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AI-driven Planning of Private Networks for Shared Operator Models

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***Abstract*—Private networks represent a key innovation in current 5G and future 6G networks, offering significant benefits, particularly for vertical industries with mission-critical industrial applications. Compared to public networks, the deployment of numerous potential private networks demands automated network planning while simultaneously meeting higher performance requirements for targeted applications. Emerging approaches have successfully utilized AI-based methodologies as a basis for automated network planning in greenfield deployments within licensed but purely private frequency bands. However, these approaches fail to include and extend brownfield implementations in public mobile networks, which would be crucial for private networks running a shared operator model. Thus, this paper presents an AI-based automated network planning methodology augmented by our recently introduced and thoroughly validated data-driven channel modeling approach, DRaGon. Further, this combined AI-based planning methodology is extended to provide automated network planning solutions for shared private networks within public macro networks. The overall planning accuracy was successfully validated with only minor deviations using public network deployments as ground truth. As a key result, we demonstrate that the performance of the presented AI-based planning method can reliably and accurately plan demand-driven network expansions for professional applications with the highest quality requirements.**

I. Introduction

Non-public or private 5G networks introduce a new dynamic in the deployment of Local Area Networks (LANs) and Metropolitan Area Networks (MANs). In numerous countries, especially in Germany, private entities are now able to build their own 5G communication networks based on the 3.7 GHz–3.8 GHz (n78) and 26 GHz (mmWave) bands. This allows for the planning and implementation of networks specifically tailored to meet the requirements of demanding applications, e.g., production environments. This stands in contrast to traditional MAN-based public mobile communication networks, which were deployed to provide a base coverage and quality for end-consumer best effort services. Accordingly, automated network planning is once again becoming a highly relevant field, as this expertise is not available in most companies and the freedom from interference of neighboring networks is expected by the regulator to ensure the safety of underlying applications.

In previous works, Artificial Intelligence (AI)-based automated network planning for greenfield (fully dedicated) deployments of private 5G networks (LANs) was successfully developed and evaluated based on the *k-means* clustering method [1] [2]. This operator model is also depicted in Fig. 1 on the bottom left. In order to precisely plan the network

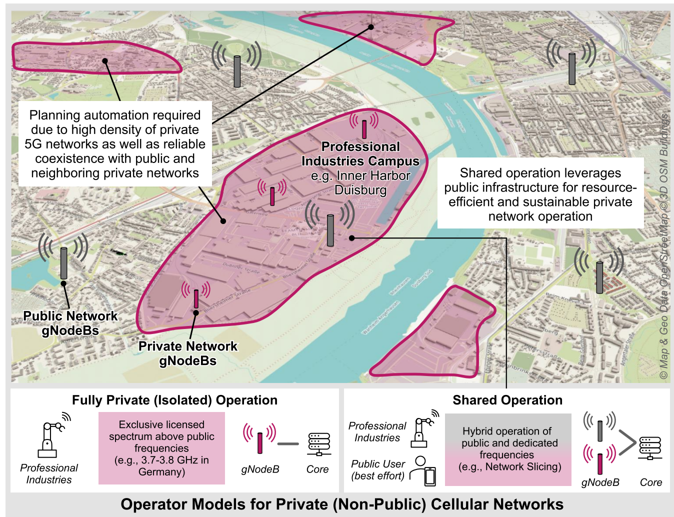


Fig. 1. Industrial private networks require automated network planning with highest reliability to meet mission-critical application requirements and simultaneous seamless operation in public mobile network environments.

for demanding applications and to avoid interference at the cell edges, highly precise Radio Environmental Maps (REMs) are required as a basis for the automated network planning method. In the previous works, ray-tracing simulations were used as a basis to generate REMs for all possible Base Stations (BSs) positions and antenna configurations. However, to further enhance the scalability and precision of the REM calculations, the Machine Learning (ML)-based radio propagation model Deep RAdio channel modeling from GeOinformatioN (DRaGon) was integrated in the course of this work, which was already proven to be more precise and faster than some commercial ray-tracing simulators as well as analytical and statistical models [3] [4].

Apart from the demand-based tailoring of 5G communication networks from scratch in the fully dedicated greenfield approach, there is also the possibility to acquire spectrum from public Mobile Network Operators (MNOs) to support vertical services. This shared operation could be realized primarily with the network slicing technology, which reserves a certain virtual share of the spectrum for applications in order to guarantee a certain quality of service (cf. Fig. 1 bottom right). However, public networks usually do not support critical applications as bandwidths are limited and the service levels are designed for best effort end-user traffic. For this reason, in this paper we want to present a brownfield approach in which gaps in coverage are automatically mitigated by adding

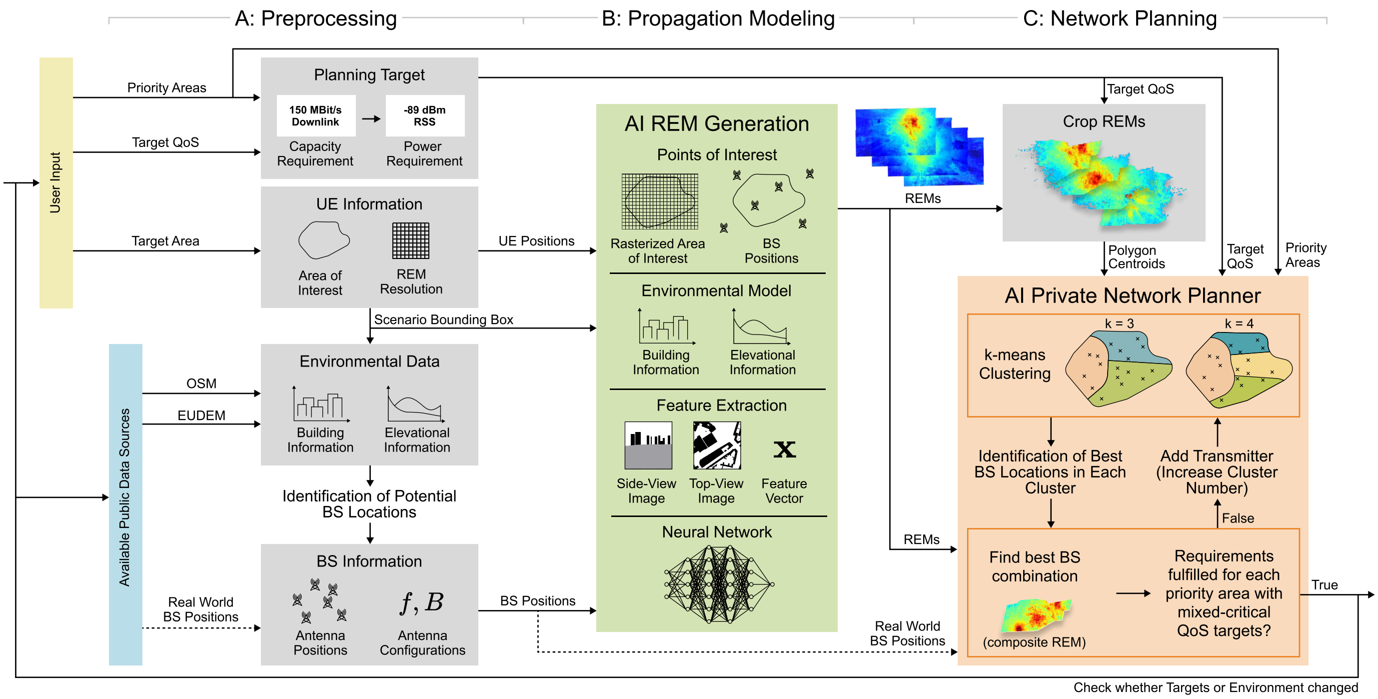


Fig. 2. Proposed Architecture for combining AI-driven radio propagation modeling and network planning.

more MNOs in the public band or by the targeted addition of non-public BSs in the n78 band. In this way, non-public LANs and public MANs can be planned in conjunction, automatically, and rapidly, based on the same approach for demanding vertical services.

The remainder of the paper is structured as follows. After discussing the related work in Sec. II, the proposed automated network planning process is described in Sec. III. Afterwards, the BS placement approach is validated in Sec. IV. Finally, a detailed performance evaluation is provided in Sec. V.

II. Related Work

Regarding automated network planning, there are related works in the context of using ML for this purpose. Gazda et al. present in [5] an unsupervised Self-Organizing Map (SOM)-based method for automated coverage planning. In [6], the *k-means* method is also used to place antennas with different radiation patterns. However, in both of these works, no detailed REMs are generated and utilized, as well as no detailed capacity planning and no consideration of the cell configuration is included. In [7], similar to the scenarios in this work, existing networks are optimized via clustering methods regarding their network utilization.

Moreover, there are works that focus on Convolutional Neural Network (CNN)-driven radio propagation modeling. The authors in [8] utilize six synthetic images as input data. There, two CNNs work in parallel: one that depicts the building side-view of the extended direct path as well as the receiver and transmitter distances, and one that depicts the building top-view as well as the distances' top-views. In contrast, in [9], not only synthetic images but also aerial photos are used in combination. Also, the elevation is taken into account and the direct path distance is fed into the CNN as numerical feature. Eller et al. propose a model in [10] that processes four synthetic input images depicting the direct path's surroundings and the distances to the BS and User Equipment (UE). The model input is extended by a numerical feature vector specifying the channel characteristics.

III. Description of Proposed AI-driven Automated Network Planning

The proposed AI-based network planning approach is illustrated in Fig. 2. The process chain is mainly based on [1]. In order to start the network planning, a target Quality of Service (QoS) and area must be specified by the user. Afterwards, the preprocessing (see Fig. 2-A) starts. This includes the conversion of the target Data Rate (DR) to Received Signal Strength (RSS) as described in [11] based on the following Time Division Duplex (TDD) Uplink (UL)/Downlink (DL) configuration: DDDDDDDDSSUUUU. Furthermore, public data sources are utilized to build an environmental model of the scenario and to extract real world BS positions if necessary. These informations serve as the basis for the deep propagation modeling (cf. Sec. III-A) and subsequent network planning (cf. Sec. III-B) with the extended components explained in Sec. III-C to III-E.

A. The DRaGon Model - Deep Propagation Modeling

In [3], we proposed a deep learning-based method to accurately predict the path loss for a specific receiver-transmitter pair. The evaluations showed that the proposed DRaGon model is more accurate than state-of-the-art solutions like empirical models and ray-tracing software. DRaGon's simplified architecture is illustrated in Fig. 3. Based on the points of interest (receiver-transmitter coordinate pairs), a 3D environmental model incorporating building shapes and heights as well as

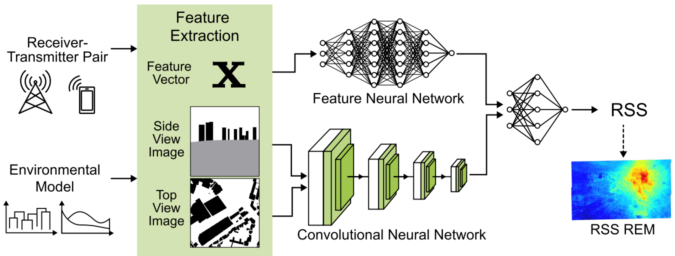


Fig. 3. Details on deep learning propagation modeling based on the DRaGon approach.

elevation data is utilized for DRaGon's feature extraction. The latter outputs two distinct synthetic black-white 2D images showing the direct path's side-view and the receivers top-view together with 13 numerical features. The latter holds position-related features (differences in latitude, longitude, and elevation, heights of transmitter and receiver), communication-related features (frequency, bandwidth, empirical path loss estimation), and features of the direct path between transmitter and receiver (3D distance, number of intersections with the terrain, distance through the terrain, number of intersections with buildings, distance through buildings).

The Deep Neural Network (DNN) consists of a CNN, which processes the image samples in six convolutional layers each followed by a batch normalization and max-pooling layer. In parallel, a Neural Network (NN) processes the numerical features in four hidden fully-connected layers. A second NN processed the CNN's and feature NN's outputs using one hidden fully-connected layer. Note that the DNN does not directly output the RSS, but the correction of the empirical path loss estimation. The model is trained on an extensive data set collected in different cities located in Germany and Denmark using the public networks and with a hyperparameter configuration resulting from massive hyperparameter tuning. The exact hyperparameters are provided in [12].

As DRaGon's feature generation process takes part in `c++` while its ML is performed in `python`, we utilize `pybind` in order to make the `c++` functions accessible for `python` and to allow an automatization of the whole DRaGon and network planning process. To make the channel estimations as efficient as possible, we implemented an interface that returns a set of features together with the environmental images for the predictions of an entire REM for one BS, when given the corresponding BS information and a bounding box of the area of interest. Instead of returning a list of images, a single large image is generated, which forms a mosaic of the individual image samples. This procedure is further accelerated by the parallelization of the feature generation such that each process generates the REM to one BS.

B. Rapid Automated Network Planning based on Clustering

In [1] and [11], the rapid AI-based automated network planning method based on clustering was presented, which is capable of coverage and capacity planning for greenfield private 5G network deployments. The simplified architecture of the planning process is illustrated in Fig. 4. For each BS of interest corresponding REMs are required resulting from highly detailed radio propagation calculations, like ray-tracing and the DRaGon method (cf. Sec. III-A). These REMs are used to derive their associated coverage shapes so that the REMs are first tailored to the area of interest and then further tailored based on the coverage requirements resulting in complex coverage shapes.

In order to find a network planning solution, the algorithm combines the given REMs for every possible BS position as well as antenna configurations to calculate a network plan for a given service level target based on a capacity requirement and 5G configuration, e.g., bandwidth, numerology, and so on. While exhaustive search could lead to the optimal solution, it is not feasible based on the large amount of REMs and the computation time of a single combination. For this reason, *k-means* clustering is used to spatially group the given REMs to reduce the amount of combinations. The clustering is done based on the centroids of the derived coverage shapes. Following, the best BSs in each cluster are identified and the corresponding REMs are merged to one composite REM. The number of clusters and thus the number of BSs is incremented until the service level requirement is fulfilled. This leads to a rapid calculation of a network planning solution based on the given application requirements while using highly-precise REMs instead of channel models.

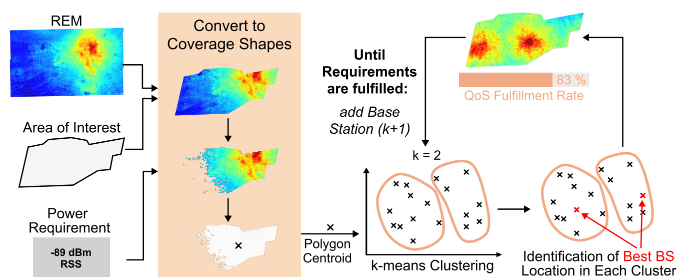


Fig. 4. Overview of k-means clustering-based automated network planning.

C. Brownfield Deployment - Utilizing existing infrastructure

Compared to the original purpose of [1] to plan 5G greenfield deployments of dedicated infrastructure in private spectrum, we added an extension that consideres existing infrastructure in the planning process and allows for a public and private spectrum mix. Therefore, we modified the procedure so that real world antenna locations can be provided as input to the process and are taken into account both in the radio propagation modeling and in the network planning. The provided antennas can be classified into two types, which need to be treated differently, described in the following.

Nearby Antennas: As antennas located nearby the area of interest are likely to affect the available power and data rate in this area, it appears reasonable to take these into account in the planning process in order to optimize the placement of new BSs when expanding already existing infrastructure. When searching for the combination of the best antennas, the already existing surrounding antennas are included. In [1], the best combination is identified on the basis of maximum coverage. As the latter is achieved rather quickly in this case, a new score is established here, which is determined from:

- relative number of REM cells with RSS > -90 dBm
- relative number of REM cells with RSS > -70 dBm
- relative number of REM cells with RSS > -50 dBm
- mean RSS normalized to range [-40, -100] dBm
- minimum RSS normalized to range [-40, -100] dBm

whereby the score is calculated as the aggregate of the individual categories and normalized to range [0,1].

Antennas inside area of interest: When enhancing existing networks to meet vertical service levels, existing hardware may appear located inside the area to be planned. In this case, the clusters produced by *k-means* clustering algorithm are utilized to identify to which cluster the existing antennas belong to. Then, all identified clusters are eliminated and the best antennas in the remaining clusters have to be found in order to densify the existing network infrastructure.

D. *Use of multiple priority areas*

Another extension is the ability to deploy multiple priority areas. The latters can be assigned to different QoS targets. The network planning process then is carried out incremental: First, the planning is performed for the priority area with the highest demand. As soon as the QoS requirement for this area has been met, the planning is dedicated to the priority area with the next highest demand until the requirements of all priority areas as well as the surrounding campus polygon are fulfilled.

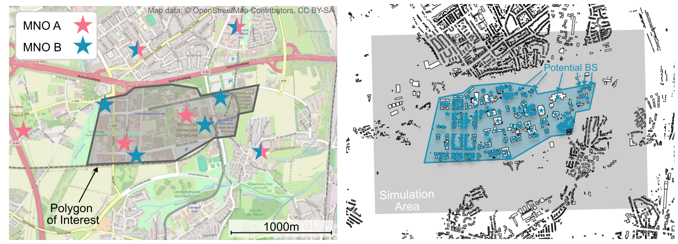
E. *Allowing for mixed frequencies*

Fully dedicated operation in the 3.7 GHz range enables high data rates, which are typically required in private networks. However, if the area to be covered is relatively large, it may be useful for resource-efficieny reasons to consider planning with lower-frequency BSs if the target QoS can still be guaranteed. The user can therefore specify whether lower-frequency BSs should be considered in the network planning.

IV. Validation based on real-world ground truth

Validation Scenario: In order to validate the antenna placement of our approach, we have identified *TU Dortmund University Campus* as a suitable scenario. To do so we utilize public german networks as a ground-truth. As german 5G networks are intended to densify the capacity of the 4G networks, but do not provide an optimal area coverage, we rely on public 1800 MHz 4G networks. We therefore refer to the antenna positions provided by public sources and extract the location data for the two german MNOs represented on the university campus. As no reliable information on the BS's sectorization is known, we model one omnidirectional antenna at each location instead of three sectors.

Fig. 5a shows the chosen polygon of interest together with the extracted BS locations for the two MNOs. In addition, Fig. 5b shows the extracted building polygons together with the simulation area as well as the identified potential antenna candidates. The simulation area includes a margin of 500 m to



(a) Validation area with ground-truth antenna positions (b) Extracted buildings and potential antenna positions

Fig. 5. Illustration of validation scenario at TU Dortmund University Campus.

the polygon bounding box and functions as the basis for the area of the REM resulting from radio propagation modeling based on DRaGon.

Validation Method: We validate our approach based on the distance between the placed and the real-world BS locations. While OpenStreetMap (OSM) offers detailed information about the buildings' shapes, it does not provide comprehensive information on the buildings' heights. To overcome this issue, we assign a default building height of 12 m to buildings for which no height information is available. However, in the context of optimizing BS positioning, this can lead to deviations from the true positions. It may happen that a building is selected for the BS placement, which in reality only has one floor, while a nearby building may not perform as well in our simulation, but would be preferred in reality due to its greater building height. Furthermore, there might exist restricted zones, where mobile network BSs are not allowed to be placed, but this information is not available. To address these issues, we consider the top five network planning results here and analyze the distance between placed and true BS for all those five solutions. In this process, we analyze how the distance behaves depending on the amount of expert knowledge available about the environment. Therefore, we start with greenfield-like planning, where no information about existing infrastructure is given. Then, we analyze how accurate the BSs are placed when the polygons surrounding BSs are known. Further, we incrementally add the number of known BSs located inside the polygon of interest. This validation process is performed for both MNOs and the target QoS for the network planning process is set to 100 Mbit/s DL.

Validation Results: In Fig. 6 we compare the five optimal planned BSs combinations based on the proposed network planning approach with the actual deployments for the two considered MNOs. Initially, the BSs are placed from-scratch. Due to the high Degree of Freedom (DoF), the planned locations diverge strongly from the real deployment for both MNOs. For MNO A, the positions differs by up to 550 m. As depicted in Fig. 5a, the lower left BS on the campus polygon's area owned by MNO A is located relatively close to its edge. When planning the location for an optimal coverage on the polygon's area, it does not seem appropriate to place an omnidirectional antenna at the edge of the scenario, but rather more central. Subsequently, the DoFs are incrementally reduced by first adding information about the nearby antennas and then gradually extending the established antennas inside

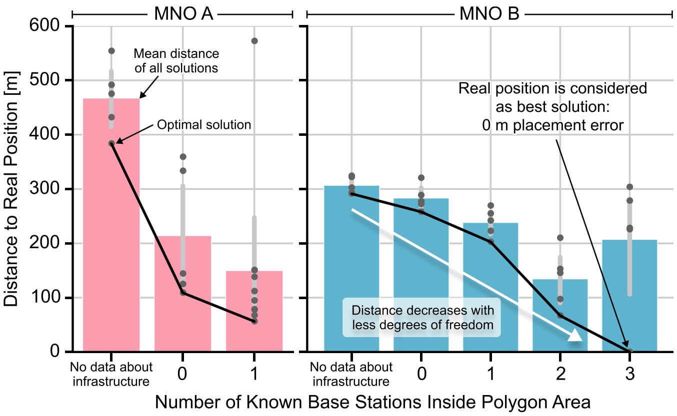


Fig. 6. Comparison of AI-planned BS positions against ground-truth data from real-life MNO confirms validity of proposed network planning process.

the polygon. For both MNOs, a trend can be observed that the planning increasingly gets closer to the real deployment as the knowledge of infrastructure increases. If one out of the two existing BSs is given for MNO A, the distance between planned and real position is around 100 m, indicating that our approach selected neighboring buildings to the one where the real BS is deployed. As pointed out earlier, we do this analysis on the basis that the public networks are ideally planned for which we have no evidence. Furthermore, we do not know all information about buildings and restriction zones that might make our solution not applicable in real-world even though it leads to better coverage. For MNO B, four BSs are deployed inside our polygon of interest, allowing us to perform a multi-stage analysis. To simplify the process, we iteratively add the BS that was the most difficult to plan in the previous stage. It can be observed, that with a decrease of the DoFs, the distance diminishes. For the last case, where only one remaining antenna needs to be placed, the best found solution is the actually the real-life deployed position. The other solutions consider buildings significantly further away than in the iterations before. This is due to the fact that the building density is relatively sparse in the BS's region.

V. Peformance Evaluation based on Professional Industrial Scenario

Evaluation Scenario: Following the successful validation of our methodology, we are now seeking to plan the network for a professional industry scenario. We identified a part of the world's largest inner harbor in Duisburg, called *Duisport Logport*, suitable for this challenge. The scenario is illustrated in Fig. 7, where Fig. 7a visualizes the evaluation area together with the existing neighboring infrastructure for MNO B with 1.8 GHz carrier frequency and 20 MHz bandwidth.

There exist multiple future applications in this area, e.g., Teleoperated Driving (ToD) tasks. Tab. I defines three types of applications together with their QoS requirement in terms of UL DR [13] that form the basis for the network planning to be performed. As some of the applications are limited to a certain area of the scenario, we identified different priority areas, which are visualized in Fig. 7b. Note that *Priority Area 3* refers to the scenario polygon itself.

TABLE I
Target QoS in the Duisport Logport scenario.

Application	**#**	**UL Requirement per User [Mbit/s]**	**Priority Area 1**	**2**	**3**
Teleoperation Crane (Indirect ToD)	5	15	x		
Teleoperation Forklift (Direct ToD)	3	30	x	x	
Other (Office)	1	35	x	x	x
		Total UL Requirement [Mbit/s]:	200	125	35

We consider three different operator models (see also Tab. II) in the following network plannings:

- *Shared Operation:* A 50%-slice of 10 MHz bandwidth is provided from the 1.8 GHz public network. In order to fulfill the QoS requirements, additional BSs are planned in non-public frequency range with 3.7 GHz carrier frequency and 50 MHz bandwidth.
- *Shared+ Operation:* Additional BSs are planned with 3.7 GHz carrier frequency and 50 MHz bandwidth for *Priority Area 1* and with 1.8 GHz carrier frequency and 20 MHz bandwidth for *Priority Area 2 and 3*.
- *Fully Private Operation:* BSs are planned with 3.7 GHz carrier frequency and 50 MHz bandwidth without considering existing infrastructure.

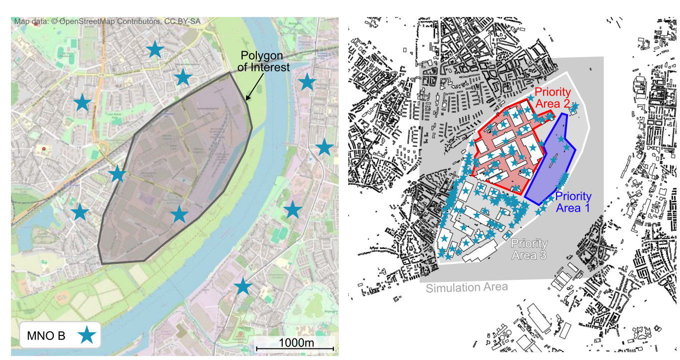
TABLE II
Considered frequency mix and operator models.

	Public Frequency		**Private Frequency**
Frequency Bandwidth	1.8 GHz 10 MHz	1.8 GHz 20 MHz	3.7 GHz 50 MHz
Shared	x		x
Shared+	x	x	x
Fully Private			x

For the evaluation, the percentage to which the QoS targets are fulfilled in the individual priority areas is analyzed using the following utility rate:

$$\text{Utility Rate} = \frac{\#\ \text{REM cells with}\ \mathrm{DR_{UL}} \geq \mathrm{DR_{UL\ Target}}}{\#\ \text{REM cells}} \tag{1}$$

Network Planning Results: Fig. 8 visualizes the QoS fulfillment rates for each priority area and operator model



(a) Evaluation area with ground-truth antenna position (b) Extracted buildings and potential antenna positions

Fig. 7. Overview of case study: world's largest inner harbor (Duisport Logport) including application-based priority areas as planning targets.

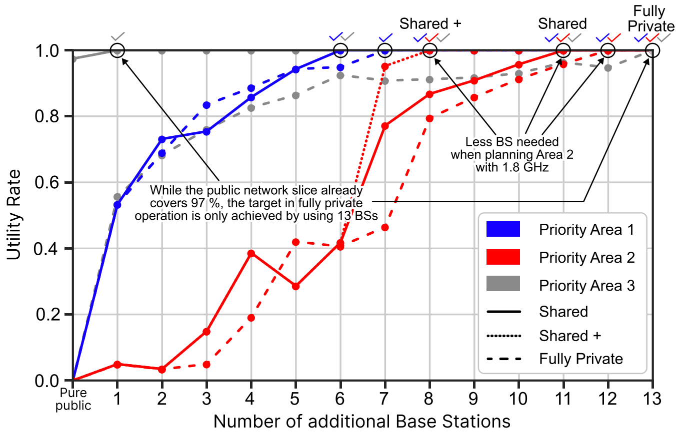


Fig. 8. Planning progress of the Duisport Logport scenario for different operator models.

plotted against the number of added BSs. In the context of a *Shared Operation*, the QoS requirement for *Priority Area 3* is almost fulfilled by the public infrastructure. For satisfying *Priority Area 1* six additional BSs are needed. While the requirements of *Priority Area 2* are already met by around 40% at this point, five further BSs are needed. In comparison, for a *Shared+ Operation* only two further BSs are used. For a *Fully Dedicated* network, the situation is similar to *Shared Operation* with the difference that for meeting the requirements of *Priority Area 1* one further BSs is needed and that the requirements of *Priority Area 3* are not fulfilled after placing twelve BSs in the scenario requiring to place one further BS.

Fig. 9 shows the planning progress for the operator model that is found to require the fewest BSs, namely *Shared+ Operation*. The planning progress is illustrated with the help of RSS and DR REMs with an increasing number of BSs. The REM resolution is set to 15 m. It can be seen that the overall UL DR is relatively low for the public network slice, as it is constrained to 10 MHz bandwidth. While for the 3.7 GHz BSs significantly higher UL DR up to 260 Mbit/s are achieved, it seems obvious that lower-frequency BSs with greater coverage are more suitable for a resource-efficient expansion in *Priority Area 2* if they still meet the QoS requirements.

VI. Conclusion and Outlook

In this paper, we presented an AI-enabled automated network planning methodology leveraging deep-learning propagation modeling for fully-dedicated and shared operator models. The validation of our proposed network planner method confirmed an accurate and highly reliable planning result against complex real-world ground-truth scenarios. In a professional industrial case study, the network planner was utilized to fulfill mixed-critical application requirements. Different operator models were successfully applied in terms of network densification to keep up with the increasing demands of professional industry scenarios, where *Shared+* approach led to most resource-efficient planning results.

In future work we plan to adapt opportunities for BS placement to meet specific environment characteristics such as restriction of unsuitable buildings or building independent placement. Further, underlying methods will be advanced to cover mmWave characteristics for propagation modeling as well as beam steering functionality. Additionally, we plan to enhance the network planning approach to indoor scenarios addressing challenging dynamics in for example logistics and manufacturing.

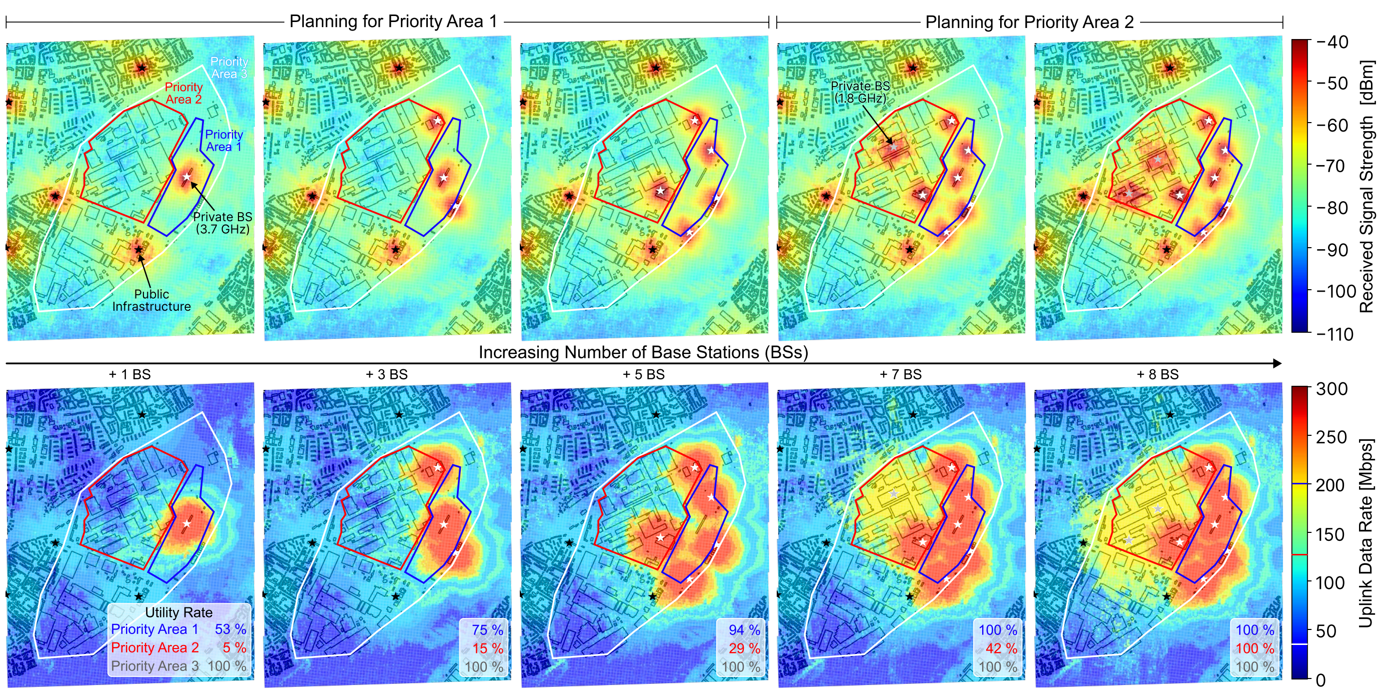


Fig. 9. Planning progress of the Duisport Logport scenario illustrated as REMs for RSS and DR for increasing BS number until planning targets are achieved when applying a shared operation with non-public frequency mix.

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