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A Novel RSS Fingerprint to Locate User Equipment UE in Remote Area

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Abstract: Location determination algorithms are widely used in cellular networks, especially in the long-term evolution (LTE) network, to enable the provision of location-based services (LBS). The increasing global demand for cellular networks has resulted in the creation of new user equipment (UE) positioning systems that align with the network's momentum. Regrettably, all of these technologies are hindered by their incapacity to ascertain the location of the UE in distant regions. This article introduces a novel method utilizing Radio Frequency (RF) fingerprinting to precisely locate UEs in remote areas. The approach entails employing a proposed partitioning model with a high level of precision, incorporating artificial intelligence and machine learning AI/ML in its fundamental state to reduce the search area. Furthermore, two algorithms are suggested: The first aims to enhance the efficiency of the battery with limited capacity by decreasing the frequency of measurements transmission. The second utilizes Jaccard similarity and incorporates the prefix filtering technique to determine matches. The algorithm is used to speed up the process of matching the fingerprint recorded in the fingerprint database with the fingerprint captured in real time. The results shows that it can reduces the transmission rate by 77.08% and achieves the lowest error rate of 35.34 m. Additionally, it exhibits a response time of 8 seconds.

Keywords: LTE, UE, AI/ML, LBS, RF Fingerprint.

1. INTRODUCTION

Location technologies, ranging from the initial first generation 1G to the latest fourth generation 4G, have been extensively utilised for commercial applications and to offer services like location-based services (LBS) and emergency response in case of accidents. The primary incentive was to generate monetary gains through the provision of these services and the promotion of the products. In recent times, cellular networks have experienced a growing dependence on them because of the wide range of services they offer, particularly the LTE network. This network has incorporated location-determining technology to aid in rescue efforts during natural disasters. The utilisation of these technologies in a different domain than their intended purpose results in variations in their performance in terms of accuracy, speed, and operational mechanism. Furthermore, similar approaches have been employed for police investigations and military objectives (law enforcement agencies), in order to help reveal the locations of local criminals, organized crime gangs, or terrorist organizations. The existing methodologies for identifying locations do not satisfy the needs of law enforcement authorities, and this emerging sector has numerous challenges as outlined in [1]. These areas function as sanctuaries and command centres for these illicit organisations to carry out their operations away from heavily populated urban areas in order to evade detection, monitoring, and legal action, as well as to minimise the risk of being detected by law enforcement officials upon their arrival from distant locations. The difficult terrain of these places offers a means of escape for these criminal organisations. Furthermore, law enforcement authorities need to provide additional criteria for UE locating methods, including stringent accuracy, cost-effectiveness, prompt reaction time, adaptability to both urban and rural settings, and efficient system implementation, as elaborated in [1]. The RF fingerprint approach, particularly using RSSI, is a widely used technique for establishing the position of a UE. This method is favored for its affordability, as it does not require extra equipment, and its reliance on the network's interaction with the UE. The RF fingerprint approach comprises two distinct phases: Offline and Online. The initial stage involves the selection of a certain area, followed by the segmentation process, data collection, and subsequent manipulations on the fingerprint database to align with the established or utilized matching algorithm. The second phase involves comparing the fingerprint obtained in real time for the UE with the fingerprint stored in the fingerprint database [2], [3], [4].

A new the applications of fingerprinting techniques were many, and the methods of utilization and implementation varied depending on the specific problem to be resolved. Furthermore, they exhibited variations in the measuring methods employed to construct the fingerprint, which facilitated the identification of the UE's location based on the specific nature of the problem at hand. The researcher in [5] suggested a series of strategies utilizing fingerprinting to address the issue of limited bandwidth in Narrowband Internet of Things (NB-IoT) transmissions in outdoor environment. Given that IoT systems depend on the integration of location information with data obtained from IoT devices, it is imperative to have a precise mechanism for detecting position. Hence, the researcher suggested employing the fingerprint technique to ascertain the location. Furthermore, the fingerprint utilized comprises measurements derived from multiple cells, encompassing four types of measurements: Received Signal Strength Indicator (RSSI), Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal to Interference plus Noise Ratio (SINR), during the offline phase. Pending the online stage, the researcher suggested utilizing the Weighted k Nearest Neighbors (WKNN) algorithm to accomplish the task of matching. This technique is specifically employed to match the fingerprint stored in the fingerprint database with the fingerprint of the UE in real time. The limitation of this method is that it is dependent on smartphones, not usable in remote areas, requires at least three eNBs, and is not compatible with non-smartphones. In [6] the researcher introduced a novel technique, referred to as compact snake optimization cSO, in order to enhance the accuracy of localization systems that rely on fingerprints in indoor environments. Furthermore, it was proposed to utilize RSSI measurements for creating fingerprints during the offline phase, and it was also recommended to employ the WKNN algorithm for real-time fingerprint matching. Furthermore, individually assess the functioning of each algorithm and thereafter integrate the two algorithms to evaluate their effect on the localization system. The findings demonstrate that the integration of both techniques enhances the precision of indoor localization. The limitation of this method, restriction to indoor environments, reliance on data from several cells to provide a unique identifier, the need for additional equipment to be integrated into the network, inapplicability in outdoor settings, and ineffectiveness in remote places. In [7] the researcher endeavored to enhance the precision of LBS systems in indoor settings. To do this, the researcher used a novel machine learning framework called Bag-of-Features BoF as a technique. The characteristics are categorized using k-nearest neighbor classification as well. Furthermore, the K-means algorithm is employed to divide these features into distinct clusters, and subsequently, the BoF technique is utilized to calculate the frequency of features within each cluster. This suggested technique utilizes RSSI data from several stations to generate fingerprints. The method then extracts features from these fingerprints, which are subsequently employed to infer location. Limitations include the inability to function in outdoor environments, the need for many stations to measure the signal, and the inability to be used in remote places. In [8] the study suggested employing Artificial Neural Networks ANN to enhance the precision of indoor localization systems that rely on fingerprinting. Additionally, it was proposed that the fingerprint may be constructed using RSSI readings. Principal Component Analysis PCA was employed to decrease the data's dimensions, serving as a way for transforming the data. The neural network use RSSI measurements as input, with the hidden layer serving as the learning model, the position is utilized as an output. Hence, the suggested system has the ability to simultaneously detect many targets. Limitations include (inability to function in outdoor environments, imprecise segmentation model, non-applicability in remote regions). In [9] the study suggested employing ANN to enhance the precision of indoor localization systems that rely on fingerprinting. Additionally, it was proposed that the fingerprint may be constructed using RSSI readings. Principal Component Analysis PCA was employed to decrease the data's dimensions, serving as a way for transforming the data. The neural network use RSSI measurements as input, with the hidden layer serving as the learning model, the position is utilized as an output. Hence, the suggested system has the ability to simultaneously detect many targets. Limitations include (inability to function in open-air settings, imprecise segmentation model, non-applicability in remote regions). In [10] the researcher suggested utilizing machine learning (ML) as a means to enhance the accuracy of Global Navigation Satellite Systems GNSS systems in metropolitan environments, where precision is compromised by the crowded outdoor environment. In addition, he proposed the creation of a fingerprint using RSS measurements from various sources, and subsequently merging these measures with GNSS systems in order to enhance precision. To enhance efficiency, employ ANN on the merged dataset to function as a regression model. Furthermore, the KNN method was employed to compare fingerprints throughout the online phase. Limitations include (compatible exclusively with cellphones, non-applicability in remote regions, high cost). In [11] the researcher suggested creating a hybrid method that combines RSS and TA measurements from the sounding reference signal (SRS) to enhance the precision of localization systems. Additionally, time-difference-of-arrival (TDOA) measurements would be used to create a fingerprint and improve the effectiveness of localization systems in indoor settings. Furthermore, a suggestion was made to employ evenly spaced sensors for measuring TDOA, and to utilize least squares and deep neural network DNN for fingerprint matching during the online phase. Limitations include (ineffective an outdoor environment, necessitates supplementary network equipment, high cost, impractical in remote regions). In [12] the researcher suggested a technique that involves transforming RSS readings obtained from several eNBs in a particular region into grayscale images. To classify these images, the researcher advocated utilizing a DNN. The fingerprint is generated as grayscale photos. In addition, he suggested employing cross-entropy as a loss function and utilizing dynamic network rate for the learning rate. Furthermore, the system utilizes the Deep Residual Network (DRN) as a hierarchical training approach, alongside a feed-forward neural network (FFNN), to provide precise location identification. Limitations include inapplicability non remote places, high expense, and computational complexity. The primary issue we are endeavoring to address is the identification of the UE within the LTE network using a solitary eNB. This is intended to assist law enforcement agencies in apprehending individuals associated with criminal organizations in remote regions. The primary cause of this issue stems from the fact that the majority of location determination methods necessitate the utilization of a minimum of three eNBs for optimal functionality [1]. Furthermore, the accuracy of the method increases proportionally with the number of eNBs present in the vicinity. Hence, in this research, we suggest utilizing RSS-fingerprinting to determine the location of the UE using a single eNB. Additionally, we recommend employing a ML approach to narrow down the search area, accelerate the response time, and minimize the search duration. The contribution of this essay can be encapsulated in:

- After thoroughly examining prior and current studies on location determination techniques, we can confidently state that we are the pioneers in successfully determining the position of a UE in an LTE network using only one eNB.
- The partition model presented in this article relies on the subdivision of the entire region into smaller sub-regions, referred to as fingerprints. Furthermore, reference points RP are strategically distributed within each fingerprint in a precise geometric arrangement to effectively capture a maximum number of fingerprint features within each sub-region. This approach differs from fingerprint-based approaches, where the RP is spread throughout the entire region's paths, resulting in the failure to capture the unique characteristics of the fingerprint and thus leading to low accuracy.
- Minimizing the transmission measurements rate between the UE and the LTE network while ensuring the network's operations and functionalities remain unaffected.
- The proposed matching algorithm operates by means of three phases. The initial phase aims to ascertain the resemblance between fingerprints using Jaccard similarity. The second stage is to identify the presence of overlapping fingerprints by utilizing overlap similarity. In the final stage, the prefix filtering technique is employed to identify the similarity coefficient with the lowest value. As far as we know, this is the initial instance where Jaccard similarity and overlap, along with the prefix filtering methodology, have been employed in UE localization methods within the LTE network.

2. A NOVEL RSS FINGERPRINTS

2.1 Selected Area

In order to simulate the issue at hand, we have selected a desert region due to its conducive conditions for criminals to conceal themselves and carry out illicit activities. The current setting renders it unfeasible for law enforcement authorities to undertake the task of chasing them. The specified region is encompassed by a single eNB, with a coverage area of 283.5 kilometers in a circular configuration. The coverage diameter measures 19 kilometers, while the coverage radius spans 9.5 kilometers. Given that the eNB consists of a minimum of three sectors, with each sector covering an angle of 120 degrees, the coverage area of each sector is 94.5 km.

It is important to emphasize that there is no precise assessment of the extent of the signal transmitted by the eNB. Based on our case study and empirical testing conducted in remote locations, we have determined that the optimal distance for receiving all LTE network services without any issues is 9.5 km, as show in Figure 2.

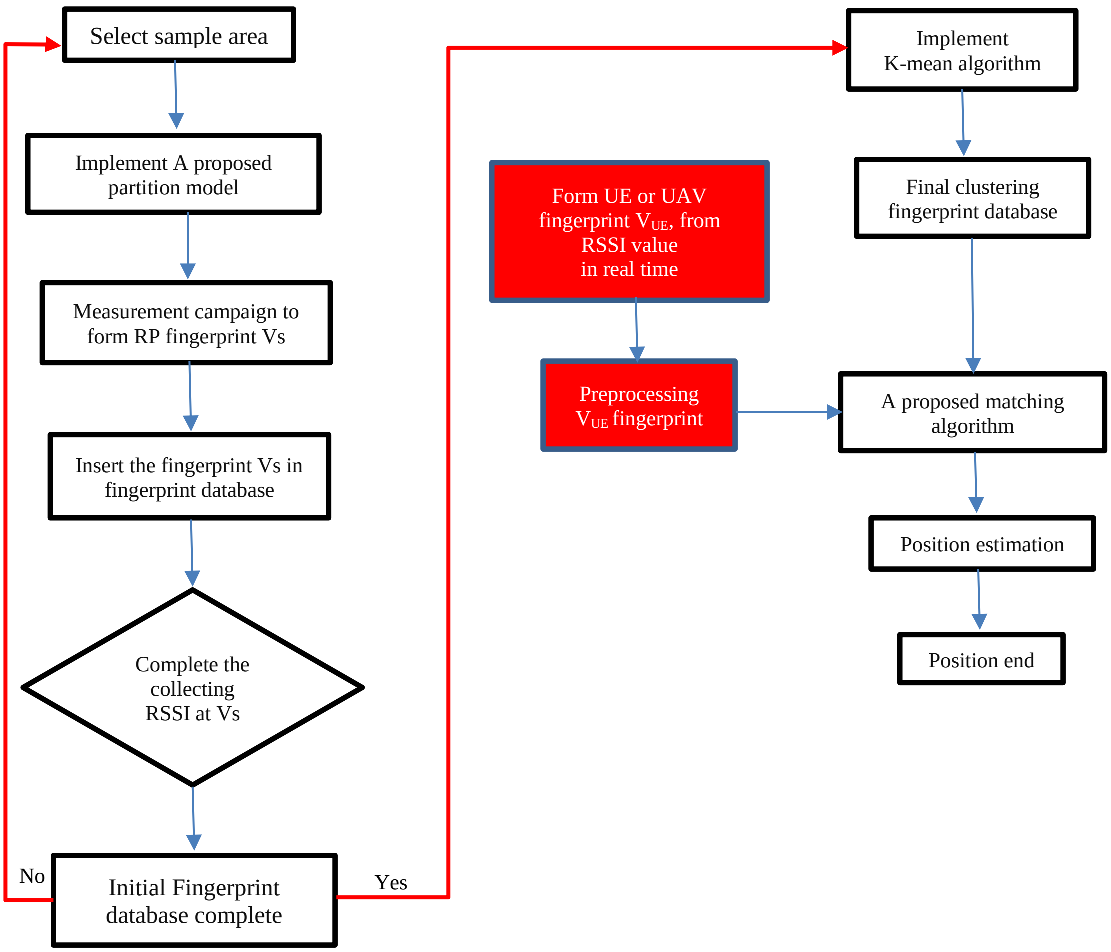

Figure 1. The diagram of the proposed method.

2.2 A Proposed Partition Model

The suggested partitioning model effectively addresses the limitations inherent in fingerprint-based approaches instead of relying utilizing distributed reference points along the paths in those areas to generate a path-specific fingerprint [5]-[12]. The primary concept in the proposed model is to partition the entire region into sub-regions, denoted as SR, and distribute reference points within each sub-region, denoted as RP. The primary objective of partitioning the entire region and allocating reference points within it is to comprehensively capture all the distinctive characteristics of that region in order to create its unique fingerprint. In the given problem, we have suggested that the area of the SR should be 500 square meters in the desert region. The suggested partition model exhibits significant adaptability, allowing for the modification of the size of the SR based on the region's characteristics (such as hilly, urban, or rural areas) without compromising the overall functionality of the technique. The overall area covered by one sector is 94.5 square kilometers. To facilitate division into smaller units, we convert this amount from square kilometers to square meters. As a result, the area of the sector becomes 9450000 square meters. Specifically, there are 189,000 SR in each sector, resulting in a total of 576,000 SR across entire eNB coverage.

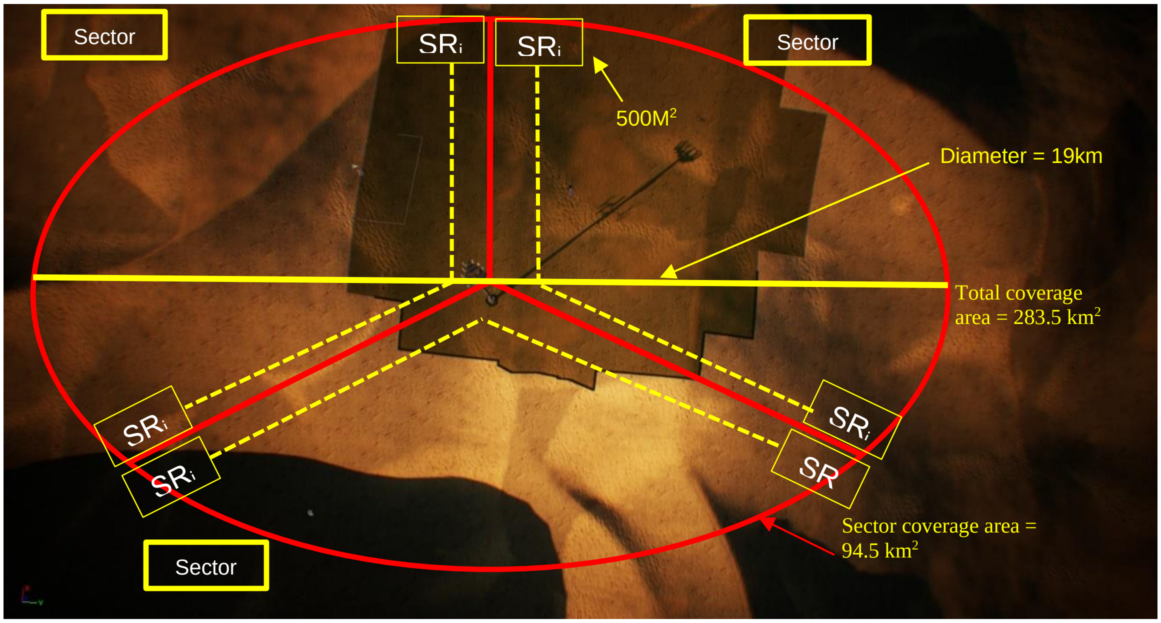

Figure 2. A Proposed Partition Model.

2.2.1 Distribution of RP In SR

A total of 24 RP is allocated in the SR to accurately and exclusively capture the distinctive characteristics of the fingerprint. The points are arranged in a perfect geometric pattern. Four RP are positioned at the corners of the square, forming a 90-degree angle. Each RP is located one metre away from the two adjacent sides. Subsequently, the remaining RP is evenly allocated inside the SR, after subtracting a distance of 1 metre from both sides. This is done considering that the square's side length measures 22.36 units. In order to express this process in mathematical terms, we adhere to the subsequent equation.

$$D = \frac{2 - SL}{1 - N} \quad (1)$$

Where D is the distance between RP, SL is the square side length, N is total RP in side length.

The distribution of RP within the SR will be organized in a grid format, consisting of four rows and six columns, as depicted in Figure 3. The purpose of identifying the four RPs in the corner is to minimize the disparity between two neighboring SRs and to aid in the identification of similarities and overlaps in fingerprints. Furthermore, there is a fixed distance of 1 meter between each successive SR, resulting in the adjacent RP being just 3 meters apart from another SR. Figure 4 depicts the configuration of the neighboring SRs and the precise distance that separates them. By substituting the given values into equation (1), the resulting expression is obtained:

$$D_1 = \frac{2 - 22.36}{1 - 6} = \frac{20.36}{5} = 4.072m$$

$$D_2 = \frac{2 - 22.36}{1 - 4} = \frac{20.36}{3} = 6.786m$$

2.3 Collection Measurements

Once the partition model has been fully implemented according to the specifics given in the previous section, the data gathering stage commences. In this stage, the fingerprints for the SR are generated in the form of a vector known as a V_{SR}. This vector or fingerprint includes several components: the eNB identifier, known as eNB_{ID}, the eNB location represented by eNB_L, the eNB sector from which the RSS measurements were obtained within the SR, referred to as eNB_{SEC}, RSS measurements at each RP point distributed within the SR from RP_1 to RP_{24}, the coordinates of the center of the SR denoted as sen (x, y), which are utilized for location matching in the online stage, and MAX (RPN) and MIN (RPN). The ultimate fingerprint will appear in this manner:

$$V_{SR} = [eNB_{ID}, eNB_L, eNB_{SEC}, RP_1, \dots, RP_{24}, sen(x, y), MAX(RP_{24}), MIN(RP_{24})]$$

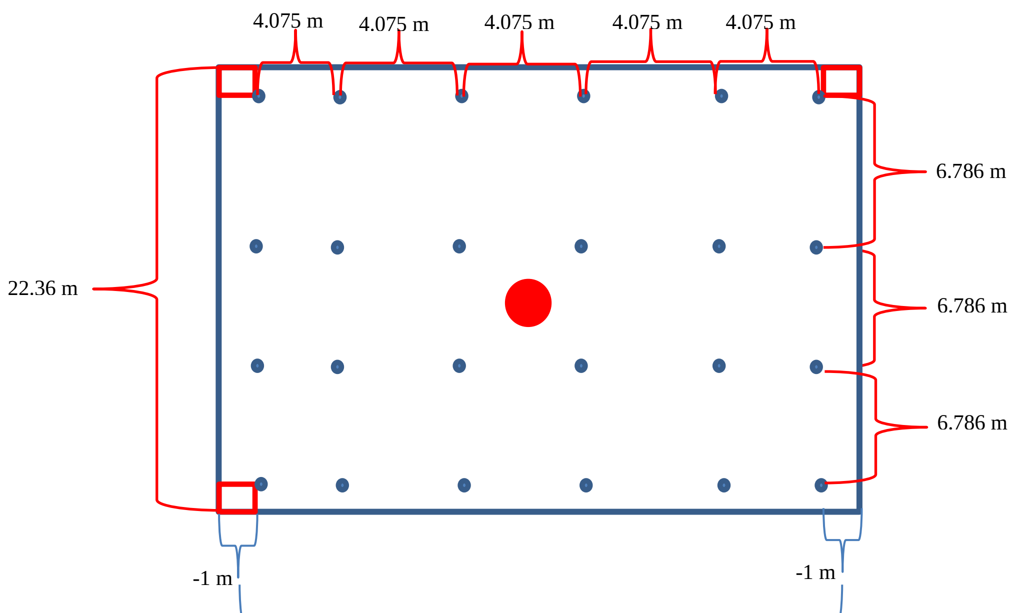

Figure 3: distributed 24 rp with sub-region.

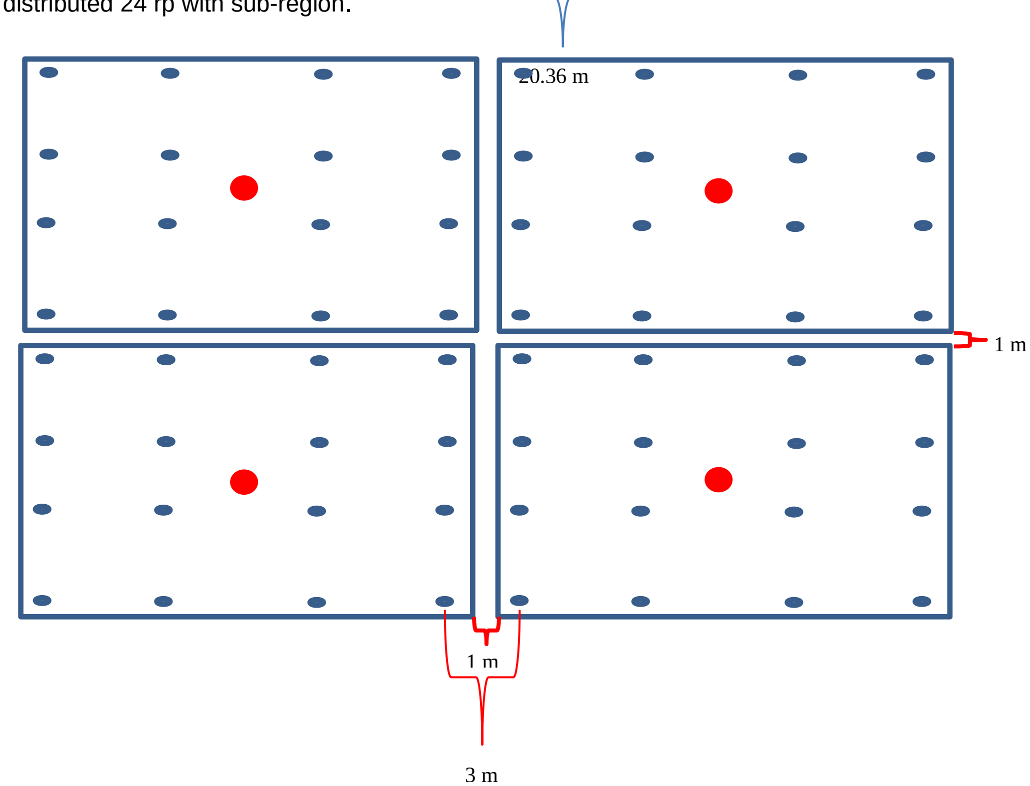

Figure 4: Distances between sub-region SR.

2.4 Building Fingerprint Database

During the data collecting phase, each SR generates its own fingerprint in the form of a vector V_{SR}, which is then placed in the initial fingerprint database. At this point, it is guaranteed that all RSS measures that make up the fingerprint are collected and that no measurement is omitted. If there is a shortage in the fingerprint measurements, the fingerprint is sent back to the collection step before being saved in the initial fingerprint database [9]- [7]. The search for a match in the initial fingerprint database is inefficient due to the large size of the data. The current search technique is time-consuming, resulting in longer response times. Hence, in order to address this issue, we suggested employing the clusters functionality through the utilization of the k-means method. The algorithm receives the centroid coordinates of the fingerprints (SR) as input, resulting in each cluster being formed by a collection of neighboring fingerprints determined by their coordinates. The clustering feature greatly reduces search time and minimizes response time. However, a new challenge arises: calculating the value of k depending on the magnitude of the available data. Various techniques, such as the gap statistic, mean shift, silhouette analysis, and elbow method, are employed to ascertain the value of k. In our particular example, we utilized the elbow approach.

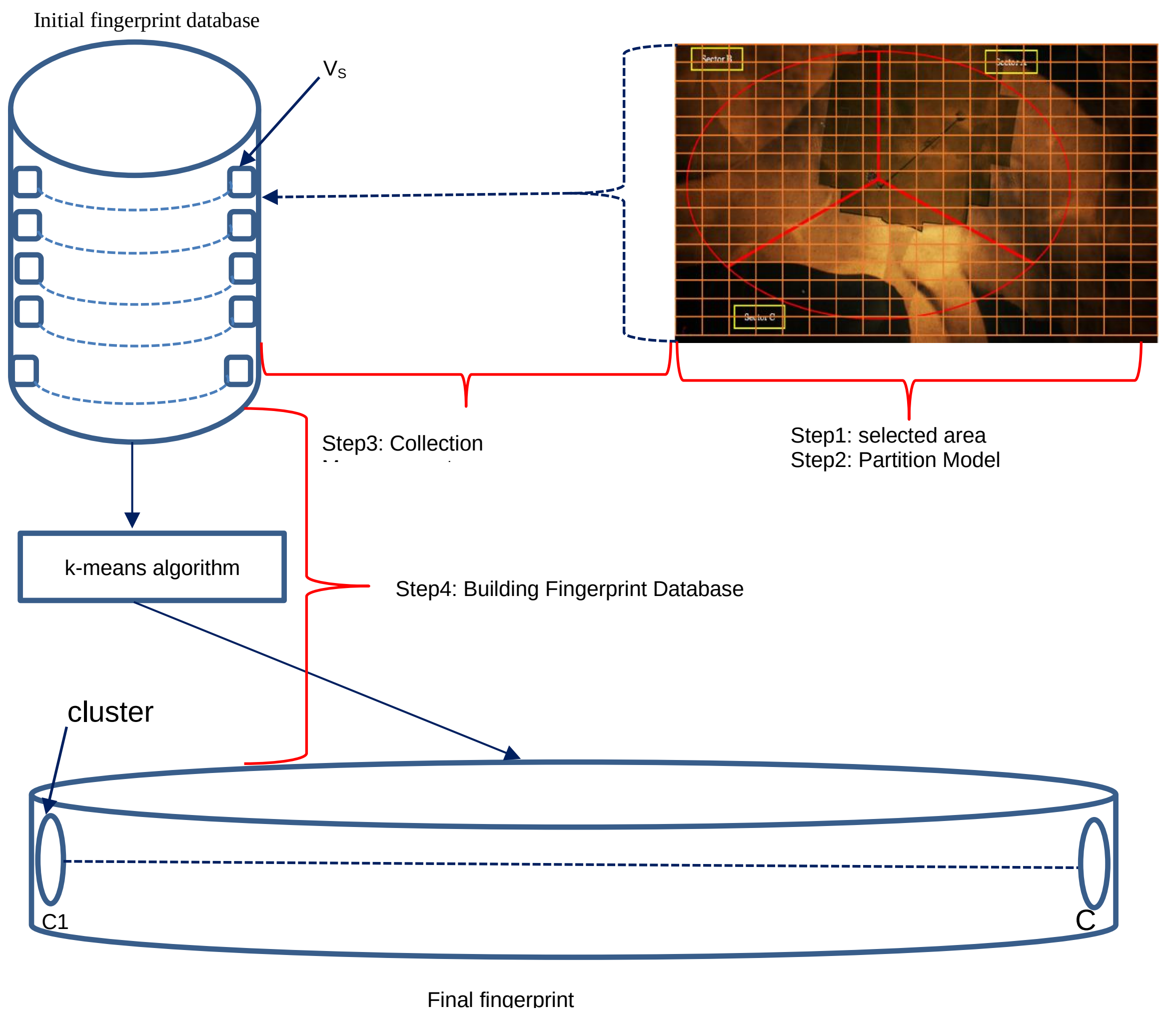

Figure 5. clustering feature.

Figure 5 depicts steps 1 to 4, illustrating the utilization of the cluster's format for the fingerprints database. A cluster is a collection of neighboring fingerprints organized according to their coordinates. This approach significantly enhances the matching process during the online stage.

2.5. Training Stage

Number of clusters	eNBloc	eNBCID	eNBsec	MINrp	MAXrp
1	(x,y)	1	1	-49.09686279	-49.09354401
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
N	-	-	-	-	-

Here, the characteristics of each cluster are identified based on the measurements and parameters of the SR it holds, aligning with the functionality of the proposed matching algorithm during the online phase. That is, seeking qualities that aid in the matching process [13], [14], [15]. Thus, each cluster is assigned a label that helps differentiate it from others based on its specific parameters, as illustrated in Table 1.

Table 1. *cluster lapel*

Table 1 displays five factors that differentiate each cluster from the others. The parameters are the eNB location, eNB ID, sector ID within the eNB, highest RSS measurement from all SRs within the cluster, and lowest measurement value. After finishing this stage, the crucial final step is testing. This stage is to confirm the accuracy and coherence of the data produced during the training phase. The data is split into two parts: 70% for training and 30% for testing. This stage is the final step in the offline process before transitioning to the matching phase in the online phase.

2.6 Online Phase

This phase represents the final step in executing our suggested approach for determining the UE's position in remote areas. Typically, in this phase, one would select a commonly used matching method or develop a new one that is appropriate for the fingerprint database. Creating fingerprints for SR involves tailoring them to the parameters of the algorithm [16], [17]. The key is to understand how the algorithm functions and then design the fingerprint database accordingly. At this point, our approach diverged from conventional ways by not only enhancing and evolving the matching algorithm but also by devising an algorithm to conserve energy for the UE. The aim is to minimize the periodic transmission of measurements between the UE and the LTE network. The UE's restricted battery capacity results in increased battery power consumption when delivering measurements often.

2.6.1 A Proposed Power Saving Algorithm

Signaling messages refer to the signals exchanged between the UE and the LTE network. This operation proceeds at regular intervals every 30 milliseconds using the two protocols LPP and LPPa [18], [19]. The primary objective of this operation is to direct calls to and from the cellular network by providing the network with essential information about the virtual location of the UE for call routing. The network has to be aware of the eNB's identification, its geographic position, and the specific sector within the eNB's service area to which the UE is connected. The UE receives signals from the eNB, conducts necessary measurements, and transmits these measurements to the network as initial location information. We developed a power-saving method to minimize redundant transmissions and preserve the limited battery capacity of the UE while maintaining seamless connectivity with the LTE network.

Our solution primarily depends on fingerprints during the offline phase and we suggest creating the fingerprint for the UE in real-time during the online phase. The fingerprint is a vector represented by Vue. The fingerprint shares the same properties as the SR fingerprint, but differs in the method used to generate the measurements. The unique RSS readings present a challenge comparable to that encountered in wireless sensor networks (WSN), where neighboring sensor nodes may transmit identical or similar data [20], [21]. This results in heightened network traffic and decreased battery life because of its restricted capacity. We are working on refining this approach by drawing on past experiences and enhancing them to address the current issue. We utilized a similarity function named Similar measurement (SM) based on the following equation.

$$Similar\ measurement\ \ (SM)(MV_{UEi}, MV_{UEi+1}) = \begin{cases} 1\ if\ \|MV_{UEi} - MV_{UEi+1}\| \leq \delta, \\ 0 \qquad\qquad\qquad\qquad otherwise. \end{cases} \qquad (2)$$

The first measurement read to create the UE fingerprint is denoted as MV_{UEi} and kept as V_{UE}. The similarity threshold, δ, is determined by practical application.

Algorithm 1 Power Saving in UE fingerprint
Require: new measure MV_{UEi+1}, unique from previous measures in fingerprint V_{UE}
Guarantee: searching for similarities measures in V_{UE}

1. For every measure $MV_{UEi} \in V_{UE}$ do
2. If (similar measur (MV_{UEi}, MV_{UEi+1})) =1 then
3. f (MV_{UEi}) ← f (MV_{UEi}) + 1
4. Delete MV_{UEi+1}
5. Else
6. Add MV_{UEi+1} to the fingerprint V_{UE}
7. f (MV_{UEi+1}) ← 1.
8. If sum (MV_{UE}) = 24 then
9. end

Algorithm 1 stores the initial measurement in the UE's fingerprint vector and then compares any subsequent measurements to the original one. If the condition is satisfied, the second measurement is removed, and the first measurement is retained. If the criterion is not satisfied, the second measurement will be included in the fingerprint. This step is iterated until all UE fingerprint measurements are finished. In the method, we determined both the similarity of measurements and introduced an index for the frequency of measurements in the fingerprint, which represents how often the same measurement occurs during the fingerprint creation process. The primary goal is to streamline and expedite the matching process in real-time, resulting in a quick response time. The algorithm now reduces the process of delivering similar measurements by 40% by requiring the UE to only submit unique measurements.

This study is the first to utilize the similarity and frequency of measurements to create a real-time fingerprint of the UE in the online phase, reducing the need for measurement transmission between the LTE network and the UE. Therefore, reducing the consumption of limited battery capacity.

2.6.2 A Proposed Matching algorithm

The proposed algorithm we are investigating utilizes JACCARD similarity and prefix filtering to match the UE fingerprint in real time with the SR fingerprint stored in the database [20]- [22]. Integrating these two notions into location determination algorithms is unprecedented, given there is no prior evidence of their application.

- **JACCARD similarity**

The primary objective of utilising JACCARD similarity is to determine the similarity between two fingerprints A and B as an initial step using the following equation.

$$\mathrm{J}\ (\mathrm{V_{SR}}, \mathrm{V_{UE}}) = \frac{|V_{SR} \cap V_{UE}|}{|V_{SR} \cup V_{UE}|} \geq t \qquad (3)$$

Where t is the similarity threshold between the two fingerprints.

Reaching this stage signifies the initial identification of fingerprint resemblance, which decreases the number of pointless searches, lowers computing usage, and so quickens response times. Determine the number of intersecting measures based on the similarity threshold of measurements δ between fingerprint $V_{SR} = [M_{SRi}, \ldots, M_{SR24}$ and fingerprint $V_{UE} = [M_{UEi}, \ldots, M_{UE24}$, relative to the total number of measurements in the two fingerprints using equation (3). Completing this phase enables progression to the subsequent stage in the algorithm to determine the level of matching with increased precision.

- **Prefix Filtering Technology**

This strategy operates by computing the shared prefix between two groups, rather than considering all components from both groups. This technique was employed to identify fingerprint similarities due to its minimal computing consumption, which enhances the efficiency and accuracy of fingerprint matching [20]-[21]. Initially, the measurements of the two fingerprints need to be organized in either an ascending or descending order, based on the problem type and solving method. We have suggested an ascending order, so we require the following definition:

Definition 1 Ordering Measurements (OM): *Sort the measurements of fingerprint V_{UE} in ascending order based on its frequency index, which is the result of algorithm (1) used during the fingerprint creation. Sort V_{SR} fingerprint measurements in ascending order.*

We must transform equation (3) into overlap similarity:

$$J(V_{SR}, V_{UE}) \geq t \leftrightarrow O(V_{SR}, V_{UE}) \geq \alpha \qquad (4)$$

Where, $\alpha = \frac{t}{1+t} \cdot (|V_{SR}| + |V_{UE}|)$

We also require a function to determine the quantity of overlapping pairs between fingerprints V_{SR} and V_{UE}. The function is referred to as the overlapping pair's function and is represented by the symbol $\cap_P$, as defined below:

Definition 2 Overlapping Pair's Function (OPF) $\cap_P$***:*** *Two fingerprints V_{SR} and V_{UE} are considered overlapping if and only if the outcome of their intersection consists of similar ordered pairs, as determined by a Similar measurement, so we define:*

$V_{SR} \cap_P V_{UE} = \{(MV_{SR1}, M_{UE1}) \in V_{SR} \times V_{UE} / SM(MV_{SR1}, M_{UE1}) = 1\}$

The approach of creating identical ordered pairs from the point of intersection between the two fingerprints, as described by the aforementioned formula, substantially simplifies the real-time matching procedure. Furthermore, it is necessary to assess the functioning of the aforementioned formula in order to verify the resemblance of the fingerprints and pairs that are produced when the formula is applied, as outlined below:

$$J(V_{SR}, V_{UE}) \geq t \leftrightarrow |V_{SR} \cap_P V_{UE}| \geq \alpha = \frac{t}{1+t} \cdot (|V_{SR}| + |V_{UE}) \qquad (5)$$

After establishing the method for determining similar measurements and understanding the degree of similarity and overlap between the two fingerprints, as well as the notion of the frequency of measurement occurrence during the construction of the fingerprint for the UE in the online stage. It is now necessary to integrate this final concept with the prefix filtering technique, which aims to enhance the precision of finding matches between the two fingerprints. It is now necessary to indicate the prefix for each fingerprint based on the frequency of its readings, as illustrated in (5).

Algorithm (2) MATCHING.

Require: *C* is a set of clusters, V is a milt sets of victors in cluster c, each victor their element is stored by ordering O, each measure in V_{UE} fingerprint is stored by ordering O based on their frequency, measure similarity threshold δ, a Jaccard similarity threshold *t,* an overlap similarity threshold α, set the fingerprint size to (16,24,36).

Guarantee: Match is a match vector of measurements with V_{UE}.

```
M← Ø
i ← Ø(1 ≤ i ≤ total number of cluster in C)
l←1
for each c_i ∈ C do
    if c_{i-id} == V_{UE-id} and c_{i-sec} == V_{UE-sec} then
        if min c_i ≥ min V_UE and max V_UE ≤ max c_i then
            for each v_sj ∈ c_i do
                for k ← 0 to N do
```

9: if $|MV_{SK} - MV_{UEl}| \leq \delta$ then
10: f $(MV_{sk}) \leftarrow$ f(MV_{UEl}) +1
11: $par_{k,l}\ (V_{Sj}, V_{UE}) \leftarrow (MV_{sk}, MV_{UEl})$
12: else
13: l ← l+1
14: end if
15: end for
16: if sum_f(MV_S) / min (V_{Sj}) + min $(V_{UE}) \geq$ t
17: $p\_v_j \leftarrow (|V_{Sj}| - \alpha + 1)$
18: $p\_V_{uav} \leftarrow (|V_{UE})| - \alpha + 1)$
19: if sum $(par_{\square}(V_{Sj}, V_{UE})) \geq \alpha$ then
20: Match ← $V_{Sj-cordenaet}$
21: else
22: else
23: end for
24: end if
25: end if
26: end for
27: return Match

The proposed matching algorithm (2) conducts an initial assessment to identify the cluster to which the V_{UE} fingerprint belongs. This is done by comparing the eNB_{ID} and eNB_{SEC} values of the V_{UE} fingerprint with the eNBCID and eNBsec values of the cluster in its label, as illustrated in Table 1. In order to guarantee that the V_{UE} fingerprint matches the cluster, it is necessary to compare the MIN and MAX (RSS values) between the fingerprint and the cluster, as indicated in steps (5, 6). Following this phase, the degree of similarity between the V_{UE} fingerprint measurements and the V_{SR} fingerprints inside the cluster, determined based on the threshold δ, is assessed by considering the frequency of both the V_{UE} measurement and the V_{SR} measurement. When the criterion is satisfied, two measurements are taken and retained as a pair, and the second measurement of the V_{SR} is advanced. In the event that the condition is not satisfied, one proceeds to the subsequent measurement in V_{UE}, and continues this process for the remaining measurements (7-15). After finishing, the algorithm verifies if the total frequencies of the V_{SR} fingerprint exceed the similarity criteria for both fingerprints t. The next step is to verify that the number of identical pairs of the two fingerprints has exceeded the overlap threshold α. If the condition is met, the algorithm sets up the coordinates of the middle of the current V_{SR} as the location of the UE, and the steps continue if it is not verified.

3. EXPERIMENT SIMULATION AND RESULTS

The OMNET++ simulation kernel library (C++) was utilised in conjunction with the Python programming language to replicate the functionality of the LTE cellular network in remote desert regions . The components were fitted in an HP OMEN laptop including an Intel Core i9 processor, 32 GB of RAM, and 2 terabytes of SSD storage.

3.1 Experiment Setup

A single eNB was utilized to serve three sectors, namely A, B, and C. The coverage angle of each sector is 120 degrees. Therefore, the total coverage angle of the eNBs is 360 degrees. The eNB has a coverage radius of 19 km, resulting in a total coverage area of 283.5 km2. Hence, the extent of coverage for a single sector is precisely 94.5 square kilometers. The eNB's overall coverage area is partitioned into SRs, with each SR measuring 500 square meters.

Table 2. Simulation parameter

Parameter	eNB radius	eNB sector	Sector angle (A, B, C)	eNB coverage	SR space	Total SR	Signal power of eNB	wavelength	eNB antenna gain	UE antenna gain	Number of phase shift
Values	9.5 km	A, B, C	120, 240, 360	283.5 km2	500 M2	576000	40 dB	0.5m	3	3	4

3.2 Simulation Performance in Offline Phase

The simulation was performed once and lasted around 1 hour and 35 minutes. It was conducted to create the LTE network environment and collect RSS measurements from the dispersed RP and pre-defined in the SR, as described in Section 2.2. During this time frame, signaling messages were transmitted 15,800,000 times using the Lpp and Lppa protocols [18], [19]. Throughout this procedure, RSS readings were recorded for a total of 13,824,000 RP that were spread throughout all SRs. Within the coverage region of the eNB, there were a total of 576,000 SRs. Furthermore, the fingerprints for each SR were created as a vector (V_{SR}) based on the criteria outlined in Section 2.3. Table 3 displays a representative selection of the fingerprints that were recorded.

Table 3. *fingerprints sample at each SR.*

eNB_{ID}	eNB_{L}	eNB_{SEC}	**RP1**	**.**	**.**	**.**	**RP24**	**X**	**Y**	**MIN**	**MAX**
1	8980.768555	1	-42.58097404	.	.	.	-42.8784	27955.34	34338.34	-42.8784378	-42.58097404
1	8980.768555	1	-44.20933289	.	.	.	-44.387	34535.46	30106.02	-44.401285	-44.20933289
1	8980.768555	1	-44.36926904	.	.	.	-44.5696	30004.42	30038.94	-44.56962	-44.36926904
1	8980.768555	2	-49.03412515	.	.	.	-49.0412	36831.5	27117.82	-49.0511677	-49.02414077
1	8980.768555	2	-49.05284218	.	.	.	-49.06	36830.5	27095.46	-49.0698603	-49.04290109
1	8980.768555	3	-49.08100496	.	.	.	-49.0541	36763.42	42654.5	-49.081005	-49.05414845
1	8980.768555	3	NULL	.	.	.	-49.0623	36741.06	42676.86	-49.0834175	NULL

3.3.3 Clustering Feature and Training Data

Once the pre-processing stage is finished to ensure that all RSS measurements are recorded in each RP, the fingerprints (SR) are then divided into clusters using the k-means algorithm. The elbow method was used to choose the ideal k value relative to the size of the data used, as the k value = 576 at a rate of 1000 SR per cluster. Figure 6 shows the operation of the elbow method to choose k. The primary objective of this procedure is to effectively decrease the search space in real-time, resulting in a notable improvement in response speed. Once this step is finished, the data undergoes a training process to validate its accuracy, as well as to assign a label to each cluster that aligns with the suggested matching algorithm. Table 4 displays the results of the training procedure.

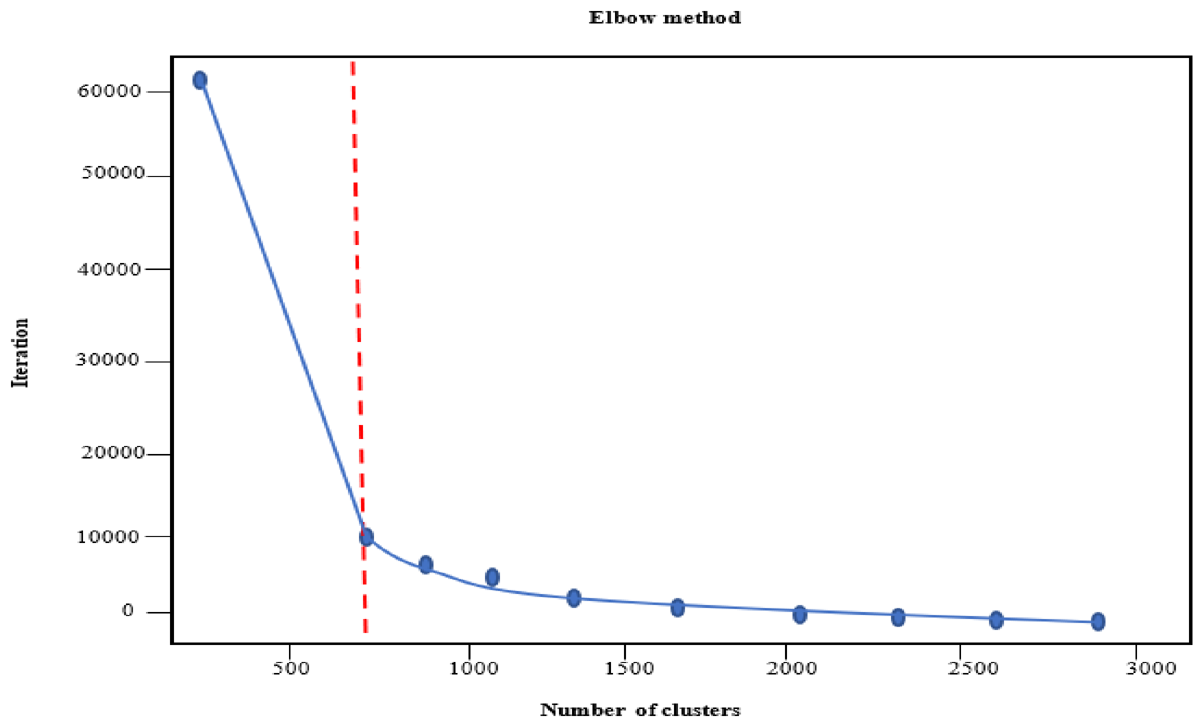

Figure 6. elbow method.

***Table 4**. sampling of the training procedure*

Number of clusters	eNBloc	eNBCID	eNBsec	MINrp	MAXrp
1	8980.768555	1	1	-49.09686279	-49.09354401
2	8980.768555	1	1	-	-
-	8980.768555	1	2	-	-
-	8980.768555	1	2	-	-
-	8980.768555	1	3		
-	8980.768555	1	3	-	-
-	8980.768555	1	1	-	-
-	8980.768555	1	1,3	-	-
-	8980.768555	1	3,2	-	-
-	8980.768555	1	2,1	-	-
-	8980.768555	1	3,1	-	-
-	8980.768555	1	2	-	-
-	8980.768555	1	1	-	-
-	8980.768555	1	2	-	-
576	8980.768555	1	6	-	-

Table 4 displays the fixed values of eNBloc and eNBCID, which correspond to the coordinates and identifier of the eNB location. These values remain constant as we are only considering a single eNB. The eNBsec varies based on the positions of the SRs within a cluster. Likewise, the values of MINrp and MAXrp are similarly modified based on the RP values found in the SRs inside a particular cluster. Figures 7 and 8 show the shape of the data before and after the training process, respectively, Figure 9 also shows the portion of data allocated for the testing.

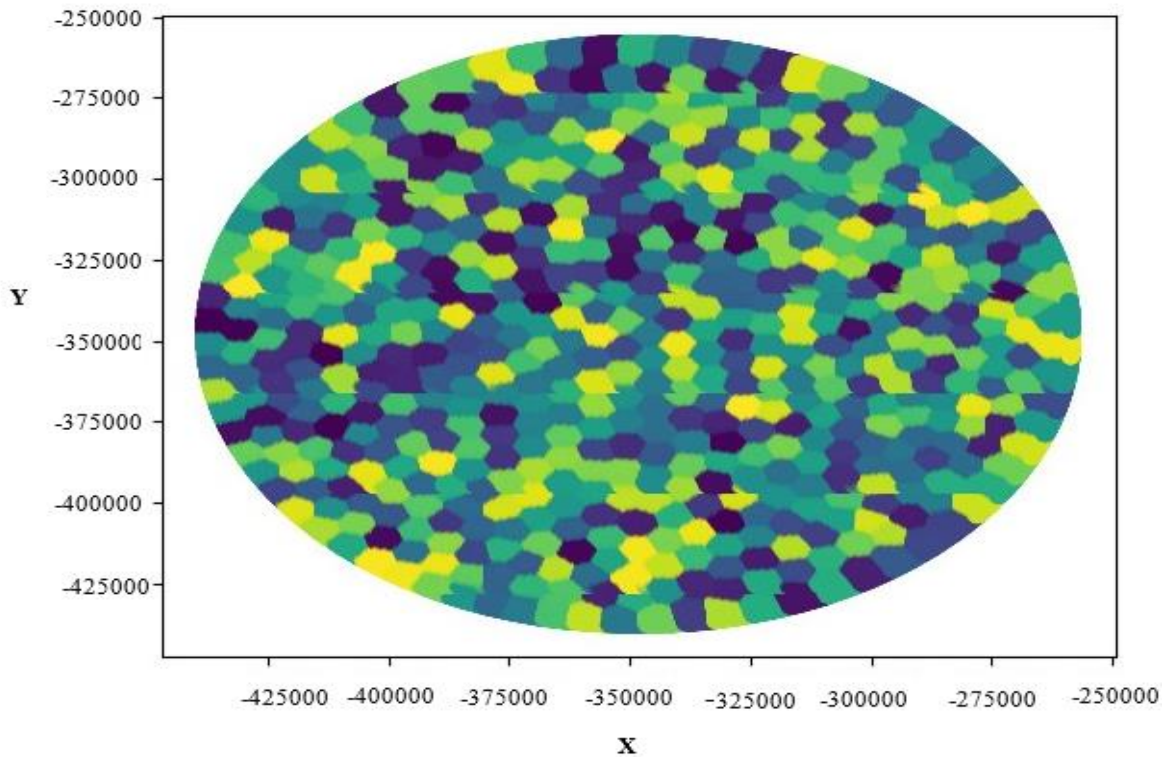

Figure 7. all fingerprint**.**

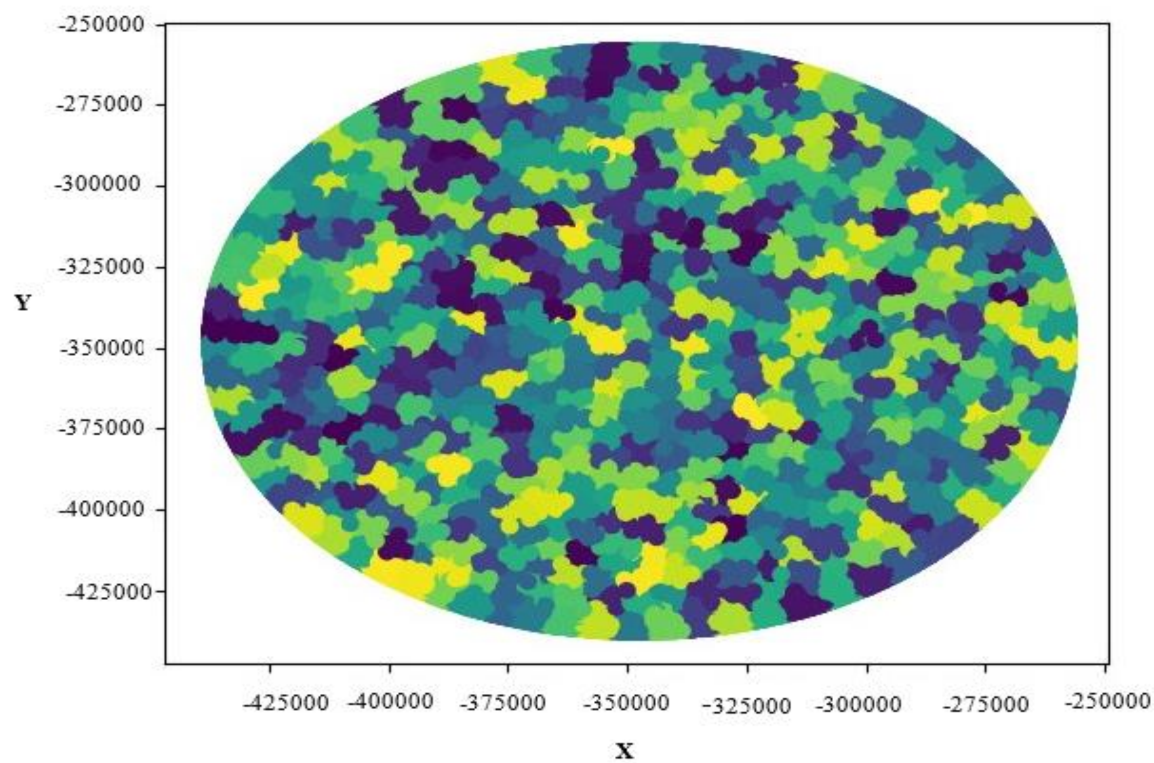

Figure 8. 70% fingerprint for training

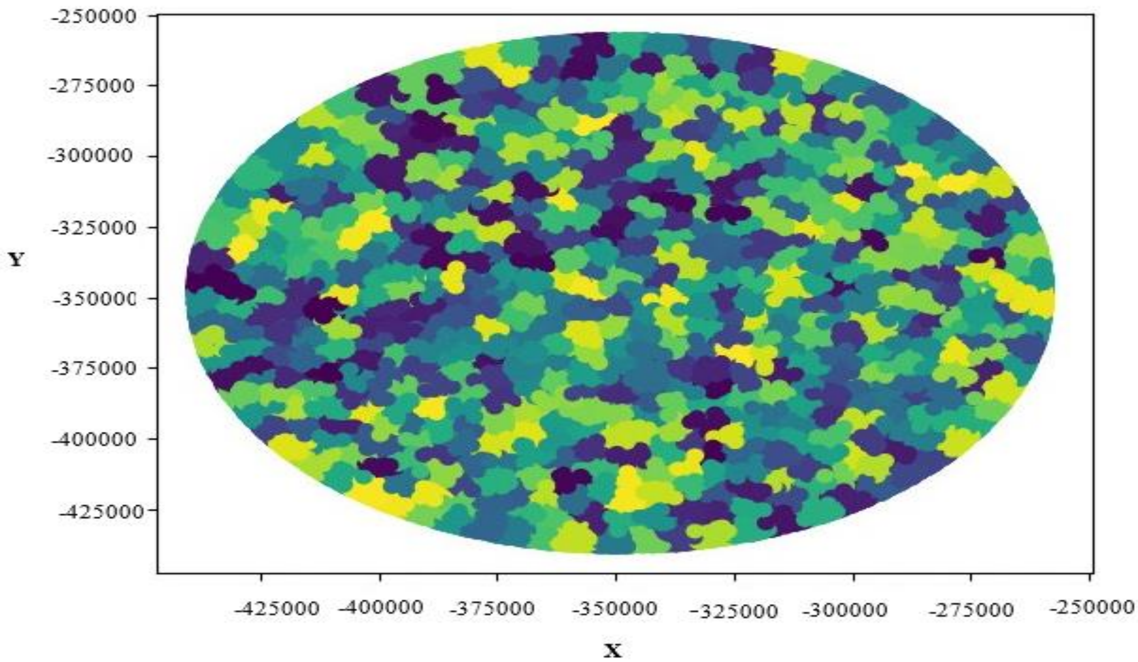

Figure 9. 30% fingerprint for testing

3.4 Simulation Performance in Online Phase

During the online phase, a total of four UE was utilised, each running on separate operating systems, namely IOS and Android, with an average of two from each operating system. In the first case, two devices were placed near the eNB position and other devices are placed at the boundary of the eNB coverage. In the second case, the devices were randomly distributed to test the accuracy of the matching algorithm (2). In the initial step, algorithm (1) establishes the measurement similarity threshold δ as -0.0005 db and proceeds to generate a unique fingerprint for each UE. Creating one fingerprint requires 750 milliseconds, so creating four fingerprints in real time takes 3000 milliseconds, which is equivalent to three seconds. The algorithm generates an index that represents the occurrence rate of measurements in a single fingerprint. The fingerprint generating process is considered complete when the overall frequency of measurements reaches 24. Put simply, the fingerprint does not need to comprise 24 measurements. Put simply, the UE fingerprint comprises five measures, with a total frequency of 24. Table 5 displays the fingerprints of the UE at various locations.

Table 5. *fingerprints of four UE*

UE	M_{UE1}	M_{UE2}	M_{UE3}	M_{UE4}	M_{UE5}	M_{UE6}	M_{UE7}	eNBCID	eNBsec
UE_{IOS1}	-20.061279	-19.967064	-20.248314	-20.153938	-20.058891	null	null	1	A
ind_{IOS1}	5	8	7	2	2				
UE_{IOS2}	-49.080406	-49.077736	-49.073311	-49.088234	-49.085785	-49.080894	-49.075996	1	B
ind_{IOS2}	4	7	4	2	2	3	2	1	C
UE_{AND1}	-39.509491	-39.508347	-39.530251	-39.527954	-39.526825	-39.552162	null	1	C
ind_{AND1}	9	4	5	3	2	1			
UE_{AND2}	-49.064758	-49.080902	-49.075958	-49.090607	null	null	null	1	A
ind_{AND2}	8	10	2	4					

Table 5 displays four fingerprints, each accompanied by an index indicating the frequency of their measurement's occurrence. It is seen that the first fingerprint comprises five measurements, the second comprises seven measurements, the third comprises six measurements, and the fourth comprises four measurements. However, the total occurrence frequency index for each fingerprint adds up to 24. The first fingerprint reduced the process of sending the measurement to the network by a reduction rate of 79.17 due to the similarity of the received measurements. Similarly, the second fingerprint reduced it by a reduction rate of 70.83, the third by a reduction rate of 75, and the fourth by a reduction rate of 83.33. Therefore, we achieved a 77.08 reduction rate in the transmission of measurements between the LTE network and the UE, resulting in a direct improvement in the efficiency of the UE's limited battery capacity.

Additionally, Algorithm (2) necessitates the initial establishment of the Jaccard threshold $t = 0.25$, which determines the level of similarity between the two fingerprints, as well as the overlap threshold $\alpha \cong 9$ for the elements of the two fingerprints. As previously stated, both the measurements of V_{UE} and V_{SR} are globally ordering according to OM. The algorithm (2) selects the necessary cluster by comparing the eNBCID and eNBsec, as well as the MIN and MAX values for both the UE and cluster label. The algorithm initially compares the first measurement M_{SRi} from the V_{SR} with all the V_{UE} measurements based on the threshold δ. If a match is not found, it proceeds to the second measurement. When the condition is satisfied, the measurement occurrence frequency index $f(M_{Sri})$ is incremented by one simultaneously. By finding the overlapping measurement when constructing the overlapping ordered pairs, this phase allows us to enhance the effectiveness of matching. The algorithm subsequently generates ordered pairs of overlapping measurements based on the preceding stage. Furthermore, the algorithm evaluates the total of the measurement occurrence frequency index sum_ $f(V_{Sri})$, which indicates the common elements between the two fingerprints, to determine if it satisfies the t threshold. When the condition is satisfied, the prefix for the two fingerprints is computed. However, if the condition is not satisfied, it proceeds to the next V_{SR} inside the same cluster. Once the prefix for the two fingerprints is computed, the frequency of overlapping pairs is evaluated to determine if it meets or exceeds the α threshold. Once confirmed, if the two fingerprints are overlapping, the algorithm will provide the coordinates of the centre of the V_{SR} as the real-time location of the UE.

3.5 Performance Evaluation

In order to assess the effectiveness of the suggested strategy, the evaluation process was divided into two distinct stages. The initial phase involves assessing the performance of the suggested matching algorithm, with a focus on WKNN, which is a frequently employed algorithm in location determination techniques. The efficacy of the suggested partitioning model in current fingerprints is assessed in comparison to the partitioning model used in traditional fingerprints during the second step. Utilizing four measures, namely Root Square Error (RSE), and Root Means Square Error (RMSE).

During the initial phase, the MAE and CDF are employed to compute the error in position between the real location of the UE_{ac} and its estimated location UE_{es}, using the Euclidean distance. Let C_{SR} it is the number of fingerprints SR in one cluster, MAE is defined as [7].

$$MAE = \frac{1}{C_{SR}} \sum_{i=1}^{C_{SR}} \sqrt{(UE_{ac} + UE_{es})^2} \tag{6}$$

The CDF graphic illustrates that the likelihood of a positioning error being equal to or less than a certain distance. The data visualizes the extent to which positioning errors of SRs are distributed and provides a comparative analysis between the suggested technique and WKNN.

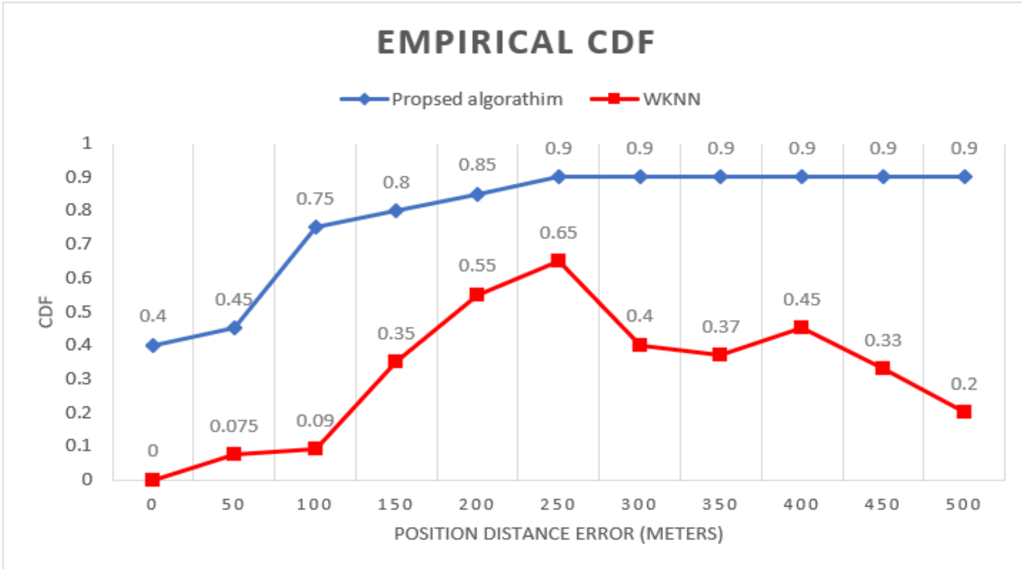

Figure 10. CDF of SR 22.36m *22.36m.

During this phase, simulations were conducted inside a specific fingerprint region of 22.36 m * 22.36 m. The implemented matching algorithm (2) successfully attained a (MAE) of 35.34 m. The obtained outcome is much inferior to that of WKNN, as seen in Figure 10.

In the second step, we include the partitioning model suggested in our present approach with two distinct partitioning models derived from two separate traditional methodologies [23], [24]. RES and REMS were used to compare their respective outcomes for assessment. In order to accomplish this objective, we will assume that the coordinates of the current position of the (UE) are (UE_X, UE_Y) and the coordinates of the anticipated fingerprint (SR) are (SR_X, SR_Y). The RES can be determined using the following formula [25]:

$$RES = \sqrt{(UE_X - SR_X)^2 + (UE_Y - SR_Y)^2} \qquad (7)$$

Given that there are four UEs spread out within the coverage area of the eNB, we can assume that the simulation will be run four times, the RMSE is:

$$RMSE = \frac{\sqrt{RES_1^2 + \cdots + RES_4^2}}{4} \quad (8)$$

To accurately determine the actual location rate of the UE, we assumption that there are anticipated fingerprints (SRexp). The acceptable fingerprints (SRacp) are determined based on the outcome of the first stage, where they must be less than 35.34 meters. The calculation for the rate of acceptable fingerprints (SRacpR) is as follows:

$$SRacpR = \frac{SRacp}{SRexp} \qquad (9)$$

The simulations were conducted a total of eight times, with four instances using the partition model suggested for the present technique, and the other four instances employing the partition model derived from older methods. Due to the division of the eNB's coverage area into three sectors A, B, and C, the UEs were strategically placed at varying distances from the eNB, including the outermost edge of the coverage. Table 6 demonstrates the advantages of our suggested strategy compared to previous methods, regardless of whether the UE is in close proximity to the eNB or at the periphery of coverage.

***Table 6**. Location accuracy*

Partitioning model	UE	Near$_{eNB}$	Far$_{eNB}$	Sector	Respond time
Our approach		20.48m		A	2.5s
Our approach		26.89m		B	3s
Our approach			30.76m	C	6s
Our approach			32.93m	A	8s
Traditional		100.23m		B	54
Traditional		123.44m		C	45
Traditional			212.25m	C	240s
Traditional			246.77m	B	200s

Table 6 demonstrates the superiority of our suggested technique compared to previous methods, not only in terms of the lowest error rate but also in response time. The variation in outcomes is attributed to the conventional techniques depending on the functioning of a minimum of three eNBs. Furthermore, the partitioning model used in these systems lacks effectiveness.

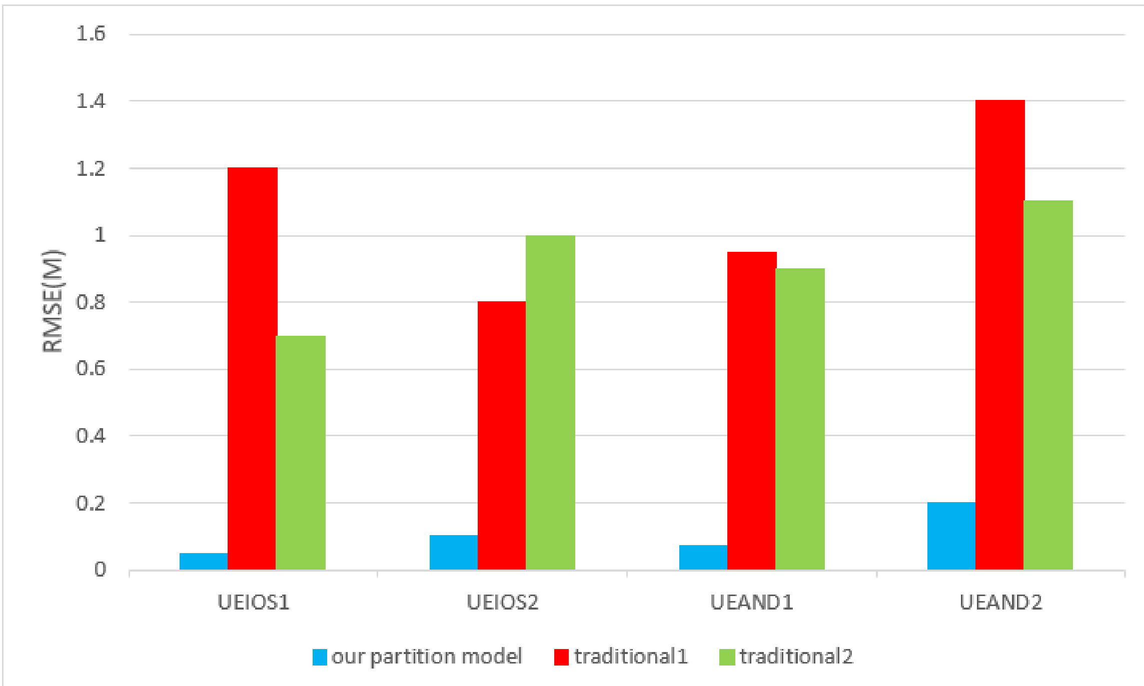

Figure 11. A Novel RSS Fingerprint accuracy comparison with traditional methods

Based on Figure 11, it is evident that the RMSE of the suggested partition model is significantly reduced compared to other conventional techniques. According to these findings, the suggested partition model possesses the capability to accurately identify the position of the UE with the least meter of errors. We conducted tests on several scenarios to evaluate the effectiveness of our proposed technique, specifically focusing on the positioning of the UE within the eNB coverage area. One crucial scenario we examined was when the UE is positioned at the periphery of the coverage area. Our technique has consistently demonstrated exceptional performance in all circumstances.

4. CONCLUSION

This article introduces a new and innovative method called Novel RSS Fingerprint, which can accurately pinpoint the location of a UE in remote area using only one eNB. This represents a groundbreaking approach in positioning techniques that utilize the full LTE network without requiring the addition of extra devices to the network. This circumstance was perceived as a predicament that necessitates attention since it poses obstacles to law enforcement authorities, as the majority of approaches depend on a minimum of three eNBs. In order to accomplish this objective, a division model was suggested that allows us to efficiently collect RSS measurements in each RP within the SR. The 24 RPs within each SR were also strategically arranged to enable comprehensive measurement coverage and the creation of distinct and unique fingerprints. Furthermore, this research presents a proposed method aimed at mitigating the power consumption of the UE battery, which is constrained by its limited capacity. The system does this by reducing the average measurement transmission rate by 77.08%. In addition to the prefix filtering strategy, a matching algorithm was suggested that utilized jaccard and overlap similarities. These notions are being employed for the first time in location determination methods. The findings demonstrated that our suggested approach had the most minimal margin of error, amounting to 35.34. Furthermore, our new method was compared to established methods, and it demonstrated the lowest REMS rate among all other methods. Our method is highly efficient in accurately determining the location of the UE, irrespective of its distance from the eNB, as it has undergone extensive testing in many scenarios. Additionally, it boasts an impressive response time of 8 seconds.

Important note: So far, according our knowledge the findings were attained for the first time in an LTE network using a solitary eNB, without any further devices being included into the LTE network. This article introduces the use of Jaccard and overlap similarities, together with the prefix filtering methodology, in location determination techniques, which has not been previously documented.

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