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Rapid Network Planning of Temporary Private 5G Networks with Unsupervised Machine Learning

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***Abstract*—Private 5G networks are considered key enablers for allowing industrial companies to deploy fully digitized production environments in an ad-hoc manner. Based on the foundation of exclusively assigned frequency spectrum resources, a guaranteed quality of service level can be achieved. However, strict requirements and regulations regarding antenna placement and interference with neighbors impose tough challenges on enterprises without expertise in communication network planning. For closing this gap, we propose an unsupervised learning-based network planning framework capable of rapidly and autonomously finding suitable solutions for antenna placement based on given environments and service quality, while satisfying regulatory restrictions. Results show that our proposed system reliably and rapidly calculates antenna positions and powers for realistic private 5G network scenarios. Temporary network deployments, e.g., Formula 1 tracks inside the given private 5G network, can be planned within minutes based on pre-calculated radio environmental maps.**

I. Introduction

An increasing amount of emerging application domains are moving towards fully digitized environments, aiming at improving the efficiency and flexibility through the deployment of automation and data exchange technologies. A major field of this new generation of transforming environments, such as the field of Industrial Internet of Things (I-IoT), is addressing challenging and diverse requirements on underlying communication infrastructures. In this context, a key feature of upcoming 5G is a new generation of private 5G networks, also referred to as campus or non-public networks. These private physical or virtual cellular systems are aiming at providing reliable wireless connectivity for demanding and even critical applications, while maintaining full control and flexibility for private use by industry, public institutions and local authorities. A significant advantage to provide and ensure this increased Quality of Service (QoS) demand is the opportunity to operate even private networks in licensed spectrum bands. While in some countries, mobile network operators offer private network solutions based on e.g., network slicing approaches, other countries have opened specific spectrum bands for local and dedicated use. However, even unlicensed spectrum can be seen in cases of closed and controllable environments as a valid solution for private networks, such as remote rural areas.

A. Elaborating the Need for Automated Network Planning

The deployment of private 5G networks is not only discussed in the reference application of stationary long-term networks, but also of particular relevance when a temporary network with still very demanding requirements for the communication network has to be realized locally. Examples of such temporary networks are major international events (Formula 1, America's Cup), where large amounts of data are required for event operation as well as for the real-time integration of the audience with low latencies and high reliability. In our previous research regarding Radio Access Network (RAN) slicing, optimal network planning was identified as the main prerequisite for the operation of low latency slices [1]. Also, in the field of automated intralogistics, non-stationary ad-hoc 5G network operation is essential for the continuous adaptation of reliable network solutions to very rapidly changing application environments. Not least, highly reliable static as well as temporary communication networks are also essential for emergencies or disasters, e.g., to provide temporary or static hospitals with a reliable communication solution for all medical emergencies or remote operations (cf. Fig. 1). However, despite short-term deployment goals for ad-hoc 5G networks or when local conditions change rapidly in static networks, deployments for such demanding requirements call for extensive and reliable network planning in advance. Current planning methods are very well designed for the long-term and reliable operation of cellular radio networks, but associated with significant limitations for rapid planning objectives. On the one hand, a high level of resources and expert know-how is required for the operation of specialized tools, while on the other hand the high manual effort and the required wealth of experience for fine-tuning and monitoring do not do justice to the rapid pace of use. As a consequence, the necessary planning quality cannot be achieved cost-efficiently with a large number of consecutive or parallel network areas.

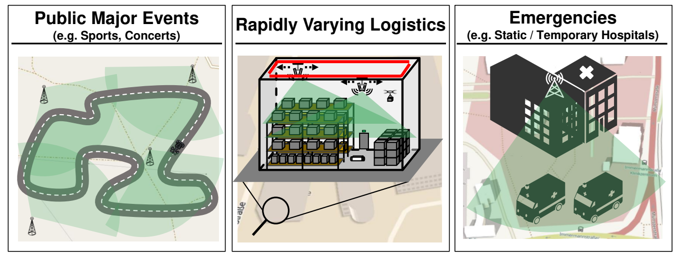


Fig. 1. Example application domains for static and temporary private networks with high demand for automated and fast network planning results.

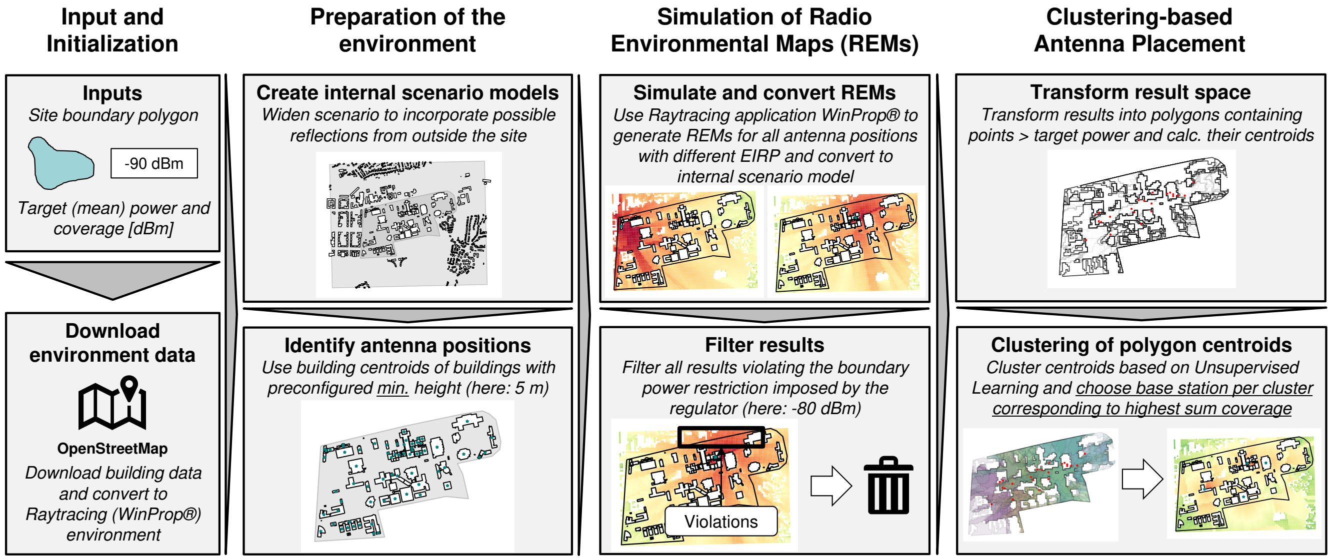


Fig. 2. Overview of the processing steps of the Automated Network Planning Framework from user input to network planning result.

B. Proposed Automated Rapid Network Planning System

To this end, this paper proposes a concept for an automated network planning system that effectively supports potential private 5G network operators in the detailed specification of the required network design. For this purpose, a Machine Learning (ML) procedure is used which utilizes clustering-based unsupervised ML methods. The network planning framework is then evaluated using a realistic private 5G network with temporary deployments. The proposed system for automated network planning is presented and detailed in Sec. III.

The remainder of this work is structured as follows: Sec. II gives an overview of related work regarding automated network planning concepts. The detailed description of our proposed and developed system is given in Sec. III, followed by its evaluation in Sec. IV. Finally, a conclusion and details to future work are presented in Sec. V.

II. Related Work

Related work in the field of automated network planning mainly focuses on traditional approaches rather than utilizing ML. Often optimization concepts like genetic algorithms are used in combination with analytical (channel) models, e.g., in [2] as well as in [3]. Similar works were conducted by Zhang et al. [4] using a bio-inspired approach called Particle Swarm Optimization, as well as by Allen et al. [5] relying on the so-called Simulated Annealing. A related approach based upon Nested Square Pattern is utilized in [6] but with the aim of optimal object localization rather than network planning. The main difference of the described approaches above to the novel concept introduced in this work is the complexity of the underlying environment, i.e., the channel model or terrain information used, as our automated network planning system can easily scale up complexity by integrating any (network) simulation software, and possibly Hardware-in-the-loop (HIL) concepts. In contrast, above works use analytical channel models, neglecting local conditions. Furthermore, in contrast to the traditional approaches, our system can incorporate regulatory restrictions into the network planning. There is also related work using ML in general for network planning purposes, e.g., by Morocho-Cayamcela et al. [7] to lower the environmental uncertainty in wireless propagation with deep learning. Moreover, Dai et al. [8] successfully implement and analyze an ML-based network planning system based on genetic and greedy algorithms. Similar to the approach presented in this paper, Unsupervised Learning methods are used in [9] and [10] for automated network planning. Finally, ML (Deep Neural Networks) is used in [11] to predict channel conditions in a given area based on its satellite images, which is planned to be incorporated to further improve the accuracy and computation speed of the environment model.

III. Methods

The developed automated network planning framework will be described based on Fig. 2, progressing from top left to bottom right.

In the input and initialization phase, the 5G Campus Network Planner that we previously developed and which is available online[1] serves as a starting point for the automated network planning described in this work. It supports the planning of a private 5G network by staking out an area, e.g., the company's premises, and provides a predicted fee for acquiring the frequency usage license. In our work, the given polygon determines the area, in which the automated network planning should be conducted.

This polygon serves as the input for our pre-processing system, which prepares the environment for the automated network planning framework. For this, a bigger rectangle around the private network polygon is created to incorporate possible

[1] Available: https://campusnetzplaner.kn.e-technik.tu-dortmund.de

TABLE I

PARAMETERS PASSED ON TO THE ALTAIR WINPROP© RAY-TRACING SIMULATION FRAMEWORK

Parameter	Description	Value
Antenna position	Positions based on longitude, latitude, and height	Building centroids (min. height *5m*)
Antenna output power	Equivalent Isotropically Radiated Power (EIRP) in *dBm*	[15, 18, 21, 24, 27, 30, 33, 36, 39, 42]
Antenna height offset	Offset between building height and antenna height in *m*	5
Antenna radiation pattern	The radiation pattern of the deployed antennas	Omnidirectional
Antenna frequency	Center frequency in *GHz*	3.75
Simulation model	The simulation model used in the ray-tracing software	Standard Ray Tracing (SRT) model
Prediction height	The height level where the received power is evaluated in *m*	1.5

reflections from outside the site into the Radio Environmental Map (REM) simulations which follow later. Environment data which mainly consists of building information is downloaded automatically from OpenStreetMap (OSM)[2] based on the polygon of the premise and its surroundings. The different polygons and the respective buildings are then converted into an internal representation based on the Python programming language (ver. 3.7) library *geopandas*[3] which includes convenient modules for converting different geographic coordinate systems and conducting geometric calculations. Additionally, for the simulation of the REMs the OSM map is also converted into a 3D environment usable by the Altair WinProp© ray-tracing simulation software. The next step is to identify possible antenna positions. For this, our framework uses centroids of buildings with pre-configured minimum height of $5\,\mathrm{m}$.

Now, the REMs can be calculated based on the identified antenna positions. The network planning framework provides an interface for integrating different methods for calculating the REMs. In this case, an interface to the Altair WinProp© ray-tracing simulation software was developed and utilized. Table I provides an overview of the parameters passed on to the ray-tracing software. The specific frequency of $3.75\,\mathrm{GHz}$ is chosen based on the newly available private mobile network frequency band in Germany (and, in the future, possibly in other parts of the European Union).

After all REMs for every antenna position and configuration are calculated the results which consist of received powers in dBm within the defined polygon are converted to the internal scenario representation based on *geopandas*. These results are then further pre-filtered according to user-defined specifications, such as regulatory aspects, in order to exclude invalid solutions in advance. This ensures that the ML converges faster. In this case, the received power at the private network boundaries must not be higher than $-80\,\mathrm{dBm}$ which approx. corresponds to the regulation imposed by the German Federal Network Agency (Bundesnetzagentur). After all the pre-processing and pre-calculation of REMs is completed and invalid results are filtered, the clustering-based antenna placement is initiated.

From this point on, all results are cached and available for later antenna placement evaluations without repeating the previous steps. This is particularly interesting in light of the fact that spatial prioritization can be performed within the private 5G network. This enables very fast reconfiguration of antenna positions, for example to plan temporary events such as Formula 1 races within the existing private 5G network, without having to recalculate REMs.

Before applying the clustering method the result space is transformed based on the minimum received power specified by the user which is $-90\,\mathrm{dBm}$ in this case. Every REM is consequentially transformed into one polygon each containing all parts of the map which indicate a received power $\geq -90\,\mathrm{dBm}$. In Fig. 2 (and also in Fig. 5), the boundaries of these polygons are indicated as overlapping "puzzle pieces". In the same figure, the red dots indicate the centroids of these polygons which represent the results space of the clustering method. In this work, *K-means* [12] was chosen as the clustering method. Other (density-based) clustering methods like DBSCAN and OPTICS were also tested, but found to be unsuitable for this application (due to the non-configurability of the cluster size).

After the clustering method is trained and each centroid is assigned to a cluster, the polygon that forms the maximum area together with the polygons of other clusters is selected for each cluster. Then, base stations or antennas corresponding to these polygons are chosen for deployment, with the maximum output power possible. Since invalid solutions are already pre-filtered, this results in the network with the highest signal quality possible using omnidirectional antennas and the given regulatory aspects. Thus, the maximum coverage with the target power is achieved without having to consider all possible solutions, speeding up the process significantly. In the next section, an exemplary network planning scenario is described on the basis of which the framework was evaluated.

IV. EVALUATION

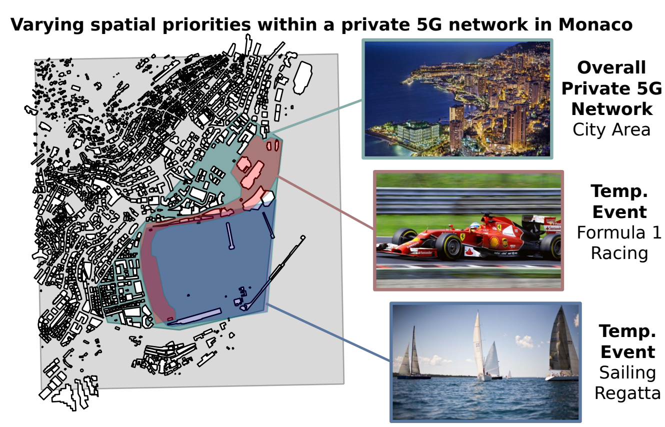
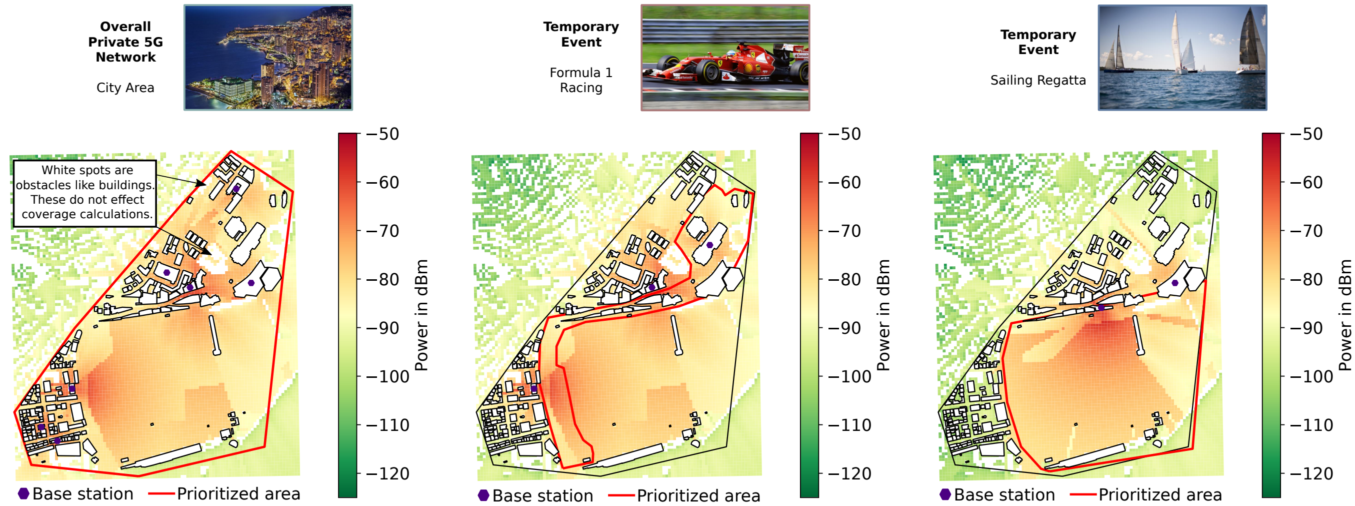


Fig. 3. Evaluation scenario comprising a residential portion of Monaco, which represents the overall private 5G network. In addition, two temporary events an F1 track through Monte Carlo and a Sailing Event area at Port Hercule.

[2]© OpenStreetMap contributors (https://www.openstreetmap.org/copyright)

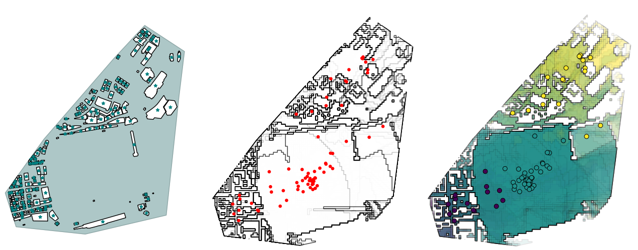
[3]geopandas 0.9.0



(a) City - Base stations: 7, Coverage: 94.99 % (b) Formula 1 - Base stations: 3, Coverage: 97.59 % (c) Sailing - Base stations: 2, Coverage: 94.74 %

Fig. 4. Example results of the automated network planning with at approx. 95 % coverage ratio based on the *K-means* algorithm and a coverage goal of $-90\,\mathrm{dBm}$ within the spatially prioritized boundaries (red line), using omnidirectional antennas (purple dots) and avoiding received powers outside of the boundaries exceeding $-80\,\mathrm{dBm}$.

The evaluation of the automated network planning framework is based on the comparison of three different scenarios within a single overall private 5G network. For this, a part of the city-state of *Monaco* was chosen, which is presented in Fig. 3. The first simulated scenario is represented by the green area, which depicts the overall private 5G network in a residential area comprising *Monte Carlo* and *Port Hercule*. Thus, large-scale network planning is carried out first, which is based on macro network planning. Within the area two different temporary events are held, a Formula 1 (F1) race (red area) through Monte Carlo and a sailing regatta (blue area) at Port Hercule. The goal is to show that when a given overall private 5G network is planned and thus REMs are pre-calculated, the network planning of temporary events within the area can be rapidly calculated by our proposed network planning framework based on spatial prioritization. Identified antenna positions are marked by teal colored points in Fig. 5a.



(a) (b) (c)

Fig. 5. Overview of the *Monaco* scenario comprising of possible base station locations on building centroids (a), the corresponding results space after REM simulations (b) as well as an example clustering solution for 3 clusters using the *K-means* clustering method (c). The solution space is comprised of polygons which represent locations with the required signal quality. The red dots depict the centroids of those polygons, which are subsequently used to cluster the possible base station locations.

After calculating all REMs based on these antenna positions and filtering invalid solutions the results space is transformed for the clustering method according to Sec. III. In Fig. 5b, the black lines and the red dots indicate the resulting polygon borders and centroids, respectively. After the scenario is preprocessed and prepared, the *K-means* algorithm is applied to the resulting polygon centroids using the default parameters[4]. The number of clusters is incrementally increased from 1-8 and corresponds directly to the number of base stations. An example clustering result for the *K-means* method is depicted in Fig. 5c for cluster size 3, where the different colors distinguish the clusters. It is shown that there is a reasonable spatial distribution of the clusters.

In Fig. 4, exemplary network planning results and their corresponding REMs are depicted from left to right for the overall *city*, the *F1* racing and *sailing regatta* temporary events. Here, the REMs are depicted as heat maps to display the received power within the private 5G network and its surroundings in dBm. For all three scenarios, a solution with a coverage of approx. 95 % is presented. This corresponds to a cluster amount of 7, 3 and 2 for the city, F1, and sailing scenarios, respectively. It can be seen that the spatial distribution of base stations through the clustering approach seems reasonable and provides a realistic and expected result for all three scenarios, taking into account the regulatory constraints. Furthermore, a more detailed comparison can be conducted looking at Fig. 6. There, the coverage ratio of the set target of $-90\,\mathrm{dBm}$ within the given prioritized area is plotted as a function of the number of clusters, which here directly represents the number of base stations. It can be seen that the sailing scenario can already be covered very well with a small number of base stations. The F1 scenario is, due to the more complex shape of the prioritized area polygon, at a saturated

[4] scikit-learn 0.24.1

coverage of $94.74\,\%$ starting with 3 deployed base stations. On the contrary, the city scenario which requires a macro-network oriented planning due to the larger area to be covered, provides a more differentiated picture. Here, it becomes clear that a cost-benefit analysis must be carried out, since, for example, $95\,\%$ coverage can only be achieved starting with 7 base stations. Accordingly, it may be worthwhile to forego the last percent coverage in favor of the costs.

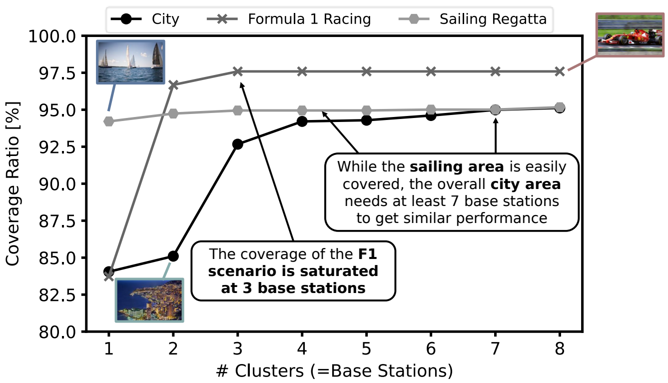


Fig. 6. Relation between *K-means* cluster size (also here: amount of base stations) and coverage ratio. While the sailing and F1 scenarios can already be covered very well with a small number of base stations, the city scenario requires a large number of base stations to achieve the same high coverage.

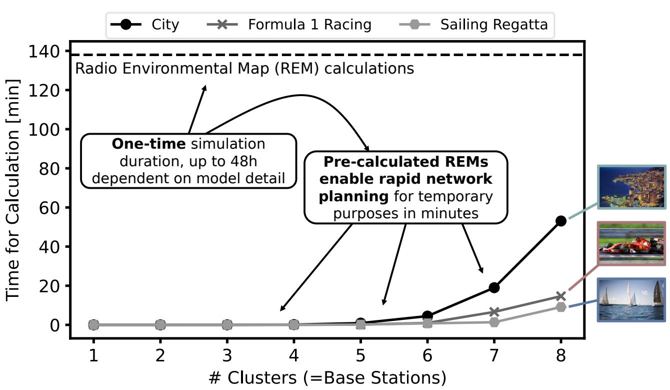


Fig. 7. Relation between *K-means* cluster size (also here: amount of base stations) and time for calculation. Note that the simulation duration of the REM calculations are one-time only. After pre-calculation of REMs, rapid network planning for temporary purposes is enabled in minutes for the different events.

In Fig. 7, the relation between the cluster size and the time for calculation[5] in minutes is depicted on the x- and y-axis, respectively. Here, the dashed line at the top shows the duration of the REM calculations (here: $139\,\mathrm{min}$, dependent on model detail up to $48\,\mathrm{h}$), which is performed only once and can be used for all network planning runs thereafter. The network planning calculation times for scenarios are shown with the solid lines depending on the number of clusters. It can be seen that the planning of temporary events within a private 5G network can be performed within a few minutes, which is one major strength of this framework.

[5]Hardware and operating system used: Intel Core i7-7700 3.60 GHz (4 Cores, 8 Threads), 16 GB RAM, Windows 10

V. Conclusion and Outlook

In this paper, we presented a clustering-based approach for automated network planning. While automated network planning concepts already exist, these are often limited by the environment model, which is based on traditional channel models. In contrast, we present a solution easily able to integrate complex (3D ray-tracing) network simulations or even HIL concepts. In conclusion, reasonable as well as optimal results can be acquired with this automated network planning system, able to deal with a target network planning solution while being confronted with restrictions, including those imposed by frequency usage terms or the owner of the premises (e.g., no-go-areas). The network planning of temporary deployments inside the premises can be determined within minutes after calculating the REMs. Premise owners, e.g., industrial companies, with plans to operate a private 5G network can thus be effectively supported by our system in terms of network planning, an expertise that is not present in most enterprises. In this context, the *K-means* algorithm provides the best parameter set for network planning, while providing reasonable results. For future work, we plan to extend the automated network planning framework. Furthermore, different antenna types will be supported, e.g., sector or beamforming antennas. The optimal alignment of sectors or beams can be established by including other ML concepts, such as Reinforcement Learning (RL). Additionally, capacity planning will be incorporated, which also integrates network slicing dimensioning. Also, the integration of indoor network planning is aspired, which brings its own specific challenges. In order to further validate this concept, a newly developed ML-based radio field simulation [11] and own 2D-based ray-tracing concepts will be included.

Acknowledgment

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