Indoor Radio Dot Placement Optimization using UE Positioning and K-Means Clustering

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***Abstract* — Indoor deployment with low cost and high capacity has shown to be a cost-effective solution in 5G wireless networks. In indoor 5G networks, Radio Dot (RD) units handle the wireless interfacing between UE devices and the core network. Strategic placement of indoor 5G RD units to ensure higher coverage of the space with optimal performance is challenging, since various factors could affect signal penetration, including floor plan, building materials, wall construction, frequency band, interference, dynamic factors like user density, etc. Most static parameters are well considered during the deployment stage, with deployment tools and network planning strategy. However, the dynamic impact of user density and distribution on channel quality and performance is still an open research area. With the user equipment (UE) positioning and channel quality indicator (CQI), the areas with poor channel quality data could be detected and further analyzed to dynamically determine RD locations and adjust accordingly for better network performance, without extra radio hardware costs introduced. This paper adopted the K-means clustering algorithm to evaluate the scenario where all the RD unit locations can be adjusted. Further, a Node Adjustment algorithm for RD units was proposed to improve indoor 5G network performance for a cost-efficient solution. The number of UEs and their distribution were simulated, and a comparative evaluation was conducted for different algorithms and various scenarios. The experimental results showed that considering dynamic information to adjust RD unit placements in a building could provide a cost-efficient solution to optimize indoor 5G network performance.**

Keywords — Small Cell, Radion Dot, Indoor 5G Deployment, K-Means Clustering

I. Introduction

In indoor 5G wireless communications, Radio Dot (RD) deployment is a promising and economical way to increase system capacity in a flexible manner with low cost. In indoor 5G networks, RD units handle the wireless interfacing between UE devices and the core network [1]. RD units, as low-power radio transmitters, produce radio waves for indoor broadband coverage. Advantages of indoor placement technology include low cost, flexible deployment, and effective system capacity enhancement; this is required to meet the ever-growing capacity, traffic, and coverage requirements of mobile networks. Although indoor deployments have been demonstrated to be a cost-effective solution, the problem of best estimating the RD number and positioning for deployment remains a challenge [2]. Deploying indoor RDs for wireless communications involves careful planning and consideration of various factors that affect signal penetration; these include floor plans, wall types (concrete, drywall, glass), and conflicting signal interference. The objective of indoor deployment is to achieve higher network coverage with the benefit of lower cost.

Strategic placement of RD units to ensure higher coverage of the space with optimal performance has always been a challenge for indoor wireless communications [3][4]. System performance heavily depends on the deployment location of RD units. Therefore, a mechanism is required to ensure that an RD's location is effective not only in the initial deployment, but also RDs location can be adjusted based on field situations over time. Indoor deployment with high coverage and lower cost has been a crucial topic [5] since those aforementioned factors need to be considered. Most of the static factors are considered during the deployment stage. However, dynamic coverage adjustment from user density and distribution is still an area that needs to be addressed. In addition, factors that affect user data and consumer trends can change over time. Areas that receive a high volume of traffic, such as popular hot spot locations, recognized branding stores, or high-demand food outlets, can change in the fields. The capacity requirements could be changed as well due to the number of User Equipment (UE) devices connected to the network in different areas. Hence, it is important to dynamically adjust RD locations to reflect the capacity and UE distribution changes and optimize the channel quality of the network.

Indoor planning tools like Ericsson Indoor Planner (EIP) [6] and iBwave [7] are widely used in network planning and deployment stages to strategically place RD units for better coverage, which have taken much static information into account already. RD placement based on dynamic situations, where the environment or the positioning of devices is subject to change, poses additional challenges compared to scenarios with static parameters [8][9]. With user equipment (UE) positioning introduced, the location of UEs could be collected. Distribution of users and network traffic demands could be captured within an indoor space. Capacity might need to be adjusted based on real-time demands; combined with Channel

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Quality Indicator (CQI) data, the areas with poor channel quality could be identified. By leveraging machine learning techniques, the data could be further analyzed to dynamically determine RD locations that can achieve better indoor channel quality and optimize network performance. This can be realized based on moving existing radio hardware without further introducing extra hardware costs.

This paper proposes a step forward using unsupervised machine learning, i.e., the K-means clustering algorithm. The aim is to evaluate the performance impact from dynamic information, mainly user density and distribution, to quantitatively evaluate 5G RD adjustment algorithms that can better accommodate cost-effective performance enhancement.

The main contributions include:

- The introduction and simulation of UE distributions and evaluation of channel quality improvements by considering both static floorplan and dynamic UE factors based on an industrial network planning tool.
- Design of the K-means clustering algorithm and an extension of it for Node Adjustments for a potentially balanced approach between cost-effectiveness and network performance improvements for RD unit placements.

The rest of the paper is organized as follows. Section II describes the background of indoor wireless architecture and the high-level design principles. Section III describes the proposed design. Section IV presents evaluation results and analysis. Finally, Section V is the conclusion and some future directions.

II. Indoor Architecture and Deployment Strategy

A. Indoor Architecture

Figure 1 presents the overarching structure of the indoor RD system.

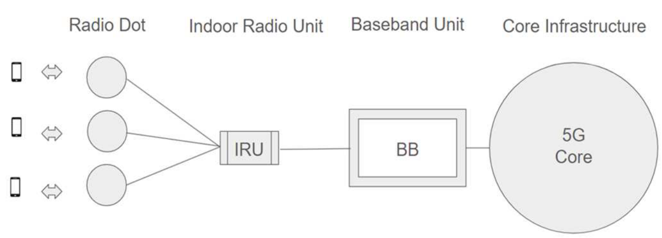

Fig. 1. Indoor Radio Dot System Overview

The main difference conceptually and hardware-wise between the indoor RD system and the traditional 5G outdoor scenarios is the inclusion of the Indoor Radio Units (IRU) and RD units. Traditional deployments for 4G LTE (Long-Term Evolution) and 5G NR have UE's wirelessly connecting to base stations directly of various naming conventions, the most widely known being Next-Generation Node B (gNodeB) stations. Indoor RD system functions fundamentally differently from the role of base stations being replaced with the Baseband Unit (BB). These BB units then have further wired connections to multiple IRU devices, with each IRU unit further supporting wired connections with RD units. Each IRU can support up to a maximum of 8 or 16 RD units, depending on the hardware specifications of the IRU used, the size of the floor, coverage and performance requirements, etc., in the deployment [10]. The BB units have wired connections to multiple IRU devices, with each IRU unit further supporting wired connections with RD units.

For indoor 5G networks, RD units handle the wireless interfacing between UE devices and the core network. An RD unit used as a low-power radio transmitter produces radio waves for indoor broadband coverage [10]. The functionality of IRU is primarily the aggregation of signals and power provision to the RD units. The IRU provides full radio functionality and is further connected to a Radio Access Network (RAN) to offload the baseband, and it aggregates signals to minimize signal interference.

B. Design Proposal

Ideally, all RD units have a balanced workload, or each RD is connected to the same number of UEs. Clustering algorithms can be applied based on the initial UE positioning data to group UEs into clusters. Clustering is a natural fit for the problem of grouping UEs into clusters. Various clustering algorithms exist, such as K-means, DBSCAN, Hierarchical Agglomerative Clustering (HAC), Gaussian Mixture model (GMM), etc. [11][12]. DBSCAN performance usually suffers with varying densities, which may occur in 5G indoor deployments if there are popular spots where UEs would cluster. HAC is more computationally intensive and there are various choices for the linkage method which can impact the results. GMM assumes that data follow a mixture of normal distributions., which may not be the case for indoor applications due to events or possible popular spots.

The K-means algorithm was selected for this paper, because it is computationally efficient and scalable with dataset size. Though the number of clusters needs to be pre-determined for K-means in general, it is straightforward for this specific problem, as the number of RD units is known in the initial deployment and the number of clusters is identical to the number of RD units. K-means has a trait of minimizing global Euclidean distance values, which results in centroids having more balanced data points per cluster in deployments with a higher average distribution range [11] which is a trait highly beneficial to the target of load balancing in 5G networks [9][13]. Since K-means can reduce the average distances between UEs and RD units, it implies that small path loss would be introduced, therefore, transmission rates will be increased, and the overall system performance can be improved.

In non-uniform UE distribution scenarios, dynamic location data would be evaluated first for an optimal RD placement solution. Further, after dynamic evaluation, we still need to consider static information. To balance static and dynamic data, we will only adjust the RD units that have the highest performance impact based on user positioning and traffic density in field deployment scenarios. This approach allows for improving channel quality with minimal cost and effort.

The main concept of the proposed approach for indoor RD deployment is described as follows: UE positioning of all the UEs in a network needs to be collected and analyzed. K-means algorithm is then applied to generate a UE distribution view. Then, the clusters having the highest density can be detected and the CQI data can be evaluated for each cluster. The closest RDs of UEs from the initial deployment can then be identified and may be replaced with high-performance clusters based on the quality calculation. The network-wide performance can then be evaluated, allowing for optimization in signal coverage with minimum cost. CQI is adopted as it is a measure of the quality of the communication channel between a mobile device and a base station [14]. In LTE and 5G networks, CQI is a feedback mechanism where the mobile device provides information to the base station regarding the quality of the radio channel. The CQI value indicates the signal quality, interference level, and other factors affecting the wireless communication link. A higher CQI typically corresponds to a better channel quality

In summary, here are the steps:

- Identify all UEs' positions.
- Apply the K-means algorithm to obtain a UE distribution view.
- Calculate network performance with CQI based on monitored data simulated from the indoor planning tool.
- Adjust RDs based on the UE distribution view obtained.
- Evaluate the performance improvement by comparing the channel quality conditions after the RD adjustment.

III. EXPERIMENTAL DESIGN

The goal of the experimental design process using the indoor planning tool EIP [6] was to improve network performance for UE's in a two-dimensional space in correlation with a provided floor plan image and how changes to RD placement affected overall performance. CQI is derived from Reference Signal Received Power (RSRP) obtained from EIP. RSRP is a key parameter used in mobile communication networks, including LTE and 5G. It represents the power level of the Primary Synchronization Signal (PSS) and the Secondary Synchronization Signal (SSS) in the downlink [15]. The following steps represent an abstraction of the experimental design pipeline:

- UE positional datasets were synthesized such that nodes representing two-dimensional UE positions were generated pseudo-randomly based on traffic events and adjustable data parameters.
- The K-means algorithm was used for data clustering based on centroid placement, as RD units could be represented as cluster centroids, with nodes assigned to the clusters representing UEs wirelessly connected to an RD.
- RSRP was simulated with the EIP indoor planning tool, based on the RD placement from K-means results. Performance was evaluated based on UE's channel quality abstracted from the RSRP generated with the K-means based RD placement.
- Performance evaluation metrics could then be obtained by performing rudimentary data analysis equations on CQI metrics in correlation with centroid groups, allowing for metrics, such as global CQI average, local cluster CQI average, and centroid density to be obtained.
- A node adjustment algorithm was further investigated for a cost-efficient solution.

The experiments were built using Python version 3.10.6 utilizing various modules, such as `sklearn` (for machine learning methods like the K-means algorithm), `NumPy` (for array processing) `PIL` (Python Imaging Library for image processing or RGB pixel values), `matplotlib` (for cluster visualization), `random` (for random number generation), and `randomcolor` (for random color generation) libraries. EIP was used to generate the RSRP resulting from the movement of RD placements.

A. Data Collection and Simulation

The UE positioning data were simulated using the pseudo-random generation method in a 2D space. In addition, simulation data can cover various kinds of scenarios in the fields for better reliability, since UE positioning data is unique for each different location, environment, and economic market. Before data generation, a floorplan image, initial heatmap image, and initial centroid coordinates are always provided. A heatmap is a graphical representation of data where values in a matrix are represented as colors. It is a way to visualize the intensity of data at different points. Figure 2 shows a base floorplan image from the fields.

Fig. 2. A Sample Floorplan Image

CQI is the main metric used for quality evaluation. EIP only provides a function to simulate RSRP based on the RD placement and generate RSRP heatmaps accordingly. The CQI metrics are then converted from the RSRP. An RSRP heatmap is a visualization of the received signal from a cell in a cellular network at various locations. RSRP values are typically measured at different geographical locations which are divided into a grid where each cell corresponds to a specific location. Each cell is assigned a color based on the RSRP value at that location. A color scale using the RGB code represents the signal strength. The color representation and interpretation for the RSRP heatmaps are evaluated in Decibel Milliwatts Units (dBm). Figure 3 shows the RGB to RSRP dBm mapping provided by EIP. This scale is the basis from which numeric metrics were extracted from the RGB pixels produced by EIP. Dark red indicates stronger RSRP signals. CQI mapping from RSRP was devised based on [16][17].

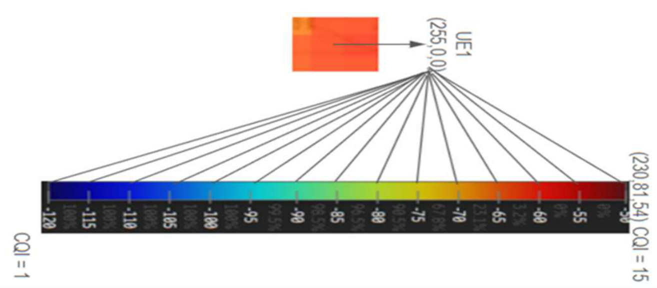

Fig. 3. RGB to RSRP dBm Mapping

The initial centroid coordinates in this paper were obtained from default RD coordinates generated from the EIP tool based on the floorplan design. These initial RD locations are generated from the tool's goal to maximize signal coverage using factors of balanced coverage, signal interference, and wall density metrics. CQI data was calculated from RSRP simulated with the EIP tool. When this is deployed in the fields, both UE positioning and CQI data will be obtained from the fields.

B. Implementation of RD Deployment Algorithms

Two algorithms were designed to support RD deployment decision-making: K-means and Node Adjustment algorithms. The K-means algorithm is mainly used for the scenario when RD redistribution is feasible. The Node Adjustment Algorithm is designed for cost-efficient solutions. TABLE I depicts the input variables used for those two algorithms.

TABLE I. INPUT VARIABLES FOR PSEUDOCODE ALGORITHMS

Notation	Definition
N	Number of RD units
V	Number of Centroid Adjustments
OA	Array of Origin Centroids
UEP	2D Array of all UE Positions
KA	Array of K-means Centroids
CS	Array of Cluster Sizes for KA
oCQI	Array of CQI Cluster Averages for OA
kCQI	Array of CQI Cluster Averages for KA

The K-means algorithm for RD placement is presented below. There were multiple purposes for applying the K-means algorithm for indoor RD placement. The direct purpose was to determine the impact of optimizing the Euclidean distance between UE's and RD centroids versus the potential offset of negatively impacting static parameters, such as signal interference or signal penetration defined in the EIP indoor planning simulation tool. K-means has the potential for CQI performance increase, although it has the major drawback of requiring the re-adjustment of all RD placements to properly function, which can be time consuming and may have physical drawbacks regarding hardware placement viability.

Algorithm 1: K-Means Algorithm

Input: N, V, OA, UEP
Output: K-Means Labels and List of Centroids

1. if OA is empty:
2. K-Model = Run K-Means(Cluster Number = N, random_state = 0).fit(UEP)
3. else:
4. K-Model = Run K-Means(Cluster Number = N, random_state = 0).fit(OA)
5. Labels = K-Model.predict(UEP)
6. Cluster Centers = K-Model.cluster_centers_
7. return Labels, Cluster centers

The number of RD units in the algorithm equals the number of clusters for this problem. UE positions in a 2D array need to be provided. Original centroids based on the indoor planning tool are optional. If no centroids are provided (OA is empty), the new centroids could be extracted based on optimized Euclidian distance and RSRP could be generated with EIP accordingly. This allows for CQI evaluation of the K-means distribution model. If centroids are provided (OA is not empty), it allows for a grouping of UEs based on the pre-existing RD locations. The output variable Labels represent UE classification corresponding to each cluster. Further, any changes made to the original set of centroid placements could show grouping adjustments. The corresponding RSRP can further be generated, allowing for comparative CQI evaluation between original and new RD placements.

The Node Adjustment algorithm acts on adjusting the placement of the original centroids from initial deployment to the locations of the highest density centroids obtained from the K-means algorithm to readjust the workload of RD units. The number of centroids being adjusted is defined by a configurable parameter V as shown in TABLE 1. The algorithm sorts the input list of K-means centroids in descending order based on the cluster sizes. The algorithm then sequentially walks through the sorted K-means centroid list V steps and moves the closest available original centroid to the K-means centroid location defined by the iteration step. A centroid from the original placement that has already been moved cannot be moved again in the same algorithm data batch. This results in V number of centroids from an original EIP deployment to be moved to the theorical number of V "highest density" areas, with the nearest ones being moved as an attempt to not disrupt global signal coverage to an excessive degree. The Node Adjustment algorithm is presented as follows.

Algorithm 2: Node Adjustment Algorithm

Input: N, V, OA, KA, CS.
Output: Set of N Post-Adjustment Centroids.
Conditions: A Centroid that has been adjusted by the algorithm cannot be adjusted again within the same iteration of an algorithm call.

1. Sort KA by indexes of CS after being sorted by size in descending order
2. Make a Copy of OA as OC
3. for step = 0 up to V // the number of centroid adjustments
4. kNode = KA[step]
5. Initialize List of Distance Vectors as DV
6. for oNode in OA:
7. Append Absolute Value Distance Vector of |kNode – oNode| to DV
8. end for
9. Extract the Minimum Vector as MV from DV

```
    Extract the Array Index of DV[MV] as Min Index
    Replace the Centroid at OC[Min Index] with kNode
end for
return OC
```

The Node Adjustment algorithm requires the cluster densities and centroid locations calculated from the K-means algorithm. The primary purpose of the Node Adjustment algorithm is to provide a middle ground between potential performance increases and cost requirements for real-time deployment scenarios. Since the algorithm performs only minor adjustments to the centroid locations by replacing some of the original centroids deployed with high-density centroids extracted from the K-means model, the target for this algorithm is to provide minor performance increases for high-density areas, while at the same time reducing the cost and efforts required to adjust many RD placements. Since the Node Adjustment deployments are similar in design to the original deployment, a strength of the Node Adjustment algorithm is that the signal strengths of the resulting RD placements are normally still strong for even signal distribution across a building's floorplan, making it the practical for maintaining high signal coverage of a building while also allowing for performance increase.

IV. Evaluation Results and Analysis

Different UE distributions have been simulated, pseudo-random, highly condensed, and sparse events distributions. Events were assumed to draw UEs to closer to their locations. The K-means algorithm as well as the Node Adjustment algorithm were evaluated. The K-means algorithm was implemented using the `sklearn` library. Events were considered as UEs may gather around events. Three scenarios were tested for performance evaluation:

- 3 RD EIP deployment with low CQI coverage: The experiment was to evaluate the performance of the RD placement algorithms for UE traffic density, size, and event radius in the environment of a low global CQI signal coverage area.
- 6 RD field deployment with high CQI coverage: An initial 6-node deployment experiment was evaluated for different scenarios and algorithms.
- 6 RD controlled events: The experiment was designed to simulate scenarios in a more controlled manner to test for edge case strengths and weaknesses of the algorithms.

A. 3 RD Coverage Results

Four datasets were generated to test the K-means and singular Node Adjustment algorithm to evaluate CQI performance: (i) two default state scenarios with an event number equal to the number of RD units, (ii) a highly condensed event scenario with a large amount of UE traffic, (iii) high event density per given event radius, and (iv) a low traffic scenario with less density per event scenario.

TABLE II. Results for 3RD Low CQI Coverage Test Case

Batch #	# of UE's	# of Events	Event Metrics		Method	CQI Average (Total)
			Size	Radius		
1	100	3	25-30	5-15	EIP default	13.18
					K-means	14.04
					Singular	13.11
2	200	2	37-45	2-10	EIP default	13.06
					K-means	14.285
					Singular	13.545
3	50	4	20	15-20	EIP default	12.7
					K-means	13.78
					Singular	10.86
4	100	3	25-30	5-15	EIP default	14.11
					K-means	14.4
					Singular	14.07

EIP default: deployment without considering UE distribution

TABLE II depicts the result for the 3 RD low CQI coverage test case used to evaluate the performance concerning variable UE traffic density, cluster size, and event radius in meters in a low CQI signal coverage area. Overall, the performance of K-means was shown the best, while the performance of the singular node adjustment was even lower than that of the static EIP default plan without considering the UE distribution.

The following figures illustrate an example from TABLE II. Fig. 4(a) is the original default EIP deployment for batch 1 and Fig. 4(b) shows the corresponding clustering results generated from `matplotlib`, where the dark triangle represents the RD centroids. Visualizing information is useful for improving understanding, decision-making, and management. Figures 5 and 6 illustrate the results of K-means and Node Adjustment algorithms, respectively.

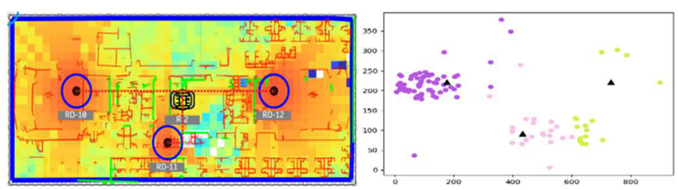

Fig. 4. (a) Origin EIP Deployment (b) Clustering View

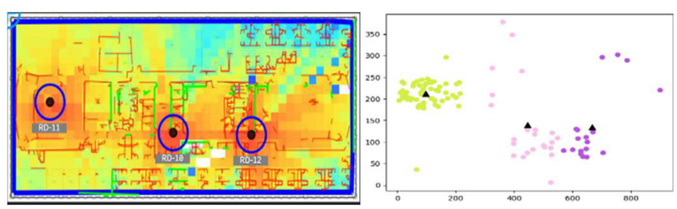

Fig. 5. (a) K-means Deployment (b) K-means Clustering View

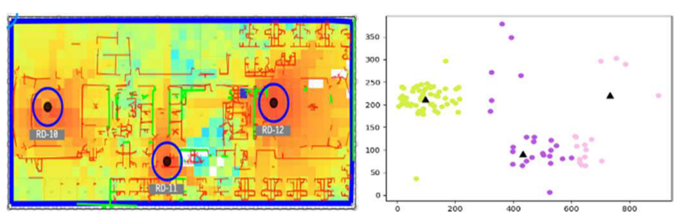

Fig. 6.(a) Singular Node Adjust. Deployment (b) Singular Node Adjust. Clustering

B. 6 RD High CQI Coverage Results

The same original floorplan as the previous experiment was used as the base truth for this result set. This experiment follows the same steps as the 3 RD deployment experiment with an addition of double node adjustment. Similar four datasets were generated: two original default states with normally distributed data, an event-condensed high-density dataset, and a low traffic wide distribution dataset.

TABLE III. RESULTS FOR 6 RD HIGH CQI COVERAGE

Batch #	# of UE's	# of Events	Event Metrics		Method	CQI Average (Total)
			Size	Radius		
1	100	6	12-15	6	EIP default	13.48
					K-means	14.48
					Singular	12.89
					Double	14.47
2	200	3	25-30	6	EIP default	14.75
					K-means	14.84
					Singular	14.815
					Double	14.835
3	50	6	8-12	0	EIP default	14.14
					K-means	14.24
					Singular	14.3
					Double	14.66
4	100	6	12-15	0	EIP default	14.29
					K-means	14.69
					Singular	14.25
					Double	14.31

TABLE III shows the CQI results for various algorithms. Two RD movements showed performance improvement. Fig. 7 depicts 6 RD field deployment with EIP default static parameters without considering UE distribution and the simulated RSRP heatmap. Fig. 8 shows the two RD node adjustments for four batches with different numbers of UEs and events: batch 1 (top left), batch 2 (top right), batch 3 (bottom left), and batch 4 (bottom right).

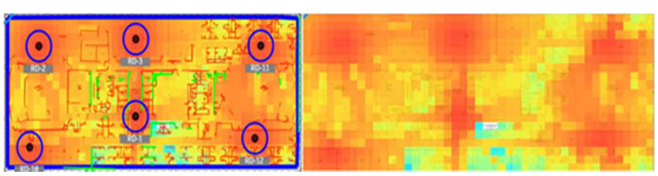

Fig. 7. Default Static 6 RD Deployment and Simulated RSRP Heatmap

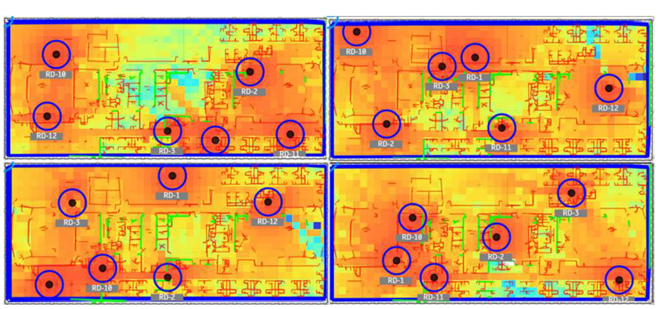

Fig. 8. RD Adjustment based on K-means for 6 RD High CQI Coverage

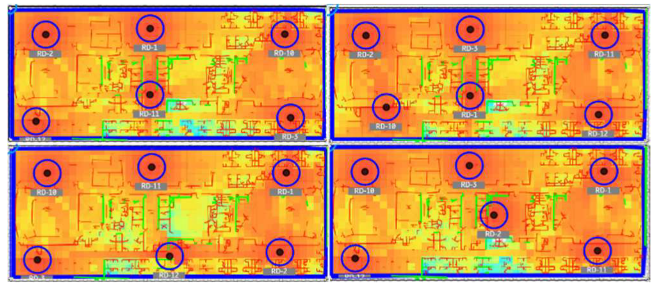

Fig. 9. Results for Singular RD Node Adjustment for 6 RD High CQI Coverage

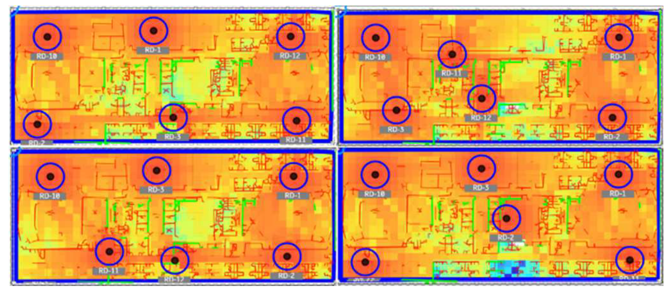

Fig. 10. Results for Double Node Adjustments for 6 RD High CQI Coverage

C. Controlled Event Results

UE distributions were simulated with 4 different scenarios. Batches 1 and 2 simulated a scenario where a number of UEs were congregated around areas of poor signal strength. The results showed positive outcomes for both the K-means method and node adjustment algorithms. Batches 3 and 4 were to test for scenarios with no event distribution, essentially in an attempt to replicate even distribution scenarios. The results of the K-means method and node adjustment algorithms were shown again to be successful for these edge cases. TABLE IV shows the results.

TABLE IV. RESULTS FOR CONTROLLED EVENTS

Batch #	# of UE's	# of Events	Event Metrics		Method	CQI Average (Total)
			Size	Radius		
1	100	1	50	6	EIP default	12.43
					K-means	14.67
					Singular	14.5
					Double	14.33
2	100	2	25	6	EIP default	12.35
					K-means	14.4
					Singular	13.48
					Double	13.63
3	100	0	0	0	EIP default	14.21
					K-means	14.53
					Singular	14.25
					Double	14.35
4	100	0	0	0	EIP default	14.08
					K-means	14.28
					Singular	14.36
					Double	14.41

D. Cross Analysis and summary

The results showed that K-means had the best performance consistency compared to the original static based EIP designs. The Node Adjustment algorithm resulted in a performance increase consistency, for certain UE distribution scenarios.

If UE distribution with strong event driven density, adjusting the RD nearby to the density areas provides consistent improvement for cost efficiency. The number of RDs to be adjusted depends on the UE distribution pattern. For UE distribution with single density area, the singular node adjustment algorithm performed better. For UE distribution with two density areas, double adjustment algorithm provided better performance. If the UE distribution doesn't have a clear pattern, K-means demonstrated consistent performance enhancement. TABLE V summarizes the comparison.

TABLE V. ALGORITHM TRAIT COMPARISON

Algorithm	Pros	Cons
K-means	1. Highest CQI performance improvement consistency. 2. 2. Balanced distribution of UEs across RD placements (optimal for load balancing). 3. High and Consistent performance for low RD, low CQI coverage scenarios.	1. Complete RD redistribution (potential uneven global signal distribution). 2. Highest potential for hardware limitations (wire length, location inaccessibility, etc.). 3. Increased cost and effort for redistribution
Node Adjustment	1. Reasonably high CQI improvement consistency for high signal strength deployment scenarios 2. Lower cost and effort for deployment. 3. Lowest risk of hardware limitations. 4. Best suited for the situation when UE distribution has clear number of high-density events. 5. Lowest change to global signal consistency (can be very similar to original deployment scenarios)	1. Suitable for certain UE distribution only, mainly pattern with clear density focused. 2. Not suitable for the scenario when the number of events is drastically greater than the number of nodes adjusted. 3. Not suitable for low RD deployment scenarios/weak global coverage.

V. CONCLUSIONS AND FUTURE WORK

The goal of this research was to provide performance improvement options for indoor 5G networks. Network planning tool EIP was used to generate UEs and RSRP for evaluation of various scenarios. UE positioning data was used with clustering algorithms to allow for dynamic RD repositioning based on the analysis of network traffic information. Using the K-means clustering algorithm improved the performance if movements of RDs are feasible. The proposed Node Adjustment algorithm based on the output of K-means further demonstrated to be an effective approach for consistent CQI improvement. Further, the Node Adjustment algorithm showed a better option as a cost-efficient solution when UE distribution has a clear density pattern.

Simulation of UE positioning and CQI data from practical field deployment scenarios should be further tested. Also, the model needs to be further evaluated in complex environments with variance floor plans, wall types and different materials, and signal interference levels. Scalability and the frequency of the algorithm execution could be investigated depending on performance requirements and specific events. Investigation with other planning tools could be considered for more advanced machine learning techniques.

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