Supplementary Material
Comparison with iBwave Design: A Case Study of Park City Hospital, Utah

***Abstract*—This supplementary material benchmarks the proposed multi-stage framework that combines stochastic geometry and integer linear program based optimization for the dimensioning of indoor enterprise networks form a practical perspective. Specifically, we study the placement of radio nodes (RNs) to meet target reference signal received power (RSRP) levels. The proposed framework is compared with commercial network planning software - *iBwave Design*, using both 3GPP-based statistical and ray-tracing propagation models. The results highlight the efficacy of our framework in achieving precise network dimensioning with fewer RNs, demonstrating comparable or improved performance in signal strength and quality metrics. The study underscores the importance of integrating advanced optimization methodologies for efficient and cost-effective network planning.**

I. Introduction

We consider the framework introduced in the paper titled “A Framework for Enterprise Network Dimensioning” for planning and dimensioning indoor enterprise networks. We provide strategies for employing the framework in real-world deployment areas and compare the performance of the proposed framework with a commercial radio network planning software - iBwave Design (e.g., see [1], [2] for applications of iBwave Design in wireless network planning).

A. Background of Commercial Software for Network Planning

Indoor radio network planning has been an area of extensive research, driven by the increasing demand for seamless wireless connectivity in complex indoor environments such as offices, shopping malls, stadiums, and industrial facilities [3]. Numerous methodologies and tools have been proposed, each addressing the unique challenges posed by indoor deployments, including multipath propagation, shadowing effects, and material-specific signal attenuation [4]–[7].

Early approaches to indoor network planning relied on empirical models, such as the COST 231 multi-wall model [8] and the ITU-R indoor propagation model [9], which provided simplified predictions of path loss based on statistical fitting to measured data. While computationally efficient, these models often lacked the granularity needed to capture the intricate interactions of radio waves with indoor structures. This inhibits an accurate characterization of the variance of performance across the deployment area. To address these limitations, deterministic models based on ray tracing have gained prominence. Studies such as those by Kunisch and Pamp [10] introduced advanced ray-tracing techniques to model signal reflections, diffractions, and transmissions with high accuracy. Several of such features are integrated together in commercial software such as iBwave Design [1], Remcom [11], WinProp [12], Ranplan Professional [13], etc. The key feature of the most of this software is accurate ray-tracing predictions followed by manual intervention for radio node (RN) placement. Recently, some of these software have introduced a feature of automatic radio node placement. However, the algorithms for such automatic placement rely only on the geometry and dimension of the deployment area and do not perform any rigorous optimization procedures. In this supplementary material, we compare the performance of the integer linear program (ILP) framework introduced in the paper with the automatic placement tool of one such software - iBwave Design, in terms of the number of RNs recommended by the two strategies.

B. Contents of the Supplementary Material

- **Basic comparison with iBwave:** The approach presented in the paper is benchmarked against iBwave Design, a commercial network planning software, using both 3GPP-based statistical models and ray-tracing simulations. By analyzing the number of RNs required to meet target RSRP levels, we demonstrate that our framework achieves comparable or superior network coverage with fewer RNs, thus optimizing deployment efficiency while maintaining high-quality service metrics.
- **Practical usage considerations:** To address the computational complexity of ILP for large deployment areas, we propose an iterative optimization approach that integrates stochastic geometry-based modeling with ILP. This method approximates optimal RN placement while significantly reducing computational overhead. Our comparative analysis using real-world deployment scenarios, such as Park City Hospital in Utah, demonstrates that the proposed iterative framework provides an effective balance between computational efficiency and deployment accuracy.
- **Comparison on real maps:** We conduct an extensive evaluation of RN placement strategies by comparing our framework with iBwave's automatic placement tool across different deployment environments. Our findings highlight that iBwave tends to overestimate the number of required RNs, leading to unnecessary hardware costs. Moreover, we analyze the impact of RN activity on SINR and demonstrate that optimizing for RSRP rather than SINR leads to more practical and cost-effective indoor network designs. This insight is particularly valuable for enterprise 5G deployments where low RN activity is common.

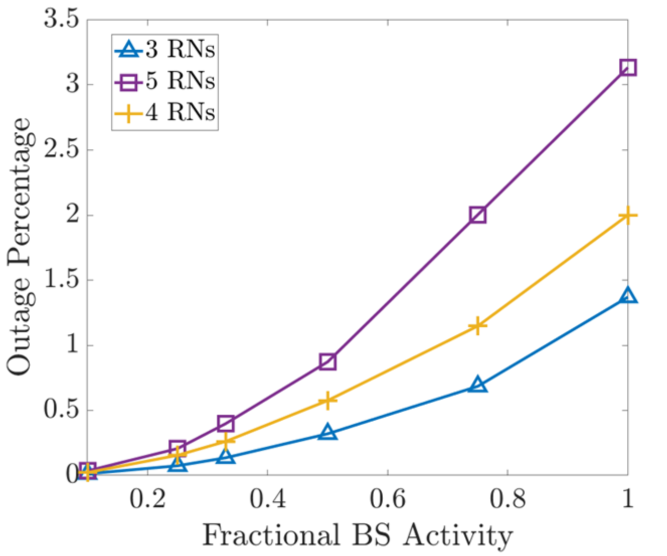

Fig. 1. Impact of fractional RN activity on the user equipment (UE) outage.

In Section II, we introduce the system model and design considerations, outlining the key parameters and propagation models used in our study. Section III provides a review of our proposed ILP framwork. In Section IV, we compare our approach with iBwave Design, evaluating the performance in terms of RN count, signal coverage, and computational efficiency. We further analyze real-world deployment scenarios, such as the Park City Hospital, to validate our methodology. Section V discusses the broader implications of our findings and provides concluding remarks along with potential directions for future research, including the integration of machine learning for adaptive network planning.

II. System Model and Design Considerations

We focus on the target reference signal received power (RSRP) as a planning metric, i.e., we optimize the placement of RNs so as to guarantee a minimum RSRP requirement in a given fraction of the deployment area. Then, we study the trends of the signal to interference plus noise ratio (SINR) as a consequence of such a deployment strategy. This is contrary to planning the deployment for optimizing SINR directly. This is due to the fact that typically, indoor enterprise networks experience low per-RN load. This is demonstrated at Fig. 1 where the outage percentage of a UE is plotted against the fractional base station (BS) activity. Lower the RN activity, lower will be the outage due to a reduced SINR. Thus, an over-deployment of RNs in terms of SINR may not always lead to a poor SINR. Accordingly, from a UE perspective a deployment strategy that guarantees a target RSRP is suitable.

A. Propagation Environment

We consider two types of propagation models as discussed below.

1) Statistical Model:: The first is the statistical path loss model taken from 3GPP specifications [14]. Let the transmit power of the RNs be P. A transmit-receive pair of Euclidean distance d has a received power $KhPd^{-\alpha}$, where $K = \left(\frac{c}{4\pi f_c}\right)^2$ is the path-gain constant, α is the path-loss exponent, and h represents the small-scale fading. We denote by $\ell_{\rm r}(d)$ and $\ell_{\rm m}(d)$ as the path-loss to the receiver from the indoor RNs and the macro base stations (MBSs), respectively. 3GPP recommends that without modeling the penetration losses from individual walls, an appropriate value of α (e.g., 3) can effectively emulate the indoor propagation environment [14]. Let the channel noise power be be N_0.

2) iBwave Ray-Tracing Model: The fast ray-tracing procedure employed by iBwave for indoor wireless coverage estimation is designed to efficiently model signal propagation in complex indoor environments. The procedure accounts for the interplay of diffraction, reflection, and scattering phenomena that significantly impact radio wave propagation in enclosed spaces. The core methodology involves geometric modeling, where the deployment area is first represented as a three-dimensional model with detailed spatial and material properties of walls, floors, ceilings, and other structural elements. Each surface is assigned specific electromagnetic parameters, such as permittivity and reflectivity, which influence wave interactions. Then, the transmitter is modeled as the source of numerous rays that are launched in all directions. These rays are traced through the 3D environment using deterministic algorithms, capturing interactions with surfaces through reflection, refraction, and diffraction. For each ray, the signal attenuation is computed by considering free-space path loss, reflection coefficients, diffraction effects around obstacles, and material absorption. A recursive approach is used to handle multiple interactions (e.g., multi-bounce reflections). At any given receiver location, the cumulative contribution of all incoming rays is computed using vector addition of signal amplitudes and phases. This process accounts for both line-of-sight (LOS) and non-line-of-sight (NLOS) components. To enhance computational efficiency, iBwave employs several optimization techniques, including adaptive ray sampling, spatial partitioning, and pruning and thresholding. The accuracy of the fast ray-tracing procedure has been validated against empirical measurements, demonstrating its reliability in predicting key performance metrics such as signal strength, coverage maps, and interference levels.

B. RN Model

We select the Ericsson RD4479 (New Radio) as the candidate RN for our comparative analysis. It has a maximum transmit power of $P = 24$ dBm. The antenna gain is $G = 2.15$ dBd, which is equal to 4.3 dBi. The carrier frequency is $f_c = 3.5$ GHz, the bandwidth is 10 MHz, and the tone width is 30 kHz.

III. Adaptation of the Proposed Framework

To employ our framework proposed in the paper, we specify the target RSRP, the reliability threshold (β), the MD (MD) threshold (t) as inputs to the model. Recall that β represents the fraction of transmission attempts in which the RSRP at a UE exceeds the target RSRP under fading. Additionally t refers to the fraction of network realizations (here with uniformly random deployment) in which the RSRP at the UE

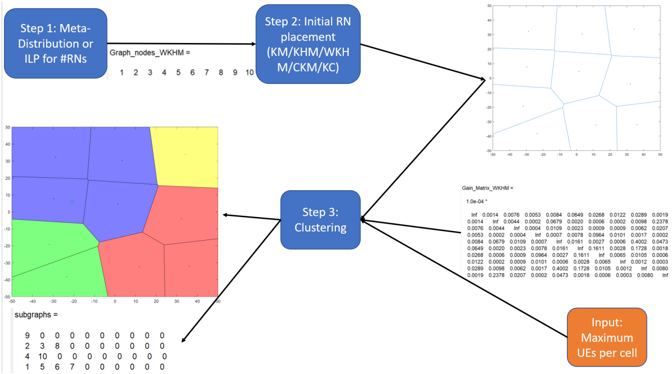

Fig. 2. An example step-by-step flow of the proposed framework in the paper.

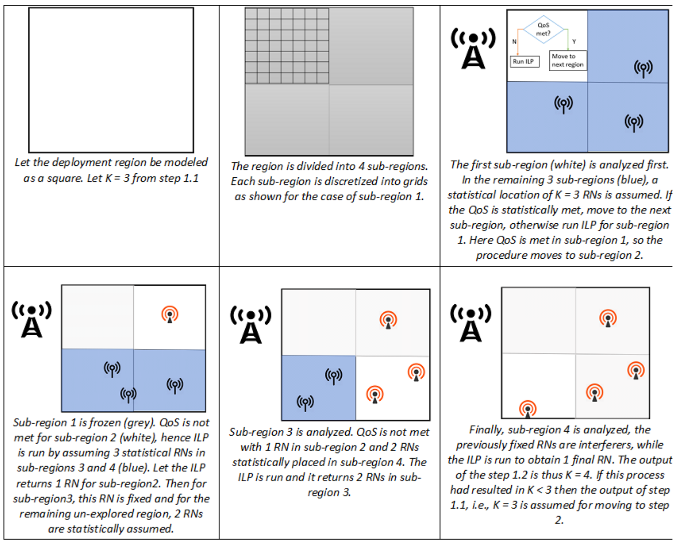

Fig. 3. Illustration of the iterative framework that leverages SG and ILP for real maps.

exceeds the target RSRP. We select $\beta = 0.9$ and $t = 0.9$ for the 90-th percentile fading and the 90-th percentile network environment. However, as discussed next, the value of t is re-adjusted for a worst-case RSRP planning. An illustration of the control flow of the framework is shown in Fig. 2, where the output of the first step is the number of RNs. This is followed by one of the different initial RN placement algorithms to come out with initial locations. Finally, the admission control step creates larger cells as shown. Each large cell of a distributed antenna system (DAS) is shown with a distinct color. For a detailed discussion of the framework, please refer to [].

A. A Combined Approach with ILP and MD

As we shall see in the next section, the ILP framework is computationally expensive for larger deployment areas or for very fine grids. In order to take advantage of both the statistical framework as well as the ILP formulation, we propose an iterative procedure that locally employs the ILP based optimization while approximating the interference field using stochastic geometry. This procedure is illustrated in Fig. 3. The entire region is divided into sub-regions. Then, starting from the first sub-region, the ILP optimization is employed in each sub-region while uniformly deploying RNs

Target RSRP	iBwave (Low Overlap)		iBwave (Medium Overlap)		Our Recommendation
-95 dBm	83	+6%	117	+50%	78
-100 dBm	36	+16%	51	+64%	31
-105 dBm	17	+13%	26	+73%	15
-110 dBm	8	+14%	12	+71%	7
-115 dBm	5	+25%	7	+75%	4
-120 dBm	2	0%	4	+100%	2

Fig. 4. Comparison of the number of RNs recommended by our framework and that recommended by iBwave for a square shaped deployment area of dimensions 300 m $\times$ 300 m.

Target RSRP	PS (Low Overlap)		PS (Medium Overlap)		Our Recommendation
-95 dBm	45	+9%	62	+51%	41
-100 dBm	20	0%	28	+40%	20
-105 dBm	9	-10%	13	+30%	10
-110 dBm	6	+20%	8	+60%	5
-115 dBm	3	+50%	4	+100%	2
-120 dBm	1	0%	1	0%	1

Fig. 5. Comparison of the number of RNs recommended by our framework and that recommended by iBwave for a square shaped deployment area of dimensions 215 m $\times$ 215 m.

in the rest of the deployment area. The number of such RNs is obtained by the MD framework. Once the ILP is run for a given sub-region, the RN locations so obtained is fixed for that sub-region. The procedure is repeated until all the sub-regions are optimized.

IV. Comparison with iBwave

The automatic node placement tool by iBwave is designed to automate the placement of network nodes in wireless system designs. The tool specifies three overlap options for RN: low, medium, and high, in increasing order of redundancy in coverage regions by RNs. The high overlap region enables the most conservative design and overestimates the number of RNs needed by a high factor. We do not consider this setting in iBwave since our focus is to minimize the number of RNs. In what follows, we consider only the low and medium overlap mode in iBwave.

A. Custom Maps with 3GPP Statistical Path Loss Model

First, we compare the results estimated for simple custom maps with the 3GPP statistical path loss model. We consider a square shaped deployment area. Fig. 4 shows the comparison for a the case when the area is 1 million square feet, i.e., approximately 300 m $\times$ 300 m square region. Generally, indoor enterprise networks are planned for -100 dBm target RSRP, unless the client specify otherwise. We note that for a target RSRP varying from -95 dBm to -120 dBm, iBwave consistently overestimates the number of RNs to be deployed. The same observation holds for a smaller area of 500K square feet, i.e., approximately a dimension of 215 m $\times$ 215 m.

Naturally an over-deployment results in an improved RSRP experience by the UEs. Fig. 6 shows the higher RSRP experienced by the UE. In particular, we see that iBwave recommends 8 RNs with a medium overlap setting and 6 RNs with the low overlap setting. On the contrary, our MD framework recommends 5 RNs. Then, we employ weighted k-harmonic means (WKHM) step to obtain the location of the 5 RNs. Following this, we place the 5 RNs manually in the iBwave environment in the locations recommended by the WKHM algorithm. We note that our prediction of the RSRP

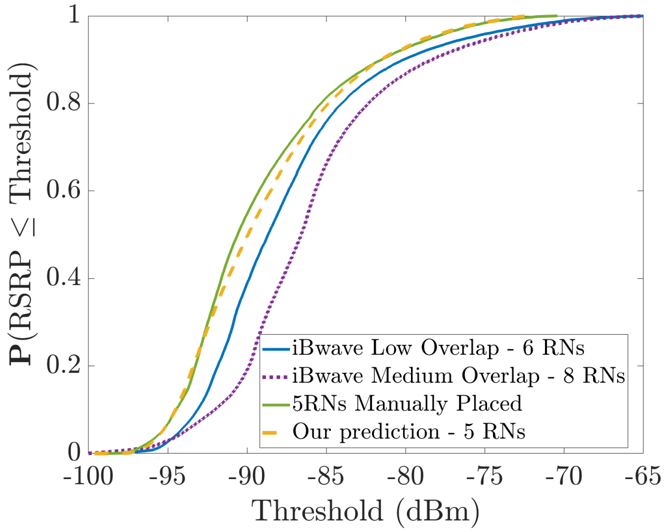

Fig. 6. RSRP performance comparison of the MD based RN placement with the iBwave recommendation.

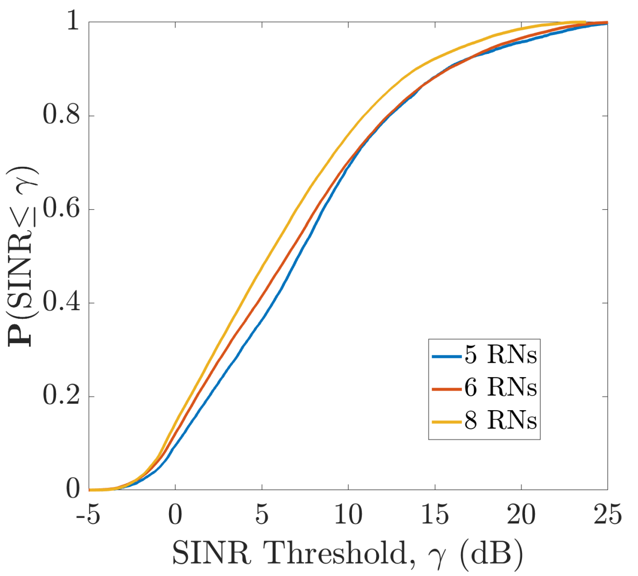

Fig. 7. SINR performance comparison of the MD based RN placement with the iBwave recommendation.

distribution closely matches the iBwave prediction. This also validates our framework from the perspective of a commercial planning software.

Fig. 7 shows that a higher number of RNs, albeit results in an improved UE RSRP, may degrade the SINR and accordingly, the experienced quality of service (QoS). However, as noted in Fig. 1, the degradation in SINR may not have a significant in realistic indoor scenarios that experience limited load.

B. Real Maps With Ray-Tracing

It must be noted that a square shaped deployment area albeit useful to derive performance trends and scaling laws, is limited in practical insights. For that, we consider real maps to test our deployment methodology. Fig. 8 shows the scenario that we study in this paper. It consists of one floor of the Park

Fig. 8. Map and example indoor propagation environment of the Park City Hospital, Utah.

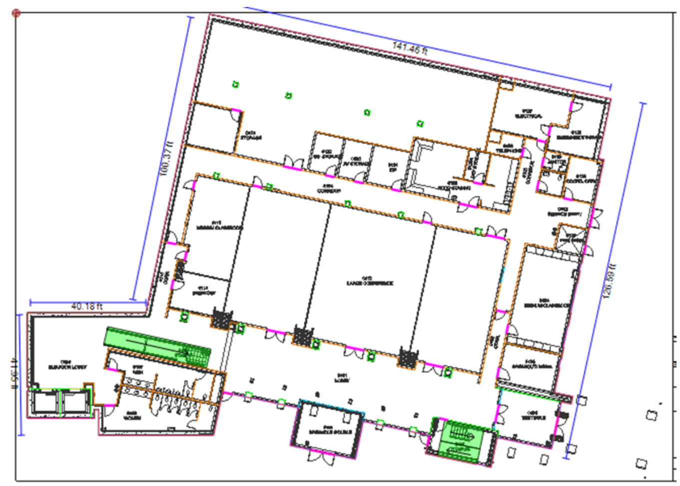

Fig. 9. A part of the considered map and the corresponding dimensions.

City hospital in Utah, USA. Apart from the map it shows the propagation environment consisting of office-type wall material and potential deployment locations on the ceiling.

First, let us consider a part of one floor as shown in Fig. 9. We employ the MD framework to obtain the number of RNs to be deployed and then leverage KM to specify the locations in which the RNs are to be placed. This is compared with the iBwave recommendation A part of the floor, i.e., the Blair education center is shown in Fig. 9. We use this section of the map to compare the performance of the ILP framework with the iBwave recommendation. In particular, employing the automatic placement tool in iBwave results in

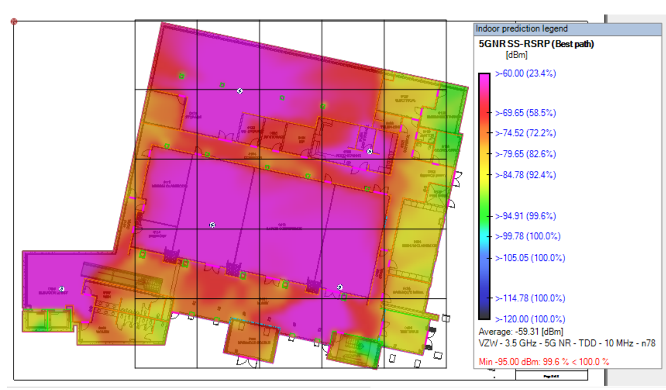

Fig. 10. iBwave recommendation for the number of RNs.

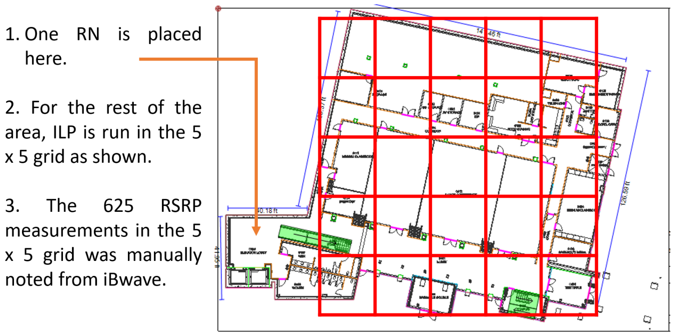

Fig. 11. ILP Formulation

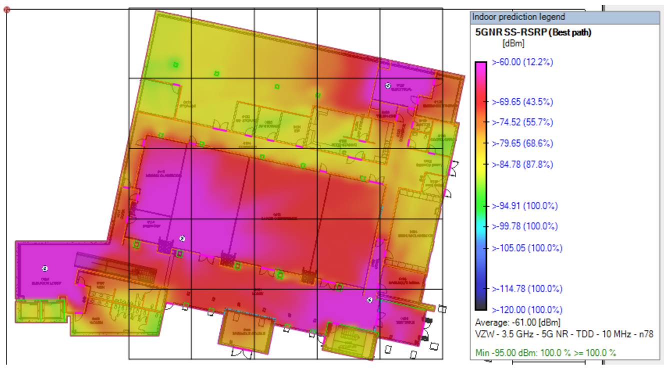

Fig. 12. ILP Result

a recommendation of 5 RNs as shown in Fig. 10.

In order to employ ILP to this map, we need to discretize the map into grids. Due to an extended portion of the map, we place an RN apriori in the extended portion while discretizing the rest of the map into a 5 $\times$ 5 grid. Although it does not cover the rest of the area, ILP results in a 100% coverage with 4 RNs as shown in Fig. 12. We plot the RSRP and the SINR for this map as shown in Fig. 13 and Fig. 14.

We apply the joint framework illustrated in Fig. 3 in the real map as shown in Fig. 15. We create a 3 $\times$ 3 grid a the location shown and place RNs in the rest of the map using the SG framework. This results in an RSRP baseline heatmap as

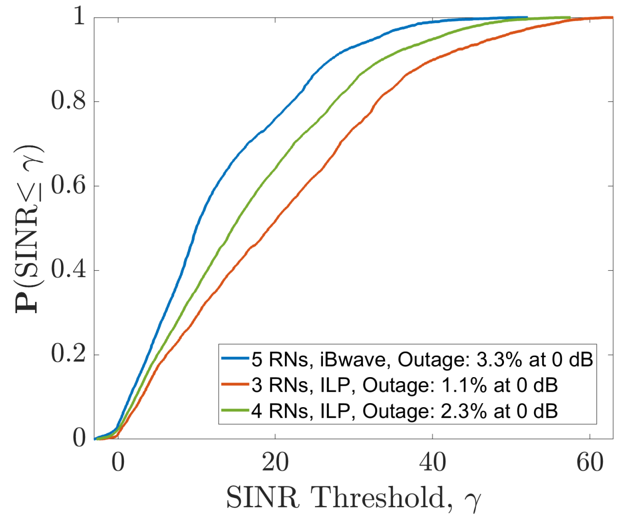

Fig. 14. Comparison of SINR performance of the ILP framework with that recommended by iBwave.

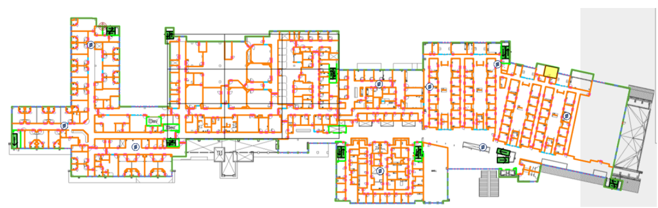

Fig. 15. Illustration of the application of joint framework in a real map.

shown in Fig. 16. Then, applying the iterative application of SG and ILP solution results in a recommendation of 12 RNs by our framework as shown in Fig. 17 and its corresponding performance is shown in Fig. 18. Similar to the previous case, here we observe that the iBwave recommendation albeit results in an improved RSRP performance, our framework achieves a better SINR while satisfying the RSRP constraint.

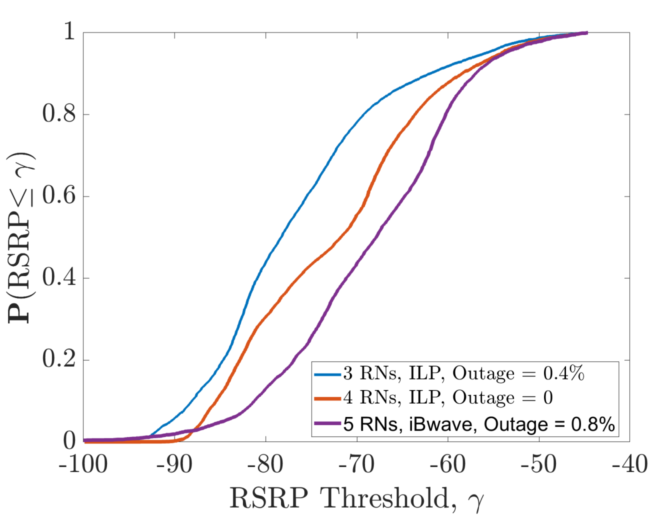

Fig. 13. Comparison of RSRP performance of the ILP framework with that recommended by iBwave.

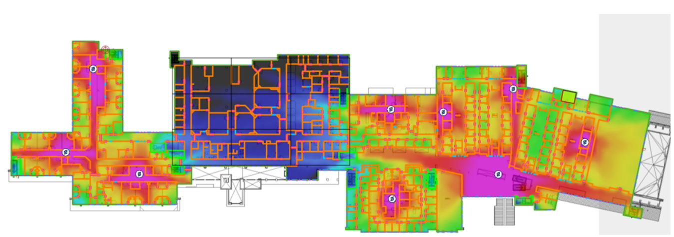

Fig. 16. Generating the RSRP matrix in the joint framework.

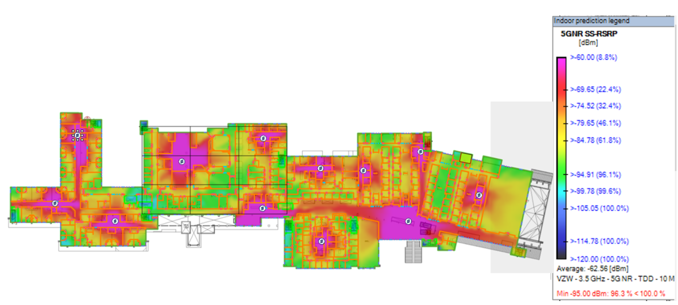

Fig. 17. Output of the joint framework.

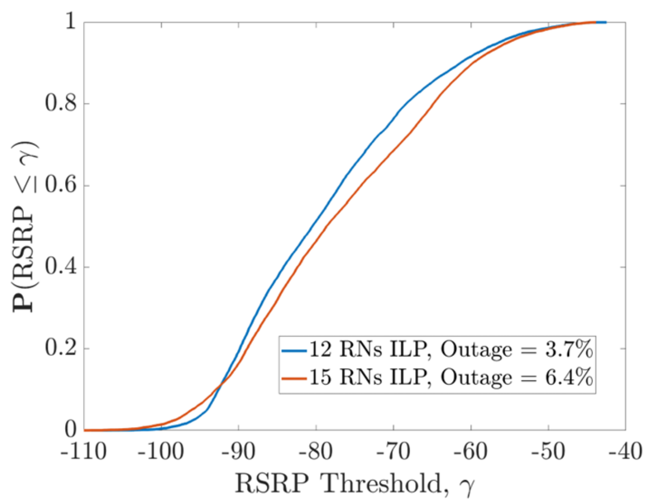

Fig. 18. Comparison of the RSRP performance of the joint framework with iBwave recommendation

V. Discussion and Conclusion

This study presents a comprehensive framework for planning and dimensioning indoor enterprise networks, with a particular focus on optimizing RN placement to meet stringent RSRP targets. Through a detailed comparison with the iBwave Design software, the framework demonstrates its capability to achieve robust network performance while minimizing the number of deployed RNs. The findings validate the framework's ability to maintain high signal quality and minimize interference, particularly in real-world scenarios involving complex indoor propagation environments. This research contributes to advancing the state-of-the-art in network planning by providing a scalable, efficient, and adaptable solution for 5G and beyond. Future work could explore integrating machine learning-based optimization techniques and real-time adaptability to further enhance network planning capabilities.

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