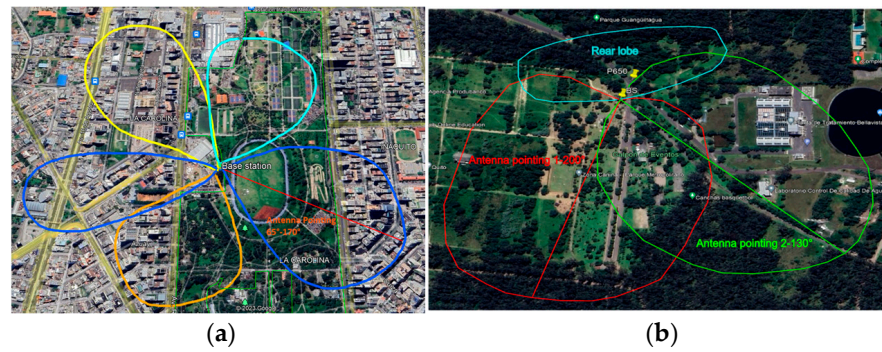


Figure 4. (a) Coverage Area 1 and antenna orientation. (b) Coverage Area 2 and antenna orientation.

For Coverage Area 2, shown in Figure 4b, key characteristics such as the antenna height (approximately 9 m), number of antennas, and orientation are crucial for the network coverage and signal quality. With two antennas using a sectorized approach, Antenna 1 has an azimuth of 200° , and Antenna 2 has an azimuth of 130° , both vital for effective link connections. These attributes directly impact the DoA predictions, essential for optimizing the LTE network service quality. ML techniques, particularly supervised learning with linear regression, can enhance the DoA prediction accuracy by identifying the radio frequency (RF) parameter patterns.

3. Results

3.1. DoA Estimation in Coverage Area 1

3.1.1. Analysis of Radiofrequency Parameters and DoA Ranges

The BS's coverage area is divided into several geographical regions based on the cell's sector distribution. Figure 5a illustrates the RSSI values at different distances across various DoA ranges, with the DoA divided into 20° increments from 0° to 360° . The reference signal received quality (RSRQ) at different distances, shown in Figure 5b, also varies across three DoA ranges, suggesting potential relationships between these parameters. The figures indicate that both the RSSI and RSRQ are dependent on the distance within each DoA range.

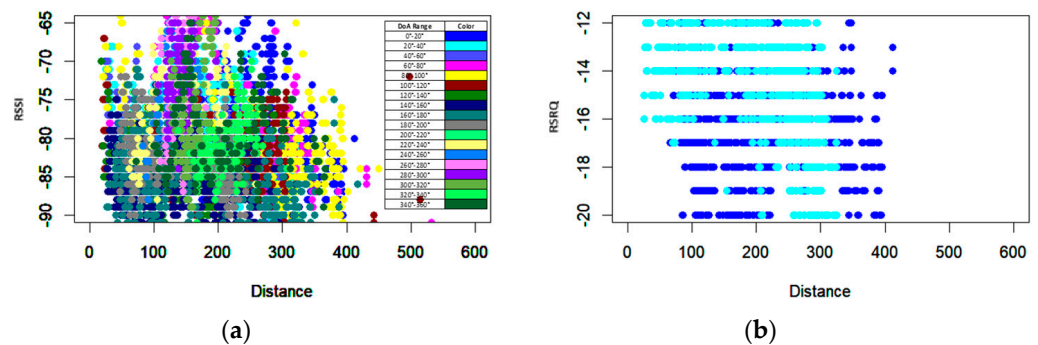


Figure 5. (a) RSSI dispersion for different DoAs as a function of the distance. (b) RSRQ for three DoA ranges as a function of the distance in Coverage Area 1.

3.1.2. Correlation Matrix

Multiple ranges were selected to accommodate the sectors provided by the BS, delineated as follows: Range 1: 0° – 65° , Range 2: 65° – 80° , Range 3: 80° – 170° , Range 4: 170° – 250° , Range 5: 250° – 305° , Range 6: 305° – 360° .

Due to irregularities at the sector boundaries, additional models were developed. Figure 6a shows distinct correlation coefficients among the parameters, reflecting the spatial variability and signal propagation complexities. These variations require tailored models to accurately capture the signal behavior across sectors and ranges. Figure 6b

presents the correlation matrix for the 340–360 degree range, where the correlation values between the DoA and other variables are higher than in Figure 6a.

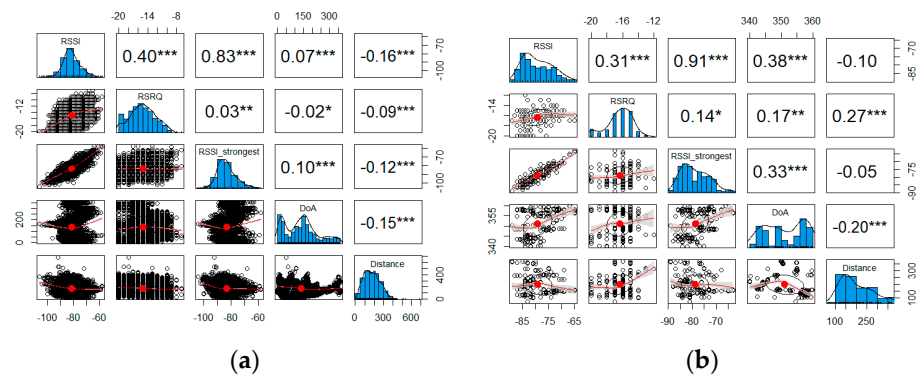


Figure 6. (a) General correlation matrix in Coverage Area 1. (b) Correlation matrix in a 340–360 degree range within Coverage Area 1. The more asterisks, the more significant the result.

3.1.3. Model Summary Using DoA Ranges

The proposed analysis effectively mitigates the influence of certain parameters, facilitating the formulation of a DoA estimation model in a five-sector scenario. The models presented in Table 3 characterize the signal propagation within specified ranges, detailing the range covered, the corresponding derived equation, and the associated errors for each entry.

Table 3. Summary of the DoA estimation models in Coverage Area 1.

Range	Equation ¹	Evaluation	
		RMSE	R ²
0°–65°	DoA = 129.6 – 3.74 × 10 ^{−7} (D × RSRQ × RSSI × RSSI _{strongest} – RSSI)	15.78	0.37
65°–80°	DoA = 48.770943 – 0.476991 × RSSI + 0.103709 × RSRQ	3.63	0.15
80°–170°	DoA = 244.19740 – 0.53929 × RSSI – 0.80461 × RSRQ	16.68	0.54
170°–250°	DoA = 326 – 1.065 × 10 ^{−6} (D × RSRQ × RSSI × RSSI _{strongest} – RSSI)	13.15	0.71
250°–305°	DoA = 114.6 + 7.454 × 10 ^{−6} (D × RSRQ _j × RSSI × RSSI _{strongest} – RSSI)	10.71	0.47
305°–360°	DoA = 321.7 + 3.416 × 10 ^{−4} D ² + 1.802 × 10 ^{−38} × RSSI ²⁰ _{strongest} + 1.54 × 10 ^{−5} × RSSI ³	14.54	0.26

¹ Model for DoA estimation.

3.2. DoA Estimation in Coverage Area 2

3.2.1. Analysis of Radiofrequency Parameters and DoA Ranges

In the analysis of the RSSI as a function of the distance within various DoA ranges, the correlation between the RSSI values and the distance from the BS shows a non-linear trend [15]. The dataset, segmented into discrete DoA ranges, reveals that the RSSI values generally decrease with an increasing distance, consistent with the free-space path loss model. However, this attenuation is not uniform across all the DoA ranges [16].

Figure 7 depicts a scatter plot of the RSSI values, color-coded for different DoA ranges determined by the mobile device’s geometric position relative to the BS. Each DoA range represents a specific angular sector around the BS. The colors in the scatter plot visually segment these sectors. Certain DoA ranges show more pronounced decreases in the RSSI with the distance, indicating a directional dependence of the signal attenuation. This variation could be due to factors such as the antenna radiation patterns, environmental obstacles, or multipath effects relative to the BS. Overall, the RSSI’s dependence on the distance varies across the DoA ranges, reflecting the complex interaction between the propagation environment and the antenna characteristics. This study’s approach, using segmented DoA ranges, offers a detailed understanding of this relationship and sup-

ports the development of predictive models tailored to the directional nature of wireless signal transmission.

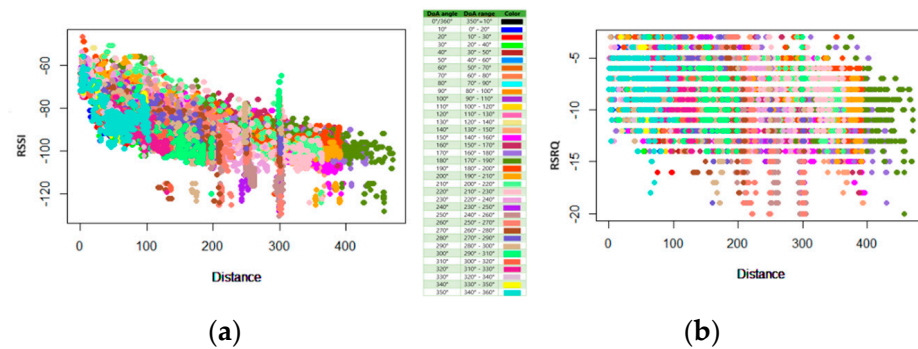


Figure 7. (a) RSSI dispersion for different DoAs as a function of the distance. (b) Scatter plot of RSRQ for different DoAs as a function of the distance in Coverage Area 2.

3.2.2. Correlation Matrix

Based on Figure 8a, the decision to create multiple models for each specified range, rather than a single model, was driven by observing the varying trends in the RF parameters as a function of the DoA. It was concluded that three distinct models should be developed for each designated range. The analysis indicated that a single model is inadequate for accurately predicting the DoA across all the observed ranges due to differing trends in the RF parameters. Figure 8b shows the correlation matrix for a specific range of 340 to 360 degrees, where the correlation values between the DoA and other variables increase compared to Figure 8a. To address this, separate models are designed for the following specified ranges: Range 1: 0°–150°, Range 2: 150°–220°, Range 3: 220°–300°, Range 4: 300°–360°.

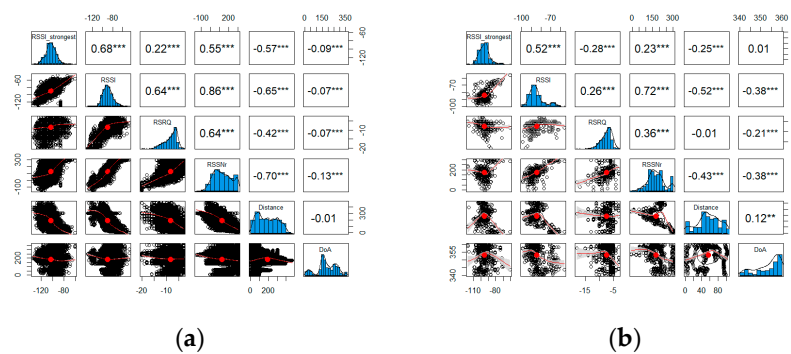


Figure 8. (a) General correlation matrix in Coverage Area 2. (b) Correlation matrix in a 340–360 degree range within Coverage Area 2. The more asterisks, the more significant the result.

For each range, a new dataset is created to filter the DoA within the specified range. Correlation matrices are then obtained based on these filters [17]. Custom models are developed for each range, using all the attributes and fitted according to the correlation matrix for its respective range, as proposed in [18]. The accuracy of each fitted model is evaluated within its defined range, allowing assessment of the model performance across different DoA segments [19]. This approach, necessitated by the non-uniform behavior of the RF parameters at different angles [20], ensures that the predictive performance is optimized for each DoA range [21].

3.2.3. Model Summary Using DoA Ranges

The table summarizes the results of various models used to estimate the DoA in Coverage Area 2. The models are categorized into two types: “General” and “Ranges”.

Each category includes different equations for estimating the DoA, with the effectiveness evaluated using two well-known metrics: RMSE (root mean square error) [22], and R^2 (coefficient of determination).

As shown in Table 4, the general model covers the full angular range, while specific equations are designed for segmented ranges. The model efficacy is assessed using the RMSE, which measures the prediction accuracy, and the R^2 , indicating the variance explained by the model. The segmented approach shows that the tailored models yield more accurate estimations within specific angular intervals, enhancing the model performance understanding across different ranges.

Table 4. Summary of the DoA estimation models in Coverage Area 2.

Range	Equation ¹	Evaluation	
		RMSE	R^2
0°–150°	$(-4.969 \times 10^{-7} \times D + 9.921 \times 10^{-5} \times \text{RSSI}) \times \text{RSSN}_r \times \text{RSRQ} \times \text{RSSI}_{\text{strongest}} \times \text{RSSI} - 3.487 \times 10^3$	17.93	0.89
150°–220°	$2.693 \times 10^{-7} \times \text{RSSN}_r \times \text{RSSI} \times \text{RSSI}_{\text{strongest}} \times \text{RSRQ} \times D + 3.737 \times 10^3$	13.12	0.55
220°–300°	$(-1.528 \times 10^{-3} \times D - 8.819 \times 10^{-4} \times \text{RSSN}_r) \times \text{RSSI} \times \text{RSSI}_{\text{strongest}} + 1.791 \times 10^{-8} \times \text{RSSN}_r \times \text{RSRQ} \times D \times \text{RSSI} \times \text{RSSI}_{\text{strongest}} + 2.136 \times 10^3$	17.27	0.34
300°–360°	$(-8.540 \times 10^{-5} \times \text{RSSI}_{\text{strongest}} - 1.791 \times 10^{-5} \times D) \times \text{RSSN}_r \times \text{RSRQ} \times \text{RSSI} + 3.270 \times 10^3$	14.41	0.47

¹ Model for DoA estimation.

4. Conclusions

This paper addresses the DoA estimation problem in a real cellular network, proposing a novel method based on real radio frequency measurements and known radio infrastructure characteristics. Unlike traditional methods that use antenna array signals as input, this approach leverages changes in the radio frequency parameters within the spatial domain of cell coverage. The modified linear regression models for a five-sector coverage area outperform those for a three-sector coverage area. Future research should explore the analysis of radio frequency measurements, particularly because mobile devices are frequently connected to the considered BS. Additionally, iterative refinement of the estimation algorithm based on experimental feedback, considering communication obstructions, and working with an isolated BS offer promising directions. During data collection, events such as cell reselection and handover affected the DoA estimation accuracy. Future work will focus on theoretical analysis of the proposed method, improvements in the RMSE, and testing the method in dynamic environments to ensure its robustness and accuracy.

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