OPTIMIZATION OF WIRELESS NETWORKS INFRASTRUCTURE USING ARTIFICIAL INTELLIGENCE METHODS

DOCTORAL THESIS

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# CONTENTS

## 1 Introduction
1.1 Research Motivation .......................................................... 4  
1.2 Problem Statement .......................................................... 4  
1.3 Dissertation Scope and Goals ............................................... 5  
1.4 Thesis Outline .............................................................. 6  

## 2 Mobile Networks in 5G+ Era and Their Deployment
2.1 Mobile Networks in 5G+ Era ................................................. 6  
2.1.1 Existing Cellular Networks – Issues and Challenges ................. 7  
2.1.2 Emerging 5G+ Use Cases, Applications, and Enablers ............... 7  
2.2 Supporting Network Infrastructure ....................................... 8  

## 3 Algorithms Solving Location Covering Problems
3.1 Exact Approach ............................................................. 8  
3.2 Meta-heuristic Methods .................................................... 9  

## 4 Location Covering Model for Deployment of Base Stations
4.1 Location Covering Model for Deployments on Greenfields ............. 10  
4.1.1 Problem Formulation .................................................. 11  
4.1.2 Consideration of Special Cases .................................. 12  
4.2 Location Covering Model For Urban, Suburban, and Rural Deployments . 13  
4.2.1 Network Coverage and Capacity Problems ....................... 14  
4.2.2 Wireless Interference Considerations ............................. 16  
4.2.3 Capacitated Network Area Coverage with Existing Services ....... 18  
4.2.4 Consideration of Uplink and Downlink Capacities and Selection of Unnecessary Areas . 19  
4.2.5 Model Computational Complexity Considerations ............... 21  
4.3 Summary of Contributions of This Chapter .............................. 21  

## 5 BTS Deployment in Urban, Suburban, or Rural Areas
5.1 Simulations of Base Stations Deployment in Greenfield Areas ........ 22  
5.1.1 Proposed Enhancement of Genetic Algorithm ...................... 22  
5.1.2 Testing Dataset For Enhanced Genetic Algorithms .............. 23  
5.1.3 Simulations and Results .............................................. 23  
5.2 Simulations of Base Stations Deployment in Urban, Suburban, and Rural Areas .... 25  
5.2.1 Computational Concept ............................................. 25  
5.2.2 Propagation Models .................................................. 26  
5.2.3 Employment of Developed Models ................................ 26  
5.2.4 Base Station Parameters Settings ................................. 28  
5.2.5 Simulation of Different Deployment Scenarios .................... 30  
5.2.6 Simulations Utilizing Dataset From District in Central Europe .... 32  
5.3 Summary of Contributions of This Chapter ............................. 33  

## 6 Conclusion
6.1 Open Questions and Discussion ........................................... 35
1 INTRODUCTION

Nowadays, the fifth and beyond generations (5G+) of wireless networks is one of the topics that resonate in the industry. The 5G+ brings the new expectations of a huge amount of data, which requires very high throughput per device (multiple Gb/s) and per area efficiency (multiple Mbit/s/m²). Further, 5G+ enables low latency communications, high reliability, and connectivity of large amounts of heterogeneous devices [68]. Among others, the type of transmitted data is more oriented on High Definition (HD) video streaming in mobile devices, and Augmented Reality (AR)/Virtual Reality (VR) devices that are demanding for the traffic consumption (in case of VR it is expected to consume at least 10 Gb/s) [20, 39, 68]. These observations highlight the main technical objectives for 5G+ systems as follows [2, 20, 39, 68, 68]:

- High data rates per device (multiple tens of Gb/s).
- High data rates per area and a large number of connected devices.
- Ultra-reliable low-latency support for various critical applications such as Vehicle-to-Vehicle (V2V) communication.

These technical objectives require the essential modification of the network infrastructure. That is also supported by technical assumptions in 5G+ networks as they consider a higher density of base station nodes with smaller coverage ranges.

1.1 Research Motivation

The main motivation of this research is based on discussions presented in [5, 10, 16, 17, 24, 42, 52, 73, 79, 86, 93, 99, 113] on optimization of network infrastructures that provide essential services (Machine-to-Machine (M2M) communication, video streaming services, and many others). The optimal state is to provide the services (including HD video streaming services on mobile, AR, and VR) so that the cost for the network provider is as low as possible and each customer has a specific service available in a reachable distance including a sufficient quality. This optimization can be generally considered as the need to minimize the deployment and maintenance costs for network providers with the maximization of customer satisfaction. In this thesis, the optimization of network infrastructures is focused on but not limited to the optimization of base station locations. The optimization of base station locations is crucial in the deployment of 5G and beyond networks which have different requirements for their capacity and a coverage range than the previous ones. The network infrastructure needs to reduce the situations where the user requirements for data transmission overreach the maximum available capacity of base station nodes. That situation can arise, e.g., in public transportations, car traffic bottlenecks, and train stations. Generally, in locations where there may be a significant increase in data traffic.

1.2 Problem Statement

In the context of this thesis, an ideal state of affairs would be if all the base station nodes were located optimally with the optimal settings to cover a given network area. This would allow for all users to use the network reliably without any signal “white spots”, with the possibility to use throughput demanding applications as is AR, VR, or HD video streaming services. As a result, the network operators would benefit mainly in Total Cost of Ownership (TCO) due to the reduced over-provisioning. Whereas, the final network infrastructure contains only the essential number of base station nodes. Further, the user needs would be satisfied (data rates, demanding applications).

However, to meet the requirements of 5G+ networks it is suitable to apply more effective methods of planning wireless network infrastructures than are currently employed. Moreover, a dominant way of adding or removing base station nodes by network designers in the current tools is to pre-compute the expected base station nodes and find a suitable location manually. In a general sense, deployment optimization can be described as finding optimal base station locations satisfying the customer needs (available throughput,
reliability, range). During our preliminary research, multiple knowledge gaps were identified in several areas inherent to network planning essential for effective deployment.

1.3 Dissertation Scope and Goals

This dissertation thesis targets various aspects of wireless communications with respect to the growing data rates, heterogeneous connectivity, and other characteristics of 5G and beyond deployments. In particular, three research domains are studied:

1. **Mobile networks in the 5G+ era and their deployment** – the 5G+ era brings several challenges that require significant changes to the network infrastructures. The biggest challenge is to manage an extremely large number of simultaneously connected devices that can operate with high data rates (1-5 Gbps expected). This need is supported by the growing focus on use-cases and applications such as AR/VR (consuming hundreds of Mb/s) and HD video streaming. The enablers of the 5G+ generation include the research of millimeter-wave technologies (mmWave technology) that have specific characteristics (e.g., small coverage range). To handle the 5G+ requirements the network has to significantly increase the number of base stations to manage the customer needs (network densification).

2. **Deployment models considering 5G+ demands** – considering mobile networks in the 5G+ era and their main challenges, the network operators are struggling to handle the potentially extremely increasing amount of data in their networks. Since it requires significant modifications of the network infrastructures it is not feasible to find and calculate manually all the optimal locations to deploy new base station nodes. As a result, the deployment should be supported by suitable models that satisfy the capacity and other needs. In this domain, the focus is on location covering models that were widely used to find the optimal locations of facilities to satisfy the demand areas. These models were derived from the Set Covering Problem (SCP) that falls into \(NP\)-complete problems [49]. In this domain, we propose new models targeting the base station deployment considering the above-mentioned 5G+ challenges (e.g., higher capacities requirements, smaller coverage range, co-existence of existing infrastructures). Further, the consideration of the computational complexity of such a model is provided.

3. **Algorithms implementation and simulations to verify the models** – since the models are derived from an \(NP\)-complete problem, the expectations are that for larger data instances it is essential to employ artificial intelligence algorithms. Here, we search for exact methods (e.g., the branch and bound method) and further on meta-heuristic algorithms that can be employed to solve location covering problems. In this domain, several heuristic algorithms were implemented to support the developed model. The algorithms have to be modified for a particular use case to provide a feasible solution (meeting all the requirements). These are focused mainly on finding the optimal base station location with the given requirements. The base station parameter optimization is not investigated since it would require a standalone research area, however, it is a suitable part to provide a final deployment solution. We suggest the papers targeting that standalone research topic and keep it for future research.

Considering the presented problem statement and research scope, the primary research aim of the thesis is to propose and verify a model finding optimal locations for base station densification with regards to the capacity challenges in 5G+ networks.

**Research goals in questions:**

- What are the key challenges of mobile networks in the 5G+ Era (see Chapter 2)?
  - State of the art of the evolution of wireless networks and their main differences (see Section 2.1).
  - State of the art review of the main challenges in the 5G+ generations and its enablers (see Section 2.1.1).
  - Review of the covering models for finding optimal locations for base station deployment (see Section 2.2).
• What implementation approaches can be used to implement a covering models for the base station deployment (Chapter 3)?
  – Categorization of the implementation approaches for location covering optimization problems.
  – Review of optimization algorithms for location covering problems.
• How the location covering models can be used for the base station deployment considering key challenges (see Chapter 4)?
  – Proposal of a location covering model finding optimal locations for base station deployment with given requirements.
    * Developing the location model from basic requirements (coverage distance) to the more advanced requirements (e.g., capacities and interferences).
    * Consideration of computational complexity of the proposed model.
• How to utilize the algorithms for the proposed model and how to verify the model (see Chapter 5)?
  – Proposal or utilization of the algorithms implementing the proposed location covering model.
  – Creation of a sufficient datasets representing real use-cases (based on the 5G+ specifications/recommendations and available data from telecommunication companies).
  – Verification of the proposed solution using numerical simulations.
  – Discussion of the numerical simulation results.

1.4 Thesis Outline

This dissertation is organized into five chapters covering the author’s research outputs from 2017 to 2021. These outputs were published in journals with impact factors or in international conferences indexed in Web of Science or Scopus. Chapter 2 reviews the evolution of wireless networks and depicts the main challenges in 5G+. Also, it reviews the base station deployment approaches and the optimization models for possible base station localization. Chapter 3 reviews the implementation approaches that can be used to implement location covering optimization problems. These include exact methods (as is the branch and bound method) and meta-heuristic methods that can be used for use cases with large datasets. Chapter 4 presents the proposed location covering model for base station deployment (considering capacities, existing base stations in the area, interferences, etc.). Further, it contains considerations that need to be taken into account during the model implementation. Next, Chapter 5 presents algorithms application and numerical simulations verifying the proposed model, concluded with results discussion. Chapter 4 and Chapter 5 contain the main contributions together with the list of main papers that published these contributions. Finally, Chapter 6 summarizes the achieved results and concludes the thesis.

2 MOBILE NETWORKS IN 5G+ ERA AND THEIR DEPLOYMENT

In this chapter, the focus is on the mobile networks evolutions and main challenges in the 5G+ era (see Section 2.1 and Section 2.1.1) and on the models for locating the facilities to cover the selected geographic area (see Section 2.2) supporting the deployment of such networks.

2.1 Mobile Networks in 5G+ Era

It has been a long time ago since the beginning of the development of mobile networks (1G generation), launched in the Nippon Telegraph and Telephone (NTT) in 1979 as voice-only mobile systems. Since then, society has embraced mobile networks as an essential part of their lives, leading to the massive development and advancement of future generations of mobile networks [33, 71].
It has been a long time ago since the beginning of the development of mobile networks (1G generation), launched in the Nippon Telegraph and Telephone (NTT) in 1979 as voice-only mobile systems. Since then, society has embraced mobile networks as an essential part of their lives, leading to the massive development and advancement of future generations of mobile networks [33, 71]. The mobile system generations are briefly summarized in Table 2.1 [7, 31, 46, 51, 72].

Tab. 2.1: Mobile Generation Series and Their Features.

<table>
<thead>
<tr>
<th>Mobile Systems Generations</th>
<th>1G</th>
<th>2G</th>
<th>3G</th>
<th>4G</th>
<th>5G</th>
</tr>
</thead>
<tbody>
<tr>
<td>First implementations</td>
<td>1984</td>
<td>1991</td>
<td>2002</td>
<td>2005</td>
<td>2018</td>
</tr>
<tr>
<td>Services</td>
<td>Analog (voice)</td>
<td>Digital (voice, data)</td>
<td>voice + data, video calling</td>
<td>All-IP based, security, online gaming, HD televisions</td>
<td>Ultra High definition video + AR/VR applications</td>
</tr>
<tr>
<td>Data Rate</td>
<td>2.4 kbps</td>
<td>14.4 kbps</td>
<td>2 Mbps</td>
<td>20-100 Mbps</td>
<td>1-5 Gbps</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>30 KHz</td>
<td>200 KHz to 1.25 MHz</td>
<td>5 MHz</td>
<td>1.4 MHz to 20 MHz</td>
<td>100 MHz</td>
</tr>
<tr>
<td>Access Technology</td>
<td>FDMA</td>
<td>TDMA, CDMA</td>
<td>CDMA</td>
<td>OFDM</td>
<td>OFDM</td>
</tr>
</tbody>
</table>

2.1.1 Existing Cellular Networks – Issues and Challenges

When looking at current wireless network infrastructures it reveals that the network infrastructures are not prepared for a massive number of simultaneously connected devices using high data rates. In 2022 it was estimated that the global mobile traffic will grow annually by over 26 % until 2026 [106]. Cisco’s Visual Networking Index (VNI) forecasts that by 2023 there will be near to 30 billion devices connected to the network. Next, the expectations are that the fastest-growing device and connections category is M2M that will include 50 % of all connected devices. Further, since 2012 the mobile users are increasing their usage of streaming videos that represents more than half of the global mobile traffic [19]. The introduction of Ultra-High-Definition (UHD) and video streaming has a high impact on network traffic. The traffic patterns are affected by changing a mix of devices and connections in a multi-device ownership. The multiplier effect on traffic is generated by video devices. In fact, the traffic generated by the entire household today is comparable to the two hours of content of Internet-enabled HD television [20, 90].

The need to deal with the massive growth of data is further reinforced by exploring new applications and use cases in areas such as: AR/VR, Internet of Things (IoT), Device-to-Device (D2D) communications and M2M communications [4]. For example, AR/VR requires data rates in the range of several hundreds of Mbps [20, 30].

2.1.2 Emerging 5G+ Use Cases, Applications, and Enablers

The extended adoption of 5G+ cellular technology can unlock the full potential of emerging technologies as are Unmanned Aerial Vehicle (UAV), M2M, D2D, AR/VR and others. These can be used in many use cases
2.2 Supporting Network Infrastructure

To fully enable all of the use cases and their application the supporting network infrastructure has to be modified to support higher data rates with a reliable connection. To achieve this, the network designers perform network densification which includes selecting suitable locations and adding new base station nodes to increase the available capacity of the network. Without this modification, the network cannot handle new emerging applications with high data rates. For this reason, we focus on the models for selecting optimal locations for base station nodes to satisfy the requirements in 5G+ networks.

Currently, the papers published on the topic of base station deployment vary a lot. In the area of computer science, engineering, or multidisciplinary sciences (5 May 2022) there were 782 papers published on base stations locations deployment based on the Scopus database. The specific parts of the deployment are discussed in those papers. The base-station parameters as-is: downtilt, mechanical downtilt, electrical downtilt, height of a base station, the collection of three azimuths, height of a base station and transmit power and their dynamic modification are thoroughly discussed in those papers. The most suitable positions or movements of base station nodes and the associated algorithms are targeted in the next important part of the wireless networks deployment research. To meet the increasing data exchange requirements a pico base station deployment problem was formulated in, which assures the performance of coverage and quality of services. Besides, to determine the most suitable positions of micro base station nodes the proposed deployment including greedy, region-based, and grid-based algorithms. The parameters that significantly affect the key performance indicators (capacity, existing services, etc.) are not taken into consideration since it focuses mainly on the impact of location. In the Table 2.2 the overview of selected research papers on the topic of base station deployment is shown. Further, in the surveys the literature review of base station deployment is presented in more detail.

3 ALGORITHMS SOLVING LOCATION COVERING PROBLEMS

The location covering models belongs to the \( NP \)-complete class of problems. These contain the hardest problems in the computer science field. The computational complexity of the location covering problems is exponential. In short terms, for large datasets (more than 55 covering nodes) it will be essential to employ Artificial Intelligence (AI) algorithms to get a solution in a “reasonable” time. For smaller datasets, we can use exact approaches to compute the solution.

3.1 Exact Approach

Previously, we mentioned several exact methods used to solve SCP-based problems for smaller instances (less than 55 covering nodes) in a reasonable time (seconds, minutes, maximally hours). During the long period of studying of the SCP-based problems many researches applied exact methods to find a suitable solution. These exact methods generally rely on the branch-and-bound algorithm to get optimal solution. Several well-known relaxation methods were applied or modified for the SCP problem. For example, Beasley in used subgradient optimization with heuristics to bound the SCP problem. In Beasley and Jornsten employed the same method but improve the solution quality through Gomory f-cuts with a better branching strategy.

---

1 The following Scopus advanced query was used: SUBJAREA (engi OR comp OR math) TITLE-ABS-KEY (base AND station AND location AND deployment)
## Tab. 2.2: Overview of Papers Targeting the Deployment of Base Station Nodes.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Article Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tayal, Shikha and Garg, PK and Vijay, Sandip [95]</td>
<td>Optimization Models for Selecting Base Station Sites for Cellular Network Planning</td>
<td>The authors compare several optimization models for placement of an optimal number of base stations and concludes with the pros and cons of each model. The comparison is provided using a case study from Uttarakhand.</td>
</tr>
<tr>
<td>Afuzagani, Dzakyta and Suyanto, Suyanto [3]</td>
<td>Optimizing BTS Placement Using Hybrid Evolutionary Firefly Algorithm</td>
<td>The authors focus on the improvement of the firefly algorithm. They perform several tests that highlight that their improvement of the firefly algorithm can provide a slightly better solution than the standard firefly algorithm in terms of the final coverage.</td>
</tr>
<tr>
<td>Mattos, David Issa, et al. [65]</td>
<td>Automated optimization of software parameters in a long term evolution radio base station</td>
<td>With a low number of iterations the paper proposes optimization of base station parameters due to the stochastic response of KPI metrics.</td>
</tr>
<tr>
<td>Teague, Kory, Mohammad J. Abdel-Rahman and Allen B. MacKenzie [96]</td>
<td>Joint base station selection and adaptive slicing in virtualized wireless networks: A stochastic optimization framework</td>
<td>The authors find that the genetic algorithms may give a suitable solution using their two-stage stochastic optimization model investigating base station selection.</td>
</tr>
<tr>
<td>Lingcheng and Hongtao [22]</td>
<td>Propagation-Model-Free Base Station Deployment for Mobile Networks: Integrating Machine Learning and Heuristic Methods</td>
<td>The authors find that a multi-layer perceptron can be sufficient compared to other machine learning algorithms regarding the deployment of base station nodes.</td>
</tr>
<tr>
<td>Bharadwaj, Richa, et al. [22]</td>
<td>Base-station random placement effect on the accuracy of ultra-wideband body-centric localization applications</td>
<td>The authors investigate the effect of random placement of base stations in three dimensions (x,y, z-axis). They observe the impact of reconfiguration of the base station, in the horizontal and vertical dimensions, on the error reduction.</td>
</tr>
</tbody>
</table>

Several researchers in [9, 30] used primal and dual relaxations for bounding that are iteratively improved with the support of dynamic subgradient procedure fixing the variables.

### 3.2 Meta-heuristic Methods

In cases when is not possible to get the exact solution in a reasonable time, the *meta-heuristic algorithms* can be considered. These methods were applied in many optimization problems (e.g., Travelling Salesman Problem (TSP)). When we look to the semantics, the word *heuristics* comes from the Greek word *heuriskein*, which represents discovering or inventing. These methods gained interest by the researchers’ community immediately after their inception in the 1980s. The biological evolution, mathematical and physical sciences and nervous systems are one of the concepts involved in these methods. Furthermore, in this thesis a brief categorization of these algorithms is provided. The three categories of these algorithms were selected (i) evolution-based algorithms, (ii) swarm-based algorithms, and (iii) hybrid algorithms. These categories contain a plethora
of algorithms such as Genetic Algorithm (GA), Differential Evolution (DE) [78, 92], evolutionary programming and evolutionary strategies [8], Differential Search Algorithm (DSA) [21], Ant Colonies Optimization (ACO) [25, 26, 27], Artificial Bee Colony (ABC) [48], Gravitational Search Algorithm (GSA), Harmony Search (HS) [34, 62], Particle Swarm Optimization (PSO) [50, 91], [82, 83], Firefly Algorithm (FA) [110], Teaching Learning Algorithm (TLA) [80, 81], Chemical Reaction Optimization (CRO) [57, 58], Water Cycle Algorithm (WCA) [28, 85], ant colony optimization with variable neighbourhood search, genetic algorithms with variable neighbourhood search, and many more. The division of meta-heuristic methods and their assignment to the particular category is shown in Figure 3.1.

Fig. 3.1: Meta-Heuristic Optimization Approaches.

4 LOCATION COVERING MODEL FOR DEPLOYMENT OF BASE STATIONS

In this chapter, the formulation of an optimization model that can be used for various deployment scenarios is proposed. First, the design is focusing on the basic scenario of covering locations without any existing infrastructure and low density of customers. Further, the model is evolved into more complex scenarios with existing infrastructure, capacity problems, interferences, and limited resources to reconfigure the infrastructure.

4.1 Location Covering Model for Deployments on Greenfields

This base model can be used for cases, e.g., in parts of Russia or Africa where the network designers need to deploy base station nodes just to cover the needs of a few inhabitants in largely rural areas. In these cases,
it is better to let the model be as easy as possible, otherwise, the computation would be uselessly difficult. Furthermore, special cases and other considerations above this model may be useful for the implementation of more complex model derivates.

4.1.1 Problem Formulation

Assume that the area contains \( m \) possible nodes that can be used as service centres (base stations). Further, the area contains \( n \) nodes to be served (customers or customer locations). For each of these pairs \( i \) and \( j \), their distance (or in practice sufficient signal strength to establish a communication link between the service centre and customer location) is given together with optimal signal strength \( P_{\text{min}} \) that can be accepted for coverage between service centre and customer location [87, 89].

Let us consider two finite sets \( I \) and \( J \), where:

- \( I \) is the set of service centres 1, 2, \ldots, \( m \),
- \( J \) is the set of customer locations 1, 2, \ldots, \( n \).

The aim is to select the minimal set of service centres that covers all of the customer locations (each covered by at least one service centre).

Remark 1. In contrast to the models defined in Section 2.2, we will denote the set of service centers by the symbol \( I \) and the set of customer locations by the symbol \( J \), their elements by corresponding lowercase letters. Instead of \( N \) vectors, we will use the availability matrix \( A \) in the expression of the models. △

To solve this task it is essential that all of the customer locations have one or more reachable service centers (within acceptable distance). If the area contains several customer locations that are not significant (e.g., they are very far away from the others), we may consider to remove such locations from the list of customer locations.

The reachability decision is made by the computed signal strength \( d_{ij} \) (using suitable propagation models) for each pair \( i \) and \( j \), it can be expressed as \( a_{ij} = (d_{ij} \geq P_{\text{min}}) \), i.e., \( a_{ij} = 0 \) means the customer location \( j \) is not in a reachable distance (has not a sufficient signal strength) to the service centre \( i \), and \( a_{ij} = 1 \) means it is. When the condition is not satisfied, customer location \( j \) is not reachable from service centre \( i \). The value \( i = 1 \) means the service centre \( i \) is selected to the resulting set, and \( x_i = 0 \) means that is is excluded from that set.

The objective function (4.1) targets the minimal number of service centres, constraint (4.2) means that each serviced vertex is assigned at least one operating service centre. The parameter \( P_{\text{min}} \) represents the threshold of service reachability.

Based on that, the base location optimization model can be described as follows:

Minimize

\[
z = \sum_{i=1}^{m} x_i,
\]

subject to

\[
\forall j \in J : \sum_{i=1}^{m} a_{ij} x_i \geq 1 \quad (4.2)
\]

\[
\forall i \in I : x_i \in \{0, 1\}. \quad (4.3)
\]

Further, as a small extension, the weights \( w_i \) of the service centres can be considered. This may be especially beneficial if some of the possible locations to deploy base stations are easier to implement. To express that need, the \( w_i \) coefficient can be added to the objective function (4.4). Since this problem is formulated as a minimization problem smaller weights \( w_i \) represent easier deployment. With that, the model would change as follows [89, 90]:

Minimize

\[
z = \sum_{i=1}^{m} w_i x_i, \quad (4.4)
\]
subject to

\[ \forall j \in J : \sum_{i=1}^{m} a_{ij} x_i \geq 1 \quad (4.5) \]

\[ \forall i \in I : x_i \in \{0, 1\}. \quad (4.6) \]

**Example 1.** Consider the base case with the set of service centres and customer locations represented in a distance matrix with values in dBm. The \( P_{\text{min}} \) for that example scenario is set to -75 [dBm] [29, 98].

\[
\begin{array}{cccccccc}
1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\
1 & -92 & -55 & -47 & -44 & -78 & -67 & -54 & -81 \\
3 & -34 & -72 & -66 & -64 & -18 & -97 & -63 & -101 \\
5 & -79 & -97 & -76 & -103 & -86 & -28 & -102 & -64
\end{array}
\]

Since \( P_{\text{min}} = -75 \), the reachability matrix would be as follows:

\[
\begin{array}{cccccccc}
1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\
1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 \\
2 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 \\
3 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 \\
4 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 \\
5 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1
\end{array}
\]

**4.1.2 Consideration of Special Cases**

To reduce the computational complexity and to get a feasible solution for the base model, it is appropriate to take into account several considerations mentioned below. Individual considerations are shown using the reachability matrix.

- **Unnecessary or unreachable service centres:**

\[
\begin{array}{cccccccc}
1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\
1 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\
2 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\
3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
4 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1
\end{array}
\]

In the above matrix, the 5th column is not covered by any service centre. That means that the signal strength provided by any considered service centre in that customer location is too low. There are three solutions to that problem:

- Add another service centre that will have a chance to cover that customer location.
- Remove that customer location from the list since it is not important enough or very far away of all the others.
- Increase some service centre power so that this service centre can cover that customer location.

Further, the 3rd row contains only zero values. That means the service centre 3 does not cover any customer location. In this case, it is appropriate to remove that service centre from the dataset to reduce the data size and reduce the computational complexity.
• **Essential service centres**

In the above matrix, the 3rd column (customer location 3) is covered only by the 5th row (service centre 5). This points to the consideration that service center 5 cannot be omitted in the resulting set of service centers, otherwise, the model conditions would not be met.

• **Service centre as an immediate solution**

In the previous matrix, the 3rd row (service centre 3) covers all the columns (customer locations). This service centre may be considered as an obvious solution to cover the selected area. In this case, we do not need to compute the model and we can just select that as a solution.

• **Existing service centres that must stay in the resulting set**

In practice, even the areas with low density may contain some existing service centres. To deal with that “issue” the solution with “dummy” columns is presented in the previous matrix. In this matrix, it was considered that the 1st service centre and the 5th service centre are existing service centres that needs to stay in the resulting set. To achieve that in the computation, the “dummy” columns were added (the columns behind delimiter). These columns do not represent any real customer locations, however, they set for a selected existing service centre the value 1 (only once in each column). Using this, considering the model constraints (4.5) this service centre must stay in the solution since this is the only one that covers the “dummy customer location”. Another alternative to achieve that is to directly set decision variable $x_i$ to 1 in each iteration of the computation. For this example, it will be as follows $x_1 = 1$ and $x_5 = 1$.

### 4.2 Location Covering Model For Urban, Suburban, and Rural Deployments

In this section, the model design focuses mainly on capacity considerations, existing services (existing network infrastructure) and wireless interferences that are the key aspects to consider for the base station deployment. The capacity considerations are one of the key challenges in the 5G+ networks as was mentioned in Section 2.1.1. In short, this is mainly due to the increasing need for the usage of HD streaming and other
throughput-demanding services. The existing services are must-have consideration since in a urban or suburban areas the necessity to consider existing base stations is crucial. Further, the wireless network interferences are one of the key aspects to determine whether the deployment can be used in practice.

4.2.1 Network Coverage and Capacity Problems

In ?? several location covering capacity-based models were mentioned. These include capacity-based LSCP and its extension: (i) CLSCP-CA; (ii) CLSCP-EA; and (iii) CLSCP-SO. The first one assigns the operational capacities from the customer location to the nearest service centre. The second one distributes the operational capacities from the customer location to all the reachable service centres equally. And the third one assigns fragmented capacities to the customer location as the system optimal solution. Even when these models consider capacities, they are not appropriate for wireless communications base station deployment. First, these do not assign operational capacities from one customer location to exactly one service centre at a given time. For wireless, it is essential to assign user device requested capacity (throughput) to directly one base station (service centre) at a given time. Furthermore, these do not include capacities separately for downlink/uplink, and any interferences considerations. For that reason, a new location covering model is proposed.

Using the proposed model, in high perspective, we need to take into account the following two use-cases:
• Deployment of service centres to the new area or reconfiguration of the whole network infrastructure.
• Deployment of additional service centres in the area where an infrastructure with existing services is already available but without sufficient network capacity.

Both of these obviously require capacity considerations. It is not possible to assign an unlimited number of customer locations to the service centres. Especially, 5G+ deployments need to take special care of this due to the increasing number of highly throughput-intensive services.

Further, the variables and parameters used in the following mathematical models are denoted as follows:
• $c_i$, $i \in I$—capacity of service centre $i$,
• $b_j$, $j \in J$—the set of customers (or sublocations) from customer location $j$ that need a service centre,
• $y_{ij} \in \{0, 1\}$—customer from location $j$ is assigned or not to service centre $i$,
• $w_i$—the weights of service centre $i$ (can represent a base station installation costs).

To depict the customer locations assignments to the services centres, see Figure 4.1. The service centre coverage is represented by $S_i$ circle, and the assignment of the customer location to the service centre is represented by the $L_j$ color matching the $S_j$ color.

Applying assumptions, the model is formulated as follows:

The Equation (4.7) guarantees that each customer location is assigned to only one service centre at a given time.

$$\forall j \in J : \sum_{i \in I} a_{ij} y_{ij} = 1. \quad (4.7)$$
The Equation (4.8) guarantees that a service centre must have a sufficient capacities for all customers (or sublocations) from the customer locations that are assigned to it

$$\forall i \in I : \ c_i x_i \geq \sum_{j \in J} a_{ij} y_{ij} b_j. \tag{4.8}$$

To ensure that none of the customer locations is assigned to the service centre that is not included in the resulting set, the Equation (4.9) is defined:

$$(\forall i \in I)(\forall j \in J) : \ y_{ij} \leq x_i. \tag{4.9}$$

The number of relations in Equation (4.9) may be expressed as follows:

$$\forall i \in I : \ y_{i1} \leq x_i,$$
$$\forall i \in I : \ y_{i2} \leq x_i,$$
$$\ldots$$
$$\forall i \in I : \ y_{in} \leq x_i,$$

and summarizing previous relations, we can simplify them by Equation (4.10) and decrease the corresponding number of constraints from $mn$ to $m$.

$$\forall i \in I : \ \sum_{j \in J} y_{ij} \leq n x_i. \tag{4.10}$$

The capacities of all service centres in the resulting set must not be smaller than the sum of capacities of all allocated facilities in all customer locations. This is expressed by the Equation (4.11).

$$\forall i \in I : \ c_i x_i \geq \sum_{j \in J} a_{ij} y_{ij} b_j. \tag{4.11}$$

The previously mentioned considerations are noted in the following location covering capacity-based model with directly assigned capacities:

Minimize

$$z = \sum_{i \in I} w_i x_i, \tag{4.12}$$

subject to:

$$\forall j \in J : \ \sum_{i \in I} a_{ij} x_i \geq 1 \tag{4.13}$$
$$\forall j \in J : \ \sum_{i \in I} a_{ij} y_{ij} = 1 \tag{4.14}$$
$$\forall i \in I : \ c_i x_i \geq \sum_{j \in J} a_{ij} y_{ij} b_j \tag{4.15}$$
$$\forall i \in I : \ \sum_{j \in J} y_{ij} \leq n x_i \tag{4.16}$$
$$\forall i \in I : \ x_i \in \{0,1\} \tag{4.17}$$
$$(\forall i \in I)(\forall j \in J) : \ y_{ij} \in \{0,1\}. \tag{4.18}$$

The precondition of this model to find a solution is that the sum of all service centres capacities must be higher than the sum of all customer locations (see Equation 4.19), so that each customer has at least one
available service centre with a sufficient signal quality (Equation 4.20). Otherwise, the model cannot find a solution. This precondition can be expressed by the following equations:

\[
\sum_{i=1}^{m} c_i \geq \sum_{j \in J} b_j, \quad \forall j \in J : \sum_{i \in I} a_{ij} > 0.
\]

This model contains capacity definitions, however, still it does not contain wireless interferences considerations that are an important aspect in the base station deployment. In Section 4.2.2 the interferences considerations are taken into account.

### 4.2.2 Wireless Interference Considerations

When designing wireless networks and providing a sufficient user experience, one has to always consider the possible effects of radio interferences.

Interference can be divided into three categories: (i) co-channel interference, which occurs when multiple transmitters transmit the signal on the same channel, (ii) adjacent channel interference, which is caused by signals that interfere with communication in adjacent channels, (iii) impulse noise, which can result from imperfect shielding that allows energy to leak and interfere with radiofrequency devices [41, 75, 97].

There are many techniques to reduce wireless interference, e.g., software-based filters that remove unwanted in-band signals. However, most of these techniques are reducing the target interference. In this work, we focus on the source of the problem that happens when the network is not properly designed or configured. The coverage of base stations in the network has some overlaps. Usually, we want some overlaps, otherwise, the network coverage would not be homogeneous and users would experience fluctuating radio signal quality or even white spots [35]. However, there should not be too many overlaps between cells or it would cause co-channel interference along with other issues [1].

In the presented model, the wireless interference is potentially reduced by providing only acceptable cell overlaps. This can be achieved so that the base stations (service centers) coverage areas share only acceptable overlapping areas (i.e., two or more service centers do not cover the same areas or at least only a little).

This can be achieved, e.g., using the following alternatives:

1. Set-up a minimal possible distance between all service centres pairs.
2. Locate service centres as far as possible from each other.

These two alternatives can be achieved so that we extend the objective function of the optimization model and/or add additional constraints with minimum possible distance for each service centres pair. The sections below formulate this alternative.

Assume that coverage cannot be provided from a single node.

If \( d_{ij}, i, j \in I \) is the distance between centres \( i \) and \( j \), then it is possible to solve this by: (i) constraint that for all pairs of selected service centres requires a distance greater or equal than a certain threshold; and/or (ii) extending the objective so that the sum of all mutual distances of selected centres is maximized.

**The first case**, can be expressed by the Equation (4.21):

\[
(\forall i \in I)(\forall j \in I)(i \neq j) : d_{ij} \geq d_{\min} x_i x_j.
\]

The product \( x_i x_j \) in Equation (4.22) provides that this relation will be checked only for pairs of selected centres.

Since this condition is non-linear due to the product \( x_i x_j \), to reduce the computational complexity (and to avoid the algorithms implementing non-linear models), we replace the product of binary variables with the following linear equation:

\[
(\forall i \in I)(\forall j \in I)(i \neq j) : d_{ij} \geq (x_i + x_j - 1) d_{\min}.
\]

16
From the above-mentioned two alternatives to reduce potential wireless interferences, this option seems to be the best option for implementation. Furthermore, even this relatively straightforward constraint can significantly reduce the potential interferences.

The second case changes the problem to a multicriterial one. Both of the criteria can be composed of a scalarization procedure. The first criterion targets the minimization of service centres and the second targets the maximization of the sum of mutual distances. To achieve the opposite goal of the second criterion (maximization versus minimization), the second criterion will have a negative sign. Additionally, the criteria need to be unified for the same interval value ranges [0, 1].

The objective function presented by Equation (4.12) would change as follows:

\[
z = \left( \sum_{i \in I} w_i x_i \right) / \sum_{i \in I} w_i - \left( \sum_{i \in I} \sum_{j \in I} d_{ij} \min(x_i, x_j) \right) / \left( \sum_{i \in I} \sum_{j \in I} d_{ij} \right) .
\] (4.23)

Expressions in the denominators provide normalization of the terms in the objective function to the interval [0,1].

Instead of \( \min(x_i, x_j) \) in the objective function, \( h_{ij} \) the following additional constraints may be used

\[
(\forall i \in I)(\forall j \in I) : h_{ij} \leq x_i ,
\] (4.24)

\[
(\forall i \in I)(\forall j \in I) : h_{ij} \leq x_j ,
\] (4.25)

\[
(\forall i \in I)(\forall j \in I) : h_{ij} \geq (x_i + x_j - 1) ,
\] (4.26)

\[
(\forall i \in I)(\forall j \in I) : h_{ij} \in \{0,1\} ,
\] (4.27)

to move the nonlinear definition to linear one.

Since the objective contains two criteria, the importance of both of them can be represented by weights \( v_1 \) and \( v_2 \). This results in the following Equation (4.28).

\[
z = v_1 \left( \left( \sum_{i \in I} w_i x_i \right) / \sum_{i \in I} w_i \right) - v_2 \left( \left( \sum_{i \in I} \sum_{j \in I} d_{ij} \min(x_i, x_j) \right) / \left( \sum_{i \in I} \sum_{j \in I} d_{ij} \right) \right) .
\] (4.28)

Weights \( v_1 \) and \( v_2 \) allow to subtly differentiate the importance of terms in the objective function.

Considering both approaches, the first case and the second case, the final model would be as follows (for simplicity we do not integrate replacement of \( \min(x_i, x_j) \) with additional constraints):

Minimize

\[
z = v_1 \left( \left( \sum_{i \in I} w_i x_i \right) / \sum_{i \in I} w_i \right) - v_2 \left( \left( \sum_{i \in I} \sum_{j \in I} d_{ij} \min(x_i, x_j) \right) / \left( \sum_{i \in I} \sum_{j \in I} d_{ij} \right) \right) ,
\] (4.29)

subject to:

\[
(\forall j \in J) : \sum_{i \in I} a_{ij} x_i \geq 1
\] (4.30)

\[
(\forall j \in J) : \sum_{i \in I} a_{ij} y_{ij} = 1
\] (4.31)

\[
(\forall i \in I) : c_i x_i \geq \sum_{j \in J} a_{ij} y_{ij} b_j
\] (4.32)

\[
(\forall i \in I)(\forall j \in J) : y_{ij} \leq x_i
\] (4.33)

\[
(\forall i \in I)(\forall j \in I)(i \neq j) : d_{ij} \geq (x_i + x_j - 1) d_{\min}
\] (4.34)

\[
(\forall i \in I) : x_i \in \{0,1\}
\] (4.35)
∀i ∈ I : \sum_{j \in J} y_{ij} \leq nx_i. \quad (4.36)

Using this, we reduce the potential wireless interferences since we reduce the overlapping coverage between each service centres. In practice, usually, specific base station cells work at different frequencies, thus limiting interference at locations that are covered by multiple base station nodes. The wireless interference reduction can be also achieved in the post-processing phase by dynamically modifying transmission power, etc. However, it is essential to consider that even in the location selection phase. In Section 4.2.3 the consideration of existing services (existing base stations infrastructure) is discussed and integrated into the model definition.

### 4.2.3 Capacitated Network Area Coverage with Existing Services

In practice, in many use cases during the deployment, the existing infrastructure has to be taken into account. In the perfect world, we can rebuild the whole network based on the current needs to make it optimal. However, in the real world, it is not possible to remove/modify existing nodes just with a snap of a finger since it may be an expensive task to change the position of existing base station nodes. In some cases, the evaluation of short and long-term costs of keeping the existing base station nodes should be considered. The existing base station nodes may become spatially inefficient. However, in many practical cases, the enhancement of existing base station infrastructure has to be added to satisfy the growing needs of the customers. To satisfy the need of keeping the existing nodes in the resulting set, we have to change the objective function and add an additional constraint that will explicitly add existing base station (service centre) nodes to the solution as follows:

∀i ∈ E_f : x_i = 1, \quad (4.37)

where \(E_f\) represents the set of existing service centres.

The whole extended model would change as follows:

Minimize

\[(1 + \varepsilon) \sum_{i \in E_f} w_i x_i + \sum_{i \in E_f} x_i, \quad (4.38)\]

subject to:

∀j ∈ J : \sum_{i \in I} a_{ij} x_i \geq 1 \quad (4.39)

∀j ∈ J : \sum_{i \in I} a_{ij} y_{ij} = 1 \quad (4.40)

∀i ∈ I : c_i x_i \geq \sum_{j \in J} a_{ij} y_{ij} b_j \quad (4.41)

∀i ∈ I : \sum_{j \in J} y_{ij} \leq nx_i \quad (4.42)

∀i ∈ E_f : x_i = 1 \quad (4.43)

\((\forall i \in I - E_f)(\forall j \in I - E_f)(i \neq j) : d_{ij} \geq (x_i + x_j - 1)d_{\text{min}}\) \quad (4.44)

\((\forall i \in I - E_f)(\forall j \in E_f) : d_{ij} > d_{\text{min}} x_i\) \quad (4.45)

∀i ∈ I : x_i \in \{0, 1\} \quad (4.46)
where $\varepsilon$ represents the cost to build a new service centre in opposite to keep an existing one. In this model, the interferences considerations are taken into account through constraints (4.44) and (4.45) limiting the minimal distance between all pairs of service centres considering newly added service centres and also the existing ones. Furthermore, if necessary, the objective function can be also modified in the same way as in (4.28) together with existing nodes consideration.

In the objective function (4.38) and (4.49) the expressions $(1 + \varepsilon)$ and $\sum_{i \in E_j} x_i$ are constant, so they can be omitted here; they are included only for illustration.

In practice, we may encounter the situation that covering all the areas is not possible (e.g., it’s too expensive). In Section 4.2.4 the model is modified with that possibility. Further, in practice, the capacities in mobile networks are typically divided into downlink and uplink. To satisfy that need, we modify the model in Section 4.2.4 so that service centre and customer location capacities are divided to uplink and downlink communication directions.

### 4.2.4 Consideration of Uplink and Downlink Capacities and Selection of Unnecessary Areas

To define the customer locations (areas) that do not need to be covered the constraint (4.48) has to be added:

$$\forall j \in J : \sum_{i \in N_j} x_i \geq l_j, \tag{4.48}$$

where $l_j$ is the number of service centres servicing customer location $j$. When it is set to 0, it is not required to cover such location. Next, $N_j = \{i | d_{ij} \leq D_{max}\}$, where $D_{max}$ = maximum distance which will be accepted for operation between the service centres and customer locations. Generally, these locations can be removed from the input dataset.

To split the capacity in the model for the sake of the downlink and uplink requirements we assume that the capacities are divided into uplink and downlink. Practically, the user can divide its demand of 100 Mbit/s to 80 Mbit/s for download and 20 Mbit/s for upload. To satisfy that needs, we assume the following:

- $I$ = a set of service centres $1, 2, \ldots, m$,
- $J$ = a set of customer location areas $1, 2, \ldots, n$,
- $d_{ij}$ = the shortest distance between service centre $i$ and customer location $j$,
- $l_j$ = number of service centres required for servicing customer location $j$,
- $x_i \in \{0, 1\}$, where $x_i = 1$ means that service centre $i$ is selected, while $x_i = 0$ means that it is not selected,
- $C^u_i$ = uplink capacity of service centre $i$,
- $C^d_i$ = downlink capacity of service centre $i$,
- $a^u_j$ = uplink amount of customer location at $j$,
- $a^d_j$ = downlink amount of customer location at $j$,
- $y_{ij} \in \{0, 1\}$ = nonfragmented customer location $j$ is assigned (1) or is not assigned (0) to service centre $i$.

Using that, it is still essential to satisfy that customer location $j$ (for uplink and downlink at the same time) is served by exactly one service centre $i$. The full model would be then as follows:

Minimize

$$(1 + \varepsilon) \sum_{i \notin E_j} x_i + \sum_{i \in E_j} x_i, \tag{4.49}$$

subject to

$$\forall j \in J : \sum_{i \in N_j} x_i \geq l_j \tag{4.50}$$
∀ \in J : \sum_{i \in N_j} y_{ij} = 1 \tag{4.51}

∀ i \in N_j : C_i^u x_i \geq \sum_{j \in J} y_{ij} a_{ij}^u \tag{4.52}

∀ i \in N_j : C_i^d x_i \geq \sum_{j \in J} y_{ij} a_{ij}^d \tag{4.53}

∀ i \in I : \sum_{j \in J} y_{ij} \leq nx_i \tag{4.54}

∀ i \in E_f : x_i = 1 \tag{4.55}

∀ i \in I : x_i \in \{0,1\} \tag{4.56}

(\forall i \in I)(\forall j \in J) : y_{ij} \in \{0,1\} \tag{4.57}

(\forall i \in I)(\forall j \in J)(i \neq j) : d_{ij} \geq (x_i + x_j - 1)d_{\text{min}}, \tag{4.58}

where constraint (4.52) guarantees that both downlink and uplink directions from customer location \( j \) are served by exactly one service centre \( i \).

Since this model is our final location optimization deployment model, we further provide also the maximization model option as it is common in the case of location optimization models. The following maximization model uses a predefined number \( p \) of new service centres with the aim to cover as much area as possible:

Maximize

$$\sum_{i \in N_j \in J} y_{ij}(a_{ij}^u + a_{ij}^d),$$

subject to

∀ j \in J : \sum_{i \in N_j} x_i \geq l_j \tag{4.60}

∀ j \in J : \sum_{i \in N_j} y_{ij} = 1 \tag{4.61}

∀ i \in N_j : C_i^u x_i \geq \sum_{j \in J} y_{ij} a_{ij}^u \tag{4.62}

∀ i \in N_j : C_i^d x_i \geq \sum_{j \in J} y_{ij} a_{ij}^d \tag{4.63}

(\forall i \in I)(\forall j \in J) : y_{ij} \leq x_i \tag{4.64}

$$\sum_{i \in E_f} x_i = p \tag{4.65}$$

∀ i \in E_f : x_i = 1 \tag{4.66}

∀ i \in I : x_i \in \{0,1\} \tag{4.67}

(\forall i \in I)(\forall j \in J) : y_{ij} \in \{0,1\} \tag{4.68}
\((\forall i \in I)(\forall j \in I)(i \neq j) : d_{ij} \geq (x_i + x_j - 1)d_{\text{min}}\). \hspace{1cm} (4.69)

The constraints presented in the maximization model are the same as in the minimization model.

### 4.2.5 Model Computational Complexity Considerations

The size of the search space is determined by the number of all possible selections of service centres. For \(m\) service centres, according to the binomial theorem, it is equal to

\[
\binom{m}{1} + \binom{m}{2} + \binom{m}{3} + \cdots + \binom{m}{m} = (1 + 1)^m - 1 = \mathcal{O}(2^m).
\] \hspace{1cm} (4.70)

For each selection of service centres it is necessary to verify all constraints. In the case of \(m < n\) (the number of service centers is less than the number of customer locations), the constraints with the highest time complexity are those that are introduced with \((\forall i \in I)(\forall j \in J)\), which corresponds to \(mn\) and thus the total complexity is \(\mathcal{O}(2^m mn)\). In the case of \(m > n\), the most complex constraint is introduced with \((\forall i \in I)(\forall j \in I)(i \neq j)\). Based on that the resulting time complexity of these models is \(\mathcal{O}(2^m m^2)\). This computational complexity corresponds also to \(m = n\).

### 4.3 Summary of Contributions of This Chapter

In this chapter, the development of a new location covering optimization model is presented. The benefit of utilizing such a model is to have one definition to be used to find optimal locations for the base stations deployment. This can decrease the effort of network designers to compute the optimal locations. The proposed models (minimization and maximization alternative) show the main essential aspects that have to be considered throughout the deployment of 5G+ cellular networks that mainly focus on capacity and interferences challenges. In Section 4.1 the base model taking into account the data representation and relation between base stations and customer locations based on the sufficient signal strength is described. Using this model, the readers can see how the model input data are constructed and represented. Further, this chapter contains the consideration of special cases that are an important part of input data modification or for implementation purposes. In Section 4.2 the model is evolved so that the capacities and limitations of base station nodes are considered. Further in this section, the wireless interferences considerations are included in the model definition. These are very important for wireless networks to increase deployment usability. The considerations of how to manage the existing infrastructure base station nodes are also provided. These are sufficient for deployments in urban areas with a high number of existing base stations. Furthermore, the more realistic definition of capacities for wireless networks is provided by dividing the capacities to uplink and downlink. Moreover, the maximization alternative that considers the given amount of resources to deploy new base station services is provided. Finally, Section 4.2.5 considers the computational complexity of the provided model. All of these models and considerations were uniquely defined in the author's published papers (see ??) so that it conforms with the crucial challenges described in the Section 2.1.1 discussing main issues and challenges in 5G and beyond deployments.

### 5 BTS DEPLOYMENT IN URBAN, SUBURBAN, OR RURAL AREAS

In this chapter, the numerical simulations of the base station deployment are presented. First, the numerical simulations are performed on the basic scenario without capacity and interference considerations. This is important to utilize the algorithms, and practically, it can be useful in use cases that do not need to consider advanced aspects. For example in the uncovered areas or greenfields where the goal is to provide basic
infrastructure to arrange some minimal level of services. Second, the numerical simulations are performed with advanced aspects including capacities, existing infrastructure, and interference considerations. This is performed on the rural, suburban, and urban deployment use cases.

For the remaining of this chapter, we use the terminology from the theoretical parts of this thesis whose relations to the terminology in wireless networks are shown in Table 5.1.

<table>
<thead>
<tr>
<th>Mathematical Terminology</th>
<th>Wireless Networks Terminology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Service centre</td>
<td>base station node</td>
</tr>
<tr>
<td>Customer location</td>
<td>a location to cover</td>
</tr>
<tr>
<td>Capacity</td>
<td>throughput that is requested by sum of user requirements in a given location to cover</td>
</tr>
<tr>
<td>Existing service</td>
<td>base station node that already exists in the area to cover and should remain after the re-configuration or deployment phase</td>
</tr>
</tbody>
</table>

5.1 Simulations of Base Stations Deployment in Greenfield Areas

In this section, the simulations are performed on the base use-case considering new areas or green fields without any existing infrastructure. These simulations are based on the model presented in Equation 4.4 to Equation 4.6. For this use case, the implementation of several heuristic algorithms was provided. Next, a design of enhanced genetic algorithms on location covering problems is proposed.

5.1.1 Proposed Enhancement of Genetic Algorithm

The main drawback of the genetic algorithms is the population degeneration that leads to a homogeneous population. Unfortunately, the homogeneous population can make the algorithm to get stuck in a local minimum. There exists several methods that target that problem such as the Tarpeian method [53]. The Tarpeian method randomly removes individuals from the population that do not adhere to sufficient standards. Further, the Island model [55, 56] splits the population into several sub-populations that periodically exchange the individuals between them. The problem of these solutions is their implementation difficulty (e.g., the Island model requires the parallelism) or lack of robustness and stability (Tarpeian method) [53, 55, 56, 74].

To provide an alternative to these methods, a novel operator for genetic algorithms was proposed. The new operator is called war. The operator was inspired by the patterns almost periodically observed through the humans history during wartime periods. The operator consists of three stages:

(i) beforeWar is the first stage that archives a predetermined percentage $p_s\%$ of the population. This happens several generations before the actual war. This archived population is later inserted into the population so it brings the trends from the past (and most probably quite different individuals compared to the later individuals in the population). These “past” individuals simulates the fact that in the duringWar stage the population significantly changes its behavior and lifestyle.

(ii) in the duringWar stage the population is sorted by its fitness value. Further, the population is divided into $n$ “social” groups. Unfortunately, as it is in the real world, each social group suffers on a different scale. The changes or reduction in the population are based on the two factors, $p_d\%$, and $p_e\%$. The $p_d\%$ represents the “death toll” (the individuals eliminated from the population). The $p_e\%$ are individuals representing emigrants that successfully manage to save themselves and thus they leave the war area for some time. The elimination ratio is different throughout the “social groups” reflecting the differences between them. The individuals
from “higher” social groups can manage to save them easier than the individuals from “lower” social groups. Further, the archived individuals from beforeWar are inserted into the population duringWar to reflect the changing perception of the world during the war.

(iii) in the stage afterWar the emigrants from the duringWar stage immigrate back to the post-war area. In the final stage, the number of individuals should be the same as it was in the beginning.

Finally, it is important to stress that during these stages the best individual from the population has to remain in the population. Thus, the best individual could not fall into the “death toll” queue.

The whole flow of this process is shown in Figure 5.1.

![Diagram of population flow](image)

**Fig. 5.1: Process and population flow of the war operator.**

Generally, we can say that the warOperator worsens the average fitness of the population when archived individuals from beforeWar and emigrants duringWar are inserted into the later population. While it might seem bad at the first sight, this brings back solution variants that can generate individuals with higher fitness values. To optimize the application timing of this operator, the operator should be applied when the population (its fitness value) starts to plateau. It means when the population is near a local optimum (maximum or minimum). This can be measured as a percentage change in the fitness value between consecutive generations falling under a given threshold (i.e. new generations do not bring enough improvement).

5.1.2 Testing Dataset For Enhanced Genetic Algorithms

For the testing of the base model and enhanced genetic algorithms, the widely-accepted datasets from OR-Library were used. Originally, these datasets were described by J. E. Beasley in [13].

5.1.3 Simulations and Results

The simulations and results section is split into two parts. The first part is using the OR-Library datasets to verify the proposed enhanced genetic algorithms and to utilize the base model computation. The second part is dealing with the numerical simulations for the base station localization on greenfield areas.

**Simulations on OR-Library datasets**

To verify that the proposed enhancement of the genetic algorithms may give better results, we provide a set of tests for verification to highlight whether this enhancement can be a viable alternative to classical genetic algorithms. For each of these tests, 1000 measurements were performed.

In Figure 5.2(a) the classical genetic algorithms implementation is tested, showing the run of the best individual and the average fitness value of the population. The parameter settings are shown in the figure caption. We see that after 4000 iterations (generations), the classical genetic algorithm got stuck in a local minimum. The best individual stuck on the fitness value 120.
This getting stuck is exactly the case when we apply the proposed war operator. In this case, the operator was applied after 5000 generations. As was discussed earlier, the operator temporarily decreases the average fitness of the population (see Figure 5.2(b)). However, though the average fitness value of the population is temporarily decreased (worsened), it may generate better (less homogenous population) in the next generations. To show that effect, we display also the average fitness value of the population in these figures (see Figure 5.2(a) and Figure 5.2(b)). Using the war operator, the best individual reaches the fitness value of 115.

To verify the robustness of the enhanced genetic algorithms with the war operator, in the following test the different parameter settings for genetic algorithms are applied. The runs for proposed enhancement and classic genetic algorithms are shown in Figure 5.2(c). The case was for changing the population size from 100, to 200, and to 300. The higher the population is the longer it might take to produce sufficient results but the heterogeneity of the population should be higher. Red lines represents the classical genetic algorithm implementation and the blue lines represents the enhanced genetic algorithm with the war operator.

For reference comparison, the implementation of another well-known meta-heuristic algorithm was performed. The simulated annealing algorithm that is widely used in many use cases [23, 54, 64, 102, 104] was implemented. To use the simulated annealing algorithm for our deployment use case, we only add repairOperator inside the neighbour generation to provide a feasible solution. The definition of the neighbour object is the same as the individual from the genetic algorithms presented earlier. The results from that comparison are shown in Figure 5.2(e). We have to highlight that simulated annealing was significantly slower than genetic algorithms (for the use case with a population size of 200 and the number of generations equal to 7000 it was almost 10 times slower). The reason for the slowness of the simulated annealing algorithm is that the repairOperator was applied for each newly created neighbour in each iteration. This fulfils our expectation (presented in ??) that heuristic algorithms that generate a new neighbourhood/population in each iteration are not suitable for location covering problems.
Tab. 5.2: Summarised results on OR-Beasley data.

<table>
<thead>
<tr>
<th>Selection Method</th>
<th>Without War Operator</th>
<th>Using War Operator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank Selection</td>
<td>123</td>
<td>119</td>
</tr>
<tr>
<td>Roulette Wheel Selection</td>
<td>120</td>
<td>115</td>
</tr>
<tr>
<td>Pop 100</td>
<td>127</td>
<td>123</td>
</tr>
<tr>
<td>Pop 200</td>
<td>120</td>
<td>115</td>
</tr>
<tr>
<td>Pop 300</td>
<td>122</td>
<td>120</td>
</tr>
</tbody>
</table>

For reference comparison, the implementation of another well-known meta-heuristic algorithm was performed. The simulated annealing algorithm that is widely used in many use cases [23, 54] was implemented. To use the simulated annealing algorithm for our deployment use-case, we only add repairOperator inside the neighbour generation to provide a feasible solution. The definition of the neighbour object is the same as the individual from the genetic algorithms presented earlier. The results from that comparison are shown in Figure 5.2(e).

To summarize the performed tests on this OR-Library dataset, we list the results in Table 5.2.

We can conclude that the enhanced genetic algorithms using warOperator may be a viable alternative to classic genetic algorithms to solve location covering models. However, as it is well-known from the “No free lunch theorem” [108], we cannot say that any heuristic algorithm is better than others for all of the use cases and datasets. Further, we confirm our expectation that heuristic algorithms that generate a new population/neighborhood in each iteration are unsuitable for the location covering model in terms of slow computational speed. This is mainly due to the need to apply repair operator for each new individual (solution) to be certain that a new solution is valid.

5.2 Simulations of Base Stations Deployment in Urban, Suburban, and Rural Areas

The use case for advanced base station deployment requires additional investigation to satisfy the wireless network requirements. These include interferences, signal propagation, network capacities, and others. For that reason, we first summarize the whole computational concept, then we summarize the considered base station parameters, and finally, we show provided numerical simulations.

5.2.1 Computational Concept

The computational concept is divided into two steps:

1. Application of suitable propagation models to predict the radio channel conditions for each base station node and each location to be covered (see Section 5.2.2).

2. Employment of proposed models from Chapter 4 to find optimal locations to deploy base station nodes (see Section 5.2.3).

The first thing to consider before the application of the proposed solution is to device whether the actual network needs could not be satisfied just with the parameter reconfiguration. In many cases, it is not essential to add or remove network nodes in the network infrastructure and only an update of base station parameters settings may help. With this in mind, it is recommended to try parameter optimization first [22]. If it won’t help to meet the end-users requirements, we can move on to applying the proposed computational model.
5.2.2 Propagation Models

In our proposed solution, the covering relations between base station nodes and locations to be covered are based on the signal strength. Using this approach we will get the relation between each base station node and each selected area (e.g., each user location). For the proposed model computation it does not matter whether the data would be gathered using Line of Sight (LOS) or Non Line of Sight (NLOS). Here, we assume that each base station node is configured at its best for the given position to cover as many locations as possible [61, 63]. Further, this prediction has to be done depending on the deployment scenario (urban, suburban, rural area). For example, for urban/suburban areas the suitable path loss prediction models are (i) Okumura-Hata Model; (ii) Stanford University Interim (SUI) Model; and (iii) Cost 231 Hata Model [70, 76]. From that list, for 5G and beyond deployments (in urban and suburban areas) the SUI Model seems promising [70] for frequencies ranging from 2 to 11 GHz. This path loss (PL) model is expressed by the following formula:

\[
PL = A + 10\gamma \log_{10} \left( \frac{d}{d_0} \right) + X_f + X_h + s,
\]

where \(d\) is the distance between the base station node and the receiving antenna, \(d_0 = 100\) [70, 103], \(\gamma\) is the path-loss exponent, \(X_f\) is the correction for frequency above 2 GHz, \(X_h\) is the correction for receiving antenna height, \(s\) is the correction for shadow fading due to trees and other clutter and \(\lambda\) is the wavelength [70]. The other parameters are defined as:

\[
A = 20 \log_{10} \left( \frac{4\pi d_0}{\lambda} \right), \tag{5.2}
\]

\[
\gamma = a - bh_b - \frac{c}{h_b}, \tag{5.3}
\]

where \(h_b\) is the base station node height above ground in meters, and \(a, b, c\) are constants that vary with terrain.

5.2.3 Employment of Developed Models

When the propagation models are selected, the initial matrix can be constructed. The initial matrix represents the relationship between each base station node and locations to be covered. Internally, we represent that matrix as a matrix, not as a linked list to take an advantage from fast access (constant complexity) to retrieve rows and columns of a matrix. For the simulations, we define \(P_{\text{opt}}\) as

\[
P_{\text{opt}} = \{ P_{\text{opt}} \in \mathbb{R} \mid P_{\text{opt}} > -90 \ \text{dBm} \}.
\]

It is designed based on the specification of Reference Signal Received Power (RSRP) levels for Sub-6 GHz 5G cellular service mode that is briefly shown in Table 5.3 [29, 98].

<table>
<thead>
<tr>
<th>RSRP [dBm]</th>
<th>Signal Quality</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>≥ −80</td>
<td>Excellent</td>
<td>Strong signal with excellent user experience (high throughput, low delay)</td>
</tr>
<tr>
<td>−80 to −90</td>
<td>Good</td>
<td>Strong signal with good user experience (good throughput, moderate delay)</td>
</tr>
<tr>
<td>−90 to −100</td>
<td>Fair to poor</td>
<td>A reliable connection may be attained. When this value gets close to −100, the user experience will drop drastically</td>
</tr>
<tr>
<td>≤ −100</td>
<td>No signal</td>
<td>Establishing or keeping the radio connection is significantly limited or even not possible</td>
</tr>
</tbody>
</table>

Table 5.3 shows that the signal power −80 dBm or higher represents excellent signal and signal lower than −100 dBm represents the signal that becomes impossible to establish or keep a wireless connection.
The whole computational concept of the proposed models is shown in Figure 5.2.

This computational concept can be summarized in the following stages. First, we determine the locations to be covered and the theoretical locations where the base station nodes can be deployed (together with the existing base station nodes). Then, we determine the size of the initial dataset. The total number of decision nodes $X \times Y$ where $X$ is the number of rows and $Y$ is the number of columns of the initial matrix is large. We should consider parallel processing of the propagation model computation (this distinguishes whether the base station node can cover particular locations or not). For example, if $X$ will be 5000, and $Y$ will be 15,000 the propagation model would need to be calculated 75,000,000 times. The parallelism for such a computation is relatively easy to achieve since the dataset split and the computation results do not have any relations between them. When all of these threads in parallel finish their computation, the results are merged in the reachability matrix. Further, we need to decide whether we include existing services strictly in the resulting list or not. If we consider the existing services, we add dummy columns to the reachability matrix to strictly add these nodes as essential nodes as was described earlier in Section 4.1.2. In the next stage, we consider the size of the initial data in terms of the number of base station nodes to optimize. If the $X$ (base station nodes) is larger than 60 rows ($X > 60$), we can expect that the computation on the regular laptop, e.g., with a 3 GHz processor would take years [89]. However, when $X < 60$ the exact methods might be applied to get the optimal solution in a reasonable time. For the exact methods the branch-and-bound algorithm with suitable relaxations might be used (relaxations can include Dual LP, Primal-Dual, Lagrangian relaxation or Surrogate relaxations) [12, 107, 111]. If $X$ is larger than 60, we should use heuristic algorithms to achieve an approximation of the optimal solution in a reasonable time. Despite its computational complexity presented in Section 4.2.5, we among others used the GAMS optimization tool, with that we were able to compute instances with thousands of rows and columns. Additionally, we used the propriety developed module in Java to compute such a task (using heuristic algorithms). The computations were performed on a regular laptop with the following parameters: processor: Intel(R) Core(TM) i7-7700 CPU @ 3.60 GHz; installed memory (RAM): 16.0 GB; and 64-bit operating system. The whole computation is summarized in Algorithm 5.1 [90].

Algorithm 5.1 The Algorithm Representing the Whole Computational Concept to Get the Best Locations to Deploy Service Centres (Base Station) Nodes.

**Input:** $S_C = \{1, \ldots, m\}$ = the set of all service centres;  
$C_L = \{1, \ldots, n\}$ = the set of all customer locations;  
$E_s$ = the set of existing service centres;  
$P_m$ = selected propagation model;  
$D_m$ = matrix representing the distances between the elements of $S_C$ and $C_L$;  
$C_s$ = the set of possible capacities of service centres;  
$C_{cl}$ = the set of required capacities of customer locations;

**Output:** $F_s$

function computationalConcept()
    if base station parameters optimization not sufficient then
        $I_m$ ← Compute RSRP between all the $S_C$ and $C_L$ using selected $P_m$ for selected scenario;
        $R_m$ ← Convert $I_m$ to reachability matrix based on the RSRP;
        $C_m$ ← Convert $R_m$ to capacity matrix based on the $C_s$ and $C_{cl}$;
        $F_s$ ← Employ developed models;
    end if
end function
Finally, when we get the optimal base station locations, we can perform additional parameters tuning (power, downtilt, height, etc.) to provide the optimal base station configurations. Both steps (locations and parameters tuning) can be performed periodically to get the best result. However, it cannot be easily used together since it would lead to a very complex computation (NP problem as it is with NP problem in each iteration). The base station parameters tuning is out of the scope of this thesis, however, more details on this issue can be found in the paper [22].

The mathematical models presented in this work are targeting two deployment scenarios, the first one is to deploy the base station nodes to the area without the existing base station nodes, i.e., new deployment, and the second one is to deploy additional base station nodes to the area with existing base station nodes, i.e., to increase the overall network capacity.

For the first scenario, we prepared self-developed datasets to use the mathematical model for the deployment without the existing infrastructure for different scenarios (urban, suburban and rural). For the second one, we use the mathematical model that takes into account the existing infrastructure, here the input values have been obtained from publicly available data (about users, base station nodes, etc.) in the selected district of Central Europe [37, 38].

5.2.4 Base Station Parameters Settings

When the suitable propagation model for a particular deployment use case is chosen, we need to consider additional parameters. These include expected increased demanded end-user throughput due to the 5G+ applications as is AR/VR, maximal available throughput (capacity) of base station nodes, the radius for base station cells, etc. For the sake of simplification, we consider that a single base station represents a single mobile cell. All the parameters are further discussed in the next paragraphs.

The considered parameters for users throughput and base stations we based on the Cisco white paper [20] and the 5G reference guide for network operators [39]. The Cisco white paper identifies as the fastest-growing category the M2M communication (see Figure 5.3). The M2M is expected to grow to reach 14.7

Fig. 5.2: The Basic Concept of Producing the Optimal Solution (SC: Service Centre, CL: Customer Location and ES: Existing Services).
billion connections by 2023. Importantly, it can be seen that nowadays the mix of types and connection types is growing. For the network operators, it is especially interesting since it changes the traffic patterns. For example, internet-enabled services as is the video streaming (4K), HD television running for two hours per day can consume as much traffic as an entire household today. The expected user thresholds are for Downlink (DL) 100 Mbit/s and for Uplink (UL) it is 50 Mbit/s [20, 39]. Further, in 5G and beyond deployments it is expected to enable also AR, VR applications that demand very high data throughput that can range from hundreds of Mbit/s to several Gbit/s [20, 39]. For our simulations, we consider as the throughput for every considered customer location to be 43.9 Mbit/s. This value was estimated by Cisco in [20]. Cisco mentioned that globally, the average mobile network connection speed in 2018 was 13.2 Mbps, and the expected that in 2023 the speed will more than triple and it will be 43.9 Mbit/s. This expectation was based on wide usage of AR, VR and similar applications. In the presented use case, it represents the top upper limit that the network operator will allocate for one user. We used that value to design the network to handle such borderline use case [39, 90].

The expected theoretical capacity limits of a single base station node mentioned in [2, 45, 105] are as follows: (i) DL peak theoretical data rates 20 Gbit/s and; (ii) UL peak data rate 10 Gbit/s. Currently, it might be difficult to technically achieve such data rates, however, using mmWave or other technologies that are currently not available it might be achievable. It affects the parameters further on the basis of the deployment use cases (urban, suburban, and rural). The capacity of a base station node is in practice determined by a number of configuration parameters. These include: hardware setup, class of radio interface, duplex mode, number of sector carriers/baseband unit, number of users/baseband unit, number of users/sector carrier, data radio bearers, scheduling entities per slot DL/UL—cell, maximum sector carrier bandwidth, maximum throughput per connected user DL/UL, maximum throughput per radio node DL/UL and Single User (SU) Multiple-Input Multiple-Output (MIMO) layers. Any of these can be optimized on the basis of network requirements. Further, we selected for all of the use cases the 7500 users as a representative set of users for the simulations and the number of simultaneous connections/km² [6] that can be available. Further, the theoretical coverage area was computed based on the number of users and number of connections/km² [90].

For the sake of generalization, the average base station coverage range is most commonly set to 0.5 km in urban, 1 km in suburban, and 8 km in rural areas [44]. Finally, in the simulations, we use SUI model, the settings for that model were set as follows: \(a = 4, \quad b = 0.0065, \quad c = 17.1, \quad h_b \text{ ranging from 5 to 35 m, } f \text{ was under 5 GHz, } X_f, X_h \text{ and } s \text{ were calculated using the antenna height and frequency parameters).}
All of these parameters serve as input data for the proposed model, they can be any time changed without an effect on the proposed solution.

The summarized list of parameters of base stations and end-users is shown in Table 5.4.

Tab. 5.4: Summarized List of Parameters Based on the Deployment Use Case.

<table>
<thead>
<tr>
<th>Use Case</th>
<th>Combined Base Station Capacity (DL+UL) [Gbit/s]</th>
<th>Single Cell Radius [km]</th>
<th>Demanded User Throughput (DL+UL) [Mbit/s]</th>
<th>Number of Connections/km²</th>
<th>Total Coverage Area [km²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>urban</td>
<td>30</td>
<td>0.5</td>
<td>43.9</td>
<td>2500</td>
<td>3</td>
</tr>
<tr>
<td>suburban</td>
<td>30</td>
<td>1</td>
<td>43.9</td>
<td>400</td>
<td>18.75</td>
</tr>
<tr>
<td>rural</td>
<td>30</td>
<td>8</td>
<td>43.9</td>
<td>100</td>
<td>75</td>
</tr>
</tbody>
</table>

5.2.5 Simulation of Different Deployment Scenarios

Based on the parameters presented in Table 5.4, we created a datasets via Matlab for each scenario (urban, suburban, rural).

For the urban scenario, we randomly generated the 7500 users across the whole area. Further, we generated theoretical candidate locations for base stations so that each base station is generated at a distance of 100 meters from each other. Next, we generated the base station parameters and demanded user throughput (this is the same for all the deployment scenarios). For the simulation we used the same values for each base station or end-user, however, the model allows setting a different capacity for each base station as well as setting up different demanded throughput for end-user.

For the suburban scenario, we generated the 7500 users into four groups representing suburban areas. The first group has 1000 users distributed between coordinates (400,400), (400,600), (600,400), (600,600); the second group has 2000 users distributed between coordinates (1800,1800), (1800,2600), (2600,1800), (2600,2600); the third group has 2400 users distributed between coordinates (1400,400), (1400,750), (1800,400), (1800,750); and the fourth group has 2000 users distributed between coordinates (2300,3100), (2300,3550), (2750,3100), (2750,3550). The last group of 100 users was randomly generated into the whole area. Further, the theoretical candidate locations for base stations were generated in each of these groups with a distance of 80 meters and the rest was randomly generated throughout the area.

For rural scenario, we randomly generated 7500 users across the area. Further, we generated theoretical candidate locations for base stations so that each base station is generated at a distance of 600 meters from each other.

Tab. 5.5: Results of Different Deployment Scenarios.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Theoretical Number of Candidate Locations to Deploy Base Stations</th>
<th>Resulting Number of Base Station Nodes to be Deployed</th>
</tr>
</thead>
<tbody>
<tr>
<td>urban</td>
<td>289</td>
<td>11</td>
</tr>
<tr>
<td>suburban</td>
<td>421</td>
<td>12</td>
</tr>
<tr>
<td>rural</td>
<td>484</td>
<td>11</td>
</tr>
</tbody>
</table>

The performed simulations out made it possible, in a reasonable time, to achieve the results presented in Table 5.5. For these simulations, the model presented by Equations (4.29)–(4.36) was used without extending the objective function, which might be an interesting problem for further research. Possible radio interferences were reduced by Equation (4.34).
Table 5.5 clearly shows that the area size is not the biggest problem for the base station deployment, as opposed to the number of users and their required throughput which is the main aspect that needs to be considered for the 5G and beyond deployments. It is shown that even if the rural use case contains the same number of users as the suburban and urban areas, the number of the necessary base stations to cover the area is smaller or the same. This can be due to the larger number of theoretically available locations to deploy base stations on which the software can find better combinations of base station nodes to cover the whole area to meet the given requirements. The theoretical candidate locations were generated based on the assumption that larger areas should have better options to select locations to deploy base station nodes.

For the computational concept, we consider that, theoretically, a base station could be deployed in every possible place (see Figure 5.4) and then the software will produce the combination of the base station nodes locations that are optimal for the considered deployment, based on the selected aspects. However, the number of theoretical candidate locations must be limited since a very large number of these possible locations can significantly prolong the computation.

Figure 5.4 shows that in the case of an urban area, users are spread throughout the area. It is further shown here that 289 possible locations for base station node deployment were originally considered and, of these, an optimal combination of 11 base station nodes was found. The calculated solution covers the whole area meeting the specified requirements (base station capacities, demanded end-user throughput from the user and coverage range of the base station). If the area changes significantly, e.g., some areas may be closed and users may move to another district, the only essential process to do is to provide updated input parameters for the presented models [90].

The optimal combination of base station nodes is shown in Figure 5.5.
5.2.6 Simulations Utilizing Dataset From District in Central Europe

In this scenario, we consider the use case of adding new base station nodes to the area in the city of Prague. The area that was selected for that network infrastructure reconfiguration represents a typical mixed-urban environment consisting of residential areas, forests, industrial areas, etc. The list of available base station nodes in the selected area consists of 75 already deployed base station nodes on LTE (of all wireless network providers, e.g., T-Mobile, O2). This information can be extracted from a freely available data source [37, 38]. In this simulation, we consider the parameter settings for 5G+ scenarios shown in Table 5.4.

The next step was to select particular areas to cover and predict the signal strength and network traffic in those areas. The traffic had to be predicted based on the type of location since it is likely to be higher in an industry area than in a forest. First, we need to predict the signal strength in relation to each base station node as well as each selected area (e.g., each user location). This prediction was based on the deployment use case that is in a particular urban/suburban area. For that reason, the SUI propagation model was chosen. The SUI model in suburban, urban NLOS environment set the path loss exponent as $3 < \gamma < 5$ and for free space propagation $\gamma = 2$ [66].

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Prague 11 (suburban)</td>
<td>30</td>
<td>1</td>
<td>43.9</td>
<td>75</td>
<td>68,839</td>
<td>9.8</td>
</tr>
</tbody>
</table>
To simulate the model considering the existing base station nodes, the district Prague 11 was selected. This district has a total of 68,839 residents [77] (some of the residents are commuting to another district and some of them visit the district during the day, but for simplicity, we consider the size of both groups equal). Based on that data and the theoretical locations of new base station nodes, we computed the optimal locations of the base stations to satisfy the new requirements due to an expectation of an increasing number of connected devices requiring high network throughput (HD video, VR, AR and others). In addition, for the computation, we expected that all the existing base station nodes will have a total cell capacity of 30 Gbit/s per base station with a cell coverage radius of 1 km (the proposed model allows to set it for each base station uniquely). The additional parameters for that computation are shown in Table 5.6.

Using these assumptions, the dataset from the Prague 11 district was processed. The results showed that it would be essential to add an additional 31 base station nodes to provide the network infrastructure that can deal with the increasing traffic demand to meet the requirements in a few years.

Based on that computation, we can see that, for 5G and beyond, the network operators will need to significantly modify the network infrastructure to handle the increased network traffic. Here, our models will provide a value that can be of significant use.

In practice, the process of adding base station nodes is not appropriate, and usually not even possible on a large scale. This is due to the base station building process that involves a number of steps, both legal and structural. For that reason, it is advisable to add base station nodes iteratively based on the current growth of network traffic with a certain reserve. In both our models, this can be expressed by changing the input data values, e.g., multiplying the demanded end-user throughput to include the new applications in 5G+ [90].

### 5.3 Summary of Contributions of This Chapter

This chapter shows the possible usage of the solution that can improve the network planning process. Currently, the widely-used tool for network planning in the industry is Atoll Radio Planning Software (ARPS) [84]. The general planning process is shown in Figure 5.6 [67, 100].

Using that, it is essential to provide a lot of manual work that can be reduced by automated searching for optimal base station locations proposed in this thesis.
For example, the ARPS tool includes a module called Automatic Cell Planning (ACP) providing advanced planning options. However, based on the documentation [67] it is more focused on the optimization of base station parameters (e.g., modifying the antenna azimuths; setting the mechanical downtilt of the antenna, etc.).

Our proposed solution can improve the planning process in a way shown in Figure 5.7. Using that the provided solution can be almost fully automated.

```
Radio transmission  Resource allocation  System architecture  Mobile Subscriber

Automatic network design  Performance evaluation and optimization

Mobile network
```

Fig. 5.7: Sophisticated Network Planning.

First, we gather or set up the following information: (i) radio transmission (the transmission range, frequency bands, etc.); (ii) resource allocation (the budget represented for the deployment); (iii) system architecture (types of the base stations to be used in the deployment, unnecessary locations, etc.); and (iv) mobile subscriber (the expected number of users in the selected area and the expected average user traffic). Taking these input information into account, with the help of the proposed model, we can automatically find the optimal locations. The necessity for such automation is represented by the need for the re-configuration or modification of the network infrastructure to handle increased network traffic and the new requirements of the 5G+ services and applications [90].

6 CONCLUSION

In this thesis, we investigated the necessity of network infrastructure changes during the deployment of 5G+ networks. The feature-rich devices including augmented and virtual reality, high definition streaming services, and other throughput expensive applications push up these demands for the cellular infrastructure updates. This is also supported by the growing user expectations for quality of experience with such services. These emerging issues and challenges are described in Chapter 2 including the summary of technology enablers introduced to meet those ever-increasing demands. Further, this chapter highlights approaches to optimize or plan network infrastructures to support the changing needs, especially with regard to the network capacities. Here, the main focus is on location covering models to select suitable locations for the base stations’ deployment with the given needs. Chapter 3 focuses on the implementation algorithms for such covering models with regards to their computational complexity. At this point, heuristic algorithms are of the main interest due to their ability to provide feasible solutions in a reasonable time.

Next, Chapter 4 highlights the gaps of the existing models and proposed a new model considering aspects like capacities, interferences, signal strength, etc. As it is typical in location covering model proposals, the model has both variants, the maximization and minimization alternative. The maximization alternative deals with the situation where the resources are limited and the network providers are trying to maximize the coverage with the given resources. Whereas, the minimization model considers almost unlimited resources and targets the need to cover all the customers. In practice, the minimization alternative can be achieved also by removing some locations from consideration and thus running the model as we need to cover these places for sure but the other ones are not considered. Further, for this model, we considered the computational
complexity. For these models (both alternatives), the computational complexity was determined as $O(2^m mn)$. This high complexity is due to the large search space considering the number of all possible selections of base station services.

Finally, Chapter 5 verifies the model proposal with simulations on predefined use cases. Moreover, the chapter provides a description of the computational concept of the proposed solution targeting the automated network planning process. The simulations were performed on self-prepared datasets based on the network specification from ITU and Cisco technical reports. First, the simulations are targeting the simple model without advanced metrics that can be applied for base station deployments on greenfields. Using these simulations, the modification of genetic algorithms called warelimination was proposed. Second, we consider the more complex use case for rural, suburban, and urban areas targeting the typical problem of current network planning including the capacity and interferences considerations. The results show that the network providers will have to significantly update the wireless network infrastructures to support the growing need for the upcoming 5G+ services. Further, the simulations verified the model proposed to be a viable solution for the planning of the base stations deployment.

6.1 Open Questions and Discussion

Although the proposed models represent a comprehensive solution and the results have shown a clear technical impact, there are certain aspects that could be further explored and optimized. The below-mentioned list highlights the possible future research directions.

- **Consideration of the base station dynamically changing configuration during the localization.** The proposed model uses, the predefined configuration for every single base station, however, for the final network deployment/configuration the base station optimization has to be employed. The problem with this approach is that even if we include dynamically changing parameters to the model proposal, it would generate two $\mathcal{NP}$-hard/complete problems. For that reason, we omit that and suggest the adopters of the model optimize these configurations in the next processing phase. The adopters can iteratively run the proposed model together with the parameter optimization (e.g., using reinforcement learning techniques).

- **The interferences are reduced by setting the minimum distance between base station nodes or by maximizing the possible distance between base station pairs.** In the proposed model, the possible interferences are reduced by the two options, first by setting up the minimum distance between pairs of base station nodes, second approach requires modification of the objective function of the model to maximize the distance between base stations. However, there still might be another more advanced way to reduce the interferences or to increase the spectral efficiency of the solution using machine learning approaches (e.g., with reinforcement learning).

- **Consideration of dynamic network topologies.** The proposed model is defined as a static scenario. However, when the network will be set up from moving cells (e.g., UAVs utilized as flying base stations), the optimal locations have to be re-computed in a loop. This would require the model to be adaptable for such specific dynamically-changing network topologies. Otherwise, the current model has to be re-computed for new requirements periodically (e.g., every few minutes).

BIBLIOGRAPHY


**AUTHOR’S CV (RELEVANT TO UNIVERSITY)**
Ing. Mgr. Pavel Šeda

Education

2016 – 2018  (Mgr.), Masaryk University, Faculty of Informatics, Master Degree, Programme: Applied Informatics

2015 – 2017  (Ing.), Brno University of Technology, Faculty of Electrical Engineering and Communication, Master Degree, Field: Communications and Informatics

Internships Abroad

2019, 2 months Researcher, National Taiwan University of Science and Technology
- College of Electrical Engineering and Computer Science; Tchaj-wan China located in Taipei

Research Projects

2022-2023 VB01000036: Technology for Testing Cybersecurity ICT
2021-2025 VJ01010066: Electronic Speed Limitation of Vehicles in Emergency and Crisis Situations by Integrated Rescue System system
2020-2022 VI20202022158: Research of New Technologies to Increase the Capabilities of Cybersecurity Experts
2019-2021 TJ02000290: Hardware Accelerated System WithCryptographic Security for Transferring Big Data
2016-2019 VI20162019014: Simulation, Detection, and Mitigation of Cyber Threats Endangering Critical Infrastructure

Awards

Best paper award ACM SIGCSE 2022 (New York, USA). Title: Preventing Cheating in Hands-on Lab Assignments. CORE rank A conference.

Teaching Activities

MUNI FI Enterprise Applications in Java (2020,2021,2022); Programming in Java (2021) (seminars)

Publication Activities

**Category** | **Evidence**
--- | ---
Journals with IF | 5
Conferences with CORE rankings | 3
Chapters in book | 2
Publications indexed in WoS or Scopus | 24
Journals without IF | 2
Article reviews (conferences/journals) | 31
Citations (G. Scholar/Scopus/WoS) without self-citations | 44/27/13

Expert Reviewer

**IF journal**
- Sustainable Cities and Society (Elsevier journal, Q2);
- IEEE Access (IEEE journal, Q2);
- Sensors (MDPI journal, Q2)

**Conferences**
- IEEE Frontiers in Education (CORE conference rank C);
- IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (CORE conference rank B);
- International Congress on Ultra Modern Telecommunications and Control Systems (International Conference indexed in Scopus/WoS)
ABSTRACT

The dissertation is focused on “optimization of network infrastructures using artificial intelligence algorithms”. The growing requirements for network traffic in 5G+ networks require decisive modifications to the network infrastructures. The main aim of this dissertation is to design an optimization model and algorithms for selecting suitable locations for the base station deployment. The proposed optimization model reflects the essential requirements of wireless coverage in today’s networks, such as the required capacity (base stations and end-users), existing infrastructure, interference between base stations, or coverage range. Since the model represents an exponential problem that is not possible to solve for larger instances exactly in the available time, it was essential to apply artificial intelligence methods. For the computation the heuristic algorithms were selected and implemented, these are discussed in detail in the dissertation text. The proposed optimization models and algorithms are subsequently verified using suitable simulations for urban, suburban, or rural areas. The practical use of the proposed solution is considered as an additional module to existing tools, recommending the locations to deploy new base stations when the network parameters change (e.g., higher capacity requirements in certain areas), serving as a basis for further practical verification. To conclude, the main contributions are in the design of models extending classical covering problems together with the implementation using modified heuristic algorithms. Including their subsequent verification at instances with hundreds of thousands of nodes and their publication in impact journals and at international conferences.

ABSTRAKT

Dizertační práce je zaměřená na “úlohy optimalizace síťových infrastruktur s využitím algoritmů umělé inteligence”. Vzhledem k rostoucím požadavkům na síťový provoz v 5G+ sítích jsou nutné zásadní úpravy síťových infrastruktur. Tyto požadavky vytyčují řadu otázk v oblasti výzkumu. Hlavním cílem této dizertační práce je proto návrh optimalizačního modelu a algoritmů lokalizujících vhodná místa k nasazení základnových stanic. Pro vytvoření takového optimalizačního modelu bylo nezbytné reliktovat zásadní požadavky bezdrátového pokrytí v soudobých sítích, jako jsou požadované kapacity (základnových stanic a koncových uživatelů), již existující infrastruktura, interference mezi základnovými stanicemi či dosah pokrytí. Protože algoritmus hledání řešení této úlohy má exponentní složitost a pro velké instance není možné najít optimální řešení v dostupném čase, bylo nutné aplikovat metody umělé inteligence. Vzhledem k charakteru výpočtu byly zvoleny a implementovány meta-heuristické algoritmy, které jsou dány v práci detailněji rozebrány. Navržené optimalizační modely a algoritmy jsou následně verifikovány pomocí vhodných simulací pro městské, předměstské či venkovské oblasti. Praktické využití navrženého řešení je uvažováno jako dodatečný modul do existujících nástrojů, doporučující místa nasazení nových základnových stanic při změně charakteru síť (např. vyšší kapacitní požadavky v určitých oblastech), sloužící jako podklad pro další praktické ověření. Hlavním přínosem práce je návrh a implementace vlastní modifikace genetického algoritmu a návrh původních matematických modelů smíšeného celočíselného programování, výrazně rozšířujících klasickou úlohu pokrytí. Včetně jejich následného ověření na instancích se statisí prvků a jejich publikace v impaktovaných časopisech a na mezinárodních konferencích.