# Master Thesis
# MSc Metropolitan Analysis, Design and Engineering

**Title:**

A network analysis method for
optimized location planning of shared mobility hubs

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## Abstract

To tackle challenges such as climate change, air pollution, traffic accidents, or the lack of space in cities, our urban transportation systems must become sustainable, emission-free, safer, and more efficient. The introduction of shared mobility is seen as a critical component in facilitating a mobility transition in large cities, as shared mobility can promote multimodal travel behavior, leading to reduced ownership and usage of the private car.

Shared mobility requires charging solutions and parking space within the existing urban fabric. Additionally, it must have digital and physical integration into existing transportation systems. These requirements should be jointly addressed within the concept of shared mobility hubs. Recently, cities have moved from pilot testing standalone hubs to the scaling of city-wide hub networks. Planning the locations of these hubs remains a challenge for cities trying to optimize their distribution.

This research suggests an improved location planning method for shared mobility hubs, combining Multiple Criteria Decision Analysis (MCDA) and Network Analysis. Different prioritizations at the municipal decision-making level can be translated into placement strategies through MCDA. If necessary, multiple stakeholders can also be involved through a Multi-actor Multi-criteria Analysis (MAMCA). The resulting MCDA score for each spatial unit converts a multivariate problem into a single variable location-optimization problem. Utilizing single variable location-optimization tools, such as ArcGIS location allocation, specific location suggestions can be computed along with their respective catchment areas. This also allows a comparison of different placement strategies based on city-wide Key Performance Indicators (KPIs). In turn, decision-makers are enabled to compare different placement strategies in terms of their potential impacts on their objectives. This method holds the potential to accelerate micro-planning processes with defined target scenarios and data-based insights per hub location.

The improved method is developed upon the case study of Munich, considering various location planning objectives. 600 locations composed of 3 hub types are suggested in order to achieve city-wide accessibility within 5 minutes of walking time. 1000 locations of an additional hub type are suggested to achieve city-wide accessibility within 3 minutes of walking time.

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# Introduction

# 1. Introduction

## 1.1. Context

To tackle challenges such as climate change, air pollution, traffic accidents, or the lack of space in cities, our urban transportation systems must become sustainable, emission-free, safer, and more efficient. The introduction of shared mobility is seen as a critical component in facilitating a mobility transition in large cities. With the introduction of Mobility-as-a-Service (MaaS) and a strong integration with existing public transport, shared mobility can promote multimodal travel behavior, leading to reduced ownership and usage of the private car. This can contribute to less greenhouse gas emissions, less air pollution and less pressure on the traffic system as well as public spaces (ITF, 2017, 2021a, 2021b).

Shared mobility itself requires charging solutions, parking space in the existing urban fabric as well as digital and physical integration into existing transportation systems. These requirements should be jointly addressed within the concept of shared mobility hubs. Due to the actuality of the topic, there is not yet a consistent description of shared mobility stations in scientific literature. In this study, the definition of Blad (2021) is adopted with a slight modification:

***"The shared mobility hub is a place where multiple shared transport modes come together, providing seamless connectivity between shared and traditional modes, possibly including other features, ranging from retail, workplaces to parcel pick-up points."***

As the definition and interpretation of shared mobility hubs is still under discussion and allows for various interpretations, exemplary images and ambitions for networks of shared mobility hubs are presented for different cities.

Various concepts of shared mobility hubs were tested in pilots around the world, focusing on Germany pilots for shared mobility hubs are implemented in Bremen since 2003 (VCD, 2019), in Hamburg since 2013 (VCD, 2017), in Munich since 2016 (Mobilitätsreferat München, 2021a) and in Berlin since 2019 (Tagesspiegel, 2022). Recently, cities have moved from testing standalone shared mobility hubs to the scaling of these hubs to city-wide networks. Within Germany, the three largest cities are planning to build hundreds of shared mobility hubs over the next years:

- Berlin plans to develop a more dense hub network within the Jelbi program (see Figure 1, Figure 2) starting from currently 44 hubs (Tagesspiegel, 2022).
- Hamburg plans to increase the number of hubs within the HVVswitch program (see Figure 3, Figure 4) from currently 88 to 222 until 2024 (ZfK, 2022).
- Munich plans to increase the number of hubs within Mobilitätsstation program (see Figure 5, Figure 6, Figure 7) from currently 9 to 200 by 2026 (muenchen.de, 2022).

*Figure 1: Jelbi station in Berlin with shared cars, shared micromobility, public transport and parcel locker (Jelbi, 2022)*

*Figure 2: Jelbi point in Berlin with shared micromobility only (die mitte berlin, 2020)*

*Figure 3: Mobility station in Hamburg with shared car, shared micromobility and public transport (ITS International, 2017)*


*Figure 4: Mobility station in Hamburg with car sharing and public transport (VCD, 2017)*

*Figure 5: Mobility station in Munich with shared cars, shared micromobility and public transport (VCD, 2020)*

*Figure 6: Mobility station in Munich with shared cars and shared micromobility (Mobilitätsreferat München, 2021a)*


*Figure 7: Mobility station in Munich with parking for e-scooters only (Mobilitätsreferat München, 2022)*

If the long-term objective is the city-wide coverage within a short walking distance, larger cities will require hundreds to thousands of shared mobility hubs. When a large number of shared mobility hubs throughout the urban area are required, cities are challenged with the location planning for this new type of infrastructure. Quantitative location suitability analysis for strategic planning of shared mobility infrastructure is a key factor in the efficiency of these systems (Aydin et al., 2022; Kabak et al., 2018). Therefore, the need for data-based and automated methods for location planning of shared mobility hubs is emerging.

## 1.2. Existing research and gap

Location planning for transportation infrastructure and more specifically for shared mobility hubs is investigated by researchers around the globe. Most scientific sources perform spatial analysis based on polygons (raster cells or administrative areas) and Euclidean distance (Blad, 2021; Correia & Casanovas, 2022; Knaack, 2021; Liao & Correia, 2021; Zhou et al., 2020), leading to a hub suitability score per area. Spatial analysis using network theory is less common (García-Palomares et al., 2012; Tran & Draeger, 2021) and the application of network theories to location planning for shared mobility hubs has not been studied in detail. One of the scholars performing initial tests of network theories for location planning of shared mobility hubs concludes: "There is considerable opportunity for complex network theory to further inform transportation planning, especially in the context of urban mobility hubs, which due to increasing availability of extensive geospatial asset data can be readily analyzed with network statistics (Tran & Draeger, 2021, p. 2729)."

## 1.3. Research objective

From the literature review it can be concluded that application-ready location methods for mobility hubs mostly result in a heat map with hub suitability per grid cell or administrative area. The city is supposed to manually locate the shared mobility hubs one by one according to the heatmap.

In practice, this means that for each area marked as "suitable" in the initial data analysis a manual analysis is carried out. The detailed manual planning expected to answer the questions of how many hubs are actually required and where exactly their optimal location is within the suitable area. For this purpose, a qualified specialist must survey the entire area via Google Street View and usually also in person. In this way, a candidate list of possible locations for a hub is created for the considered area. Afterwards, the respective catchment area (e.g. Isochron with 5 min) must be calculated for each candidate location. Now the different possible combinations of locations have to be considered manually with the aim to maximize the coverage of the demand and to minimize overlaps of the isochrons. Then, for each selected location, the provided sharing services are determined. The placement proposal for an area created by this process is finally presented and possibly adjusted during a site visit with other involved departments as well as local politicians and residents (Hochbahn Hamburg, personal communication, February 23, 2022).

A small number of shared mobility hubs might still be placed according to local decision-makers and without advanced methodological approaches in practice. But with the upcoming creation of larger networks of hundreds or even thousands of Shared Mobility Hubs, the need for data-based and automated methods for location optimization of Shared Mobility Hubs is also emerging in practice.

A major transformation of the transport system is one of the greatest metropolitan challenges of our time. Improved methods for locating large networks of mobility hubs are of high societal relevance as they could improve the quality and speed of implementation of this new infrastructure type, whilst reducing planning cost. This could support cities in achieving their policy goals for shared mobility and mobility hubs: (1) public space improvement, (2) sustainable and liveable environment, (3) reduction of (private) car usage and ownership, (4) improvement of accessibility (van Gerrevink, 2021).

Research on the placement of shared mobility hubs often applies Multiple Criteria Decision Analysis (MCDA) and results in heat maps that show the location suitability per area. Extending the MCDA approach with location optimization using network analysis and high-resolution spatial data can lead to a better understanding of shared mobility hubs in general, underpinning the scientific relevance of this research.

### 1.4. Research questions

This research aims to improve methods for the planning of large networks of shared mobility stations. Therefore, existing approaches could be extended by network analysis methods. This way, an improved method should be able to perform location optimization in the network, including exact walking distances in the street network, competition effects between stations and comparison of placement strategies by key performance metrics. A location planning methodology using network analysis for an entire urban area could advance current research and help cities navigate the many challenges they face when scaling shared mobility stations. Therefore, this thesis aims to answer the main research through four sub-research questions.

Main RQ: How can network analysis methods improve location planning of shared mobility hubs?

- RQ 1: What methods are currently applied for location finding of shared mobility hubs?
- RQ 2: What network analysis techniques could be applied for location planning of shared mobility hubs?
- RQ 3: How can network analysis techniques be integrated into an improved location planning method for shared mobility hubs?
- RQ 4: What are the results and learnings from applying the improved method to the Munich case study?

## 1.5. Research approach

According to a literature review of Macharis (2009), extending existing evaluation methods is crucial for the successful implementation of future transportation projects: Larger transport projects require evaluation methods and science has already provided many different types of evaluation methods for this purpose. Methods like the private investment analysis, the cost-effectiveness analysis (CEA), the economic-effects analysis (EEA) have a strong focus on financial costs only. According to a literature review by Macharis (2009), nowadays the environmental, spatial and social dimensions of a project are considered increasingly important in addition to the economic dimension. Therefore, methods that can include aspects besides the economic perspective, such as multicriteria decision analysis (MCDA), are used more frequently. MCDA makes it possible to evaluate several options with multiple quantitative and qualitative criteria. MCDA is used for various purposes in transportation planning such as policy measures in passenger transport, strategic decisions, technologies, infrastructure projects and locations (Macharis et al., 2009). The last-mentioned application for location finding of transport projects shows the direct relevance of the method for this thesis. Another development for MCDA is the inclusion of various stakeholder perspectives in the analysis. Transportation projects influence or are influenced by many different stakeholders such as users, operators, and authorities. The involvement of all stakeholders is critical to the successful implementation of a transportation project. As MCDA is suitable to consider the interests of various stakeholders, Macharis (2009) introduces a multi-actor multi-criteria approach (MAMCA), which is particularly suitable for the evaluation of transport projects. This research aims to combine existing MCDA and MAMCA approaches with network analysis theories, leading to a higher level of spatial detail in the results. This can support the improvement of evaluation methods for transportation projects, in particular location planning for large networks of shared mobility hubs.

## 1.6. Thesis outline

In chapter 1, the general topic of the thesis is introduced. Chapter 2 provides the methodology for this thesis. Chapter 3 summarizes the findings of a literature review on shared mobility hubs and current location planning methods. Chapter 4 shows the results of a literature review on network analysis approaches for location planning. Chapter 5 presents the improved location planning method for shared mobility hubs. Chapter 6 describes the application of the improved location planning method for shared mobility hubs in the case study of Munich. Chapter 7 discusses the characteristics, the case study application as well as benefits and limitations of the improved location planning method for shared mobility hubs. Chapter 8 presents the conclusions of this research.

# Research methodology

# 2. Research methodology

## 2.1. Overview

To answer the main research question “How can network analysis methods improve location planning of shared mobility hubs?”, multiple more detailed research questions (RQ) are introduced. The first research question aims to understand the current methods for location planning of shared mobility hubs through a literature review. Second, available network analysis methods are investigated by reviewing the literature. The results of the previous steps are synthesized to develop an improved method for location planning of shared mobility hubs. Finally, the improved location planning method is applied to the Munich case study to test and further improve the method.

*Table 1: Research questions*

| | **Research Question** | **Method** |
|---|---|---|
| Main RQ | How can network analysis methods improve location planning of shared mobility hubs? | RQ 1.1 - RQ 1.4 |
| RQ 1 | What methods are currently applied for location planning of shared mobility hubs? | Literature Review |
| RQ 2 | What network analysis techniques could be applied for location planning of shared mobility hubs? | Literature Review |
| RQ 3 | How can network analysis techniques be integrated into an improved location planning method for shared mobility hubs? | Synthesis of previous findings to improved location planning method |
| RQ 4 | What are the results and learnings from applying the improved method to the Munich case study? | Case Study Munich - Analysis & Results |

## 2.2. Literature research on location planning methods for shared mobility hubs

To answer RQ 1, literature research was conducted on existing location planning methods for shared mobility hubs. The field of shared mobility is evolving rapidly and technological developments often outpace research and policy. Publications in scientific journals on recent innovations are limited, many up-to-date sources can be found in gray literature such as theses at universities, company websites or publications of municipalities. We applied Google Scholar and sciencedirect.com search tools (Keywords: shared, mobility, hubs, location, planning, decision, network) and snowballing techniques. Results are summarized in Chapter 3.

## 2.3. Literature research on network analysis methods for spatial planning

To answer RQ 2, literature research was conducted on network analysis methods for spatial planning. We applied Google Scholar search tools (Keywords: network, analysis, methods, spatial, transportation, infrastructure, planning) and snowballing techniques. We applied sciencedirect.com search tools (Keywords: mcda, street, network, analysis) and snowballing techniques. Results are summarized in Chapter 4.

## 2.4. Design of an improved location planning method using network analysis

To answer RQ 3, the findings of all previous sections are synthesized to design a new location planning method using network analysis. Different components from existing location planning approaches for shared mobility hubs are combined with the capabilities of network analysis methods. The improved method is presented in detail in Chapter 5.

## 2.5. Application of improved location planning method in case study

For RQ 4, the improved location planning method is applied in a case study of city-wide planning of shared mobility hubs. The improved location planning method has been continuously refined alongside the case study application to ensure that the results of this research are not only scientifically relevant but also practice-oriented. The city of Munich, Germany, was chosen as a case study for this research because it is planning to build a city-wide network of shared mobility hubs in the coming years and the author can use existing area knowledge to validate results. Taking the specific perspective of the Municipality of Munich for this study, this research aims to develop generalizable methods that are transferable to other cities. The Municipality of Munich has provided high-resolution datasets, access to decision-makers and continuous input for this research. The exact data requirements for the improved method have been defined over the course of the research implementation. Access to high resolution datasets on relevant factors required data usage agreements and results in limited options for publication of the research. The case study application is presented in Chapter 6.

# Literature review on shared mobility hubs

# 3. Literature review on shared mobility hubs

## 3.1. Shared mobility hubs

Literature review showed various terms and definitions for shared mobility stations. Due to the actuality of the topic, there is not yet a consistent description of shared mobility stations in scientific literature. Recent sources have performed in-depth literature research to compare existing definitions and synthesized their findings in new definitions:

Van Gerrevink (2021, p. 123) reviews various literature sources on the definitions of shared mobility hubs, stating that there is a variety of terms and definitions used in the literature. Their overlap is summarized “as physical locations or nodes that provide access and transfer options to a variety of different (shared) transport modes (multimodal)”. Additionally, some definitions mention “possible supplements with facilities and services such as public transit or that these places can be seen as activity centers (van Gerrevink, 2021, p. 16).”

Blad (2021) compares various literature sources on the definitions of shared mobility hubs and adopts the following definition: “The mobility hub is a place where multiple sustainable transport modes come together at one place, providing seamless connectivity between modes, additionally offering shared mobility, possibly including other features, ranging from retail, workplaces to parcel pick-up points (Blad, 2021, p. 15).”

In this study, the definition of Blad (2021) is adopted with a slight modification. The focus on shared modes is emphasized and connectivity to traditional modes is mentioned:

***“The shared mobility hub is a place where multiple shared transport modes come together, providing seamless connectivity between shared and traditional modes, possibly including other features, ranging from retail, workplaces to parcel pick-up points.”***

Another major discussion point of reviewed literature are the separation of shared mobility hubs into different types, leading to a hub typology. Literature and practice provide diverse typologies and there is no commonly agreed typology for shared mobility hubs yet:

Following a large review of typologies of shared mobility hubs, Blad (2021) separates shared mobility hubs based on their aim and their scale of operation into residential hubs, regional hubs and city hubs.

Van Gerrevink (2021) performs an extensive literature review and categorizes shared mobility hubs based on their geographic location and their scale of operation into national hubs, city hubs, city-edge hubs, regional hubs, neighborhood hubs, business park hubs, logistics hubs and temporary hubs.

For the Berlin shared mobility hub program Jelbi, hubs are separated in two categories: Jelbi stations, where all vehicle types can be rented, returned and charged. Jelbi points, where only vehicles with two wheels can be rented and returned (Jelbi, 2022).

In terms of typologies for shared mobility hubs, there are various and different approaches. This research accepts the still not completed harmonization of the concept of shared mobility hubs and concludes that mobility hubs can generally be divided into different types, but the specific way of dividing different types strongly depends on the analyst's perspective and the local circumstances. For different contexts, e.g., different countries or even cities, one can expect a customized typology each time. Therefore, the improved method for location planning of shared mobility hubs should not provide a predefined hub typology, but instead be capable of considering customized hub typologies.

## 3.2. Location planning methods for shared mobility hubs

Location planning of shared mobility hubs is a sub-topic of the research on shared mobility hubs in general. Fewer sources are explicitly addressing the issue of locating these hubs in the urban landscape. According to Tran & Draeger (2021, p. 3), "urban hubs will likely impact the structure and functioning of the overall transport network, yet there has been limited research on this in urban transport planning. The hub location problem (HLP) is a relatively new extension of classical facility location analysis and not typically addressed in urban transportation models." Below various approaches for location planning of shared mobility hubs, or similar infrastructure, are summarized.

*Table 2: Overview of existing methods for location planning of shared mobility hubs*

| Study | Catchment area calculation | Spatial unit of method | Spatial MCDA | Output of method |
|---|---|---|---|---|
| Aydin et al. (2022) | Within spatial unit | Neighborhoods | X | Manually selected locations |
| Liao & Correia (2021) | Within spatial unit | Neighborhoods | | Location potential per neighborhood |
| Correia & Casanovas (2022) | Within spatial unit | Neighborhoods | X | Location potential per neighborhood |
| Correia & Antunes (2012) | Within spatial unit | Grid cells | | Different scenarios with selected locations, comparable with KPIs |
| Blad (2021) | Within spatial unit | Grid cells | X | Location potential per grid-cell |
| Knaack (2021) | Euclidian distance | Points | | Areas with high potential |
| Kabak et al. (2018) | Euclidian distance | Grid cells | X | Location potential per grid-cell and manually selected locations |
| Kurniadhini & Roychansyah (2020) | Euclidian distance | Grid cells | X | Location potential per grid-cell |
| Zhou et al. (2020) | Euclidian distance | Grid cells | X | Location potential per grid-cell |
| Fazio et al. (2021) | Euclidian distance | Grid cells | X | Location potential per grid-cell and manually selected locations |
| Guler & Yomralioglu (2021) | Euclidian distance | Grid cells | X | Location potential per grid-cell and location selection by TOPSIS |
| García-Palomares et al. (2012) | Walking time in street network | Transport zones of traffic model | | Different scenarios with selected locations, comparable with KPIs |
| Escobar et al. (2018) | Walking time in street network | Points | | Different scenarios with selected locations, comparable with KPIs |
| Tran & Draeger (2021) | Drive time in street network | Neighborhoods | | Different scenarios with selected locations, comparable with KPIs |
| Xanthopoulos (2022) | Travel time and cost in multimodal network | Transport zones of traffic model | | Different scenarios with selected locations, comparable with KPIs |

Aydin et al. (2022) investigates a MCDA driven location planning approach for a new mobility hub in Istanbul, Turkey. Candidate locations are selected manually and reduced to a number of four alternative locations. Using AHP, the weights of various criteria for a MCDA are determined and the suitability of the four locations is compared.

Liao & Correia (2021) developed a quick scan method to indicate the potential for eHub locations per area. The potential is calculated based on factors such as socio-demographics, transport connectivity, POI and land use. Factors weights are extracted from academic studies on revealed preference of EV and E-bike demand in other cities. The method results in location potential per administrative unit, e.g. census tract, displayed in a city-wide heat map.

Correia & Casanovas (2022) conceptualizes a decision-support tool for local public administrations to prioritize locations of shared mobility hubs in the city. Shared mobility hubs are differentiated into 5 hub types using five different dimensions: urban context, transportation function, mobility spatial scale, mobility services offered at the hub and proximity to public transport. Potential indicators for the location of shared mobility hubs were collected from various sources and summarized in MCDA hierarchy tree with its three levels of analysis and all the criteria and sub-criteria. The criteria weights for the MCDA were assigned using an Analytic Hierarchy Process (AHP). Weight allocation is performed for each hub type separately, resulting in weight per category and weight per sub-indicator. The indicators are collected in administrative areas or grid cells and weights are applied to the indicators. The method results in location potential per administrative area or grid-cell, displayed in a city-wide heat map.

Correia & Antunes (2012) presents an optimization approach to depot location in one-way car-sharing systems. By considering all the revenues and costs involved, the model aims to maximize the profits of the car-sharing provider. For the case study of Lisbon, the centroids of a 1000m raster grid were used as candidate locations. The performance of the system was investigated for different scenarios, including different pricing schemes, a usage of all 75 candidate locations or a selection of the best 10 locations. Per scenario, the method results in a selection of depot locations and KPIs on the performance of the system.

Blad (2021) investigates a methodology to determine the potential of areas for regional mobility hubs. The perspectives of the end-user, the operator and the government are incorporated in a framework, which connects the perspectives with certain attributes and criteria. The criteria weights for the MCDA were assigned using the AHP approach. The factor weights are obtained from interviews with decision-makers of each perspective and fed into a multi-actor multi-criteria-analysis, which results in five scenarios with varying weight configurations. The method focuses only on the regional mobility hub type and suggests an expansion of the method on other types. The method is tested with approximations and simplifications as factor inputs, whilst an implementation with detailed data inputs is possible. The method results in location potential per grid-cell, displayed in a city-wide heat map.

Knaack (2021) investigates a methodology for finding suitable locations for neighborhood hubs in a certain neighborhood in Zwolle. Potential indicators are derived from literature and expert interviews are used to rank them in their importance for the focus neighborhood. The five most important indicators are mapped in GIS with a Euclidean distance walking buffer. Areas, where the walking buffer of the five indicators intersect, are labeled as high potential areas. The method results in polygons representing high hub potential areas.

Kabak et al. (2018) suggests GIS-based MCDA approach for the evaluation of bike-share stations, which can be considered similar to shared mobility hubs. Using the example of Izmir in Turkey, the AHP method was used to determine criteria weights of a MCDA. Within a raster grid, MCDA scores were illustrated with a suitability map. Based on the suitability map, alternative or additional locations are suggested. Lastly, existing stations were compared with suggested locations using a ratio analysis. Kabak et al. (2018, p. 57) also highlights one of the limitations of suitability maps: Every time a new location is placed, the suitability map is supposed to adapt to prevent placing another site very close to the new location. The method results in location potential per grid-cell and manually selected locations for alternative stations.

Kurniadhini & Roychansyah (2020) aim to identify the best location for bike-sharing stations by using a spatial MCDA based on a raster grid covering the research area. The values of 13 considered criteria are assigned to all raster cells within 400 m Euclidian distance to consider potential walking distances to and from the bike sharing station. Variable values are normalized and weighted using MCDA weights derived with the AHP method. The method results in location potential per grid-cell, displayed in a city-wide heat map.

Zhou et al. (2020) optimize the location of bike-sharing stations taking into account customer satisfaction and the cost of public space. It is assumed that fixed bike-sharing stations are too expensive and unscalable. Parking locations are seen as flexible, geofenced locations which can be moved around in real-time. Therefore, the location finding method is applied real-time to calculate the best stations for any given fleet distribution. Candidate parking locations are selected from available Points-of-Interest (POIs). Best station locations are selected in real time calculation using neural networks, which are applied on live demand. Calculations are based on grid cells and Euclidean distance. The method results in a set of selected parking locations and performance measures.

Fazio et al. (2021) investigates a location planning method for cycle stations, using a MCDA within 100m x 100m grid cells.  Using several criteria, a Node Index, a Place index and a Bike Oriented Development Index is calculated per grid cell. The method results in location potential per grid-cell, displayed in a city-wide heat map. Locations for bike lanes and bike parking is suggested manually by only focusing on areas with higher index values.

Guler & Yomralioglu (2021) develop a method to select locations for bike lanes and stations based on a MCDA. Weights are determined using AHP and calculated within grid cells. The method results in location potential per grid-cell, displayed in a city-wide heat map. Based on the heat map, a set of alternative locations is determined manually. The alternative locations are ranked using the TOPSIS method.

García-Palomares et al. (2012) uses network analysis to locate bike sharing stations, which can be considered similar to shared mobility hubs. In this approach, objectives of the public bike sharing systems and potential demand are determining the location of stations. Potential demand was determined from a transport model with estimations of origins and destinations per transport zone, as well as the number of inhabitants and jobs per building. The two demand factors, origin and destination trips per street address were summed to determine the total potential demand per street address. Public transport stops with high passenger capacity are considered as predefined locations for bike sharing stations. A network analysis is implemented with the ArcGIS location-allocation tool. Within a minimize impedance placement strategy, the stations are located such that the sum of all of the weighted costs between demand points and solution facilities is minimized. Within a maximize coverage placement strategy, the stations are located such that as many demand points as possible are covered by the stations within a maximal walking distance of 200m. After being located, the stations are classified into different types according to their distribution of attracted and generated trips. Finally, the two placement strategies are compared by a total accessibility score, taking into account an increasing number of stations.

Escobar et al. (2018) investigates improved locations for a bike sharing system. A network analysis is implemented with the location-allocation tool within ArcGIS. Alternative location candidates were selected manually based on sociodemographic data. The locations were optimized to improve the 500m coverage of the residential addresses of the registered users. Different scenarios were compared based on their coverage of registered users.

Tran & Draeger (2021) explore network theories for the planning of urban mobility hubs, suggesting an evaluation framework to locate mobility hubs and assess the impacts of hub locations. The hub potential is composed of several factors such as transit capacity and is calculated per network node. Therefore, the method can propose specific locations for hubs and compute catchment areas and travel time analyses. The framework includes the calculation of different placement strategies, which are then compared using performance metrics. In the method, each factor is weighted equally, resulting in a bias in favor of high-capacity modes. The method is tested in a U.S. context, assuming that the hub is reached primarily by car. The applied network theories do not take into account the competitive effects between different hubs, resulting in a dense aggregation of hubs in areas of high demand. The method results in specific locations for the hubs and city-wide performance metrics for each placement strategy.

Xanthopoulos (2022) optimizes the location, number and capacity of shared mobility hubs in Amsterdam. Candidate locations are based on the current public transport stops and manual placement. A mathematical optimization, which has budget-based limitations and aims for maximized utility gains of the population, determines hub locations to activate and their capacity. Using Amsterdam's traffic model with and without potential shared mobility hub locations, an estimation of change in modal split per scenario is calculated.

## 3.3. Spatial MCDA for location planning

The above literature review has shown a frequent application of spatial MCDA methods for location planning of shared mobility hubs. Therefore, the capabilities of MCDA methods for location planning are presented in more detail.

In general, MCDA is used for various purposes in transportation planning such as policy measures in passenger transport, strategic decisions, technologies, infrastructure projects and locations (Macharis et al., 2009). Especially the integration of MCDA with GIS can support decision-makers in solving spatial problems effectively: Disagreements for prioritizations are accommodated through the MCDA, while GIS allows for an evaluation of spatial decision alternatives through statistics and maps (Guler & Yomralioglu, 2021). This can be implemented within Spatial Decision Support Systems (SDSS), which are "interactive, computer-based systems designed to support a user or group of users in achieving higher effectiveness in decision making (Malczewski & Rinner, 2015, p. 8)." When the SDSS considers a variety of criteria as decision input, so in fact a MCDA and GIS are integrated, one can refer to Multicriteria Spatial Decision Support Systems (MC-SDSS). In this way, GIS can provide spatial data to incorporate fact-based information, while MCDA can help to mitigate disagreements about value-based decisions (Malczewski & Rinner, 2015).

When focusing on the integration of GIS and MCDA techniques, one can also refer to this approach as GIS-based MCDA (GIS-MCDA). In simple terms, geographic data as input maps are combined with decision-maker's preferences to create decision maps as an output. This allows the comparison of geographically defined decision alternatives based on criteria values and the preferences of the decision-maker. This means that the results of a GIS-MCDA are not solely dependent on the spatial findings for the decision alternatives, but are driven by the values of the decision-makers (Malczewski & Rinner, 2015).

MCDA approaches can be extended to consider the interests of various stakeholders. Macharis (2009) introduces a multi-actor multi-criteria approach (MAMCA), which is particularly suitable for the evaluation of transport projects. The involvement of all relevant stakeholders is critical to the successful implementation of a transportation project.

When comparing MCDA and MAMCA, the consideration of multiple stakeholder perspectives early on in the location planning process is an attractive advantage of MAMCA. But there seems to be no satisfactory solution for the weighting of the decision shares of different interest groups. According to Macharis et al. (2012) the often used and most pragmatic approach is to assign equal weights to all perspectives. This might not represent reality, as stakeholder influence and importance can vary in many ways. This challenge of MAMCA was also mentioned when Blad (2021) applied the MAMCA approach to the location finding of shared mobility hubs, taking into account perspectives of users, operators and city. He describes an uncertainty about the right weighting for the different stakeholder groups. Therefore Blad (2021) investigated different weights of the stakeholder shares in various scenarios.

Macharis et al. (2012, p. 615) describes a special case for stakeholder share weighting, if the government is involved in the decision making: “When the government is one of the stakeholders, which is usually the case in the evaluation of transport projects, one could say that this stakeholder represents the society’s point of view and therefore should be the one to follow. Analysis of the points of views of other stakeholders, like users, local population, and so on, will then show if a certain measure will possibly be adopted or rejected by these groups.” With this approach, other stakeholders than the government do not have an active stake in the decision making, but the MAMCA assists the government in considering their concerns.

Several of the previously presented literature on the multifaceted problem of location planning for shared mobility hubs have applied AHP and (multi-actor) MCDA. Aydin et al. (2022) uses MCDA to compare the suitability of manually pre-selected locations. Correia & Casanovas (2022) implement MCDA to illustrate a suitability score for shared mobility hubs per neighbourhood. Kabak et al. (2018), Kurniadhini & Roychansyah (2020), Guler & Yomralioglu (2021), Fazio et al. (2021) and Blad (2021) apply (multi-actor) MCDA to determine the suitability in detail throughout the study area, using heatmaps indicating a suitability score per grid cell. Especially the latter approach has a great potential to translate the location planning objectives into quantitative input network analysis techniques. This would be an extension of current research on location planning for shared mobility hubs, as none of the reviewed studies combined MCDA with network analysis methods.

## 3.4. Conclusion

In summary, the existing literature on location finding of shared mobility hubs provides typologies for shared mobility hubs (Blad, 2021; Correia & Casanovas, 2022; Mobilitätsreferat München, 2021b; van Gerrevink, 2021), frameworks to categorize a large number of indicators (Blad, 2021; Correia & Casanovas, 2022) as well as methods to weight indicators according to (multiple) stakeholders using AHP and MCDA (Aydin et al., 2022; Blad, 2021; Correia & Casanovas, 2022; Fazio et al., 2021; Guler & Yomralioglu, 2021; Kabak et al., 2018; Kurniadhini & Roychansyah, 2020; Zhang et al., 2019).

Most sources perform spatial analysis based on datasets aggregated in polygons (raster cells or administrative areas) and Euclidean distance (Blad, 2021; Correia & Casanovas, 2022; Fazio et al., 2021; Guler & Yomralioglu, 2021; Kabak et al., 2018; Knaack, 2021; Kurniadhini & Roychansyah, 2020; Liao & Correia, 2021; Zhou et al., 2020), leading to a shared mobility station suitability per area. Spatial analysis using network theories is less common (Escobar et al., 2018; García-Palomares et al., 2012; Tran & Draeger, 2021) and allows for the calculation of specific location suggestions for shared mobility hubs. Some studies calculate multiple placement strategies (Blad, 2021; Escobar et al., 2018; García-Palomares et al., 2012; Tran & Draeger, 2021). Only studies that use a network analysis to calculate the catchment area can provide specific location proposals. This enables a comparison of different scenarios with performance metrics on the catchment area coverage (Escobar et al., 2018; García-Palomares et al., 2012; Tran & Draeger, 2021).

Many of the reviewed studies have used spatial MCDA to account for the complexity of location planning problems. This complexity increases when location planning is not just for one mode, such as bike-sharing, but focuses on shared mobility hubs incorporating various modes and stakeholders. None of the reviewed studies that used network analysis techniques employed a prior MCDA. Spatial MCDA based on a high-resolution grid cell has a great potential to translate the location planning objectives for shared mobility hubs into quantitative input for network analysis. Network analysis allows for a suggestion of specific locations and a comparison of different scenarios based on performance metrics.

# Literature review on network analysis for location planning

# 4. Literature review on network analysis for location planning

## 4.1. Network analysis for spatial planning

Network analysis is widely applied to understand social networks, whilst it is still not widely used for the spatial analysis of cities. This could be related to the limited or costly tools for spatial network analysis. To understand interactions in large road networks, computationally intensive calculations further constrain the application of network analysis in spatial planning (Sevtsuk & Mekonnen, 2012). With the increasing availability of extensive geospatial data for urban areas, spatial network analysis can provide new insights throughout many disciplines (Sevtsuk & Mekonnen, 2012; Tran & Draeger, 2021). This is particularly applicable to the improved understanding of mobility and transportation in cities.

For network analysis within the GIS environment, there are vector-based and raster-based approaches. In summary, the vector-based models use features as discrete entities to represent the network, whilst the raster models use a continuous surface of raster cells with an attribute value. In general, vector models are considered more suitable for the representation of networks, particularly when it comes to the representation of clearly defined networks such as streets (Bruno & Giannikos, 2015; Husdal, 2015). Therefore, this chapter focuses on vector-based approaches to network analysis only.

## 4.2. Network analysis methods for facility location problems

The hub location problem (HLP) can be described as a new extension of classical facility location analysis. In general, facility location problems aim "to determine the position of a set of facilities in a given location space in order to provide some service to a set of actors which are supposed to patronize some of the available facilities. These actors correspond to the demand (actual or potential) that must be satisfied (Bruno & Giannikos, 2015, p. 515)". For a facility location problem, the following components can be defined:

The *location space*, the considered area for the analysis, can be represented by a network. Within this discrete location space, the facilities can only be located at predefined points. As the set of predefined points is limited, these models can also be referred to as site-selection models (Bruno & Giannikos, 2015).

The *facilities* are to be located in the location space, normally represented as points. Thereby, the aim is the optimization of interaction with other objects already existing in the location space (Bruno & Giannikos, 2015).

The *demand* represents the actors interacting with the facilities. The demand can be distributed in *sub-areas and points across the location space (Bruno & Giannikos, 2015).

The *Interactions Between Elements of a Problem* can be separated in customer-facility and facility-facility interactions. Customer-facility interactions define the way customer, or demand, is allocated to facilities, taking into account factors such as the distance between the customer and a facility. Facility-facility interactions describe the competition of facilities to cover as much as demand as possible, the so-called cannibalization effect. Facility-facility effects can also be seen as cooperation, e.g. important to assure a minimum level of accessibility to potential users (Bruno & Giannikos, 2015).

The *objective function* represents the criteria or objectives considered when locating a facility. Usually, the main objective is efficiency, which is expressed in cost reduction. Cost is often related to the distance of interactions between facilities and demand. For example, efficiency can be measured in the amount of demand, e.g. population, covered by facilities, e.g. supermarkets. Within a given coverage radius, e.g. maximum walking distance of 10 minutes, all demand counts as covered. With this approach, the optimization aims to cover a maximum amount of demand with a given number of facilities (Bruno & Giannikos, 2015).

Some facility location problems have to consider the hierarchy between different facility types: "In a hierarchical system, facilities are interrelated in a top-down or bottom-up manner at various levels of services" (Torkestani, 2016, p. 1). This means that location optimization must take into account not only efficient coverage in terms of maximum accessibility to demand from lower-level facilities, but also their effective supply in terms of minimizing transportation costs from higher-level facilities (Farahani et al., 2014). The definitions of the hierarchical location problem mention "interrelation of facilities", the levels "serving each other". This does not necessarily apply to shared mobility hubs. The different types mostly serve different purposes and different target users. There may be differences in size, but a network of smaller hubs can provide shared mobility services even without the presence of a larger hub. In the case where hub types do not explicitly have a hierarchical relation to each other, the theory of a hierarchical facility location problem is not required.

## 4.3. Integrating MCDA and network analysis methods for facility location problems

The integration of MCDA and spatial analysis in GIS, such as network analysis, are discussed in research. For example, Jelokhani-Niaraki et al. (2018) presents existing literature on the opportunities and challenges of semantic interoperability of GIS and MCDA. The study proposes an ontology-enabled framework to improve the general interoperability of GIS and MCDA. When looking into the specific case of integrating of MCDA and network analysis methods for facility location problems, the calculation of a suitability score can be beneficial to assessing facility locations according to multiple criteria. Different criteria layers can be weighted in their importance and combined to suitability score per area or location (Bruno & Giannikos, 2015), which is an important step as many network analysis methods for location planning accept only one demand criterion. The advantage of integrating MCDA and network analysis methods is thereby the possibility to summarize multiple criteria into an MCDA score prior to the network analysis steps. The idea of converting the multiple-criteria optimization problem to a single-criterion optimization problem prior to network analysis is also suggested by Malczewski & Ogryczak (1995): A single criterion can be calculated from the sum of all weighted criteria, followed by a network analysis minimizing a single-criterion problem. For example, Abd El Karim & Awawdeh (2020) summarizes various criteria relevant to quality of urban life within a MCDA score, which is later used for a network analysis to allocate public facilities with the aim of reducing the quality of urban life differences in the city. In this example, the location allocation analysis was performed with low spatial resolution, using only the spatial unit of neighborhoods.

It is important to emphasize the major advantage of integrating MCDA and network analysis for location planning by converting multiple criteria problems into single criterion problems: Consequently, the multi-criteria decision problems can be solved using single-criteria optimization techniques. This means that the wide range of algorithms, software, and experience that currently exist for single-criteria optimization can be directly applied to solving multi-criteria problems. This is very beneficial for location optimization problems, given the importance single-objective optimization has for location theories, the location allocation modeling, and the computing of location decision problems (Malczewski & Ogryczak, 1996).

## 4.4. Review of network analysis tools

Several network analysis tools could be applied to improve existing approaches for location planning of shared mobility hubs. There are various methods to measure relevant metrics and the most suitable has to be selected according to the aim of the research, individual characteristics of the city and the data availability. The detailed review of network analysis tool can be found in the appendix.

Space syntax helps to understand configurational spatial relationships of the street network. It can therefore help to quantify a street's connectedness and accessibility within the street network using concepts such as 'centrality' or 'betweenness'. This can be relevant to the location planning of shared mobility hubs, as their locations should be well-connected and accessible within the street network. Furthermore, shared mobility hubs are intended to provide widespread decentralized infrastructure that extends throughout the city and are easily accessible by walking. Within space syntax, especially local integration analysis, e.g. an axial integration analysis with three topological steps or an angular choice analysis with a metric radius of 400-800 m, could help to understand the suitability of streets for shared mobility hubs. Many space syntax measures can be calculated through a plug-in for QGIS (van Nes & Yamu, 2021).

Urban Network Analysis (UNA) toolbox provides methods to describe the spatial patterns of cities using mathematical network analysis methods. The overall aim to understand spatial relationships in networks is similar to space syntax, both focus on concepts such as "centrality" or "betweenness". But the UNA toolbox addresses a number of shortcomings of previous approaches, e.g. the use of only nodes and edges as network elements, as well as the importance of buildings to the understanding of the interaction of streets. Therefore, it introduces buildings as a new network element besides nodes and edges, as well as weighted representation of the network elements. This could further increase the suitability of the measures for location planning of shared mobility hubs. To better understand the total covered demand of shared mobility hubs, the reach and the gravity measure could calculate (weighted) demand in a certain walking distance of a location. The closeness and the betweenness measure could be used to place shared mobility hubs in locations with high human activity, specifically with high presence of pedestrians. The closeness measure could quantify a location's proximity to POIs and the betweenness measure could quantify the potential amount of passersby traffic. The UNA tool is implemented as an ArcGIS toolbox extension and can thus be easily integrated into workflows (Sevtsuk & Mekonnen, 2012).

QGIS offers two main network analysis algorithms: The calculation of shortest paths between a set of points in a network and the service areas of facilities in a network. This can help to identify service areas of potential locations for shared mobility hubs according to the walking distance in the street network. Currently, QGIS does not offer calculation of optimal facility locations in a network (QGIS, 2022).

ArcGIS offers a greater selection of network analysis functionalities compared to QGIS. Besides tools to calculate the shortest paths between a set of points in a network and the service areas of facilities in a network, ArcGIS also offers a closest facility solver to compute the travel costs between a set of incidents and the best facility for each incident. Most importantly, ArcGIS offers a location allocation solver, which selects facility locations from a set of location candidates based on the potential interactions of each facility location with demand points. The location allocation solver can select optimal locations with different objectives and is able to consider many factors highly relevant to the location planning of shared mobility hubs. This includes the consideration of only selected candidate locations, the maximization of covered demand within a certain walking time threshold as well as competition effects between hub locations in close proximity. Distance decay functions can be considered to maximize the probability of attendance. As the location allocation tool solves a combinatorial optimization problem, this method can lead to very high computational effort for the location planning of a high number of shared mobility hubs over an entire urban area. Within the ArcGIS location allocation tool, heuristics are applied to reduce computing time (esri, 2022a). Murray et al. (2019) has evaluates, besides other software solutions, the general performance of the heuristics used in the location allocation solver of ArcGIS. The results are described as encouraging and of high quality, whereas their heuristically computed solutions never varied more than 7% from the optimum in the problem instances. The research underlines the fact that heuristics can find optimal results in certain cases, but it cannot be guaranteed that the heuristics solver always achieves the exact optimal result. It is important to be aware of this limitation of heuristic approaches to location allocation and communicate them clearly when presenting the results.

## 4.5. Conclusion

With the increasing availability of extensive geospatial data for urban areas, spatial network analysis can provide new insights for many location planning challenges (Sevtsuk & Mekonnen, 2012; Tran & Draeger, 2021), such as location planning for shared mobility hubs.

The hub location problem (HLP) can be described as a new extension of classical facility location analysis. In general, facility location problems aim “to determine the position of a set of facilities in a given location space in order to provide some service to a set of actors which are supposed to patronize some of the available facilities. These actors correspond to the demand (actual or potential) that must be satisfied (Bruno & Giannikos, 2015, p. 515)”.

Integrating MCDA and network analysis for location planning by converting multiple criteria problems into single criterion problems is very beneficial, as many network analysis methods for location planning accept only one demand criterion. Using this approach, the multi-criteria decision problems can be solved using single-criteria optimization techniques. This means that the wide range of algorithms, software, and experience that currently exist for single-criteria optimization can be directly applied to solving multi-criteria problems (Malczewski & Ogryczak, 1996).

The ArcGIS location allocation solver is seen as the most suitable tool to perform a location optimization for shared mobility hubs based on network analysis. As the location allocation solver only optimizes according to one criterion, the possibility to apply a prior spatial MCDA to convert the multiple-criteria optimization problem into a single-criterion optimization problem is highly relevant to this research.

# Improved location planning method for shared mobility hubs

# 5. Improved location planning method for shared mobility hubs

## 5.1. Aim of improved method

Multiple cities want to establish a large number of shared mobility hubs throughout the urban area. These large networks of shared mobility hubs can consist of hundreds or even thousands of shared mobility hubs. Cities are challenged with the location planning for this new type of infrastructure, as shared mobility hubs interact with many aspects of urban mobility, existing infrastructure and involve many stakeholders.

In research, different methods for location panning for shared mobility hubs have been investigated (see Chapter 2.2). Some of these approaches make use of high-resolution spatial data, MCDA or network analysis. In practice, none or more pragmatic approaches to data analysis for location planning of shared mobility hubs are applied. For the example of Hamburg, an initial GIS analysis is used to create maps indicating the potential demand for shared mobility hubs per area. Within the identified areas of high demand, the location, catchment areas and the characteristics of individual hubs are then investigated in qualitative work one by one (Hochbahn Hamburg, personal communication, February 23, 2022). This manual approach to location planning for city-wide shared mobility hubs is very time and cost intensive. Furthermore, the manual approach cannot use data-driven decision-making to address many aspects relevant to the objectives of this new infrastructure, because the available datasets are only included in the initial GIS analysis and are not considered during micro-planning.

Most studies reviewed in Chapter 2.2 assume that the process of location planning for shared mobility hubs can be simplified and generalized in a way that resulting methods or tools can be applied to any city in the world. This research is only in partial agreement with this perspective. On one hand, the generalization of methods is an essential strategy to be efficient in the provision of data-driven approaches to many cities. On the other hand, every city is individual in its physical characteristics, political objectives, financial capabilities and data availability. This argument supports more individualized solutions for the planning of new infrastructures such as networks of shared mobility hubs. Individual solutions can be built on a generalized framework, but must be adapted to the unique needs and circumstances of each city. This research assumes the need for city-specific spatial analysis methods using high-resolution datasets to effectively locate mobility hubs, which is in contrast to simplified methods based on publicly available data from sources like open street map. While this approach initially limits the developed method to cities with sufficient resources and good data availability, it is anticipated that this approach will provide new insights for the scaling of shared mobility hubs. Therefore, this research focuses on an individual, in-depth and data-intensive solution for one of the pioneering cities in the field of shared mobility hubs, to achieve a better understanding of the opportunities and challenges of location planning for shared mobility hubs in the short-term. The long-term goal is to ensure that such in-depth applications in pioneering cities produce results that are transferable to other cities by making minor adjustments.

This research aims to develop an improved method for location planning of shared mobility hubs along the specific challenges of the case study of Munich. Therefore, the improved method should be able to consider different placement strategies, exact walking distances in the street network, competition effects between stations and compare different scenarios with KPIs for a city-wide network of shared mobility hubs. The improved method has been continuously refined alongside the case study application, which is presented in Chapter 6. The general framework of the improved method is presented in this chapter.

## 5.2. Overview improved method

The improved method combines three components: 1) spatial MCDA, as it has proven to be a suitable method to perform complex decisions in transport planning. 2) Location optimization methods in GIS, as it considers walking routes in the street network. 3) Catchment area analysis to compute statistics on potential users for each hub location and overall scenario KPIs. This enables decision-makers to compare different placement strategies in terms of potential impacts on their objectives and to accelerate micro-planning processes through a defined target scenario and data-based insights per hub location.

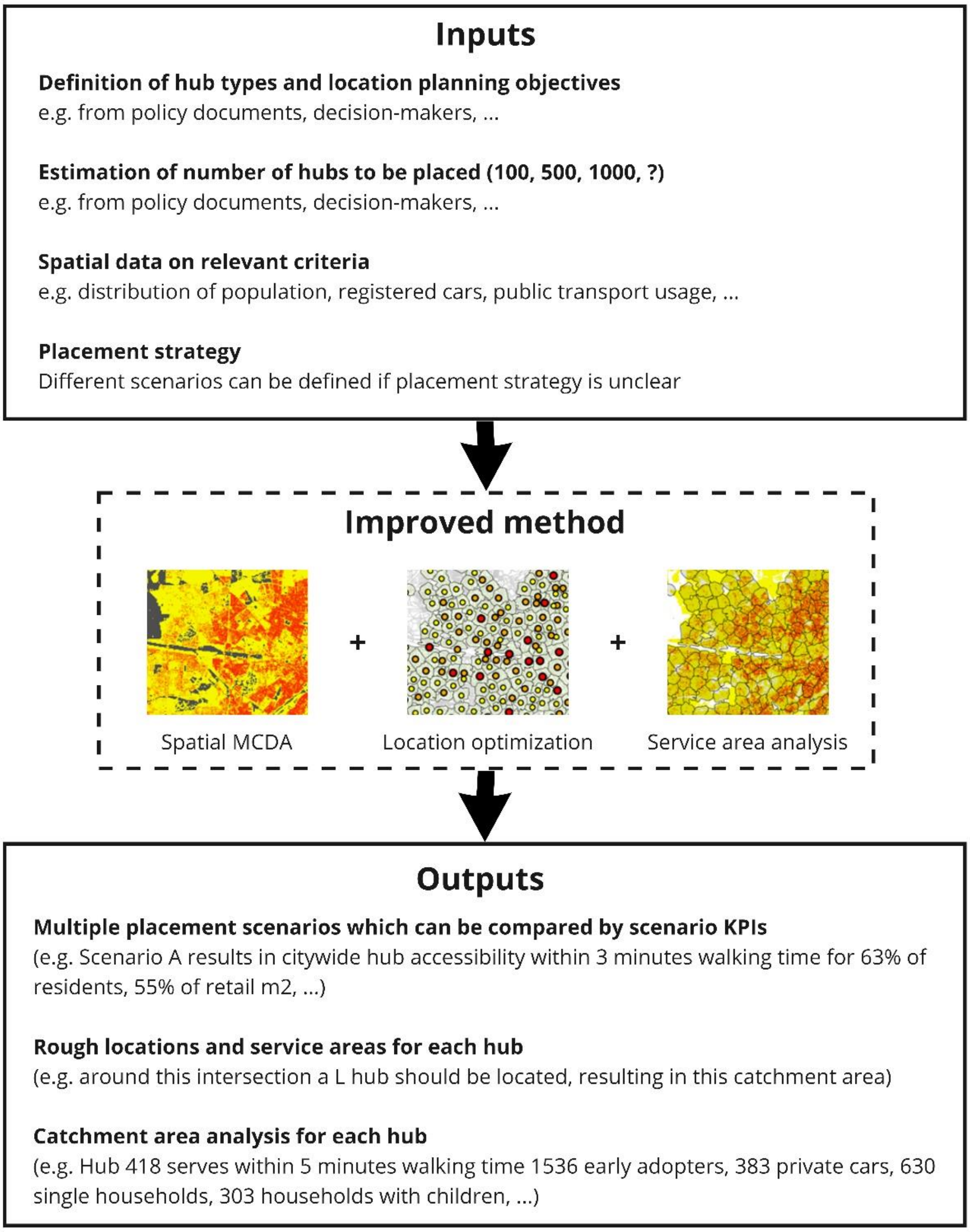


*Figure 8: Overview improved method*

## 5.3. Spatial MCDA component

A Multi Criteria Decision Analysis (MCDA) makes it possible to evaluate several options with multiple quantitative and qualitative criteria. Spatial MCDA and MAMCA have been applied in several studies on location planning for shared mobility and appear to be beneficial in considering the various criteria relevant to selecting the location of infrastructure for shared mobility. Kabak et al. (2018), Kurniadhini & Roychansyah (2020), Guler & Yomralioglu (2021), Fazio et al. (2021) and Blad (2021) apply (multi-actor) MCDA to determine the suitability in detail throughout the study area, using heatmaps indicating a suitability score per grid cell. This approach has the potential to translate the location planning objectives into quantitative input for the following application of network analysis techniques. This would be an extension of current research, as none of the reviewed studies combined MCDA with network analysis methods.

Therefore, the improved method for location planning of shared mobility hubs will apply a spatial MCDA, and if multiple stakeholders are involved a spatial MAMCA, to translate different prioritizations at the decision-maker level into placement strategies. The spatial MCDA can be implemented based on a high-resolution grid covering the research area. The resulting MCDA score for each spatial grid cell converts a multiple-criteria optimization problem into a single-criterion optimization problem.

## 5.4. Location Optimization component

A single variable location optimization based on walking distance in the street network is possible through network analysis tools in GIS. For the purpose of location planning of shared mobility hubs, the location allocation solver in ArcGIS was chosen, as it provides proven functionality in optimization of facility location problems. Based on the potential interactions of facility location with demand points, the optimal facility locations are selected from a set of location candidates. The location allocation solver can select optimal locations with different objectives and is able to consider many factors highly relevant to the location planning of shared mobility hubs. There are multiple possibilities to adapt the location allocation solver to the problem of location planning of shared mobility hubs: Exclusion criteria for locations can be implemented by restricting the set of candidates. Selection criteria can be formulated in demand weight. To translate the objectives of the selection into the model, various problem types in ArcGIS location allocation tool can be applied for shared mobility hubs:

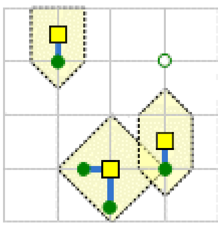

*Figure 18. Maximize Coverage chooses facilities such that as much demand as possible is covered by the impedance cutoff of facilities. In this graphic, the solver was directed to choose three facilities (esri, 2022a)*

Maximize Coverage problem type - Facilities are located such that as many demand points as possible are allocated to solution facilities within the impedance cutoff (esri, 2022a). Maximize Coverage is suitable, if covering every demand point within a certain walking time is the prior objective of location planning of shared mobility hubs (García-Palomares et al., 2012).

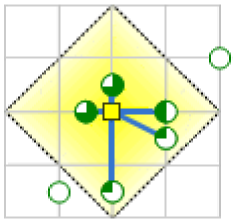

*Figure 21. Maximize Attendance chooses facilities to allocate as much demand weight as possible to facilities while assuming the demand weight decreases with distance. The demand points, represented by pie charts in this graphic, show how much of their total demand is captured by the facility (esri, 2022a).*

Maximize Attendance problem type - Facilities are chosen such that as much demand weight as possible is allocated to facilities while assuming the demand weight decreases in relation to the distance between the facility and the demand point. Maximize attendance is suitable, if a placement in close proximity to high demand points is the prior objective of location planning of shared mobility hubs. This leads to a heterogenous distribution of hubs throughout the city, with most hubs forming a dense network in high demand areas.

Furthermore, the ArcGIS location allocation tool provides an impedance transformation, which allows manipulating the effect of the distance between the facility and the demand point on the respective demand point weight allocation. The impedance transformation determines the equation for transforming the network cost between facilities and demand points, thereby calibrating how severely the network impedance between facilities and demand points influences the solver's choice of facilities (esri, 2022a). The functionality of the impedance transformation in ArcGIS is described in theory as a distance decay function. Assuming that demand for services declines with distance, locating facilities as close as possible to potential demand is an important consideration to maximize the served demand (Farhan & Murray, 2006). Within ArcGIS, the distance decay function can be included as linear, power or exponential function. If a five-minute impedance cutoff and a linear impedance transformation is selected, the probability of visiting a store decays at 20 percent per minute. Therefore, a store within 1 minute walking distance of a demand point has an 80 percent visit probability and a store four minutes away only has a 20 percent visit probability (esri, 2019). Using power or exponential functions, the decay function can be adapted to existing knowledge of user travel behavior of the investigated facility type. The graph below is an example from the RATP, the public transport operator of Paris, for the use of distance decay functions for location planning of public transport stations (Manout et al., 2018).

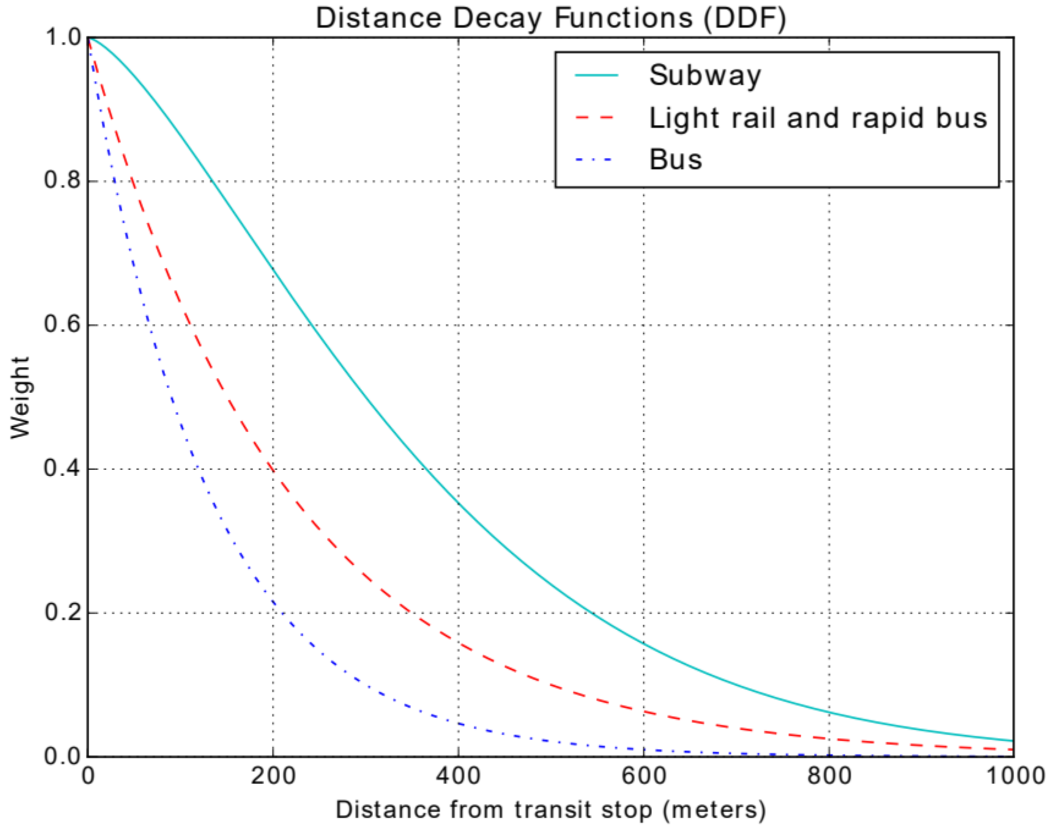


*Figure 22. Distance decay functions by transit mode from RATP data (Manout et al., 2018)*

Whilst this knowledge on distance decay exists for established facility types, e.g. public transport stations, there is no available research on distance decay functions of for shared mobility hubs. García-Palomares et al. (2012) argues that transportation planning assumes that people are willing to walk longer to public transport stations for longer average trip distances, for example 400 m for bus stops and 800 m for subway stations. In the case of bike-sharing, the average trip distance is rather short and the maximum walking distance for access to bike-sharing stations should be lower than that for public transport stations. The study uses a maximum walking distance of only 200 m for the location optimization of bike-sharing stations. Following this reasoning, it can be assumed that the distance decay functions for shared mobility stations will be much more restrictive. If further research results in a better understanding of distance decay functions for shared mobility, this can be used to improve location allocation models.

Within this research, the Maximize Coverage problem type is applied for location optimization, which only allows for a linear distance decay function. For the case study in Munich, this choice was made due to the equity focused location planning objective to achieve a city-wide maximum walking time of 5 minutes to a hub. If the improved method is applied with different location planning objectives, for example from the perspective of profitability for an operator, the maximize attendance problem with an adapted distance decay function can be a powerful tool to place hubs e.g. in the hotspots of early adopters.

When applying the location-allocation solver in ArcGIS for location planning of shared mobility hubs, it is important to consider that the location allocation solver has a rapidly increasing computational effort as the number of candidate sites, demand points, and chosen locations increases. This is due to the nature of the combinatorial optimization problem that must be solved. Therefore, this method can lead to very high computational effort for the location planning of a high number of shared mobility hubs over an entire urban area. Therefore, it is very beneficial, that the computation times for the location allocation tool in ArcGIS are reduced through the use of heuristics. For this study, the analysis was carried out on a local computer, resulting in a computing time of about one hour per location optimization. As this process is repeated many times throughout the methodology, computing time becomes a significant factor in the analysis and needs to considered for implementation planning.

Another challenge when applying the location allocation solver in ArcGIS for the location optimization of shared mobility hubs is the fact that the tool only allows for one demand weight variable, one candidate set and one cut off value. This is a challenge, as comprehensive networks of shared mobility hubs consist of different hub types (facility types) with different objectives (demand weights) and different maximum walking time (cut off). This thesis therefore suggests a sequential location allocation method. Location allocation is performed separately for each hub type, allowing for differentiations in candidate locations, demand weights and cut off values for catchment areas for each hub type. This approach allows for a tailor-made modeling of various hub types with different characteristics and objectives. To achieve this, the location allocation is performed in multiple steps. The different hub types are ranked in their placement order according to the location planning strategy. If the main objective is a strong integration between the hub network and the existing public transport system, hub types with the constraint that they have to be placed next to a public transport station should be preferred in the placement. This means that the method will select a location at a public transport station even if there is a slightly better performing location in the nearby streets. And in the overall perspective, such an approach would lead to an anchoring of the hub network at existing public transport stations during the first sequential location allocation step. Only in later steps with less restricted candidate sets, the hub network can grow towards other areas of demand. In general, this means that hub types with high relevance for the overall system and hub types with very severe candidate set restrictions should be prioritized in the placement order.

Figure 9 shows the general approach of a sequential location allocation for different hub types. First hub type A is located according to the candidate set restrictions, the weighted selection criteria and the applied cut off value. Then the location allocation is repeated for hub type B with respective candidate set, weighted selection criteria and cut off value - excluding demand weights in the catchment areas of selected locations for hub type A. Then the location allocation is repeated for hub type C with respective candidate set, weighted selection criteria and cut off value - excluding demand weights in the catchment areas of selected locations for hub types A and B. This process can be continued until all hub types are allocated.

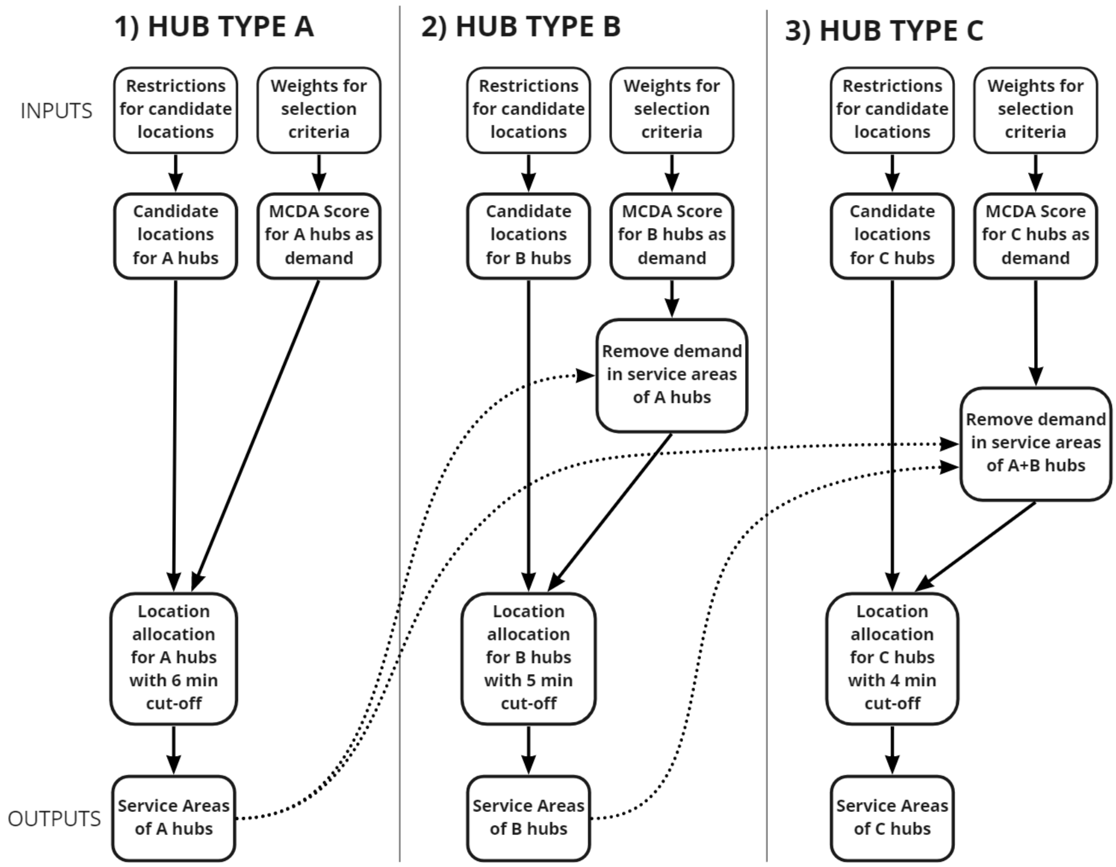


*Figure 9: Sequential location allocation for different hub types*

It needs to be considered that the sequential location allocation approach does not necessarily lead to a global optimization of shared mobility hub locations. Instead, the method optimizes the hub locations for a certain hub network configuration with constraints given by the city (e.g., the placement order of hub types and the number of hubs for type A/B/C). To reduce the uncertainties related to the impact of the constraints chosen by the city, this sequential location allocation approach is proposed in combination with the application of scenarios and scenario KPIs to enable comparison of various placement strategies.

## 5.5. Service area analysis component

The sequential location allocation suggests specific hub locations in the street network for each hub type. A service area analysis based on the street network can calculate the respective catchment area for each suggested hub location. This enables further analysis of the selected locations and their effect in regards to objectives for location planning of shared mobility hubs.

For each chosen location, the catchment area in a certain walking time is computed. For each catchment area, the coverage of certain variables can be calculated, e.g. within 6 minutes an example hub serves 806 early adopters, 383 private cars, 430 single households and 303 households with children. These figures are very valuable when planning the offered services and implementation priority per hub. A high number of registered private cars might indicate a high demand for shared cars. A high number of households with children might indicate a high demand for shared cargo bikes. A high number of young residents might indicate a need for shared bikes, e-bikes, e-scooters and e-mopeds. A high number of elderly residents might indicate demand for other electric vehicles aimed at persons with limited mobility. A high number of early adopters could indicate benefits of prioritized implementation of a location. Many conclusions can be drawn from these statistics for each hub location, simplifying and accelerating the following manual steps in micro-planning.

By aggregating the statistical results of all hub locations across the entire city, the overall scenario KPIs enable a data-based comparison of different placement strategies. For each scenario, the overall coverage of certain variables can be calculated, e.g. Scenario 1 results in city-wide hub accessibility within 3 minutes walking time for 71% of all registered private cars, 68% of all early adopters, 57% of all residents, 55% of all retail m2. The comparison of different placement strategies is an important feature of the suggested method.

There are no existing examples or best practices for implementing city-wide networks of shared mobility hubs. Therefore, the method should allow a comparison of different placement strategies for the respective city and enable decision-makers to have data-based discussions about the best performing placement strategies. In addition, the method itself and the constraints specified by the city within the sequential location allocation are still subject to great uncertainties. The calculation of several scenarios and their comparison on the basis of scenario KPIs provides a better understanding of the method itself.

## 5.6. Workflow of the improved method

This section explains and presents the overview workflow of the improved method in a table and in an illustration. The 15 steps are assigned to 7 phases. The researcher is involved in all 14 steps, the stakeholder(s) are only involved in 6 steps. Below each step is described in detail.

*Table 3: Phases and steps of the improved method*

| | | |
|---|---|---|
| **Phase 1** | **MCDA preparation** | |
| Step 1.1 | Determine overall location planning objectives and criteria | Stakeholder(s) and researcher select the overall objectives and criteria for the location planning of shared mobility hubs. |
| Step 1.2 | Ensure data availability for MCDA criteria | Stakeholder(s) and researcher filter criteria and indicators based on availability of datasets with high spatial resolution. |
| **Phase 2** | **Exclusion criteria per hub type** | |
| Step 2.1 | Set exclusion criteria per hub type | For each hub type, stakeholder(s) and researcher set exclusion conditions for candidate locations. |
| Step 2.2 | Select intersections as candidate locations | For each hub type, the researcher categorizes candidate intersections. |
| **Phase 3** | **Selection criteria per hub type** | |
| Step 3.1 | Set selection criteria per hub type | Stakeholder(s) and researcher set selection criteria per hub type |
| Step 3.2 | Calculate criteria per grid cell | The researcher calculates criteria values in high resolution grid cell |
| Step 3.3 | Indicator Standardization | The researcher standardizes all criteria values per grid cell |
| Step 3.4 | Set selection criteria weights per hub type | For each hub type, stakeholder(s) and researcher adjust criteria weights using AHP. |
| Step 3.5 | Calculate MCDA score as demand points | For each hub type, the researcher uses criteria values and weights to calculate the MCDA score per grid cell centroid. |
| **Phase 4** | **Network Analysis Layer** | |
| Step 4 | Build network analysis layer | The researcher sets up a network analysis layer. |
| **Phase 5** | **Define Scenarios** | |
| Step 5 | Define scenarios for different placement strategies | Stakeholder(s) and researcher define different scenarios representing different placement strategies. This can include varying numbers of each hub type or varying MCDA weights. |
| **Phase 6** | **Scenario calculation** | (Phase 6 is repeated for each scenario) |
| Step 6.1 | Perform sequential location allocation | The researcher performs sequential location allocation:<br>1) A hubs; 2) B hubs; 3) C hubs. |
| Step 6.2 | Perform service area analysis | The researcher computes the service area of each location and calculates statistics per service area. |
| Step 6.3 | Calculate Scenario KPIs | The researcher computes KPIs to represent the fulfillment of criteria within the whole city. |
| **Phase 7** | **Scenario decision** | |
| Step 7.1 | Decide for scenario as master plan | Stakeholder(s) compare scenario KPIs of different placement strategies and set target scenario for micro planning. |

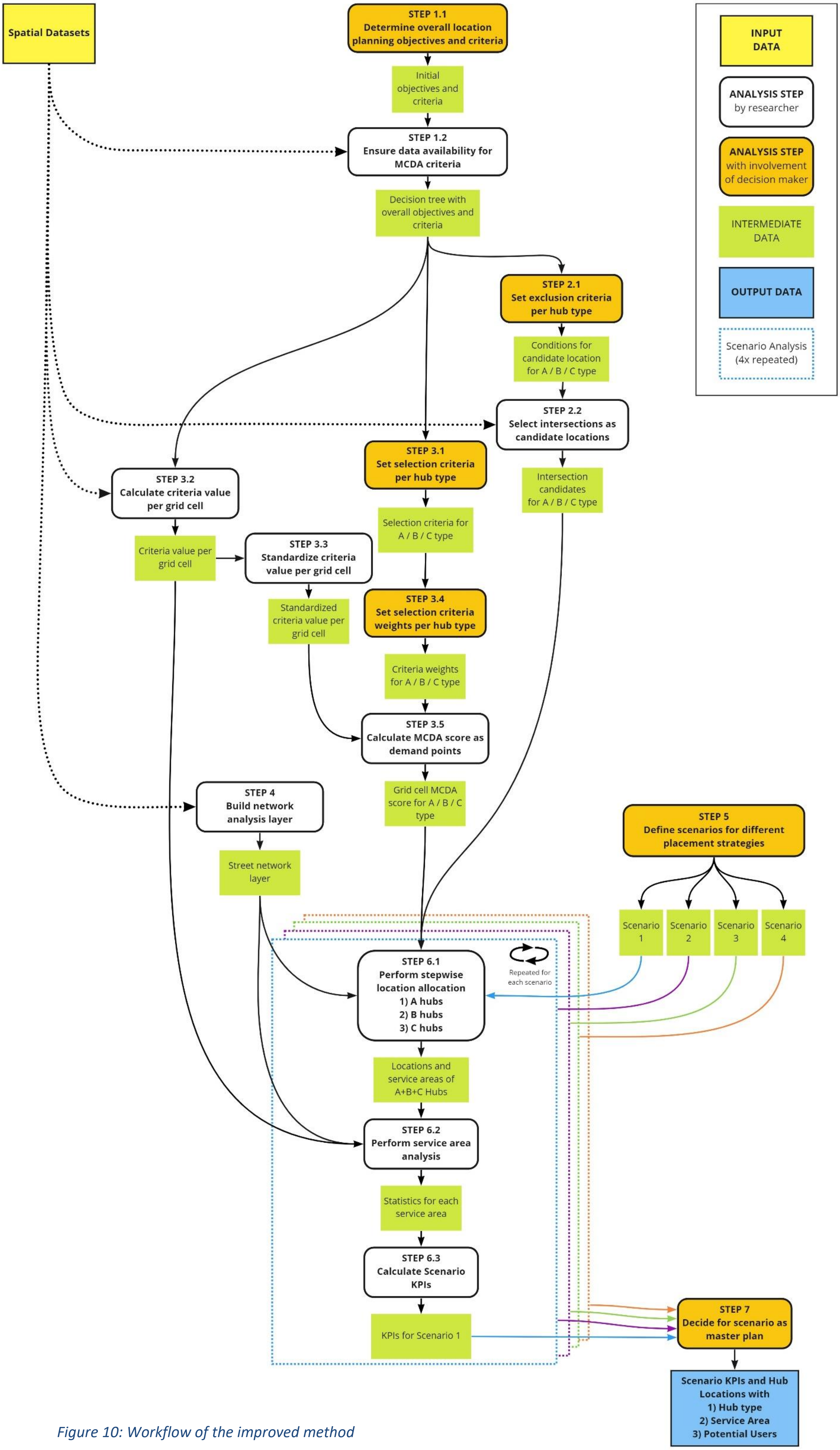


*Figure 10: Workflow of the improved method*

**Phase 1: MCDA preparation**

Step 1.1: Determine overall location planning objectives and criteria

To begin, it is important to have a general understanding of the objectives of the analysis. The improved method translates the city's objectives and decisions into automated, data-based location optimization. Therefore, the results of the method can only perform according to the prioritizations set in this step. At the end of this step, the objectives and relevant criteria for location planning of shared mobility hubs are defined based on policy documents and in discussions with decision-makers.

Step 1.2: Ensure data availability for MCDA criteria

For each identified objective and criteria, spatial data at high spatial resolution is needed to be included in the analysis. Data collection can be time intensive, as high spatial resolution data might be hard to obtain and privacy guidelines have to be followed. After data collection, stakeholder(s) and researcher filter criteria and indicators based on availability of datasets with high spatial resolution.

**Phase 2: Exclusion criteria per hub type**

Step 2.1: Set exclusion criteria per hub type

In the method used, there are two ways to consider criteria for location planning, exclusion criteria and selection criteria. This step defines the exclusion criteria only. Exclusion criteria is used to create a limited and targeted candidate set for each hub type. The selection of candidates for a hub type is dependent on the hub type's objectives. Exclusion criteria are the strongest way to influence the siting of a hub type, as any location that does not meet the criteria will be excluded in any further analysis steps. At the end of this step, stakeholder(s) and researcher have set exclusion conditions for candidate locations for each of the hub types.

Step 2.2: Select intersections as candidate locations

Based on the exclusion criteria of step 2.1, the researcher categorizes all possible candidate intersections into candidate locations for each hub type.

**Phase 3: Selection criteria per hub type**

Step 3.1: Set selection criteria per hub type

The relevant criteria for the selection of the best candidates for each hub type are determined. At the end of this step, it is clear which datasets have to be further processed to create indicators for each relevant criterion.

Step 3.2: Calculate criteria per grid cell

Based on the collected datasets of step 1.2, the researcher compiles all criteria in high resolution grid cells. After this step, each criterion is represented as a value per grid cell.

Step 3.3: Indicator Standardization

To be able to make the criteria comparable within the MCDA, the researcher standardizes all criteria values per grid cell. Using the linear max approach, every value of a criterion is divided by the maximum value in the criterion (Binsbergen, 2021). After this step, every value of the criterion is represented by a value between 0 and 1.

Step 3.4: Set selection criteria weights per hub type

The selection of the best candidates for each hub type is based on weighted selection criteria. Later in the method, the weighted selected criteria form a MCDA score per grid cell. The coverage of this MCDA score within the maximum walking distance is optimized by the location allocation algorithm to select the best performing configuration of candidate locations for each hub type. For each hub type, a decision tree is constructed. The weighting of selection criteria is adjusted using the AHP approach, which allows the decision-makers to pairwise compare the different criteria to determine overall weights. This step results in a decision tree with weighted selection criteria for each hub type.

Step 3.5: Calculate MCDA score as demand points

Using the standardized criteria values of step 3.3 and the decision tree with criteria weights of step 3.4, the researcher calculates the MCDA score per hub type in each grid cell. The MCDA score per hub type is then stored in the centroid point of each grid cell, as the network analysis requires point data as input.

**Phase 4: Network Analysis Layer**

Step 4: Build network analysis layer

Based on a dataset with all streets and paths of the city, the researcher sets up a network analysis layer. As the analysis investigates accessibility to the hub locations by foot, the network analysis should include a walking mode where distance in the network is measured in walking minutes.

**Phase 5: Define Scenarios**

Step 5: Define scenarios for different placement strategies

To account for multiple possible placement strategies, the method allows the definition of different scenarios. Placement strategies can differ in the total number of hubs placed, the number of hubs per hub type or characteristics such as walking distance per hub type. If the total number of hubs is unclear, a pre-analysis using the Maximize Coverage and Minimize Facilities within ArcGIS Network Analysist can be used to estimate a rough number of hubs needed to cover one variable, e.g. inhabitants, within a certain walking time cut off throughout the research area. For further calibration, a repeated Maximize Coverage analysis with iterated number of hubs can be used. For the scenarios, changes in exclusion or selection criteria are possible, but work intensive. At the end of this step, stakeholder(s) and researcher have defined different scenarios representing different placement strategies.

**Phase 6: Scenario calculation** (Phase 6 is repeated for each scenario)

Step 6.1: Perform sequential location allocation

Using the MCDA score per demand point from step 5.1, the candidate locations from step 5.2 and the network analysis layer from step 5.3, the researcher performs automated location optimization. This is achieved by sequential location allocation for first hub type A, second hub type B and third hub type C. As location allocation is performed separately for each hub type, it is possible to consider different candidate locations, demand weights and cut off values for catchment areas for each hub type. This step results in the locations and service areas per hub type.

Step 6.2: Perform service area analysis

The researcher calculates statistics about the coverage of certain criteria for each service area. These figures are important to understand the individual user groups of each hub location.

Step 6.3: Calculate Scenario KPIs

The researcher computes scenario KPIs to represent the fulfillment of criteria within the whole city. These figures are important to compare the effects of different placement strategies on the objectives of the city.

**Phase 7: Scenario decision**

Step 7.1: Decide for scenario

Stakeholder(s) compare the performance of different scenarios with scenario KPIs. A decision is made for one scenario as a master plan for the city-wide location planning of shared mobility hubs, which serves as the basis for further microplanning.

# Munich case study

# 6. Munich case study

## 6.1. Transportation system of Munich

With about 1.5 million inhabitants, Munich is the third largest city of Germany. Munich has a very strong public transportation system, consisting of various modes such as bus, light rail (Tram), metro (U-Bahn) and rail (S-Bahn). Since 2015, the public bike sharing system MVG-Rad is operating in close cooperation with the public transport system - public transport subscribers can rent the bikes at discounted rates. The system currently has about 4500 bikes that can be used in a free-floating zone in the city center and at 300 stations extending beyond the city borders (MVG, 2022a). Many other providers operate shared vehicles in Munich, including TIER (e-bikes, e-scooters, e-mopeds), Lime (e-scooters), VOI (e-scooters), emmy (e-mopeds), Avocargo (Cargobikes), Share Now (Cars), Sixt Share (Cars) and Miles (Cars, Vans). The city aims to integrate the various sharing providers within a MaaS app, called MVGO. Currently, only public transport, taxi, TIER and VOI are integrated in the new app (MVG, 2022b).

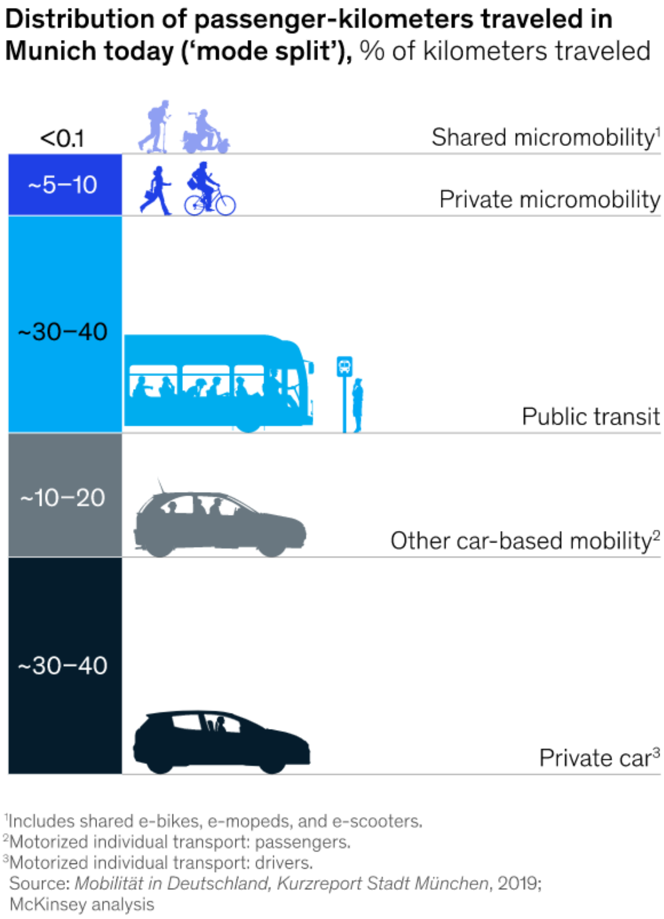


*Figure 11: Modal split for Munich in 2019 (McKinsey, 2019)*

In a case study, McKinsey (2019) investigated the modal split of Munich per travelled kilometer as shown in Figure 11. In 2019, 50-60% of all kilometers travelled in Munich still account to the car. 30-40% are travelled by public transportation and private micromobility covers the remaining kilometers. In 2019, shared micromobility provides only a very small share.

From here, McKinsey (2019) estimates the potential of shared micromobility for the mobility system of Munich, as shown in Figure 12. The base case of this study estimates that shared micromobility can account for 8-10% of all travelled kilometer in 2030. This calculation only refers to shared micromobility and does not include other shared modes such as car sharing.

Another study, initiated by the mobility department of Munich, states that 400,000 out of 1,600,000 trips per day can shift from private motorized transport to shared mobility. This would result in shared mobility contributing 8.3% of the the total modal split in Munich (Mobilitätsreferat München, 2021b, p. 24).

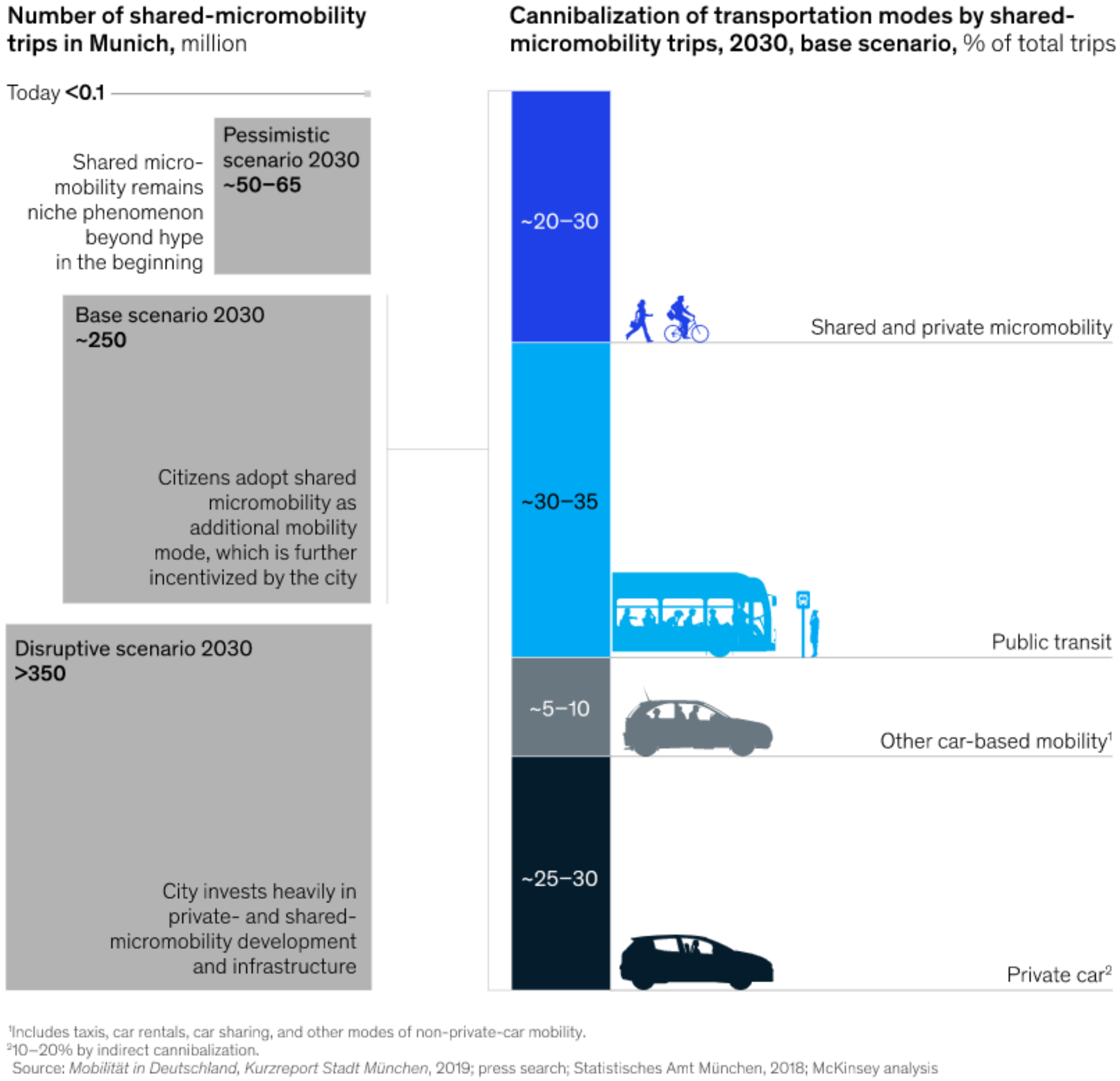


*Figure 12: Estimated modal split for Munich in 2030 (McKinsey, 2019)*

Shared mobility is an established component of the transportation system in Munich. The city attaches great importance to the further enhancement of shared mobility and its integration with the overall transport system. Digital integration is enhanced with the development of the MVGO app. The physical integration of various modes is addressed with the recent plans to create city-wide network of shared mobility hubs.

## 6.2. Shared mobility hubs in Munich

Munich has tested the concept of shared mobility hubs in several pilot projects (Miramontes, 2018). The Munich City Council has approved the Shared Mobility sub-strategy, in which shared mobility hubs are described as an essential part of the mobility transition strategy for 2035. This includes the decision to build up to 200 shared mobility hubs in Munich until 2026. This is only seen as the first phase, as the expansion of the shared mobility station network will be continued even after 2026 aiming for maximum walking time of 5 minutes to the next shared mobility hub throughout the city. In a first estimate, the number of required locations for a accessibility within 5 minutes was assumed to 1300.

(Mobilitätsreferat München, 2021b). Whilst the locations for pilot projects of shared mobility hubs were selected without any systematic decision process and more due to practical circumstances (Miramontes, 2018), the city aims for an advanced location planning method for the intended major extension of the shared mobility hub infrastructure in Munich (Mobilitätsreferat München, 2021b). Therefore, Munich will be used as a case study to validate the functionality and practicability of the suggested method. Working closely with the mobility department of the city, this study was able to include the input of city planners and spatial data with very high spatial resolution.

## 6.3. Case Study Application

The previously presented workflow of the improved method is applied to the case study of Munich.

**Step 1.1 Determine overall location planning objectives and criteria**

Firstly, the overall objectives of location planning for shared mobility hubs were determined. The mobility transition strategy for 2035 (Mobilitätsreferat München, 2021b) sets clear overall goals for promoting shared mobility. The paper served as a great starting point for further discussions and definitions. At the same time, the details of the location planning for shared mobility hubs were still very vague. Therefore, the fundamental choices for a shared mobility hub location planning were refined in several sessions with the city planners of Munich.

As a first step, the overall objectives and criteria for location planning of shared mobility hubs were discussed with the city planners, resulting in 9 objectives and 18 criteria presented in Figure 13.

Here it must be emphasized, that shared mobility hubs are an infrastructure with more stakeholders than just the city, such as shared mobility providers and shared mobility users. The overall objectives and criteria for location planning of shared mobility hubs presented in Figure 13 were developed exclusively with representatives of the city administration and were not reviewed with other stakeholders. The reasons and limitations for this approach are described in detail in Chapter 5.1.

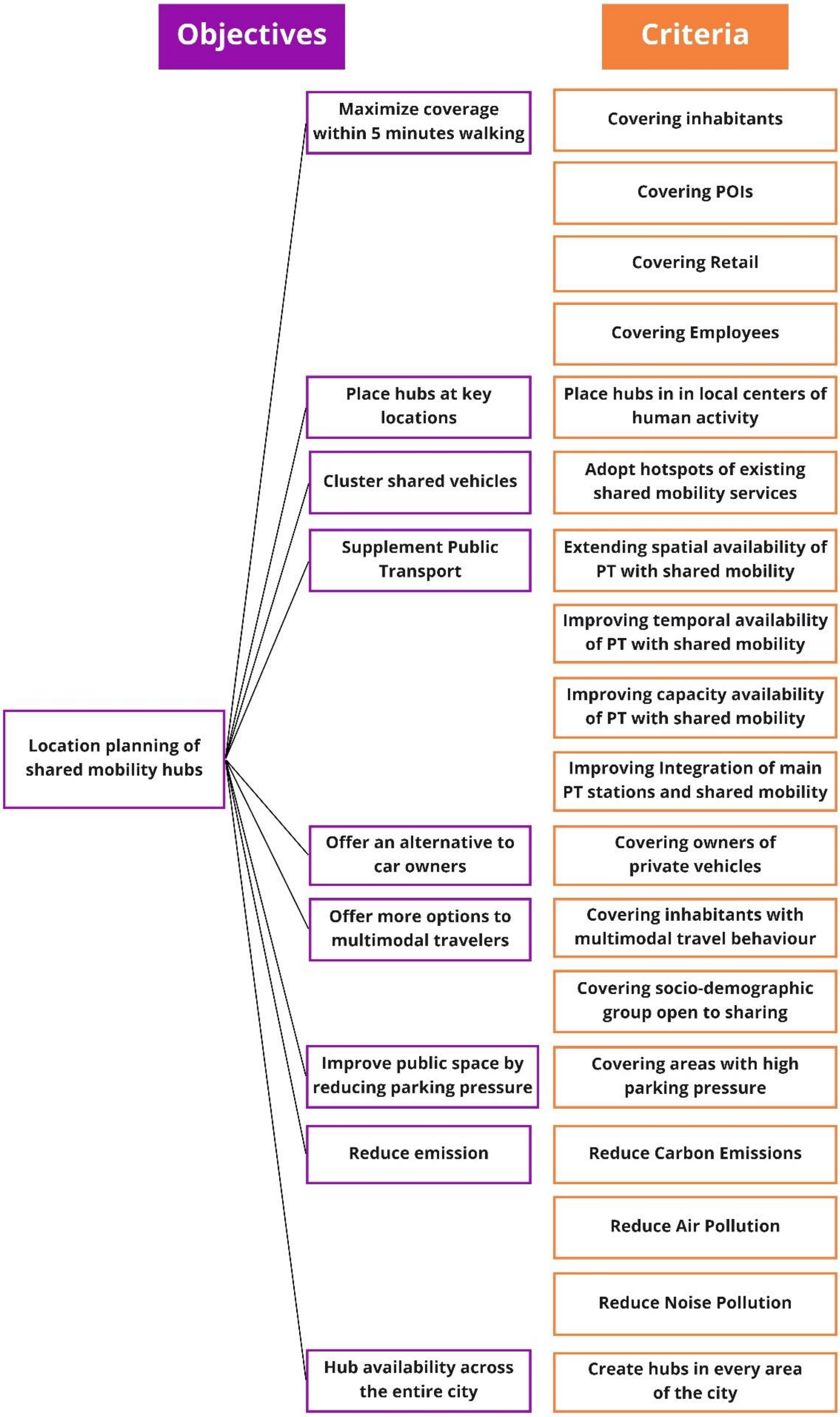


*Figure 13: Case Study Munich - Overall objectives and criteria for location planning of shared mobility hubs*

As a second step, the hub typology applied for the location planning of shared mobility hubs was further defined. Munich originally used a S, M, and L categorization for “mobility points” (Mobilitätsreferat München, 2021b, p. 31)**:**

- **Category S** offers at least two shared mobility services or one in combination with public transport. These points serve in particular as access points for spontaneous or routine trips and can be established city-wide, but especially in small-scale locations or residential areas.

- **Category M** bundles at least three offers and so-called "add-ons". These include infrastructure and service offerings with a mobility connection that offer additional services at mobility points, such as bicycle parking facilities, parking areas for cargo bikes, bicycle pumps or repair stations. These stations are particularly suitable at central neighborhood locations, development axes, intersections and popular destinations.

- **Category L** mobile points provide access to at least four shared mobility offerings, as well as public transit and other add-ons in all cases. These mobility points are predominantly located at classic nodes, strategic locations or in newly built neighborhoods.

Translating this categorization of hub types into quantitative indicators for spatial analysis turned out difficult because the differentiating factors of size and aim of each hub type were blended with each other. Therefore, the hub typology was refined in cooperation with the mobility department, resulting in a new typology mainly differentiated by the main aim of each hub type.


*Figure 14: Case Study Munich - illustrative example for hub type A (VCD, 2020)*

**Hub type A: Integration of shared mobility at major public transport transfer nodes**
Aim: Integrate shared mobility at main transfer nodes of city-wide trips
Candidates: Public Transport Stations with highest passenger transfer volume
Users: Large number of external users, a few local users
Walking Time cut-off: 7 minutes (Scenario 1), 5 minutes (Scenario 2)
Key feature: Nodes with the highest public transport connectivity, focus on external users, e.g. by providing digital information board.


*Figure 15: Case Study Munich - illustrative example for hub type B (Mobilitätsreferat München, 2021a)*

**Hub type B: Integration of shared mobility to main public transport lines**
Aim: Integrate shared mobility at main public transport lines
Candidates: Stations with high capacity / frequency public transport lines
Users: Some external users, more local users
Walking Time cut-off: 6 minutes (Scenario 1), 5 min (Scenario 2)
Key feature: High public transport connectivity, focus on local users and the combination of public transport and shared mobility as first or last mile.

*Figure 16: Case Study Munich - illustrative example for hub type C (Mobilitätsreferat München, 2021a)*

**Hub type C: Cluster shared mobility at local centers**
Aim: Cluster shared mobility at hubs throughout the city aiming for 5 min accessibility
Candidates: Local centers of human activity
Users: Mostly local users
Walking Time cut-off: 5 minutes (Scenario 1 and Scenario 2)
Key feature: High activity locations in the neighborhood, often areas without high frequency/capacity public transport, focusing on local, recurring users.


*Figure 17: Case Study Munich - illustrative example for hub type D (Mobilitätsreferat München, 2022)*

**Hub type D: Provide shared mobility parking within 3 minutes walking (only used in Scenario 2)**
Aim: Provide parking reserved for shared mobility throughout the city within 3 minutes walking time
Candidates: Every street intersection with car and pedestrian access.
Users: Local users
Walking Time cut-off: 3 minutes (only used in Scenario 2)
Key feature: Low effort design to provide reserved parking for shared modes

For Scenario 1, hub type A, B and C were applied. Different walking time cut off values were assigned to each hub type with the idea that users are willing to walk further to a shared mobility hub if shared mobility modes are combined with a very strong public transport connectivity.

For Scenario 2, certain restrictions were changed. As the results of Scenario 1 showed the unintended effect of less coverage around large public transportation hubs, for Scenario 2 the hub type A, B and C were assigned the same 5-minute walking time cut off. Hub type D was added to optimize not only for a 5-min accessibility to a shared mobility hub A, B, C, but to optimize for an additional 3-min accessibility to hub type A, B, C and D. This can be described as a re-densification of the 5-min network with hub types A, B, C to a 3-min network with hub types A, B, C, D.

It can be observed, that hub type A has the highest restrictions in candidate locations, hub type B has the second highest restrictions in candidate locations, hub type C has the third highest restrictions in candidate locations and hub type D has the lowest restrictions of candidate locations. Therefore, the optimization algorithm has more freedom in hub placement with each step of the sequential location allocation, as the set of candidate locations increases. The hubs are placed starting from the existing public transport lines, to local centers of human activity and finally aiming for full coverage across the city.

### Step 1.2 Ensure data availability for MCDA criteria

In this step, a broad database was created to select only criteria with sufficient data availability for the following analysis. For the location optimization through a combination of MCDA and network analysis, high resolution spatial data is required for each criterion, which can be challenging. Due to the involvement of the city of Munich, high resolution datasets from public sources were easier to access. Most datasets were collected from various departments of the city of Munich. Datasets on shared mobility rentals were collected from MVG, TIER and Miles. Additionally, OSM data was used, whenever other datasets were not sufficient. Many high-resolution datasets were only available through non-disclosure agreements due to data privacy regulation or corporate interests.

*Table 4: Case study Munich - Data availability*

| Name | Description | Used | Source |
|---|---|---|---|
| **Administrative areas** | Administrative areas of Munich | Yes | https://opendata.muenchen.de/dataset/verwaltungseinheiten-der-landeshauptstadt-muenchen |
| **Bike sharing rentals** | MVG Rad bike sharing rentals of 2021 | Yes | https://www.mvg.de/services/mvg-rad.html |
| **E-bike, E-Scooter and E-moped sharing rentals** | E-bike, E-Scooter and E-moped rentals of TIER within 12 months, Rentals aggregated within 50x50 m grid. | Yes | TIER |
| **Car sharing rentals** | Car rentals between August 2021 and Mai 2022 of Miles | Yes | Miles |
| **Public transport** | MVG Public transport GTFS, without S-Bahn | Yes | https://www.mvg.de/services/fahrgastservice/fahrplandaten.html |
| **Retail Points** | Location of retail, retail type, supermarkets with >300m2 categories, 16.000 points; Shops with 0m2 were estimated to 30 m2; Concentration of retail m2 outliers in one location (e.g. shopping centers) are manually distributed across different entrances. | Yes | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **EV-Charging** | Locations of public EV charging, 374 points | Yes | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Inhabitants in age groups** | Number of inhabitants per 50x50m cell, including age groups, 280.000 Polygons, "<6", aggregates less than 6 -> set to 5 inhabitants. | Yes | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Registered cars** | Number of cars per block, 10.000 Polygons, separated by private/business (many gaps),<br>Attribute AlterMW is the arithmetic mean of the years since first registration of all registered private cars in the building block. Extreme outliers with more than 100.000 vehicles per km2 were replaced by 99.000 vehicles per m2. | Yes | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Traffic zones** | Traffic zones from Traffic model with 1) source / destination car traffic volume per zone (the sum of the vehicle volume on an average working day per traffic zones). 2) source / destination public transport volume per zone (the sum of the PT trips on an average working day per traffic zones), 1.000 polygons | Yes | Geobasisdaten © GeodatenService München 2022 (Contact: Boese) |

| | | | |
|---|---|---|---|
| **Sinus Mileus** | Sinus milieu population distribution per neighborhood (477). Sinus Milieu target group research: The Sinus Milieus group people who are similar in their concept and way of life. The milieu classification is based on two dimensions: "social situation" (lower, middle or upper class) and "basic orientation" ("tradition," "modernization/individualization" and "reorientation"). | Yes | Munich (Contact: Hanke) |
| **Parking management areas** | All areas with parking management, priced parking, 73 areas, covering approx. 25% of Munich | Yes | Munich (Contact: Hanke) |
| **OSM Street Network** | Street Network for Munich with 238.043 categorized edges | Yes | https://download.geofabrik.de/ |
| **OSM POIs** | 37.187 categorized POIs within Munich | Yes | https://download.geofabrik.de/ |
| **OSM Public Transport Stations** | 2.787 categorized public transport stops (each platform of a station is counted separately) | Yes | https://download.geofabrik.de/ |
| **Street addresses** | Directory of all street addresses in Munich | No | https://opendata.muenchen.de/dataset/adressverzeichnis-der-landeshauptstadt-muenchen |
| **Land use planning** | Land use zoning, intended use by zoning plan of administration; 5.700 Polygons, covers private and public areas with less detail | No | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Actual land use** | Land use, actual use, 250.000 polygons, covers only public areas with high detail | No | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Number of households** | Number of households per block, 10.000 Polygons, "<6", aggregates less than 6 -> set to 5 households in the analysis. | No | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Buildings** | Buildings, 300.000 polygons, with usage type type of building, and number of floors, allows for calculation of building volume | No | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Schools** | 550 GPS points, with number of pupils | No | Geobasisdaten © GeodatenService München 2022 (Contact: Boese) |
| **Socially insured employees** | Socially insured employees based on the location of the employment registration, 400 sub districts | No | Geobasisdaten © GeodatenService München 2022 (Contact: Wirtenberger) |
| **Street links traffic model** | Street links from Traffic Model, some streets are not correct, mostly focused on streets for car traffic, not suitable for detailed walking analysis. 30.000 edges. | No | Geobasisdaten © GeodatenService München 2022 (Contact: Boese) |
| **Traffic POI points** | POI from traffic model, very general, 2000 points | No | Geobasisdaten © GeodatenService München 2022 (Contact: Boese) |

**Step 2.1 and Step 3.1 Set exclusion criteria and selection criteria per hub type**

Based on the overall objectives and criteria from Figure 13 and the data availability from Table 4, all possible indicators for exclusion and selection criteria can be derived. Exclusion and selection criteria were assigned to each hub type during a workshop, as shown in Figure 18.

*Figure 18: Case Study Munich - Workshop with city planners*

Selection criteria could be customized based on all data available within Table 4. Selection criteria could be selected from the following options:

- Inhabitants (without a 5 min walking distance to Public Transport station)
- Inhabitants without a 5 min walking distance to Public Transport station with service at certain time interval (e.g. at night)
- Early Adopters: Inhabitants between 16 - 44 years old, weighted by Sinus Milieu
- POIs
- Employees
- Retail m2 (without a 5 min walking distance of Public Transport station)
- Shared Mobility Rentals
- Public Transport vehicle capacity per station
- Registered private cars (without 5 min walking distance to PT)
- Registered cars within priced parking zones
- Originating Public Transport trips per inhabitant from Traffic Model
- Originating car trips per inhabitant from Traffic Model

The chosen exclusion and selection criteria are shown for each hub type in Figure 19, Figure 20, Figure 21 and Figure 22.

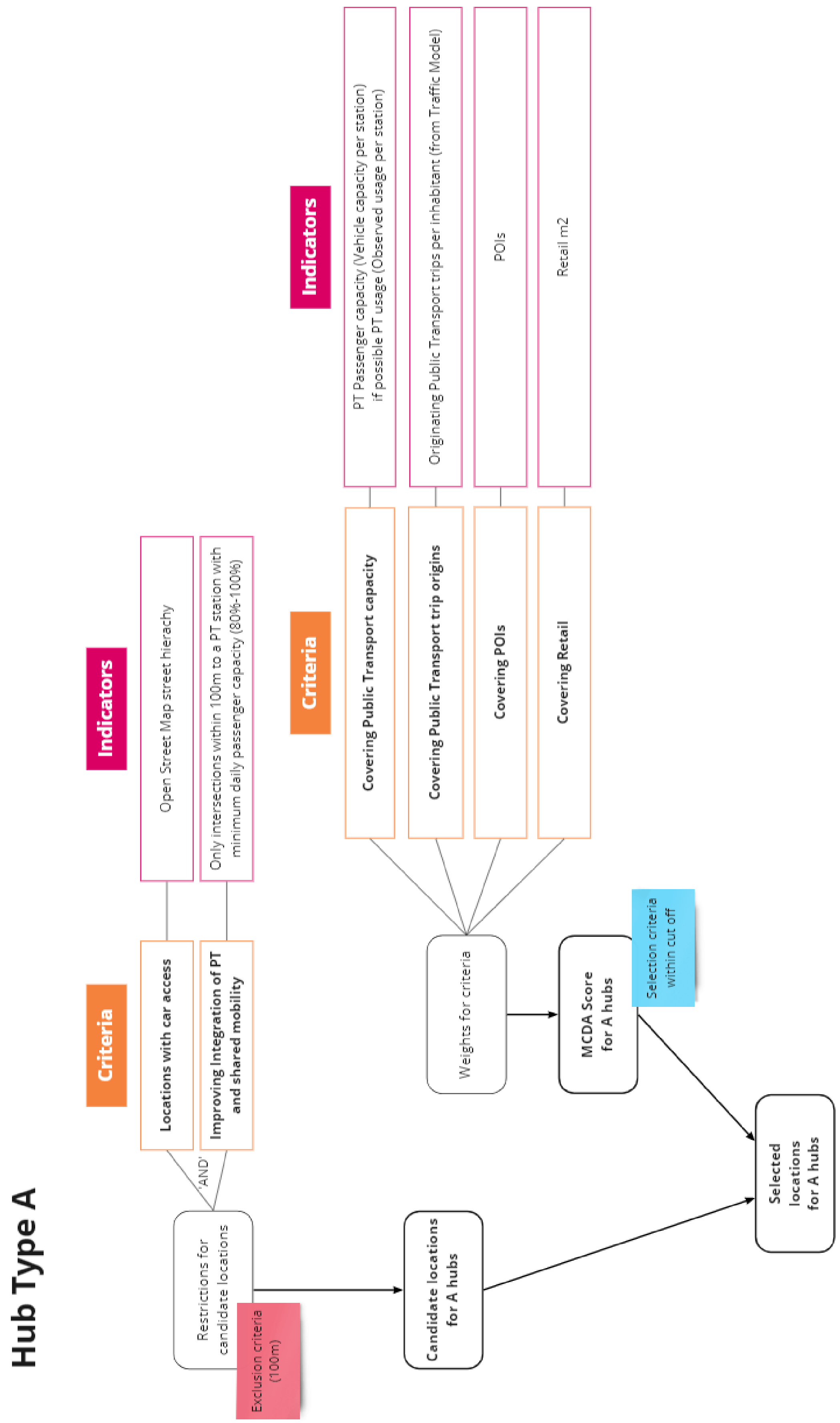


*Figure 19: Case Study Munich - location planning decision tree for hub type A*

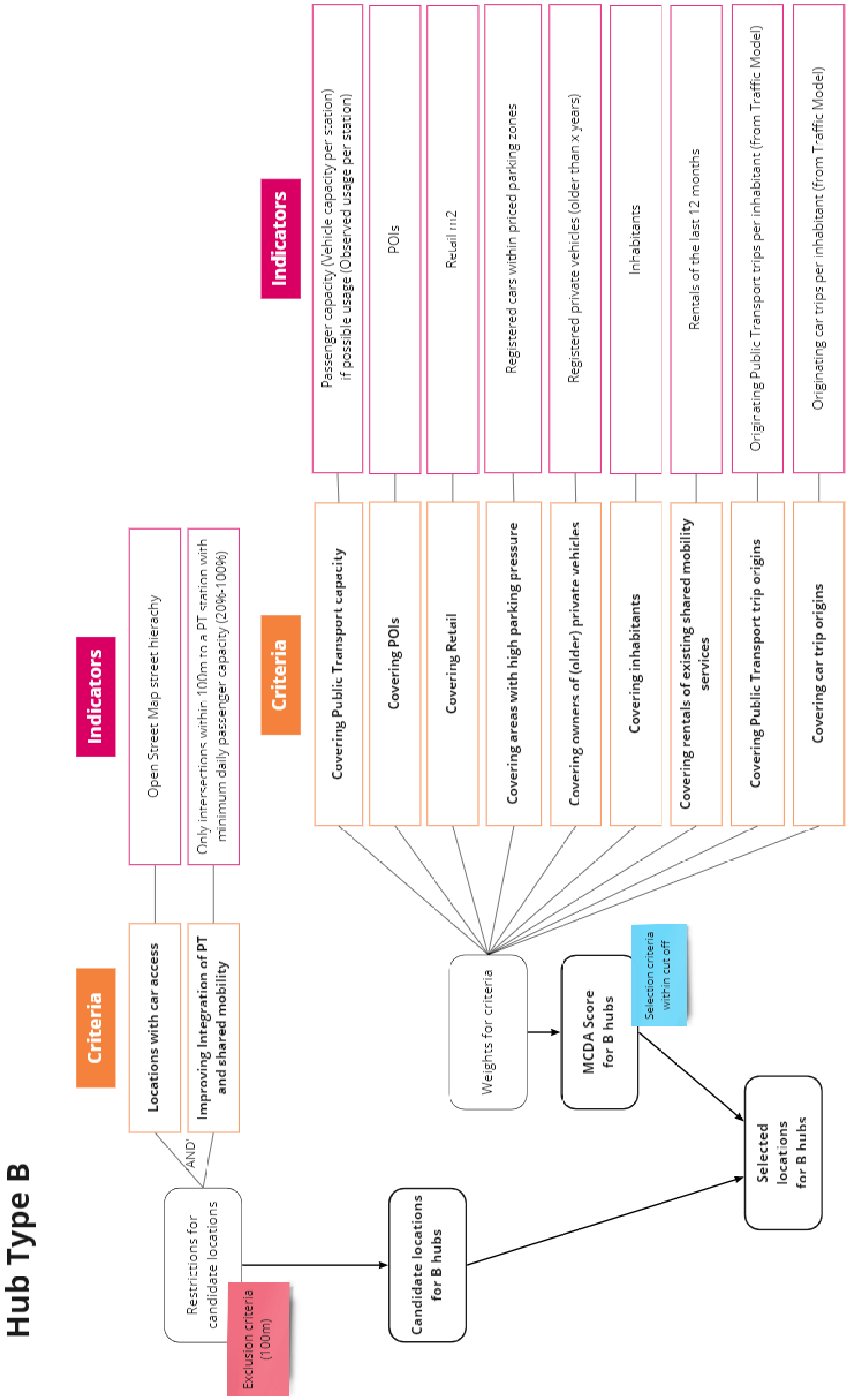


*Figure 20: Case Study Munich - location planning decision tree for hub type B*

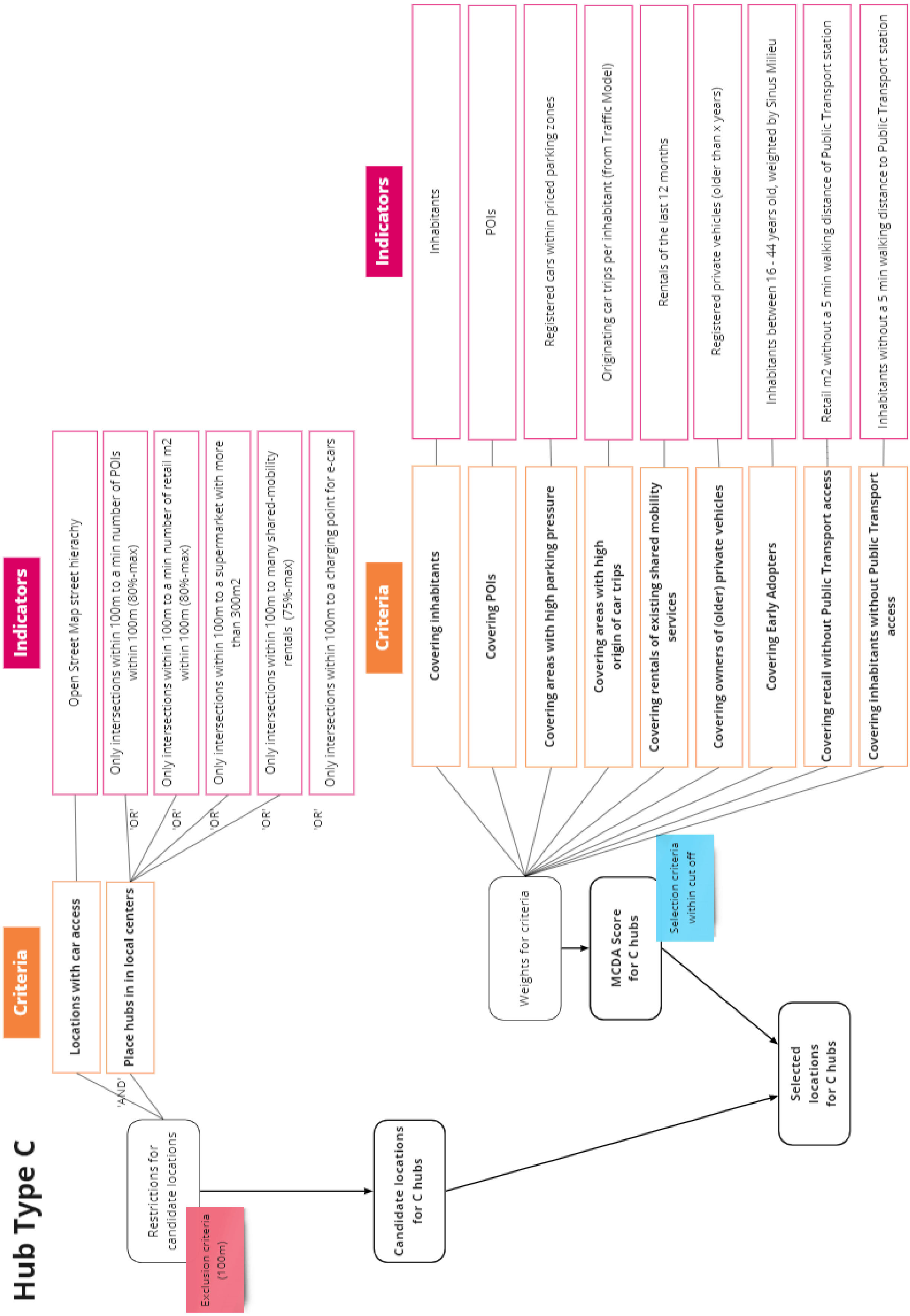


*Figure 21: Case Study Munich - location planning decision tree for hub type C*

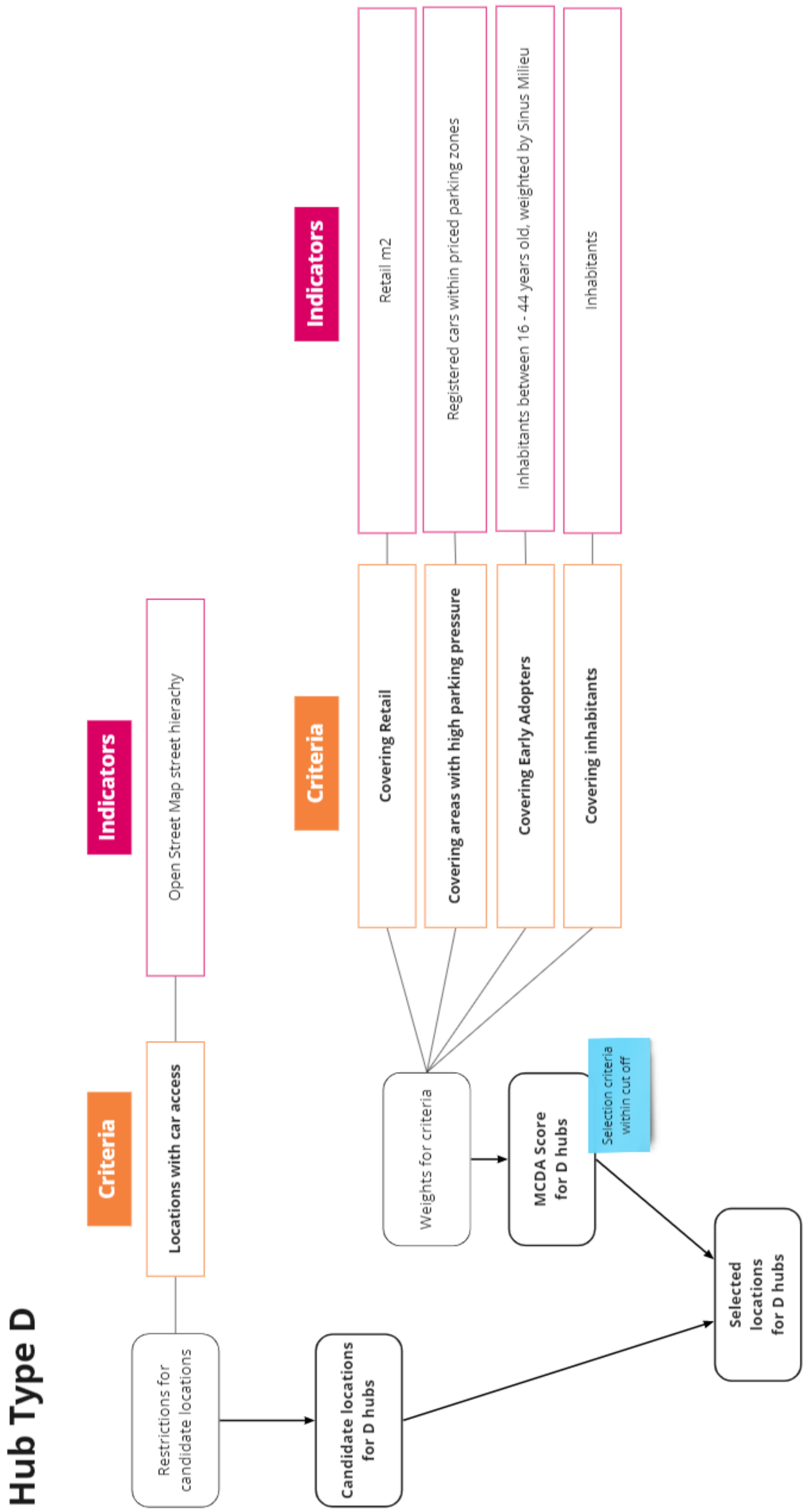


*Figure 22: Case Study Munich - location planning decision tree for hub type D*

### Step 2.2 Select intersections as candidate locations

***Candidates Hub Type A (Scenario 1)***

For Hub Type A, candidate locations are selected based on the exclusion criteria in Figure 19. Due to lack of data on public transport passenger counts, only public transport stations with two crossing rail lines were filtered. All street intersections within 100 m of the filtered stations were selected, resulting in street intersections around 38 public transport stations as A candidates. This candidate set was only used in Scenario 1.

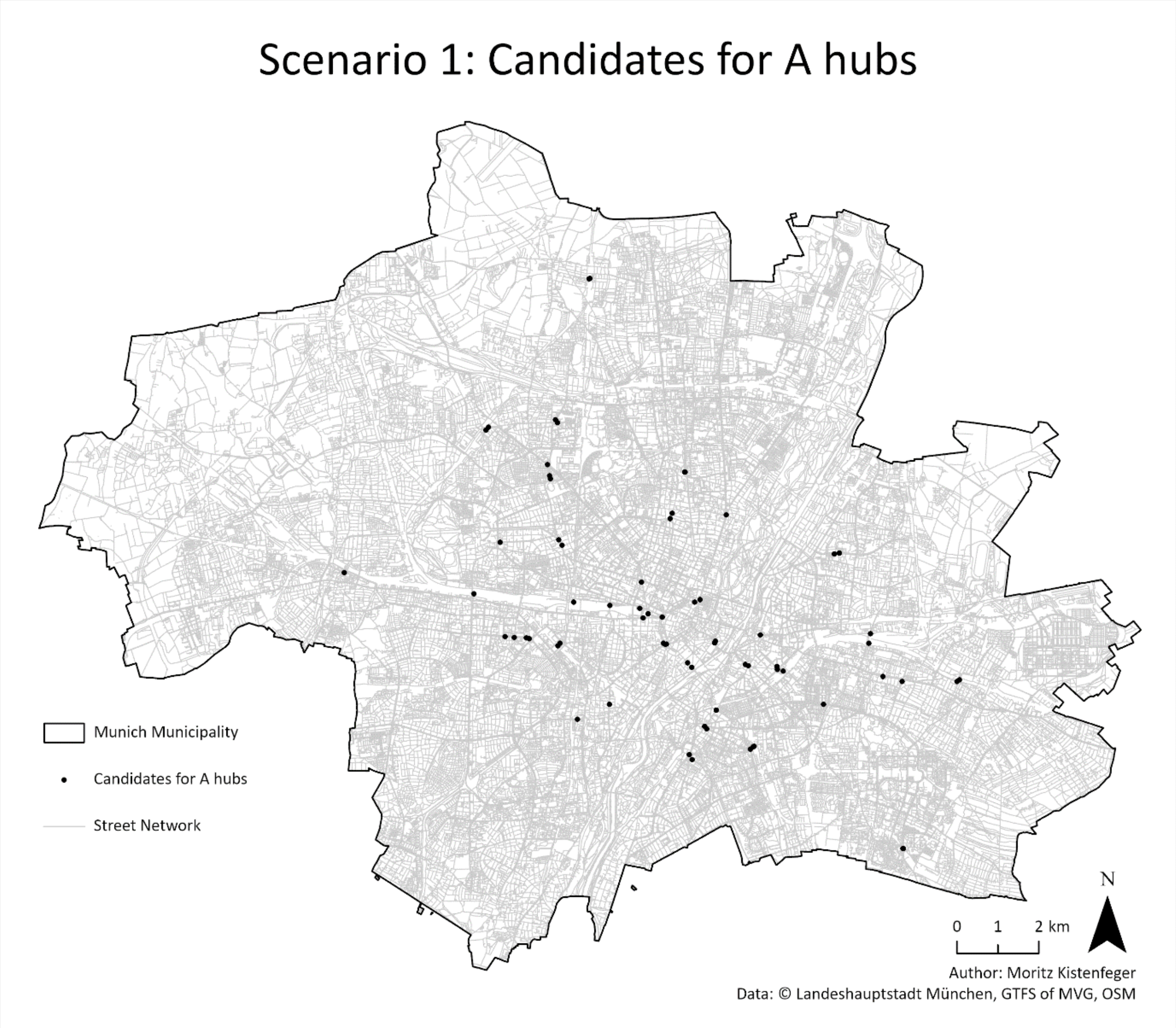


*Figure 23: Case Study Munich - Candidates for A Hubs in Scenario 1*

***Candidates Hub Type B (Scenario 1 and 2)***

For Hub Type B, candidate locations are selected based on the exclusion criteria in Figure 20. Due to lack of data on public transport passenger counts, only public transport stations with rail-based public transport lines were filtered. All street intersections within 100 m of the filtered station were selected, resulting in street intersections around 324 public transport stations as B candidates. This candidate set was used in Scenario 1 and 2.

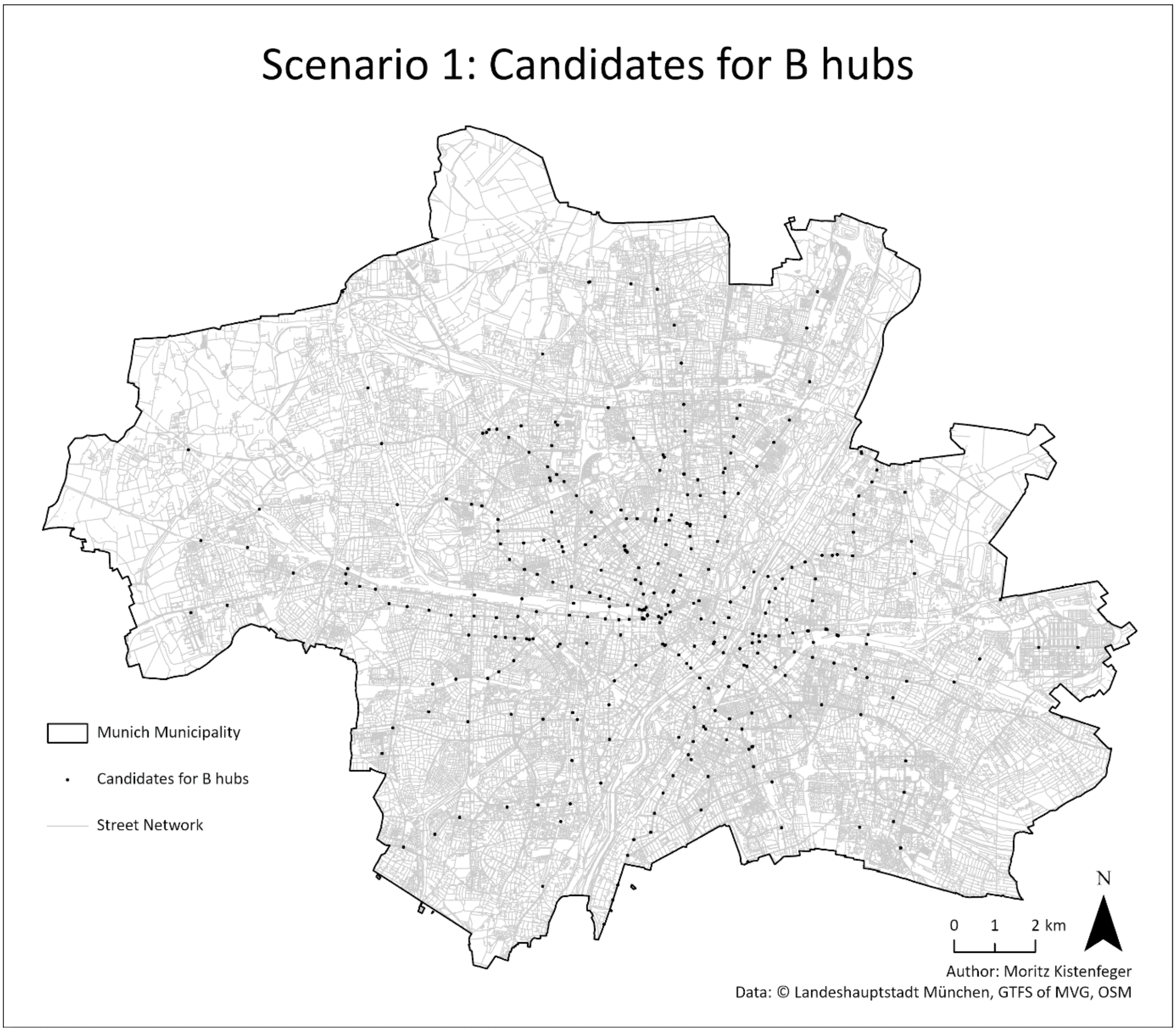


*Figure 24: Case Study Munich - Candidates for B hubs in Scenario 1 and 2*

***Candidates Hub Type C (Scenario 1 and 2)***

For Hub Type C, candidate locations are selected based exclusion criteria in Figure 21.

Intersections with car access
AND with a high number of POIs within 100m (min 2 POIs within 100 m)
OR with a high number of retail m2 within 100m (min 50 m2 within 100m)
OR with a supermarket with more than 300m2 within 100m (min 1 within 100m)
OR with carRental (min 100 within 100m)
OR with bikeRental (min 50 within 100m)
OR with ebikeRental (min 10 within 100m)
OR with emoped rentals (min 4 within 55 m)
OR with escooter rentals (min 40 within 55m)
OR with a PT station within 100m
OR with a charging location within 100 m

Selecting candidates with the above filters, the total selection included 11.619 locations as C candidates. This candidate set was used in Scenario 1 and 2.

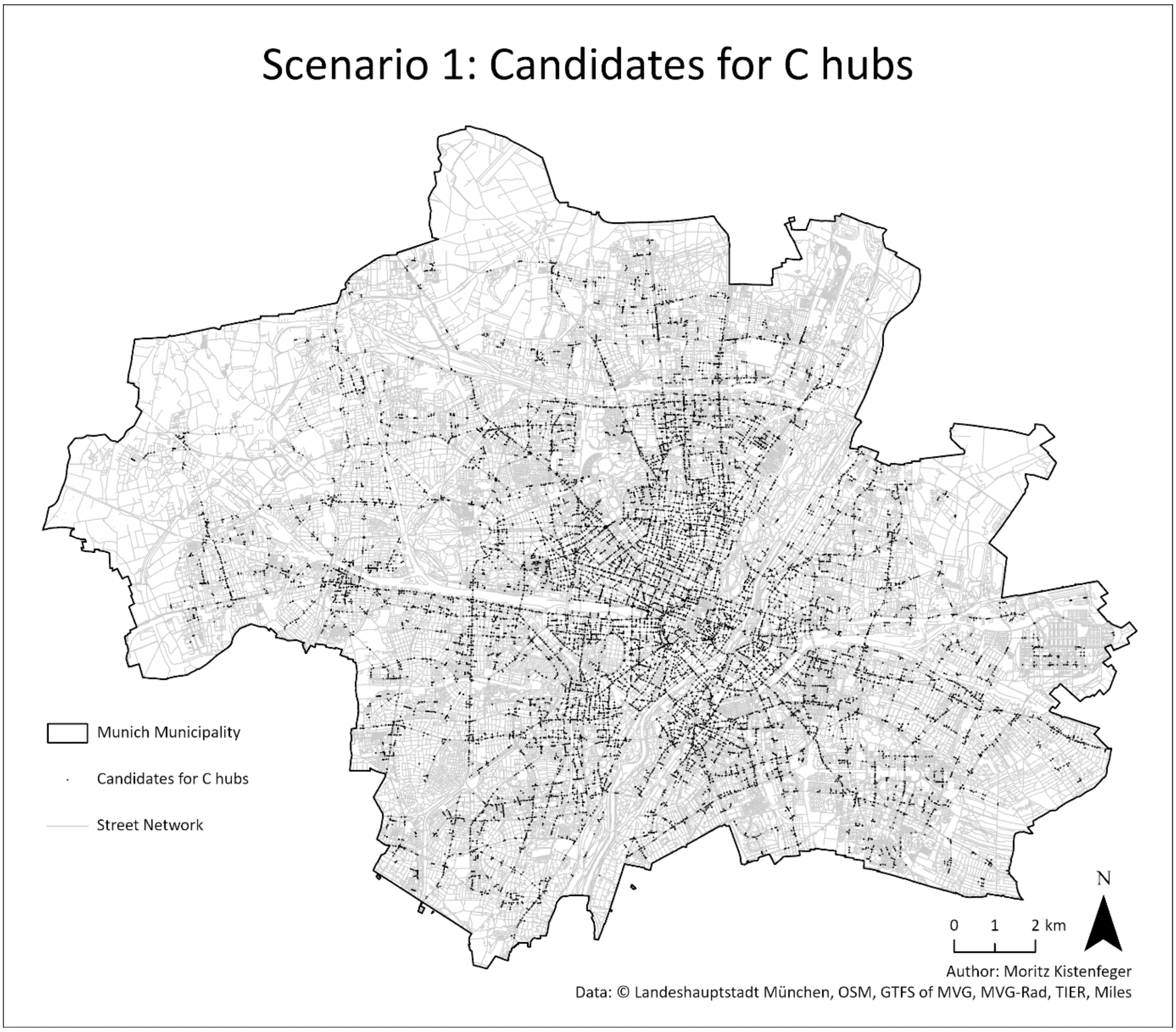


*Figure 25: Case Study Munich - Candidates for C hubs in Scenario 1 and 2*

***Manually chosen locations for Hub Type A (Scenario 2)***

In scenario 2, locations for Hub Type A were selected manually based on the exclusion criteria in Figure 19. This was mainly due to a lack of data on public transport passenger counts, making an automated selection very difficult. As the number of A candidates is very small and of strategical nature, a manual selection by transport planners seemed appropriate. As the largest interchange points within the city are well-known to transportation planners, a manual selection was quickly implemented. Therefore, this was not a candidate set for a location allocation analysis, but already the final set of chosen locations. The 19 manually chosen A hub locations were only used only in Scenario 2.

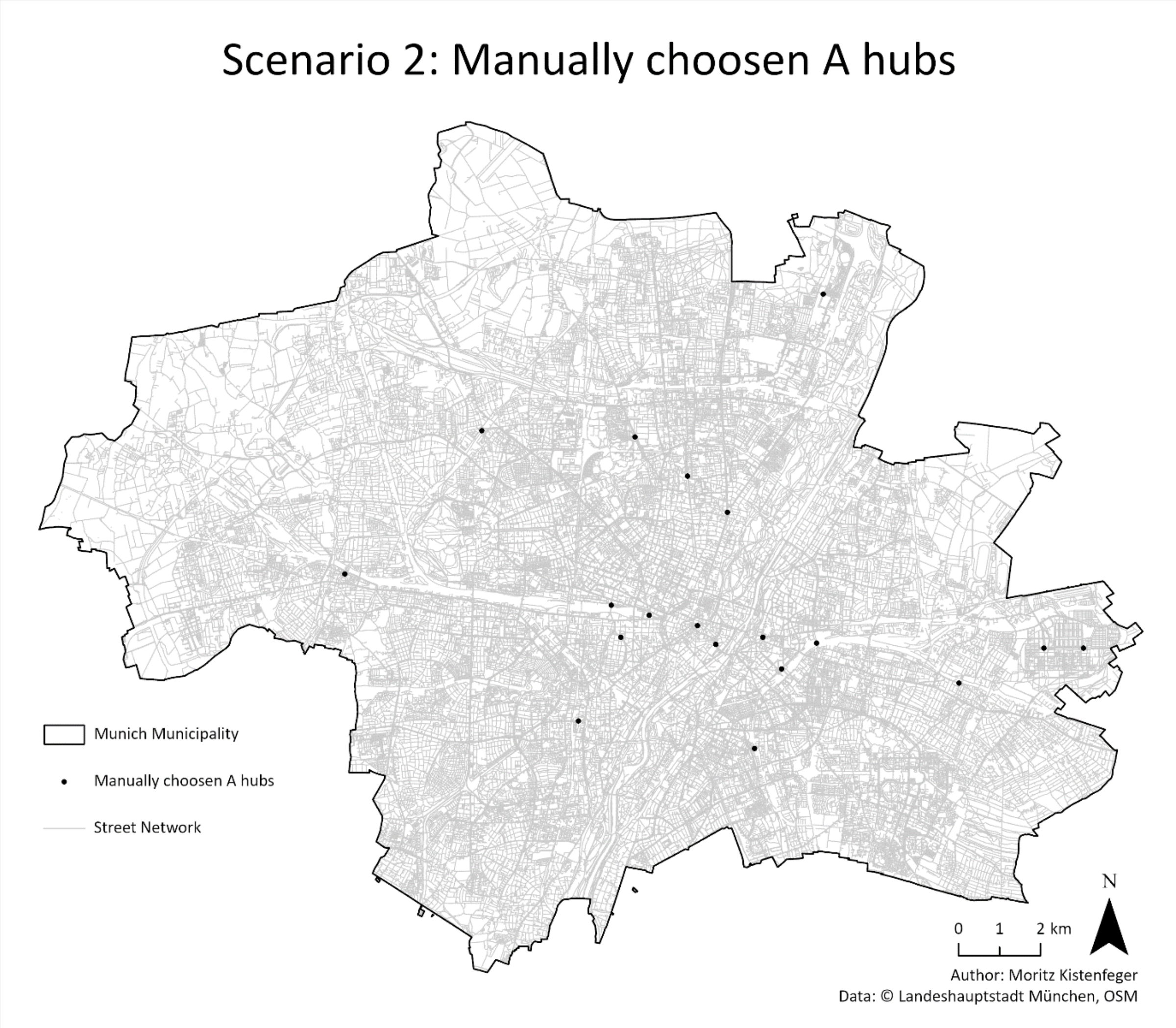


*Figure 26: Case Study Munich - Manually chosen A hubs in Scenario 2*

***Candidates Hub Type D (Scenario 2)***

For Scenario 2, hub type D was added as an additional layer to the sequential location allocation. For Hub Type D, candidate locations are selected based exclusion criteria in Figure 22. This included all street intersection with car and pedestrian access. This resulted in a total selection of 26.488 as D candidates. This candidate set was used only in Scenario 2.

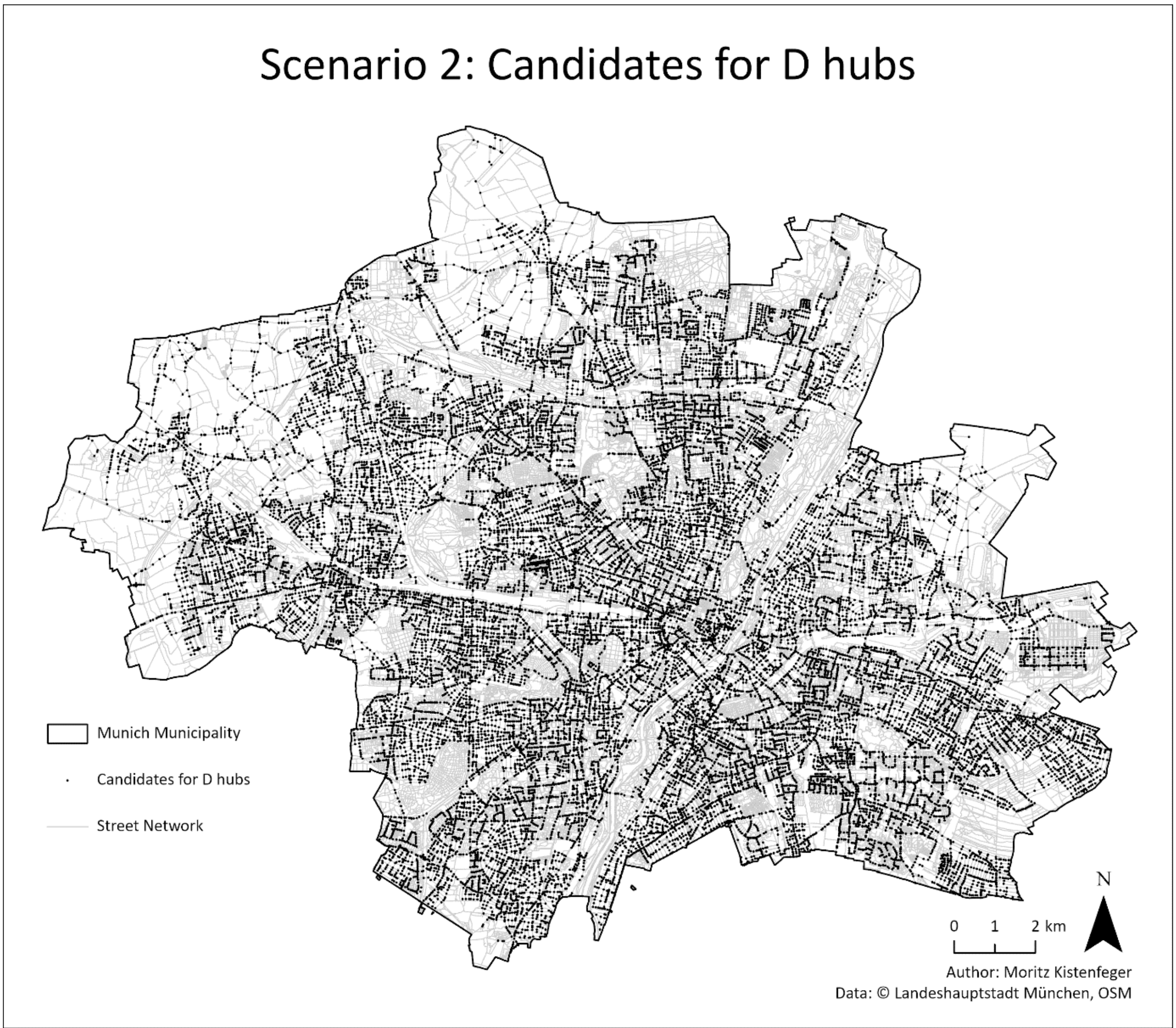


*Figure 27: Case Study Munich - Candidates for D hubs in Scenario 2*

### Step 3.2 Calculate criteria per grid cell

Only the indicators relevant to the selection criteria were further processed into a grid of polygon cells with 50m x 50m. For this, the indicator datasets were compiled into 281.188 grid cells covering Munich. This requires a transformation of indicator datasets from point and polygon format into the grid cell dataset. Indicator units stored in point datasets were transferred using the spatial join tool in ArcGIS. Indicator units stored in polygon datasets were transferred by 1) calculating the unit/area ratio in the initial polygons, 2) chopping the polygons along all edges of the grid cells using the intersect tool in ArcGIS, 3) calculating the unit for each chopped polygon based on its area, 4) using the spatial join function in ArcGIS to sum all units of chopped polygon parts within each grid cell. A similar approach could be applied to indicator units stored in lines, but was not necessary for the case study. During this process, certain indicator definitions were slightly adjusted to account for the characteristics of the available datasets. Table 5 shows all indicators compiled into the grid cells.

*Table 5: Case Study Munich - Indicators compiled in grid cells*

| Indicator | Name | Definition |
|---|---|---|
| Inhab | Inhabitants | Number of registered inhabitants per grid cell, due to privacy concerns cells with value 1-5 are assigned the value 3 |
| EaAd_Age | Early Adopters by age | Registered inhabitants between 16-44 years per grid cell, due to privacy concerns cells with value 1-5 are assigned the value 3 |
| EaAd_Sin | Early Adopters by sinus milieu | The sinus mileu groups with high traditional values and low income are removed, following the approach of (Hochbahn Hamburg, personal communication, February 23, 2022). Early Adopters by sinus milieu is calculated per neighborhood as the ratio of the early adopters group of the total population |
| EaAdop | Early Adopters By age and sinus milieu | Early Adopters by age and sinus milieu is calculated by multiplying EaAd_Age and EaAd_Sin for each cell |
| RetailM2 | Retail m2 | Retail m2 per grid cell |
| Grocery | Grocery store above 300m2 | Availability of a supermarket, 0 = no, 1 = yes |
| POIs | Points-of-interest | Points-of-interest, relevant to locations of shared mobility hubs. This includes the location of attractions, schools, shops, restaurants from OSM (to identify local centers of human activity) as well as the locations of public charging points. |
| PricPark | Priced Parking | Areas with priced parking through parking management from the city, indicating areas with higher parking pressure, 0 = no, 1 = yes |
| PriCars | Private Cars | Amount of registered private cars per grid cell. |
| PrivCar2PrPa | Private Cars in Priced Parking Zones | Number of registered private cars with cars registered in priced parking zones counted double |
| BikRen | Shared Bike Rentals | Shared Bike Rentals per grid cell within 12 months |

| | | |
|---|---|---|
| CarRen | Shared Car Rentals | Shared Car Rentals per grid cell within 8 months |
| eBikRen | Shared e-Bike Rentals | Shared e-Bike Rentals per grid cell within 12 months |
| eScoRen | Shared e-Scooter Rentals | Shared e-Scooter Rentals per grid cell within 12 months |
| ShMoRen | Shared Mobility Rentals | Number of shared mobility rentals per grid cell, sum of all sharing modes (car, e-moped, e-bike, e-scooter, bike) |
| PT_Or | Public Transport Trip Origins 2019 | Public Transport trips origins per inhabitant; from traffic model for 2019 |
| PT_VeCa | Public Transport Vehicle Capacity per hour | Per station, frequency of stops per line between 8-9am on a weekday (e.g. 12 times per hour) based on GTFS. Frequency is multiplied with vehicle capacity (Bus=80, LightRail=220, Rail=1000). As Sbahn was not included in GTFS dataset, stations were assigned a value manually. |
| HcPT5min | High-capacity Public Transport within 5 min | Areas with high capacity (only rail) Public Transport Access within 5 min walking. Bus stations were excluded from this dataset, as shared mobility intermodal trips are more likely combined with frequent and high-capacity lines and most areas of Munich are covered by 5 min accessibility to less frequent bus routes. 0 = no, 1 = yes |
| Ret_2nPT | Retail m2 without rail-based Public Transport Access | Retail m2, all retail m2 outside 5 min walking distance to a rail-based Public Transport stations are doubled |

The indicators used to build the MCDA scores for the selection of A, B, C and D hubs are presented in Figure 28 - Figure 37. To increase the contrast, a dark color is used for the value 0. As the original indicator units were stored in different data formats, their distribution can be very concentrated (e.g. GPS data) or very distributed (e.g. data on building block level).

Using a spatial resolution of 50m x 50m, mapping the variables with gradient colors on the city scale is difficult to interpret for a human. In these maps, very high and very concentrated values are only displayed extremely small and therefore hardly recognizable with the human eye (e.g. Figure 37). These maps are not intended for a human interpretation of the variables, but are only included to illustrate an intermediate computational step of the method. Within the method, the shown maps serve as a sub-step for calculating high-resolution city-wide MCDA scores for each hub type. Even the MCDA score maps are not intended for manual planning of locations, but the data processing and spatial resolution decisions are intended to compile various datasets with high spatial resolution as singly variable input for automated location optimization in the street network.

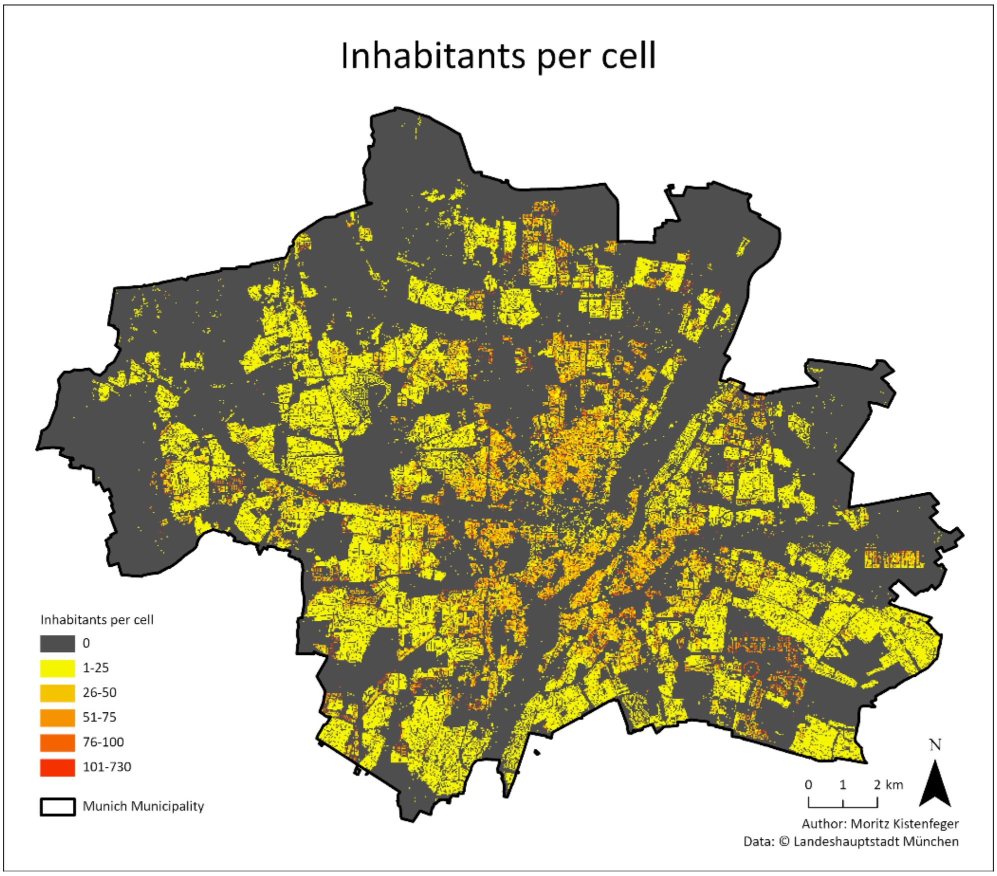


*Figure 28: Case Study Munich - Inhabitants per cell*

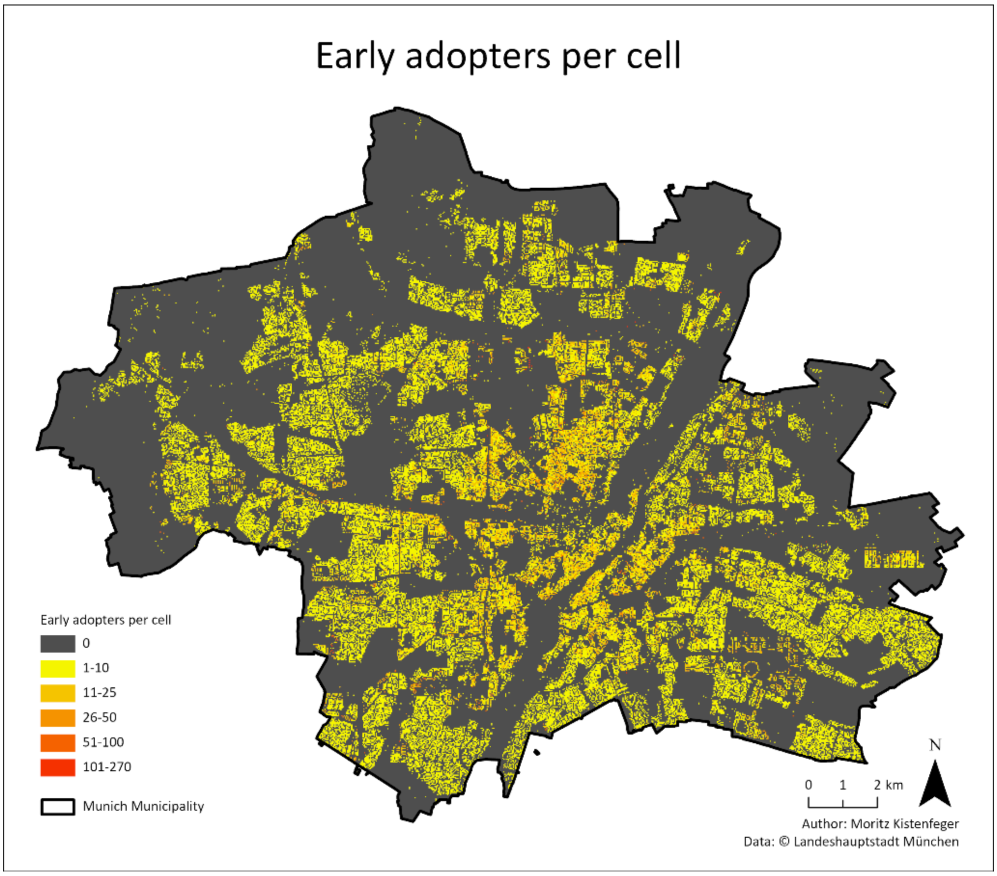


*Figure 29: Case Study Munich - Early adopters per cell*

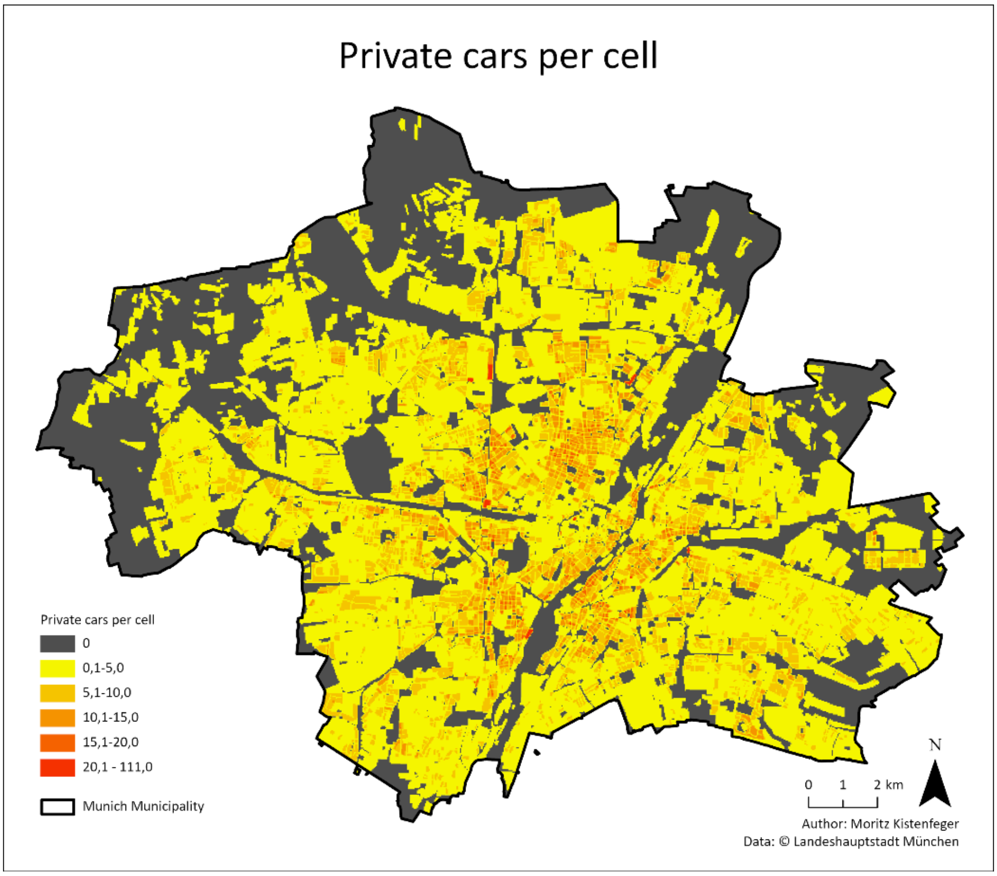


*Figure 30: Case Study Munich - Private cars per cell*

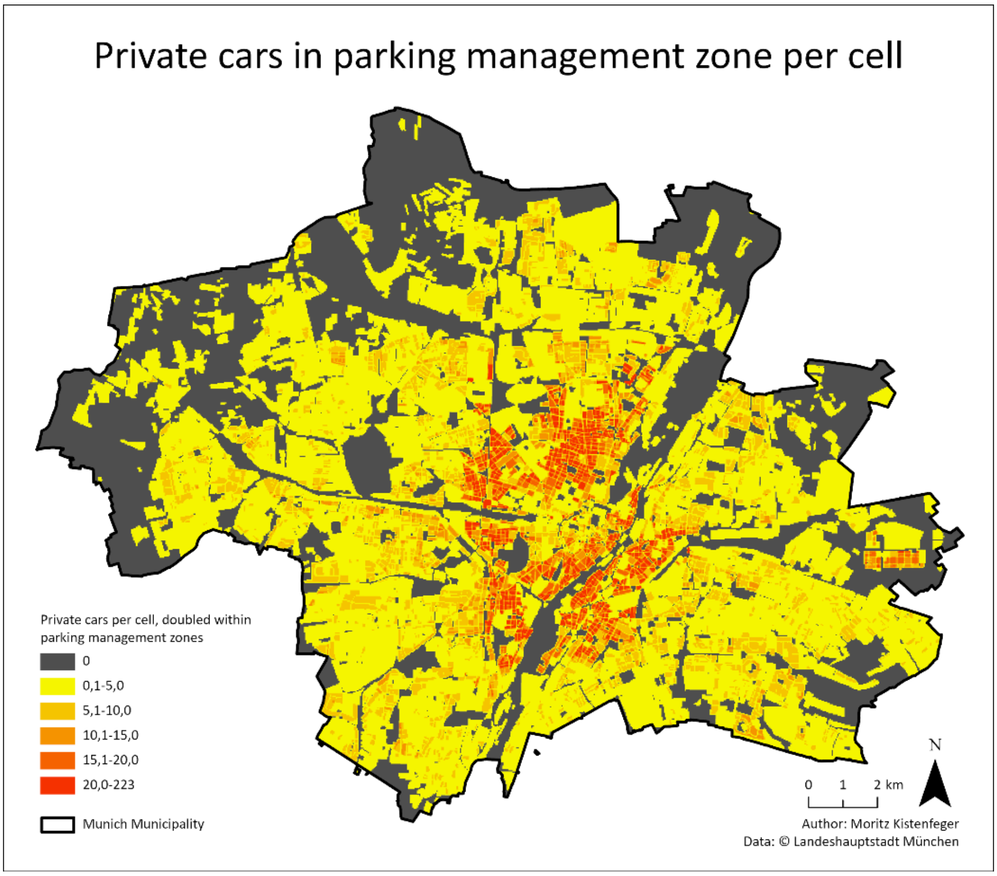


*Figure 31: Case Study Munich - Private cars in parking management zone per cell*

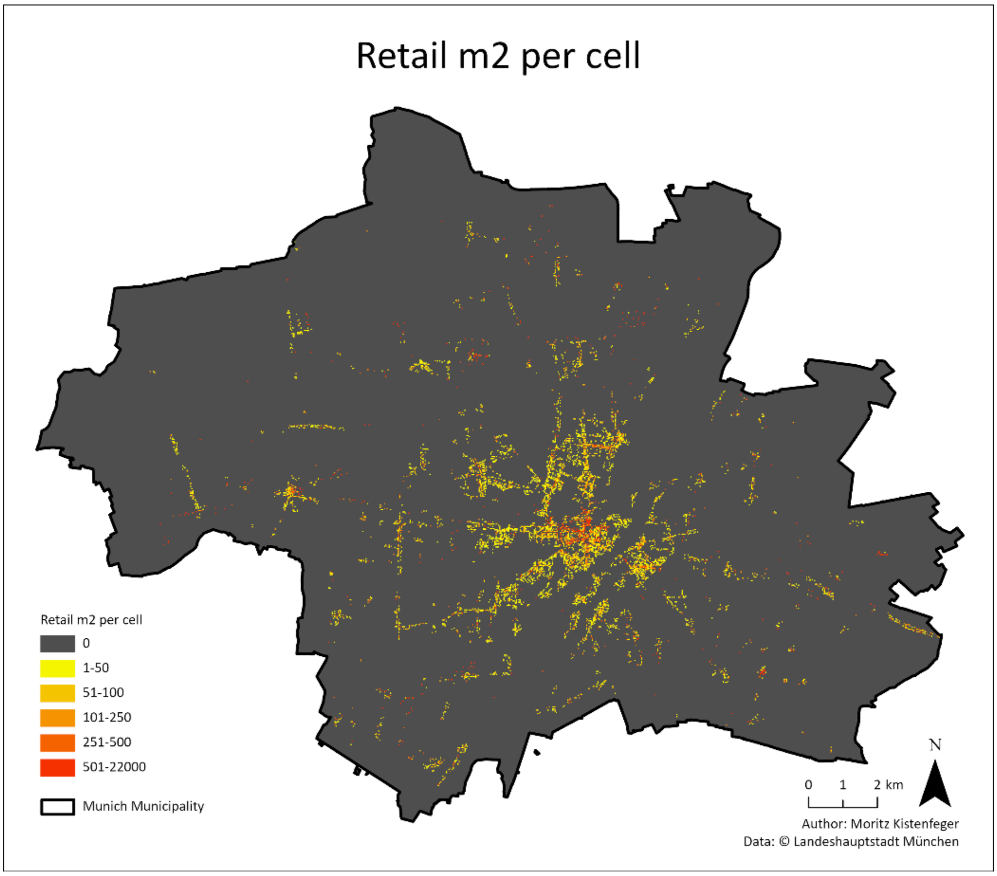


*Figure 32: Case Study Munich - Retail m2 per cell*

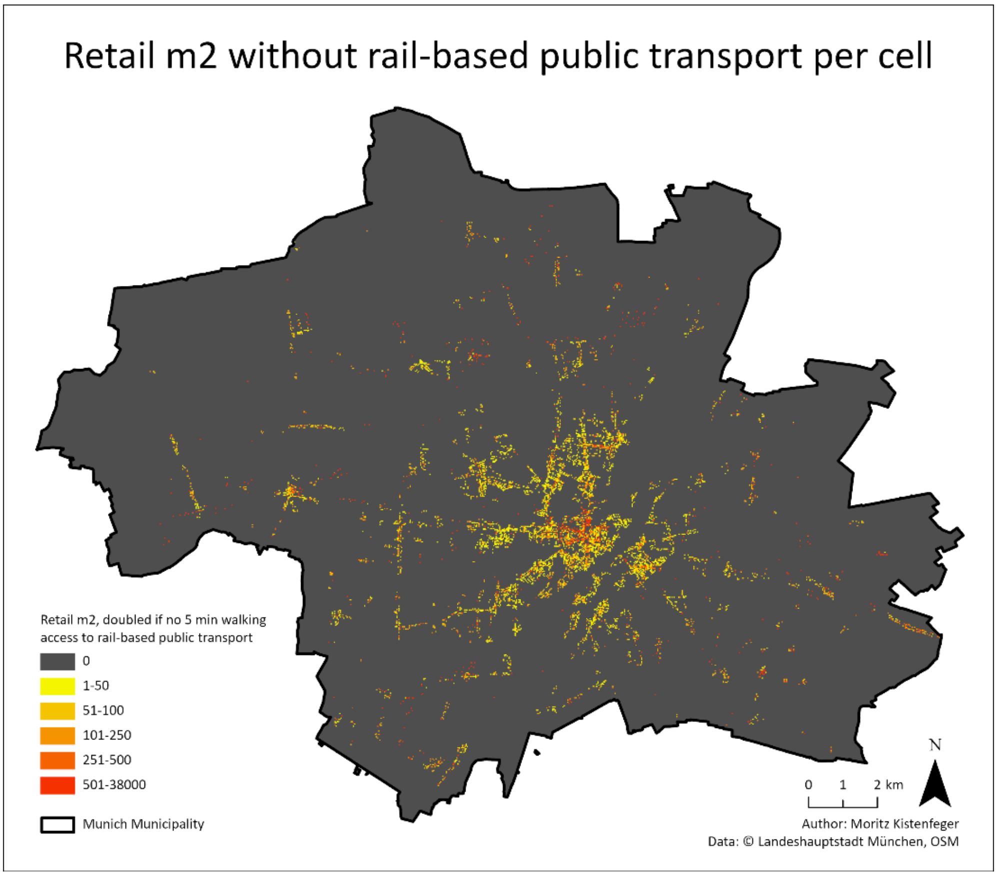


*Figure 33: Case Study Munich - Retail m2 without rail-based public transport per cell*

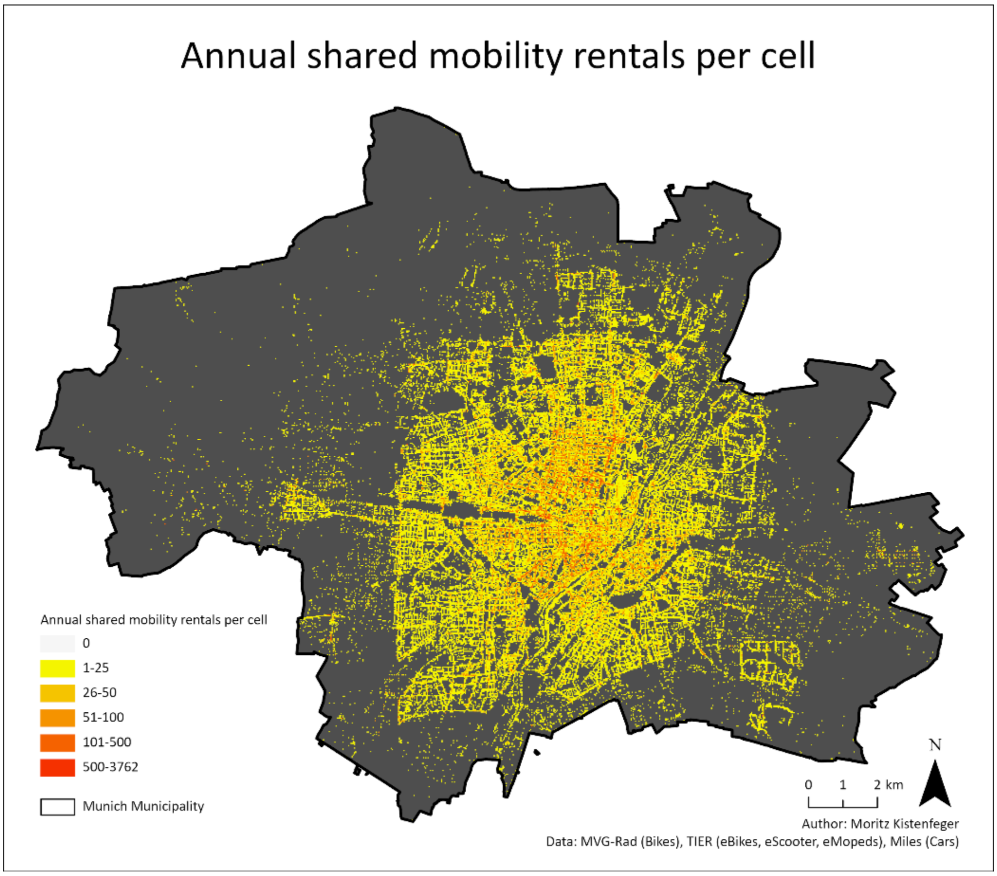


*Figure 34: Case Study Munich - Annual shared mobility rentals per cell*

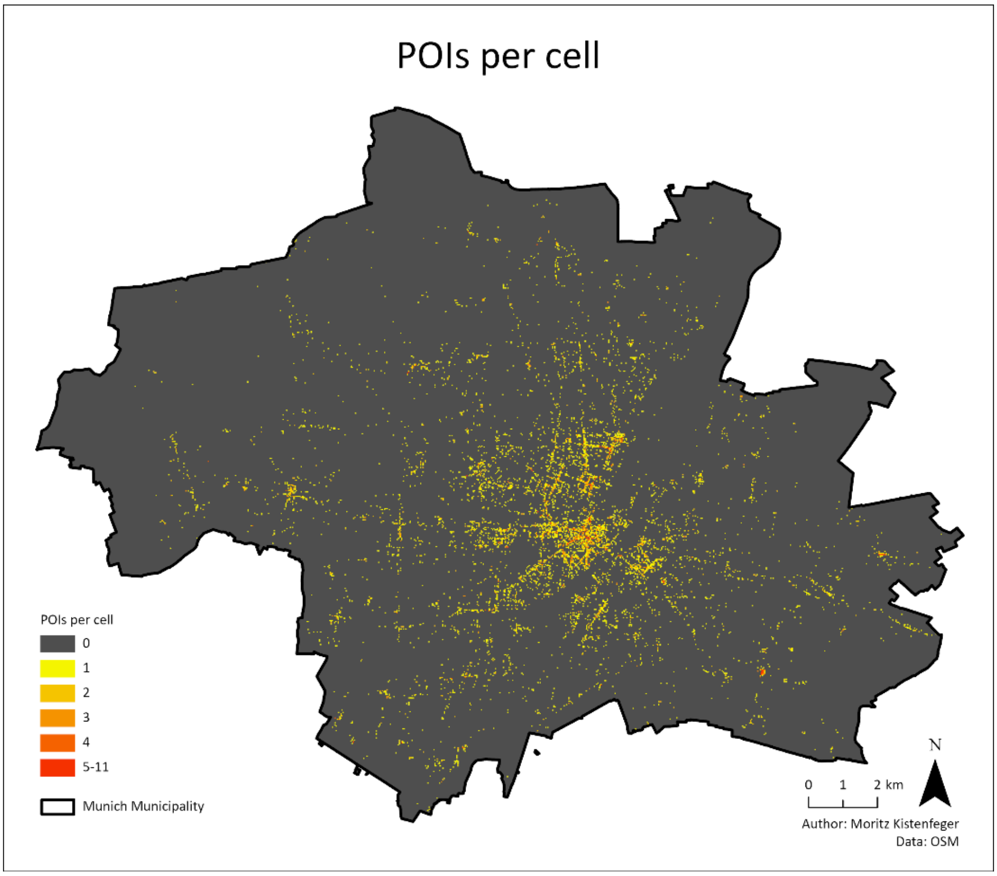


*Figure 35: Case Study Munich - POIs per cell*

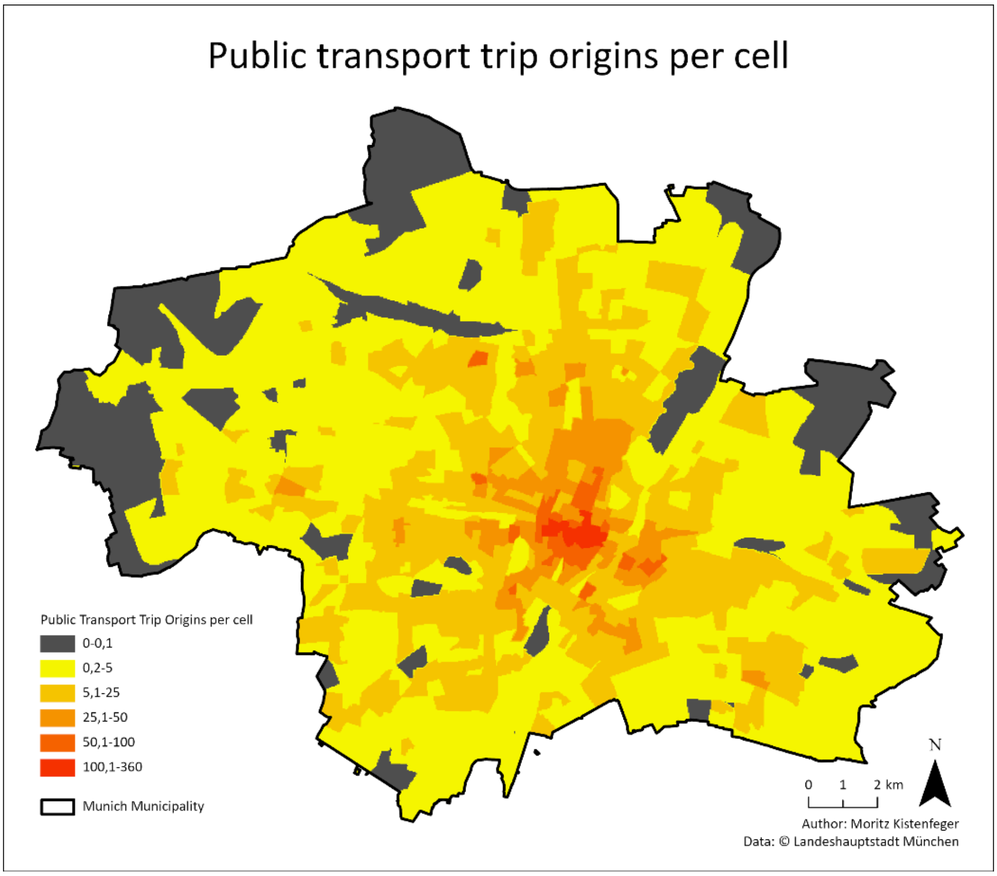


*Figure 36: Case Study Munich - Public transport trip origins per cell*

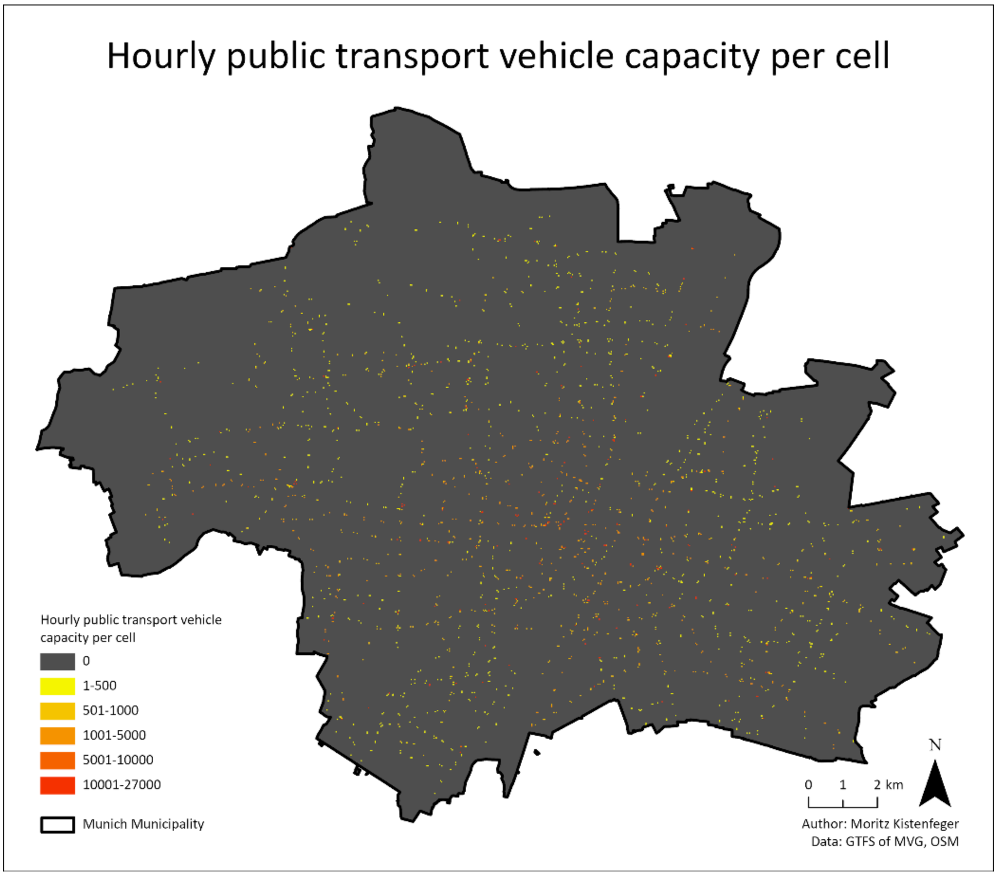


*Figure 37: Case Study Munich - Hourly public transport capacity per cell*

### Step 3.3 Indicator Standardization

To calculate spatial MCDA scores, a standardization of each indicator to the same scale is necessary. Using the linear max approach, every value of a criterion is divided by the maximum value in the criterion (Binsbergen, 2021). After this step, every value of the criterion is represented by a value between 0 and 1.

If large outliers with extreme values distort the standardization, it is possible to manually spread the value over adjacent cells. For example, a large shopping centre accumulates 100.000 retail m2 in one single point and therefore in one grid cell. To improve the performance of the location allocation, it is possible to manually split the 100.000 retail m2 equally across the five entrances of the shopping centre and manually assign 20.000 retail m2 to the grid cells at the entrance points.

### Step 3.4 Determine weights for selection criteria using AHP

The next step is to determine the MCDA weights using the AHP method. A free online tool was used to determine the weights (Goepel, 2018). The method also checks the consistency of the weights with a consistency index. This index should be below 10%. This is very useful for the robustness of the analysis, but can also lead to confusion, if weights need to be changed to become more consistent. If the Consistency Index is above 10%, the system highlights possible iterations within the AHP in light green, which lead to a lower Consistency Index. This is very helpful to achieve logical weights and a good consistency value. The AHP was implemented separately for each hub type, as shown in Table 6. It can be observed, that the chosen variables and their weights change strongly between the different hub types. For example, public transport is dominating hub type A and strongly influencing hub type B to guarantee a good integration with public transport, but becomes irrelevant for hub type C and D. POIs are relevant for hub types A, B and C to select locations with high human activity, but becomes irrelevant for the 3 min accessibility goal of hub type D. Retail has influence on all hub types, showing very strong influence especially on hub type C to place hubs in centers of human activity. Inhabitants and Early Adopters are strongly influencing Hub Type B and C, before being the main criteria for hub type D.

*Table 6: Case Study Munich - MCDA weights resulting from AHP*

| | HUB TYPE A | HUB TYPE B | HUB TYPE C | HUB TYPE D |
|---|---|---|---|---|
| Public Transport Trip Origins | 12,9% | | | |
| Public Transport Capacity | 65,4% | 16,8% | | |
| POIs | 16,2% | 16,7% | 22,7% | |
| Retail m2 | 5,6% | 8,0% | | 13,9% |
| Retail m2 (2x if further than 5 min walking access to rail-based public transport) | | | 31,8% | |
| Inhabitants | | 13,5% | 12,5% | 60,1% |
| Early Adopters | | 7,3% | 16,3% | 20,5% |
| Shared Mobility Rentals | | 18,1% | 8,4% | |
| Registered cars (2x within priced parking zone) | | 19,7 % | 8,3% | 5,4% |
| **Total:** | **100%** | **100%** | **100%** | **100%** |
| **Consistency Ratio CR:** | **7,4%** | **7,0%** | **7,5%** | **5,8%** |

**Step 3.5 Calculate MCDA score**

Using the standardized indicator values per cell and the MCDA weights from Table 6, the MCDA score for each hub type is calculated per cell. The MCDA score for each hub type is illustrated in Figure 38 - Figure 41.

The city-scale MCDA maps are only shown to illustrate a sub step of the methodology and have limitations in their interpretability for the human eye due to the very high resolution. Two things can be observed anyway: First, the maps show the maximum area to be covered for each hub type by clearly isolating areas with an MCDA value of 0. Second, the hotspots of the MCDA values can be identified. However, due to the resolution and the often very low values per cell, it is difficult to understand the distribution of the low to medium values. Especially in the outskirts very small MCDA values might seem negligible at first. However, since the following network analysis aggregates all values within a certain walking time, even the comparatively small values of the outskirts become very relevant for location optimization algorithm.

Subsequently, the MCDA score was transferred from the grid cells to a point data format, using the feature to point tool in ArcGIS. Thereby, each cell is then represented by a point in its centroid. This change of data format is necessary for the use of the MCDA score as a demand variable in the following location allocation.

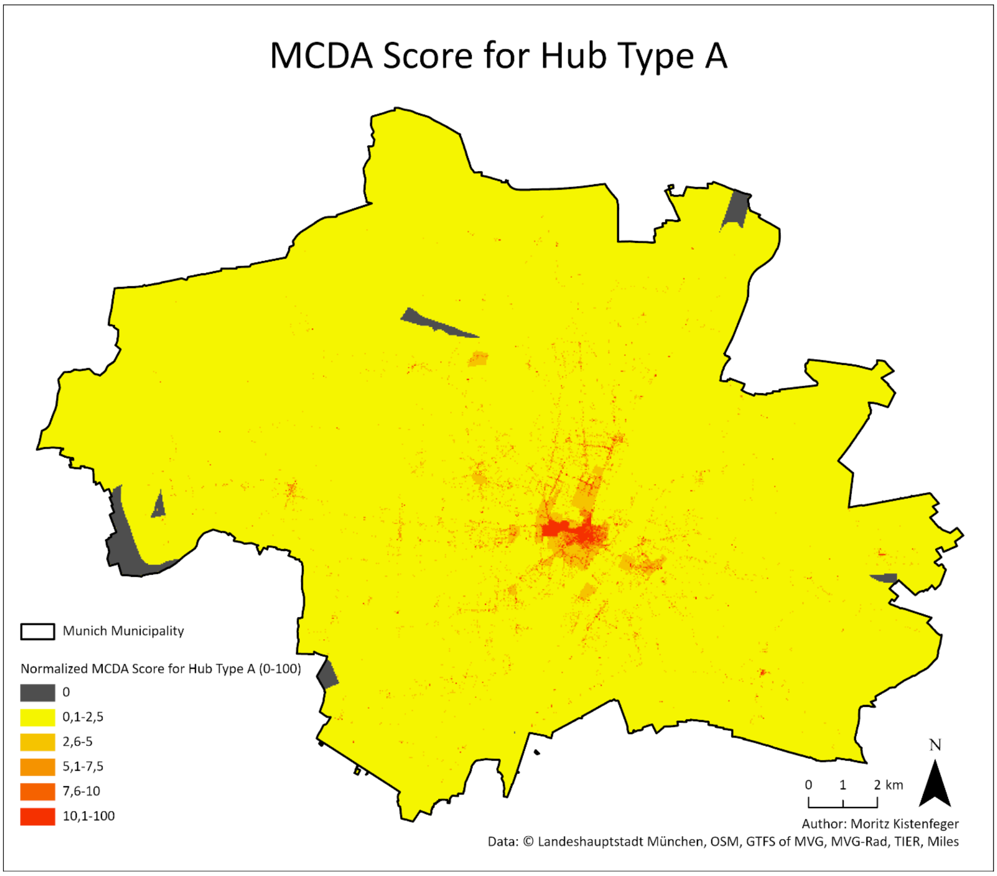


*Figure 38: Case Study Munich - MCDA Score for Hub Type A*

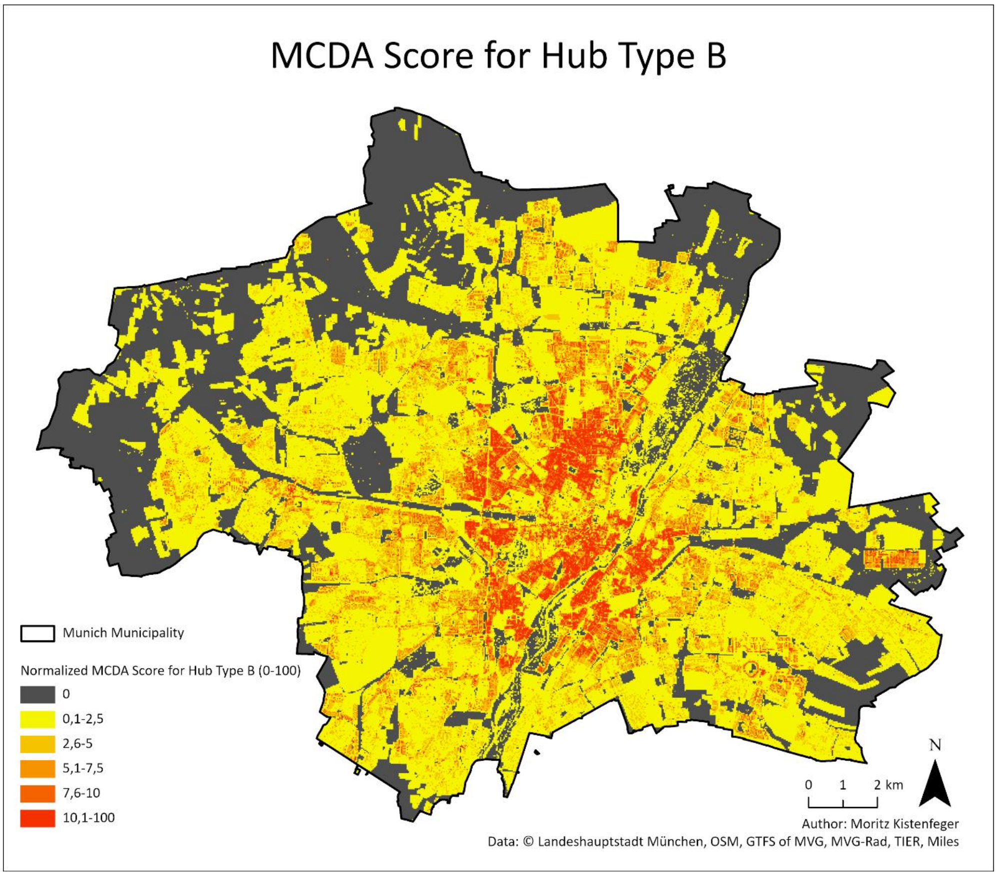


*Figure 39: Case Study Munich - MCDA Score for Hub Type B*

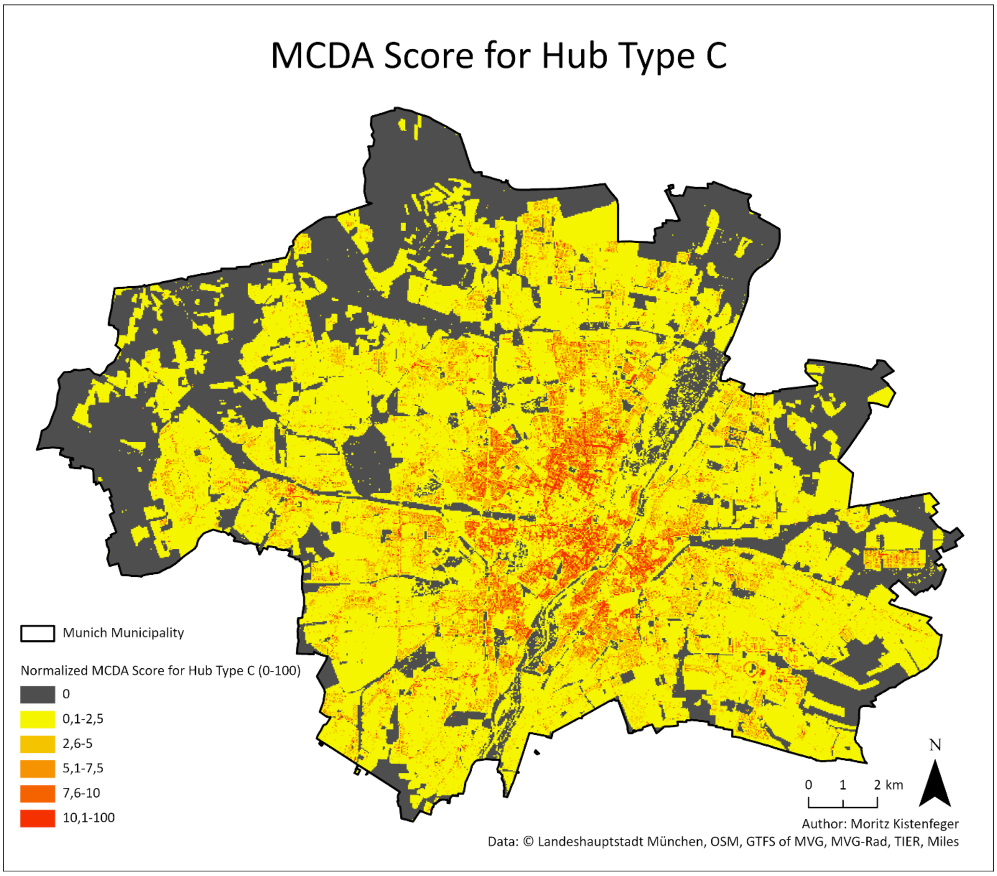


*Figure 40: Case Study Munich - MCDA Score for Hub Type C*

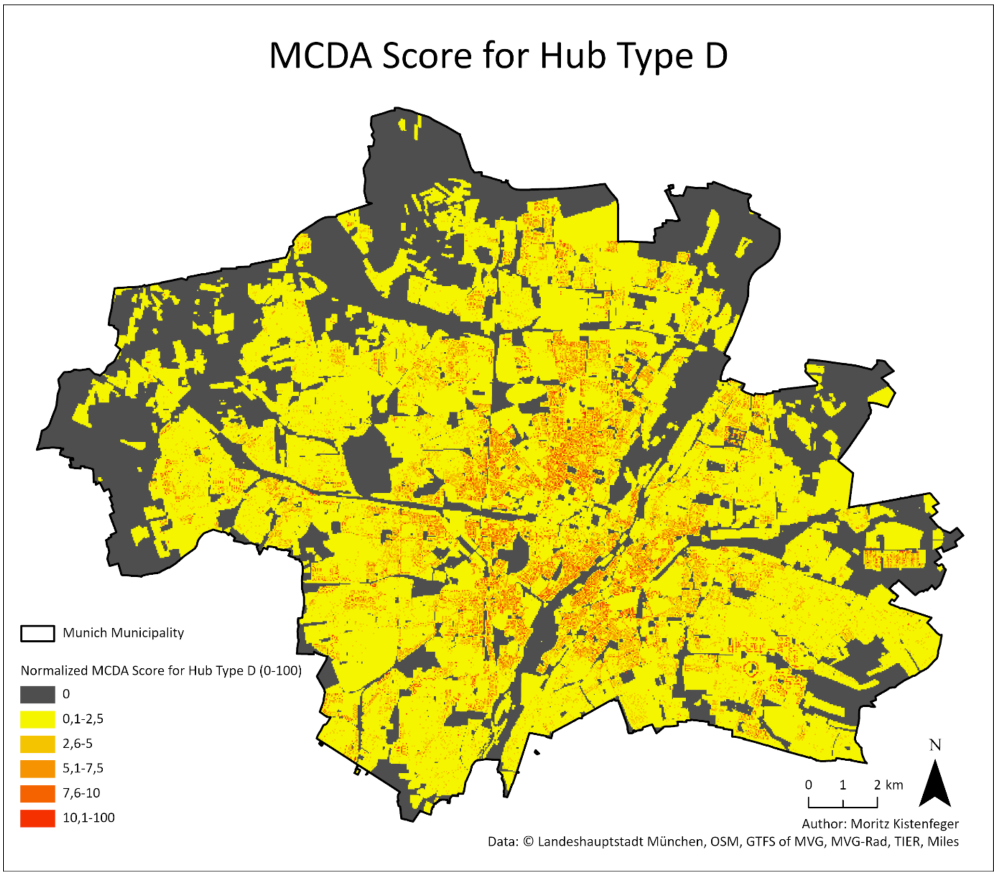


*Figure 41: Case Study Munich - MCDA Score for Hub Type D*

**Step 4 Build network analysis layer**

The network analysis layer is built in the ArcGIS network analysis extension. The street network for Munich is exported from OSM data. Only streets which are accessible for pedestrians are selected, as the network analysis will model waking time of pedestrians. After planarizing all network elements, the length of each network element is calculated in meter. Walking time per network element is calculated in minutes with an assumed walking speed of 80 meter per minute. The resulting network has 238.043 elements with a total length of 8644km. The network is constructed as network dataset in the Network Analysist Extension of ArcGis.

**Step 5 Define scenarios for different placement strategies**

There was high uncertainty about the total number of hubs required, which is an important input of the model by the decision-makers. Therefore, a first simplified pre-analysis was performed using only one variable and only one location allocation step.

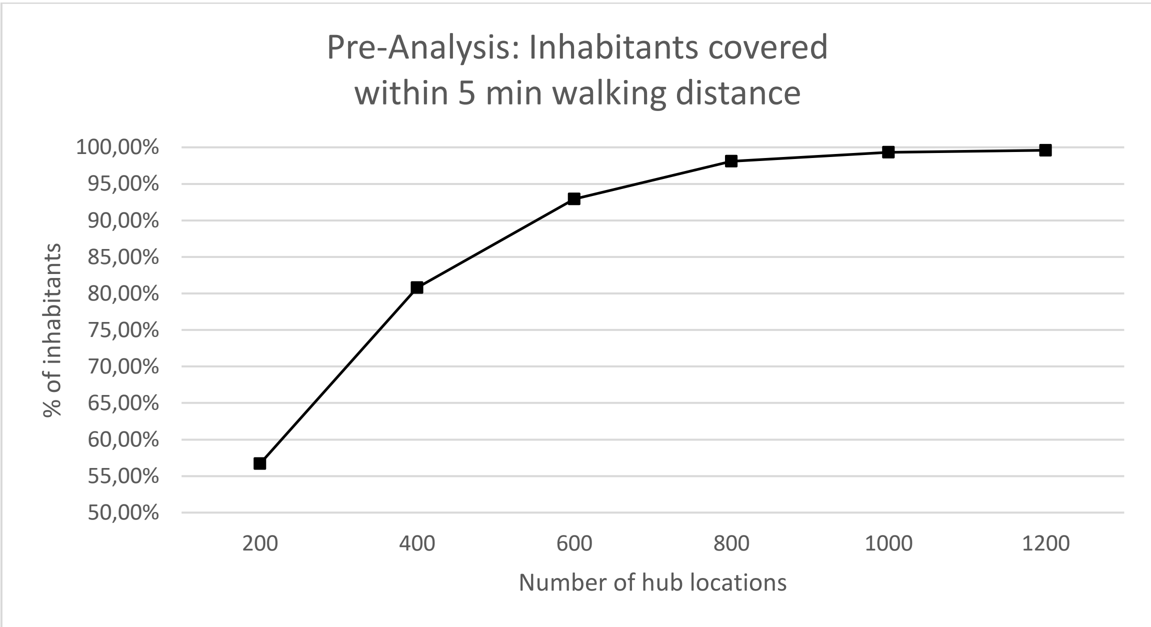


*Figure 42: Case Study Munich - Pre-Analysis of Inhabitants covered within 5 min walking distance*

The pre-analysis only optimized for the coverage of the inhabitant's criterion of the overall analysis. The analysis included all 26.488 street intersection with car and pedestrian access as candidate locations. Using the ArcGIS Location Allocation tool, the Maximize Coverage function optimized the 5 min walking coverage only of the 78.703 demand points with registered inhabitants. Other areas of the city have no or very less inhabitants but will require coverage by mobility stations due to other criteria. Therefore, Figure 42 can only serve as a rough pre-orientation of the total number of hubs required for the main analysis. As the main analysis includes the demand areas of all relevant criteria and introduces more restriction for the candidate locations, the number of required hub locations is expected to be higher. On the other hand, the intended walking time cut offs for the hub type A (7min), B (6min) and C (5min) average higher than the 5 min cut off in the pre-analysis. Taking these influences in account, a starting scenario with around 600 stations is suggested for the first main analysis.

### Step 6.1 Perform sequential location allocation

In the case of Munich, location optimization needs to consider different objectives for each hub type. By using different candidate sets, demand weight variable, and cutoff values, the different requirements for each hub type can be represented in the model. As the location allocation tool in ArcGIS can only process one candidate set, demand weight variable and cutoff value, this is implemented using a sequential approach as described in detail before in the workflow of the improved method.

Scenario 1:

For the first sequential location allocation run in Munich, the A hubs were placed based on the A Candidate set, the A MCDA score and a Maximize Coverage cut off at 7 walking minutes. An iteration approach was used to determine the correct number of A, B, and C hubs. This was a time intensive approach, as each sequential location allocation run would take up to one hour (Computer: Intel(R) Core(TM) i7-6500U CPU @ 2.50GHz; 8 GB RAM; Intel(R) HD Graphics 520). During various location allocation runs for type A hubs, it could be observed that from a certain number of hubs, the algorithm does distribute hubs throughout the whole city. This means that the very high-demand areas in the city centers are covered and the algorithm focuses on covering the high-demand areas in the suburbs. If the number of hubs is set too high, the algorithm has to choose not ideal locations from the very limited A candidate set, resulting in high cannibalization between hub placed too close to each other. This problem is mainly encountered in hub types with very restricted candidate sets as for A and B hubs, but less severe with extensive candidate sets as for C hubs. Based on the observations in the iteration runs, the number of A hubs was set to 30.

The same iteration procedure was repeated for the second sequential location allocation run for hub type B. The B hubs were placed based on the B Candidate set, the B MCDA score and a Maximize Coverage cut off at 6 walking minutes. To enable a sequential location allocation, all demands points covered by the 30 already chosen A hubs were removed in the location allocation of the B hubs. Based on the observations in the iteration runs, the number of B hubs was set to 150.

In the third sequential location allocation run, the C hubs were placed based on the C Candidate set, the C MCDA score and a Maximize Coverage cut off at 5 walking minutes. To enable a sequential location allocation, all demands points covered by the 180 already chosen A and B hubs were removed in the location allocation of the C hubs. It was initially aimed for a total number of 600 hubs, as determined in the pre-analysis. From there, different iterations were calculated in steps of 100 hubs. For each of the iterations in the number of C hubs, service area statistics were computed to compare the iterations based on coverage KPIs.

Scenario 2:

Based on the experiences of the implementations of Scenario 1, the city planners of Munich decided to change certain restrictions. Hubs of type A are chosen manually due to the lack of data on passenger transfers per public transport station, resulting in 19 locations. The maximum walking time for the service areas of hubs type A, B and C was aligned to 5 minutes. And an additional Type D hub was introduced: Basic reserved parking for shared transportation should be used to re-densify the hub network to provide improved accessibility to any of the four hub types A, B, C, and D within 3-minutes walking. As the hub types A, B and C have the same 5 min cut off for the Maximize Coverage tool, it was possible to simplify the sequential location allocation. Already chosen hubs were included in the next sequential location allocation run as so-called required candidates. This option is only possible, if the walking time cut off is equal for the different hub types. The same procedure could be applied to the location allocation run for D hubs. Because every demand point should be able to reach a A, B, C or D hub within 3 minutes cut off, the walking time cut off was equal for all hub types again.

**Step 6.2 Perform service area analysis**

Whilst the sequential location allocation is able to optimize the locations of various hub types with different candidate sets, demand weight variables and walking time cut offs, it does not allocate each demand point to the closest hub location. The output of the sequential location allocation, the optimized locations of all hub types, are used in the service area analysis tool in ArcGIS to calculate the catchment area of each hub according to the walking time cut off per hub type.

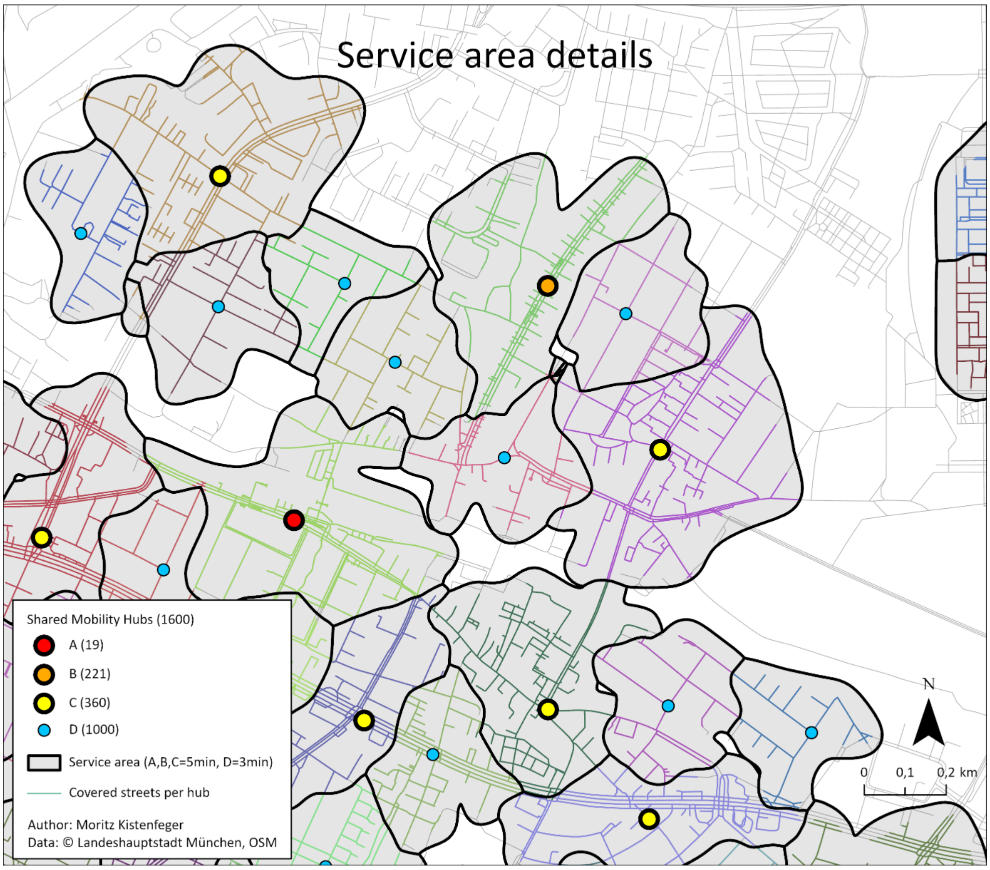


*Figure 43: Case Study Munich - Service Area Analysis*

This step has proven to be very error-prone in ArcGIS, as it requires detailed analysis of small walking times for thousands of nodes in the street network. The most accurate and robust method of representing coverage areas per hub is the covered streets assigned to the hub by the shortest walking distance, as shown in Figure 43. To calculate KPIs and illustrate the service areas per hub, displaying service areas as polygons, representing coverage, is the most suitable option. The polygon generation functionalities in the ArcGIS Network Analysis Toolbox turned out to be very error-prone, leading to missing or falsely generated polygons. For this study, the large number of service area polygons were generated in a separate procedure from the service area lines. Therefore, a combination of the Buffer Line tool and the Remove Overlap tool in ArcGIS, as well as the Delete Holes tool in Q-GIS was applied. This was a work and time intensive workaround. It seems that a dense street network combined with short distances and overlapping service areas leads to errors during polygon generation in ArcGIS.

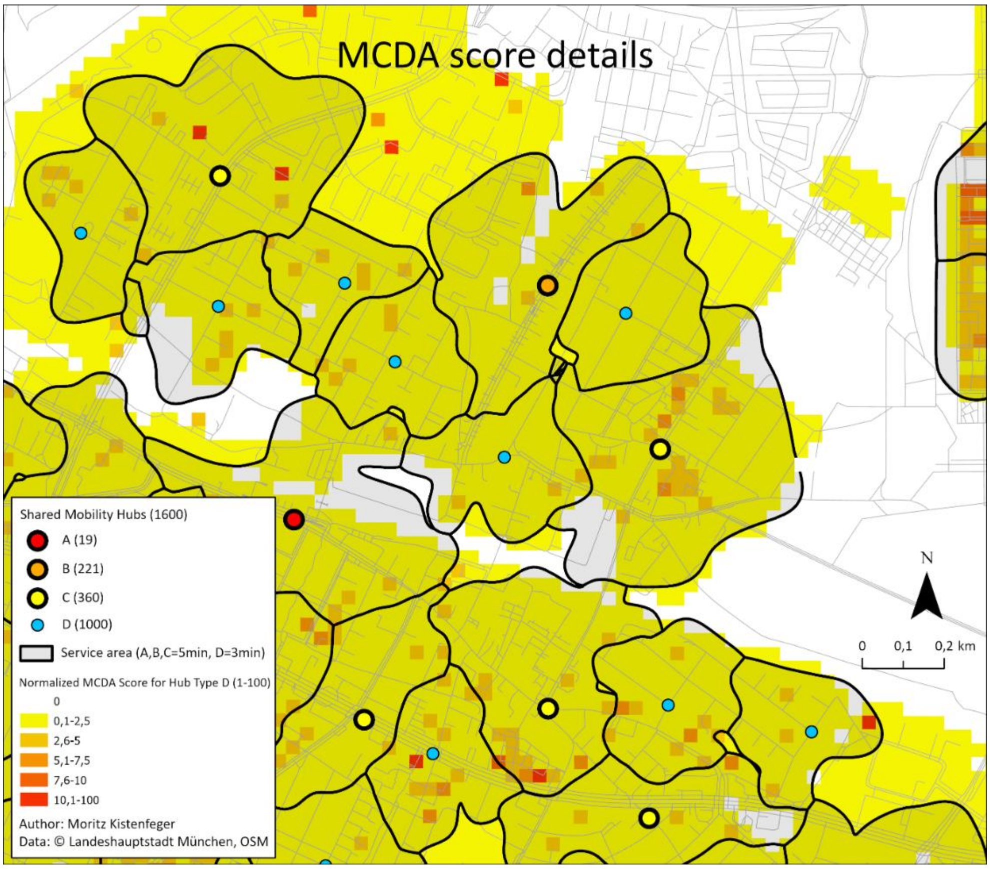


*Figure 44: Case Study Munich - MCDA score details*

With the service area polygons available, the spatial coverage of different variables can be calculated per service area using the spatial join tool in ArcGIS. For example, as shown in Figure 44, the covered standardized MCDA score can be summed per service area, allowing prioritization of locations for each hub type.

**Step 6.3 Calculate Scenario KPIs**

As a final step, overall scenario KPIs can be calculated by taking into account the total coverage of indicators of all service areas together. Relating this coverage of a certain variable, e.g. covered inhabitants, to the total number of inhabitants allows for a calculation of a coverage ratio in percent. These KPIs are very useful for decision-makers to understand the effect of different placement strategies.

## 6.4. Case Study Results

***Scenario 1***

Table 7 presents an overview of all iterations of Scenario 1 and their respective KPI coverage. The overall KPI coverage uses service areas for different cut off walking times per hub type (A=7min, B=6min, C=5min). The KPI coverage within 3 minutes always uses service areas with 3 minute cut off walking.

*Table 7: Case Study Munich - Overview Scenario 1*

| | **Scenario 1.0** | **Scenario 1.1** | **Scenario 1.2** | **Scenario 1.3** |
|---|---|---|---|---|
| **Characteristics** | | | | |
| A Hubs (7 min) | 30 | 30 | 30 | 30 |
| B Hubs (6 min) | 150 | 150 | 150 | 150 |
| C Hubs (5 min) | 220 | 320 | 420 | 520 |
| Total Hubs | 400 | 500 | 600 | 700 |
| **Overall KPI Coverage (A=7min, B=6min, C=5min)** | | | | |
| Inhabitants | 1377375 (85,2%) | 1480797 (91,6%) | 1530318 (94,7%) | 1558153 (96,4%) |
| Early Adopters | 365236 (86,5%) | 389836 (92,4%) | 401763 (95,2%) | 408343 (96,7) |
| Retail m2 | 1613007 (89,8%) | 1684718 (93,8%) | 1717494 (95,6%) | 1743345 (97,0%) |
| Shared Mobility Rentals | 1095771 (93,5%) | 1113854 (95,0%) | 1126011 (96,0%) | 1138849 (97,2%) |
| Private Cars | 450808 (79,6%) | 497617 (87,9%) | 518857 (91,6%) | 531876 (94,0%) |
| **KPI Coverage within 3 min (A,B,C=3min)** | | | | |
| Inhabitants | 756570 (46,8%) | 980054 (60,7%) | 1058501 (65,5%) | 1159532 (71,7%) |
| Early Adopters | 201969 (47,8%) | 259799 (61,5%) | 279444 (66,2%) | 305503 (72,4%) |
| Retail m2 | 1043008 (58,0%) | 1191815 (66,3%) | 1243135 (69,2%) | 1270295 (70,7%) |
| Shared Mobility Rentals | 669291 (57,1%) | 782373 (66,7%) | 814537 (69,5%) | 877430 (74,9%) |
| Private Cars | 241864 (42,7%) | 325426 (57,5%) | 355711 (62,8%) | 392622 (69,3%) |

Figure 45 and Figure 46 illustrate the increase in KPI coverage per iteration of Scenario 1 using a comparable scale. With these graphical representations, decision-makers are able to make data-based decisions for a target scenario, improving the understanding of a planned policy or infrastructure. Policy makers are supposed to make a decision for one of the four scenarios, or like in the case of Munich, adapt their strategy with the calculation of a new scenario. In this case, certain restrictions were changed and calculations were repeated to create Scenario 2.

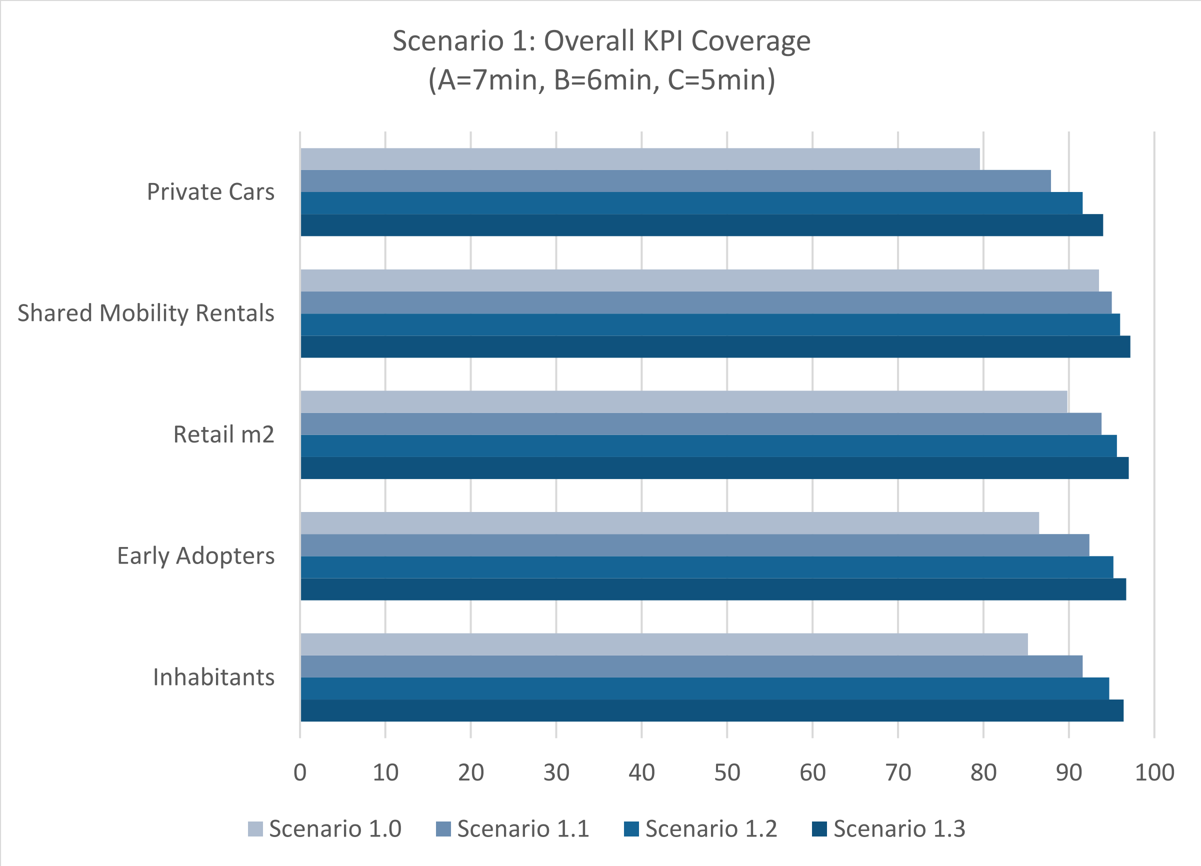


*Figure 45: Case Study Munich - Overall KPI coverage of Scenario 1*

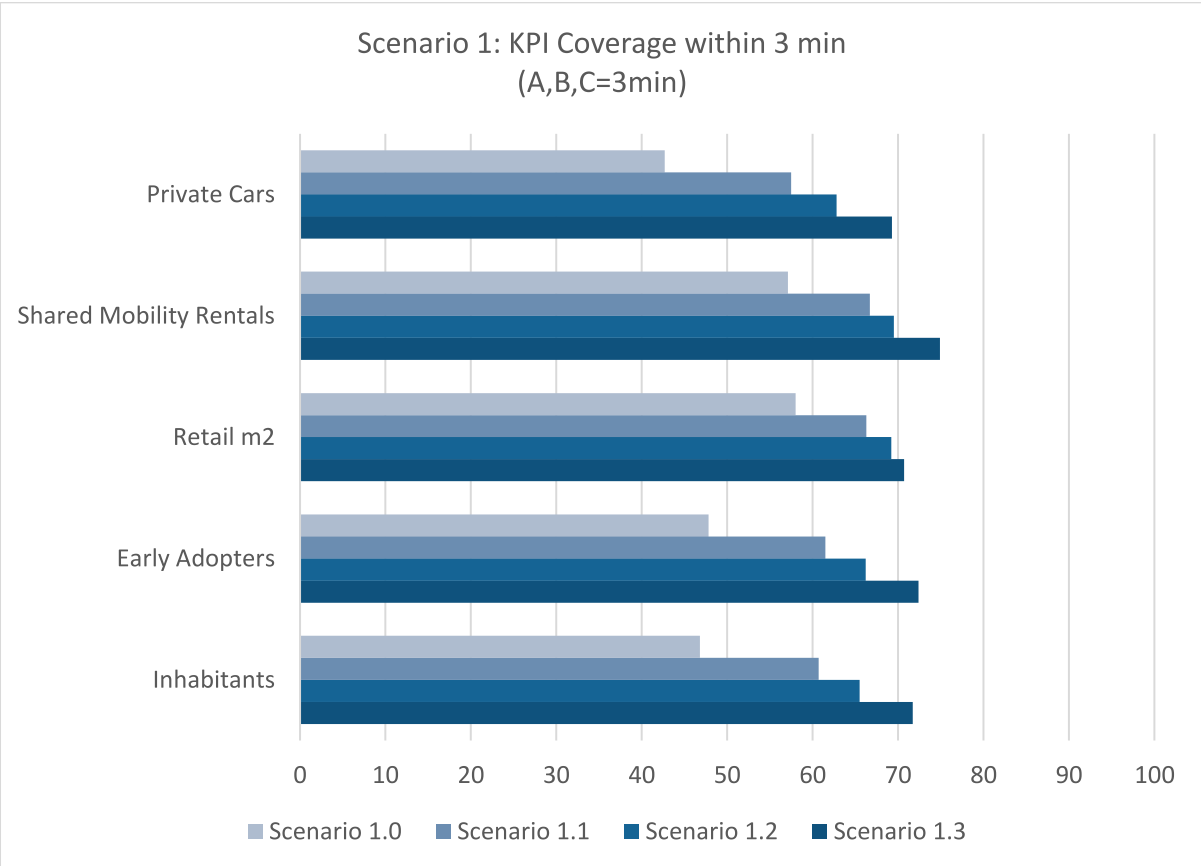


*Figure 46: Case Study Munich - KPI coverage within 3 min of Scenario 1*

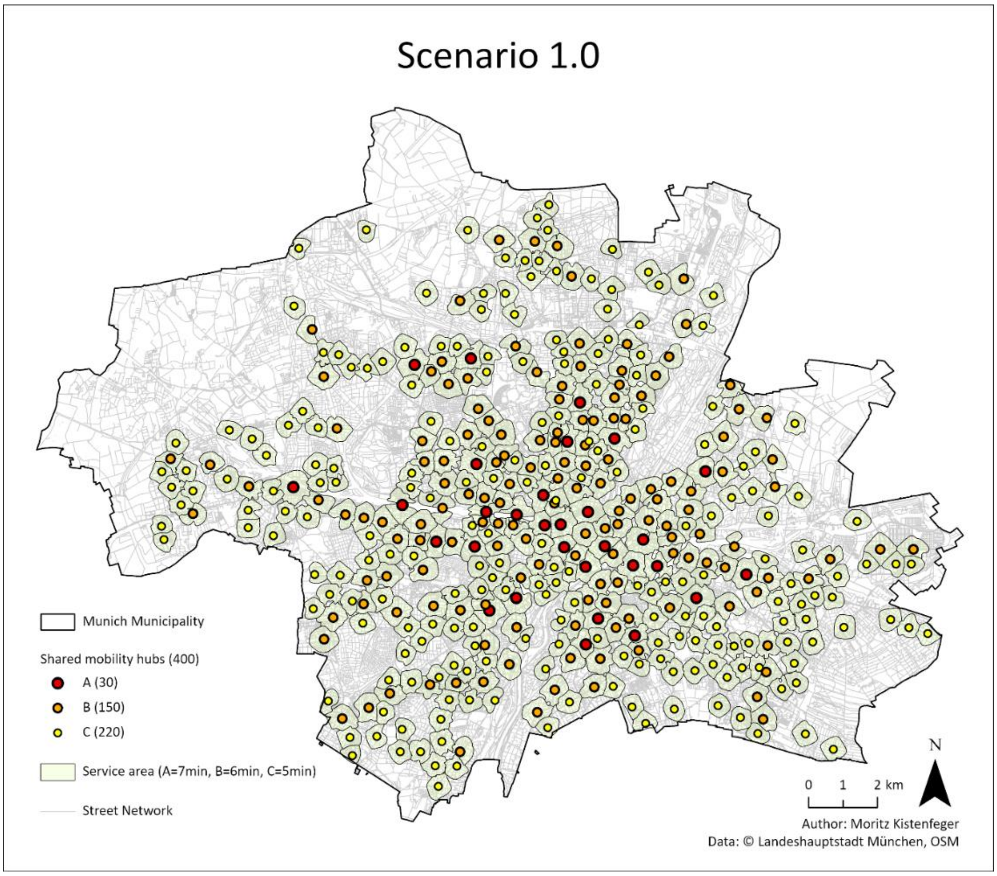


*Figure 47: Case Study Munich - Locations and service areas for Scenario 1.0*

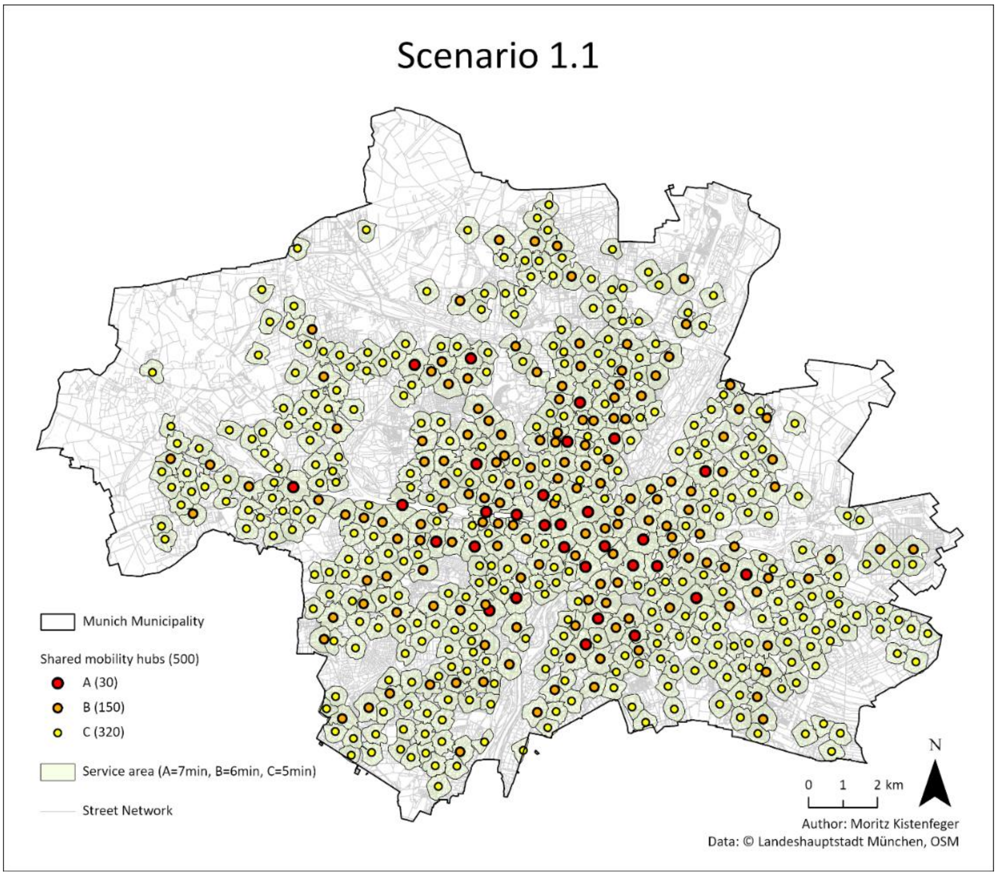


*Figure 48: Case Study Munich - Locations and service areas for Scenario 1.1*

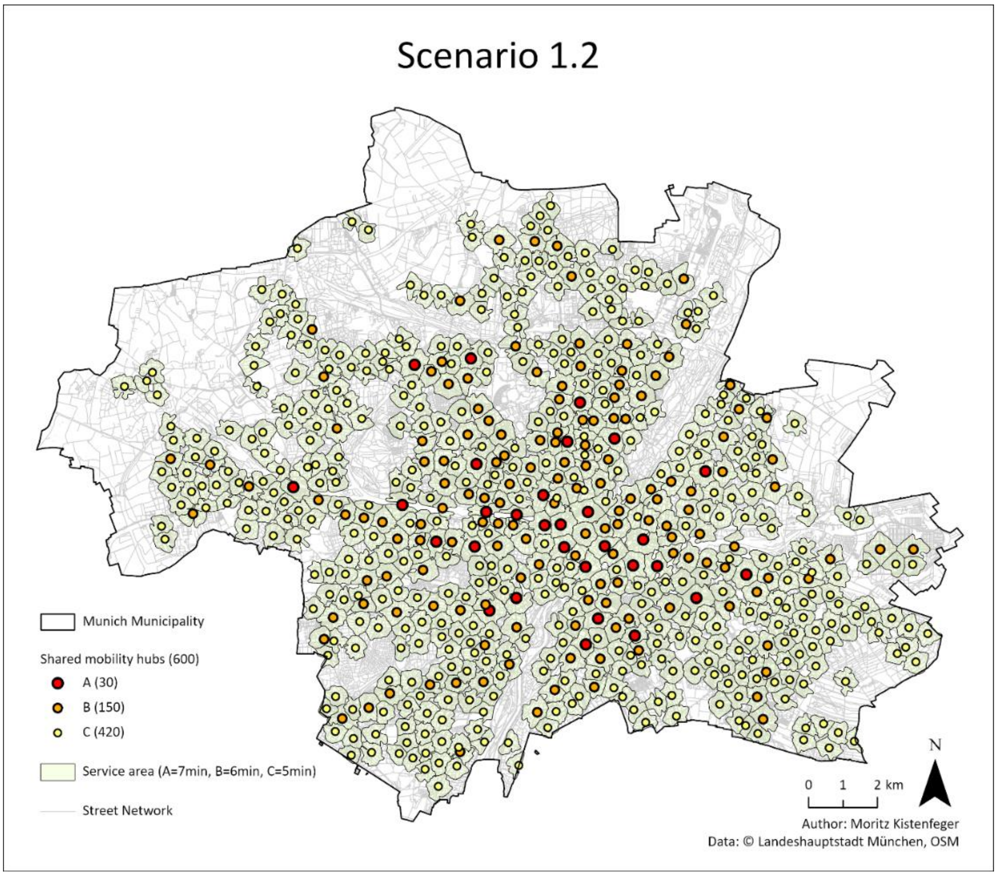


*Figure 49: Case Study Munich - Locations and service areas for Scenario 1.2*

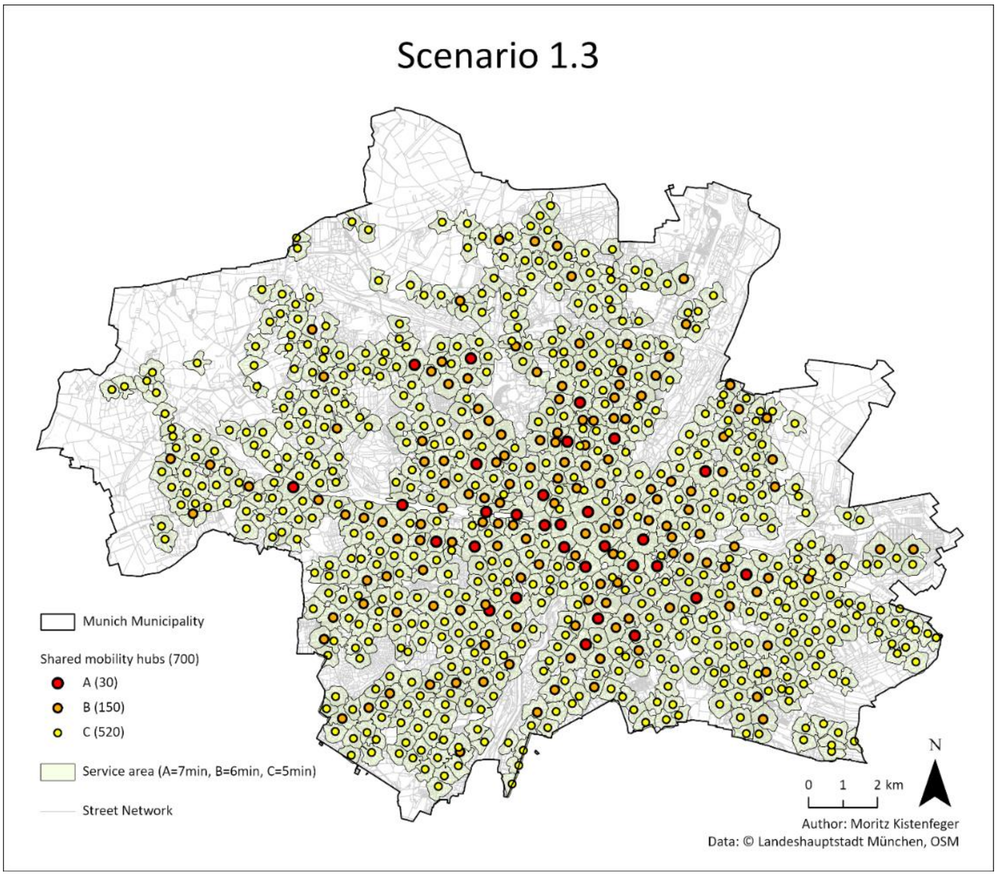


*Figure 50: Case Study Munich - Locations and service areas for Scenario 1.3*

Figure 47 - Figure 50 show the locations and service areas for each iteration of Scenario 1. When policy makers have decided for one scenario, these maps enable hub planners to assess with a single glance how many hubs are needed in a particular area. Furthermore, they can greatly speed up planning processes by focusing the planning resources on the suggested 700 rough locations, rather than considering every street in the city.

Figure 51 illustrates the coverage of the MCDA score by all service areas. The MCDA score for hub type C is chosen for the illustration, as for Scenario 1 the last sequential location allocation run with most hubs is based on this score. Overlaying the service areas with any other spatial variable will allow for a quick assessment if additional hubs are required to ensure coverage of the variable.

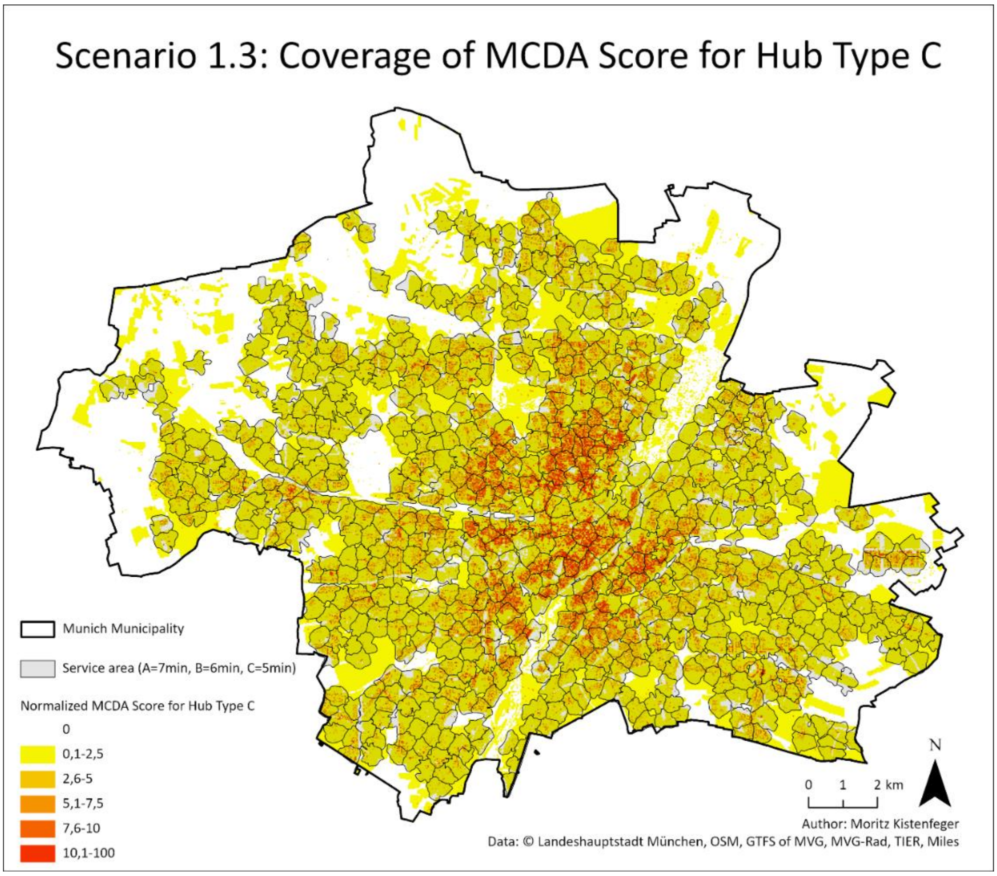


*Figure 51: Case Study Munich - Coverage of MCDA Score for Hub Type C for Scenario 1.3*

***Scenario 2***

In Scenario 2, hubs of type A are chosen manually due to the lack of data on passenger transfers per public transport station, resulting in 19 locations. The maximum walking time for the service areas of hubs type A, B and C was aligned to 5 minutes. And an additional Type D hub was introduced: Basic reserved parking for shared transportation is used to re-densify the hub network to provide improved accessibility to any of the four hub types A, B, C, and D within 3-minutes walking. Table 8 presents an overview of all iterations of Scenario 2 and their respective KPI coverage. The overall KPI coverage uses service areas for different cut off walking times per hub type (A,B,C=5min and D=3min). The KPI coverage within 3 minutes always uses service areas with 3 minutes cut off.

*Table 8: Case Study Munich - Overview Scenario 2*

| | **Scenario 2.0** | **Scenario 2.1** |
|---|---|---|
| **Characteristics** | | |
| A Hubs (5 min) | 19 | 19 |
| B Hubs (5 min) | 221 | 221 |
| C Hubs (5 min) | 360 | 360 |
| D Hubs (3min) | 0 | 1000 |
| Total locations | 600 | 1600 |
| **Overall KPI Coverage (A,B,C=5min; D=3min)** | | |
| Inhabitants | 1438458 (89,0%) | 1546657 (95,7%) |
| Early Adopters | 377702 (89,5%) | 402857 (95,5%) |
| Retail m2 | 1615666 (89,9%) | 1638455 (91,1%) |
| Shared Mobility Rentals | 1171629 (94,7%) | 1189993 (96,2%) |
| Private Cars | 484311 (85,5%) | 530616 (93,7%) |
| **KPI Coverage within 3 min (A,B,C,D=3min)** | | |
| Inhabitants | 1127418 (69,8%) | 1543394 (95,5%) |
| Early Adopters | 301422 (71,4%) | 402239 (95,3%) |
| Retail m2 | 1353667 (75,3%) | 1593280 (88,7%) |
| Shared Mobility Rentals | 996734 (80,6%) | 1166533 (94,3%) |
| Private Cars | 370094 (65,3%) | 529611 (93,5%) |

Figure 52 and Figure 53 illustrate the increase in KPI coverage per iteration of Scenario 2 using a comparable scale.

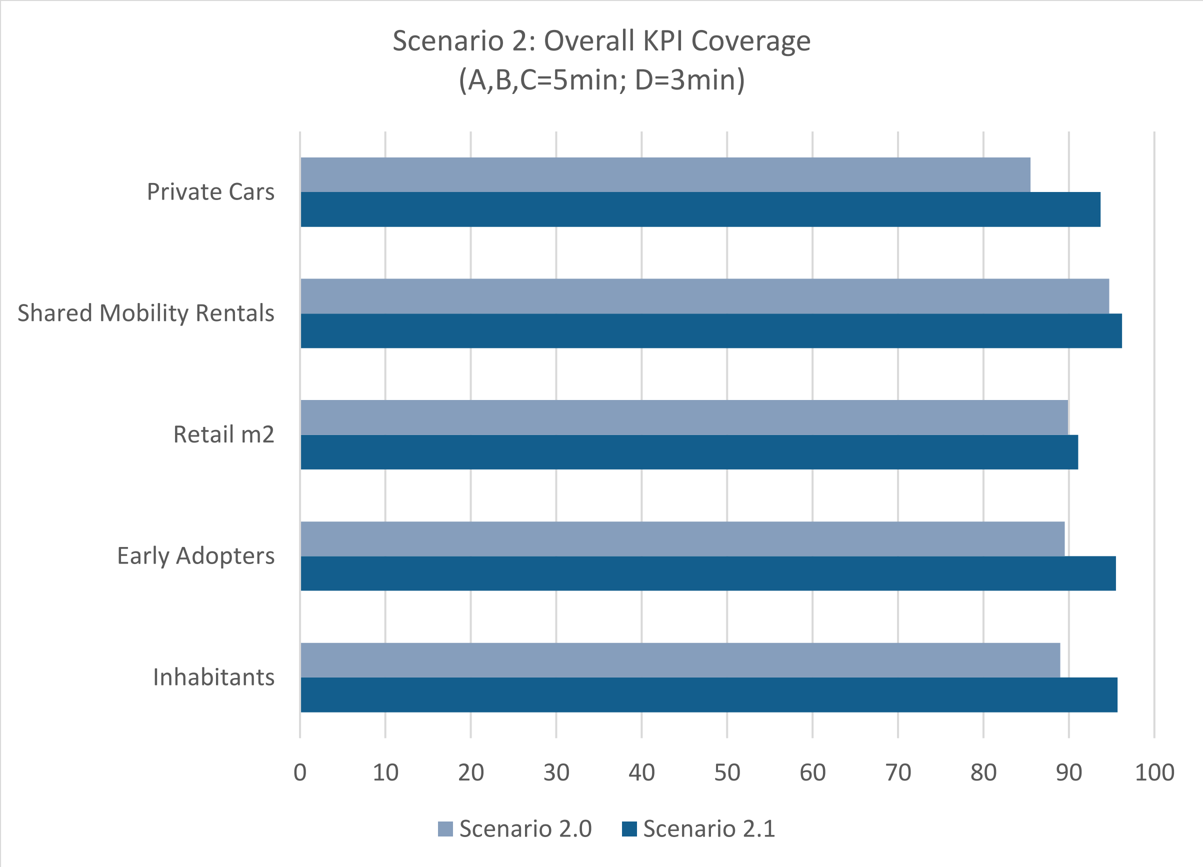


*Figure 52: Case Study Munich - Overall KPI coverage of Scenario 2*

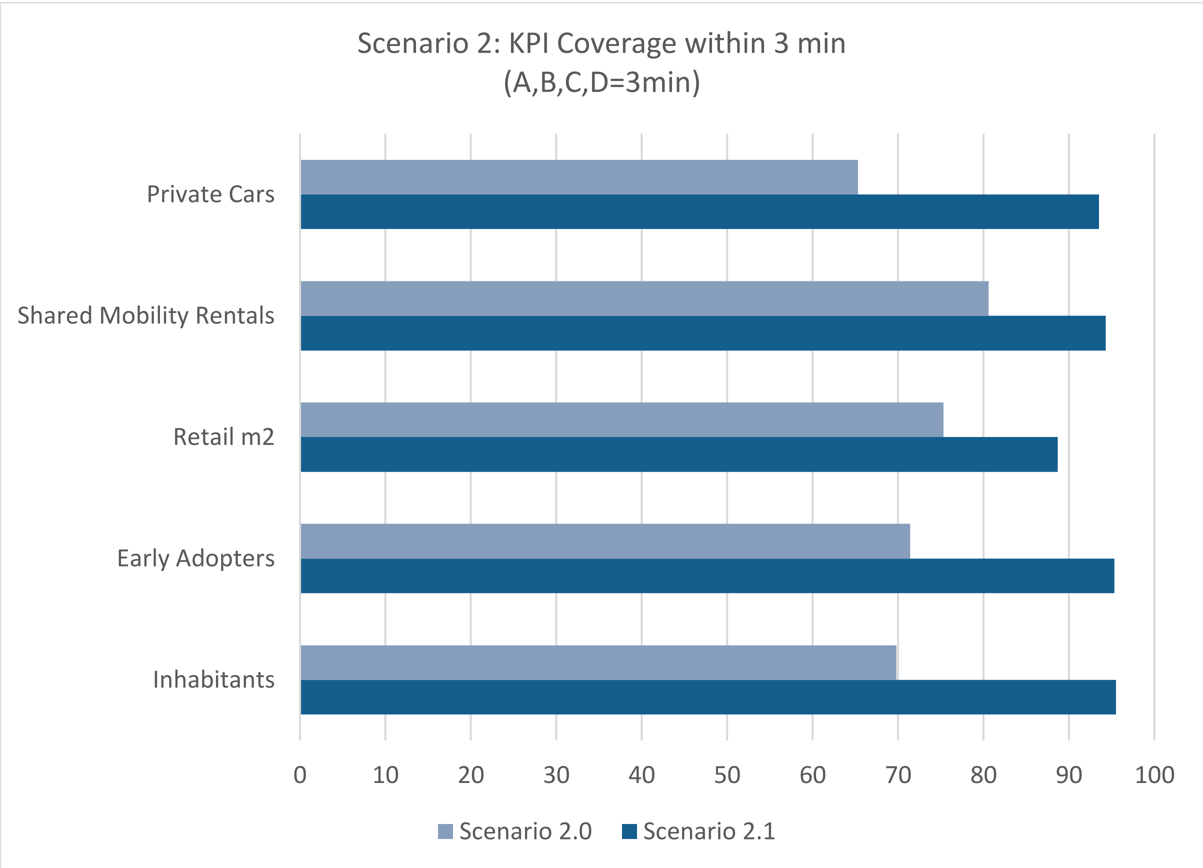


*Figure 53: Case Study Munich - KPI coverage within 3 min of Scenario 1*

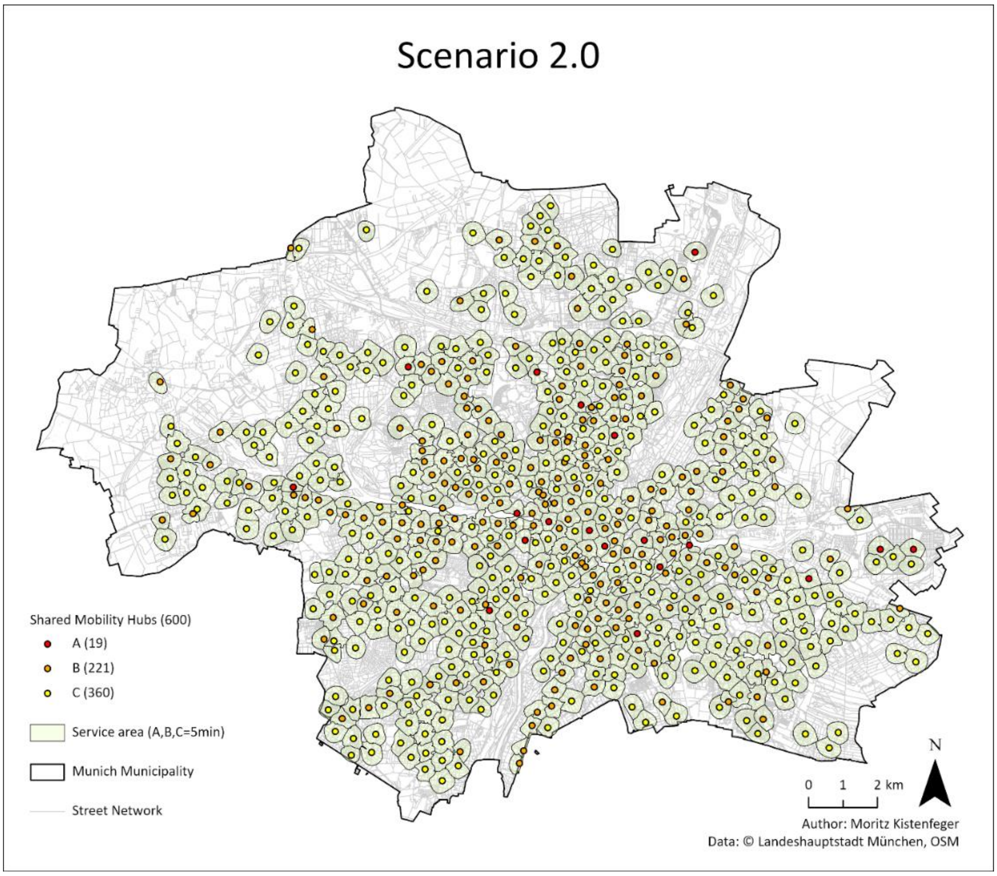


*Figure 54: Case Study Munich - Locations and service areas for Scenario 2.0*

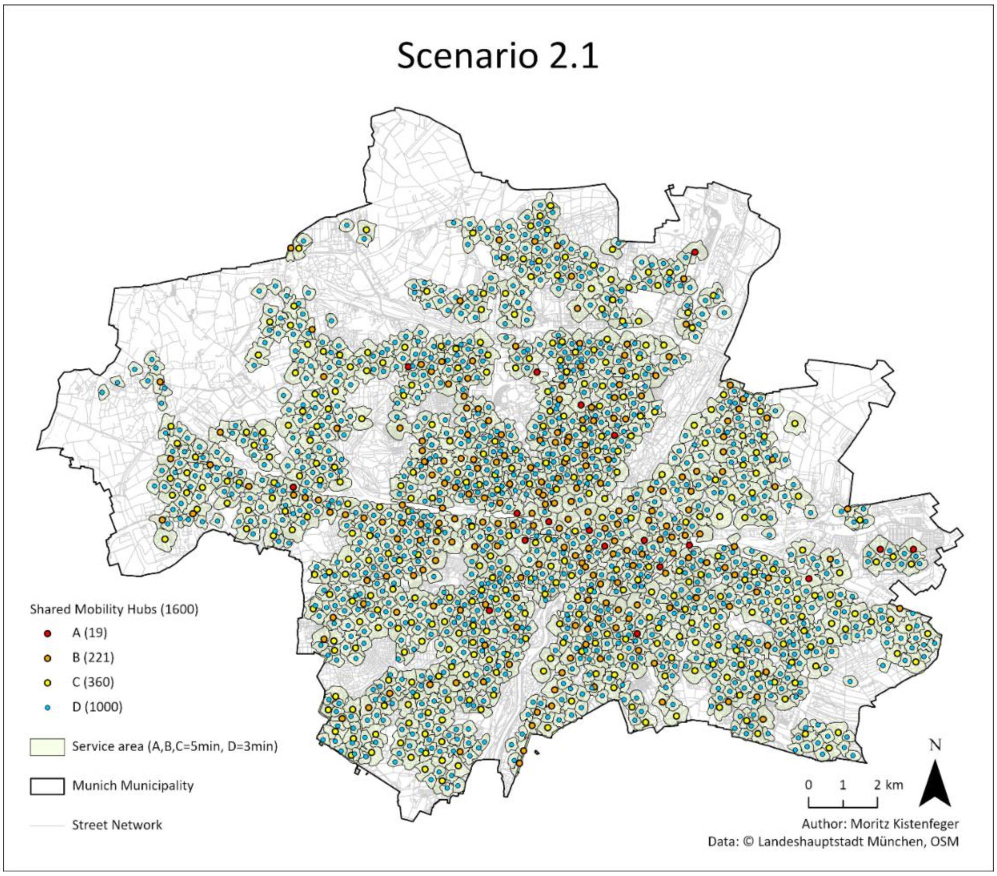


*Figure 55: Case Study Munich - Locations and service areas for Scenario 2.1*

Figure 54 and Figure 55 show the locations and service areas for each iteration of Scenario 2.

Figure 56 illustrates the coverage of the MCDA score by all service areas. The MCDA score for hub type D is chosen for the illustration, as in Scenario 2 the last sequential location allocation run with the largest number of hubs is based on this score.

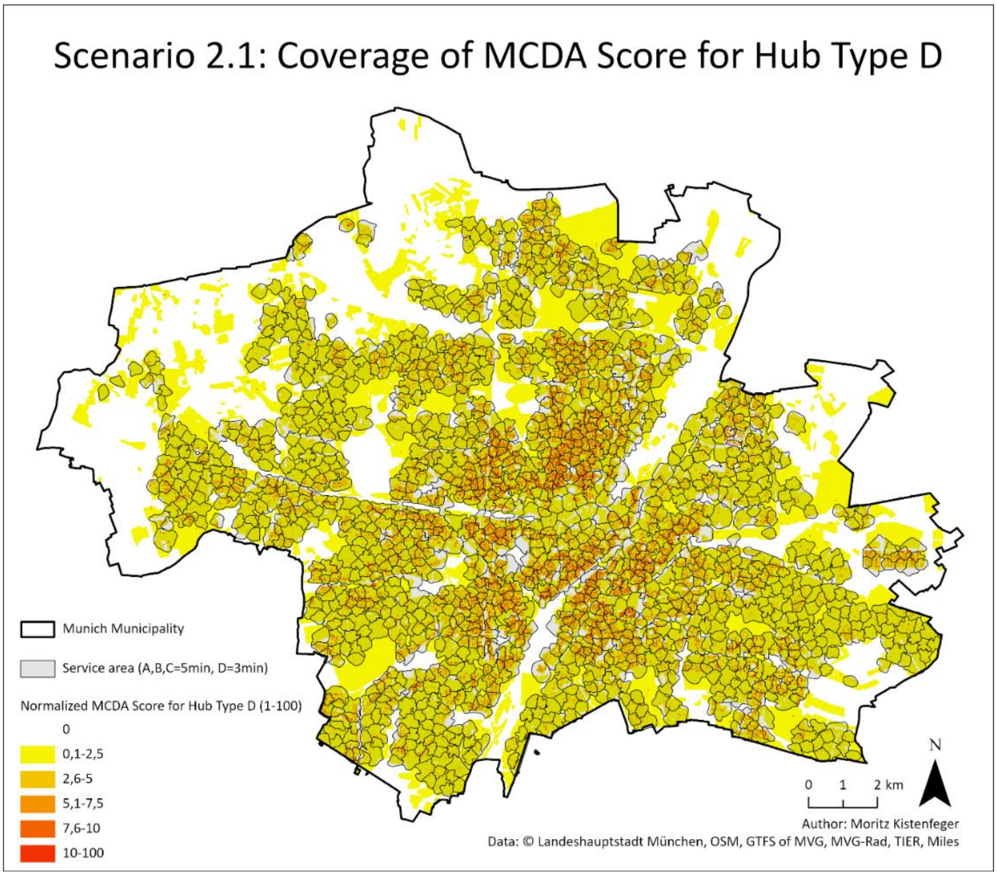


*Figure 56: Case Study Munich - Coverage of MCDA Score for Hub Type D for Scenario 2.1*

The final output of the method are individual service area statistics for each suggested hub location as shown in Table 9. Any variable can be queried in the table and compared on maps, for example, the number of retail m2 per service area shown in Figure 57. This enables fast and data-driven microplanning for each individual hub, including decisions on the size of each hub, the modes offered and the prioritization in the deployment of the hubs.

Detailed maps of areas where the author of the study has local knowledge, such as Figure 57, were also used to test the accuracy of the results. The results for Munich appeared consistent and logical. Undesired patterns, such as the occasionally very close proximity of stations, can be attributed to the highly restricted candidate sets for some hub types and the high concentration of demand in certain areas.

*Table 9: Case Study Munich - Summed indicators per service area for the Trudering neighborhood*

| | FacilityID | sMCS_D1 | Inhab | EaAdop | RetailM2 | PrivCar | POIs | ... |
|---|---|---|---|---|---|---|---|---|
| 1 | 254 | 2,251833 | 1552 | 370,608975 | 5876 | 677,818661 | 11 | |
| 2 | 252 | 2,022185 | 1433 | 323,323563 | 0 | 643,387002 | 0 | |
| 3 | 571 | 1,735311 | 1220 | 277,069237 | 0 | 586,008616 | 0 | |
| 4 | 586 | 1,674698 | 1116 | 339,832762 | 5570 | 402,173724 | 35 | |
| 5 | 574 | 1,627931 | 1114 | 285,537329 | 1548 | 532,601363 | 10 | |
| 6 | 580 | 1,451955 | 974 | 315,333784 | 2560 | 321,861016 | 10 | |
| 7 | 1520 | 1,386464 | 970 | 234,743636 | 245 | 436,270355 | 0 | |
| 8 | 13 | 1,326722 | 942 | 202,043015 | 750 | 427,718576 | 18 | |
| 9 | 1541 | 1,271131 | 935 | 182,113965 | 1160 | 324,564172 | 10 | |
| 10 | 1563 | 1,296282 | 910 | 228,334264 | 0 | 375,938327 | 2 | |
| 11 | 583 | 1,283069 | 874 | 223,434722 | 1985 | 418,357938 | 6 | |
| 12 | 257 | 1,232667 | 867 | 193,206477 | 0 | 426,186278 | 7 | |
| ⋮ | | | | | | | | |

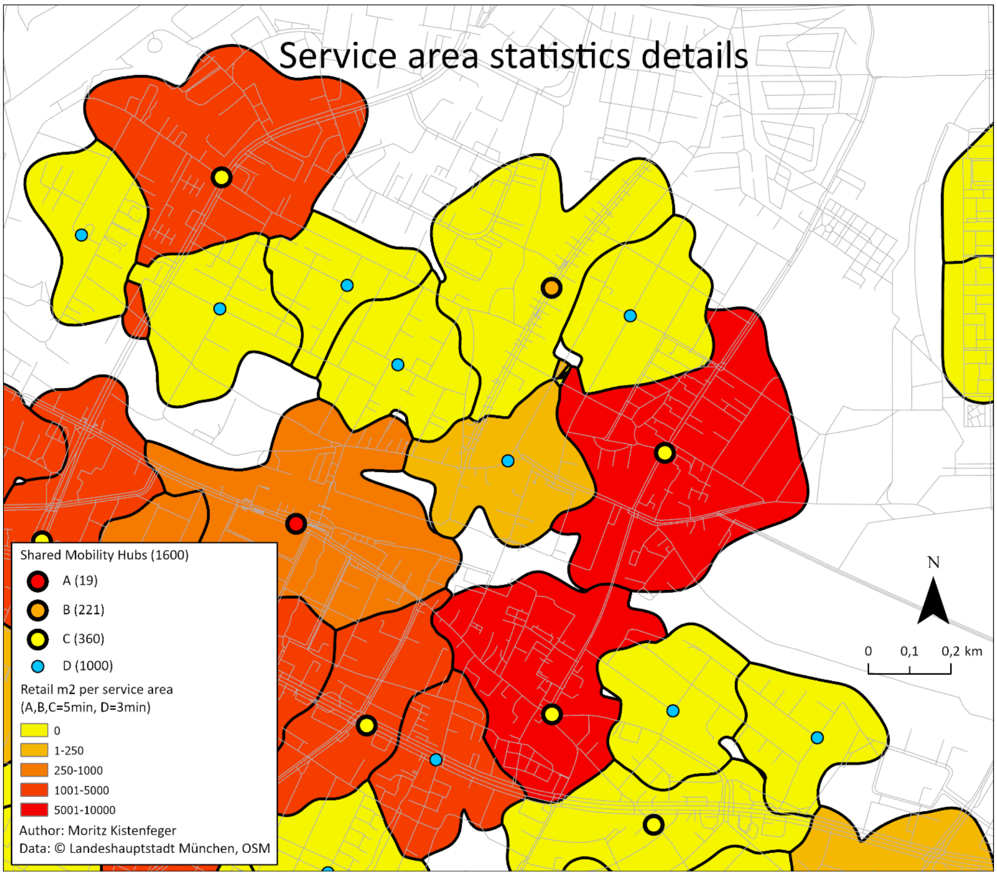

*Figure 57: Case Study Munich - Map based on statistics per service area for the Trudering neighborhood*

## 6.5. Case Study Validation

The results of the improved method were compared with manual hub planning. The mobility department of Munich has started to locate hubs based on manual analysis. In some areas, such as the city centre, hub planning is already under discussion with the local councils or even under implementation. The intermediary results of the manual planning are compared with the results of the location optimization method presented in this research. The proposed locations are shown as large circles to illustrate that they should be considered as rough indications of the hub location and that a manual micro planning is required to determine the exact hub location.

Figure 58 shows the city centre of Munich with a comparison of hubs located through manual analysis and hubs located through Scenario 2.0 of the improved method. The manually planned hubs are arranged in close proximity to each other around the city centre and its pedestrian zone. It is remarkable that the manually planned hubs are sometimes only in 200 m distance from each other. Perhaps the city planners were already aiming for a 3-minute walkability in the city centre during manual placement, which would explain why so many of the manually placed hubs are located so closely to each other. In the improved method, A hubs were manually selected by the city and were thus predefined. For B hubs, all public transport stations with rail-based public transport were considered as candidates and the selected hub locations form a ring around the city centre. For C hubs, all intersections with high human activity and car access were considered as candidates, which in the city centre includes the vast majority of intersections outside the pedestrian zone (see Figure 25). The selected C hubs locations supplement the ring around the city centre and also complete coverage within the ring. If targeting for a 5-minute walking accessibility, the 10 hub locations suggested by the improved method seem logical. The 13 manual placed locations do follow a similar pattern, but are positioned closer to each other. It can be concluded that the improved method is able to optimise the locations of the hubs with the aim of maximising coverage within 5 minutes walking time with as less hubs as possible. At the same time, it can be assumed that in the manual placement justified factors lead to several hubs being close to each other and that these factors are not sufficiently taken into account in the automatic method.

Figure 59 shows the city centre of Munich with a comparison of hubs located through manual analysis and hubs located through Scenario 2.1 of the improved method. A, B and C hubs are placed identically as in Scenario 2.0. The algorithm has placed around seven D hubs in the city centre to achieve a 3-minute walking accessibility. The distribution of manually placed hubs and automatically placed hubs is much more similar in Scenario 2.1, some D hubs are suggested precisely on the manually placed locations. This can be seen as a positive sign for the quality of site planning through the improved methodology.

For the example of the city centre, the improved method seems to optimise the hub locations in a satisfactory way according to the given restrictions. Finally, it must be emphasised that a newly proposed method such as this needs additional sensitivity analysis as well as further and more rigorous validation to assess reliability for future applications.

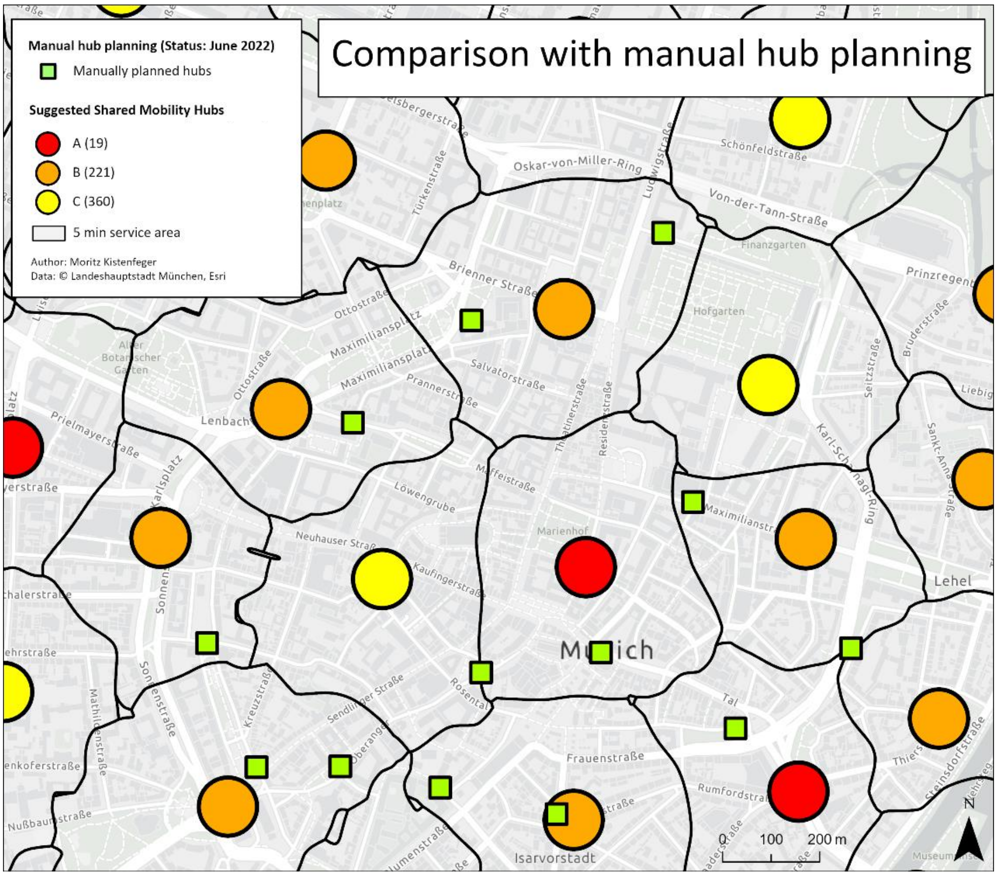


*Figure 58: Case Study Munich - Scenario 2.0 - Comparison with manual hub planning*

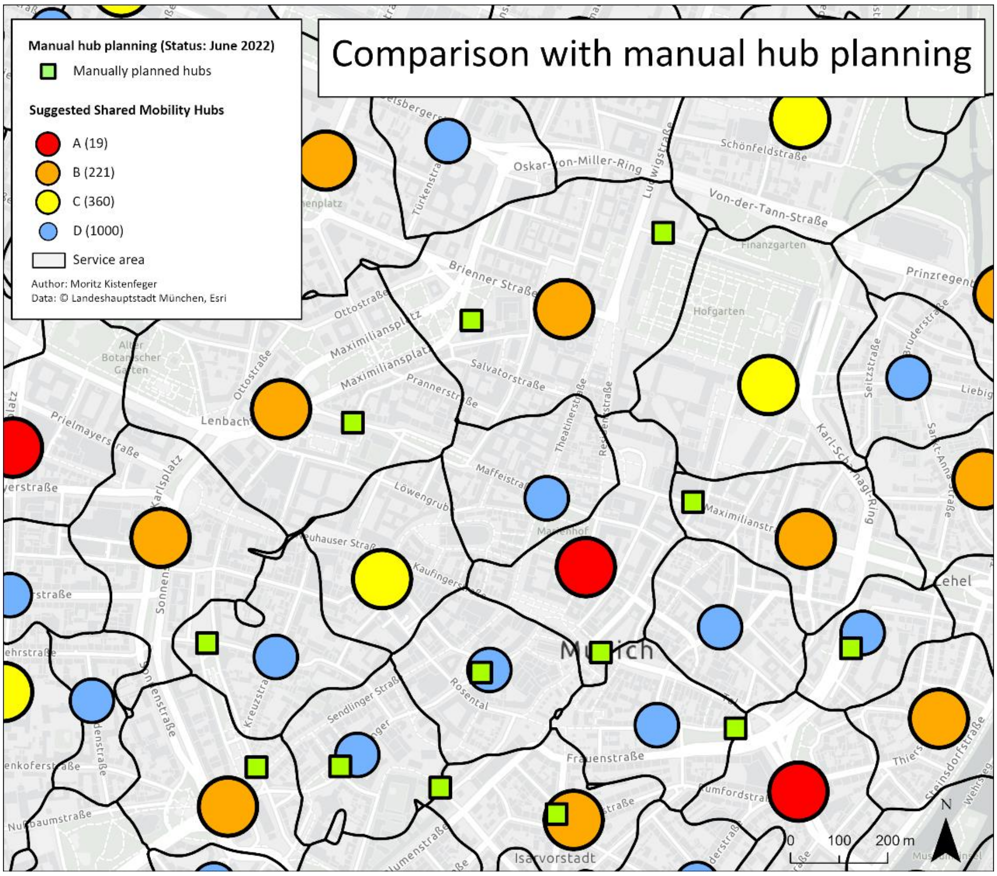


*Figure 59: Case Study Munich - Scenario 2.1 - Comparison with manual hub planning*

# Discussion of the improved method

# 7. Discussion of the improved method

## 7.1. Characteristics of the improved method

An improved location planning method for shared mobility hubs was presented in Chapter 5. A combination MCDA and Network Analysis is used to represent complex location planning problems. Different prioritizations at the decision-maker level can be translated into placement strategies through MCDA and, if necessary, multiple stakeholders can be involved through a MAMCA analysis. The resulting MCDA score for each spatial unit converts a multivariate into a single variable location optimization problem. In this way, single variable location optimization tools, such as ArcGIS location allocation, can compute specific location suggestions and their respective catchment areas. This also allows a comparison of different placement strategies based on city-wide KPIs.

Using exclusion criteria, which limit the set of location candidates, hubs can be placed very targeted, for example at public transport stations or places with a high level of human activity. This can be important to achieve a good integration of shared mobility hubs with public transport stations or increase visibility and safety of hubs by placing them at high activity locations.

The selection criteria relevant for choosing the locations are compiled into a MCDA score per grid cell. Various criteria area weighted in their importance using AHP, allowing a selection of the locations based on a single variable.

Since there are several hub types with different objectives, location optimization needs to be done according to the priorities and restrictions of each hub type. This might require different candidate locations and candidate selection strategies such as Maximize Coverage, Maximize Attendance or Maximize Impedance with different cut off values per hub type. This exceeded the standard functionality of e.g. the ArcGIS location allocation tool. Therefore, a sequential allocation approach was applied, where hub types with strong restrictions of the candidate set are placed first. These are usually also the most influential hub types, as the first hub types are expected to be strongly tied to existing transportation infrastructure, e.g. train station. In several steps, all other hub types follow according to their restrictions in candidate locations.

Different placement strategies can be compared through KPIs of the computed location suggestions. This promotes the refinement of the placement strategy and can thus improve the overall quality of the infrastructure rollout.

Once a satisfactory target scenario is created for the city to implement, all location suggestions and their individual catchment areas can be exported. By statistics on the catchment area of each individual hub location, the micro-planning of the hubs is strongly assisted and accelerated by data-driven processes. This allows to plan the size of the hub, the modes offered and also the prioritization in the implementation on the basis of data insights.
The improved method maximizes the city-wide coverage for given constraints and considers the competition of stations located close to each other. If initial constraints are changed, e.g. the number of hubs or already existing hubs, certain stations will change their location due to different

competition effects. Alternatively, one could repeatedly ask "Where should I place the next 100 hubs?" alongside the expansion, but a better optimization of locations is possible if an overall target scenario is calculated initially. In this way, the algorithm can place the stations with less restrictions and more efficiently. The overall target scenario not only accelerates location planning, but also supports the long-term strategic and financial planning of the expansion. In conclusion, the planning tool developed in this master thesis focuses on the calculation of the overall target scenario for a city-wide network of shared mobility hubs. This should enable decision-makers to steer the expansion of this new infrastructure according to their related objectives whilst decreasing the cost and duration of planning.

## 7.2. Case study application of the improved method

Even if only the city administration is involved, the location planning for shared mobility hubs is interwoven with various other infrastructures and comes with diverse, sometimes even conflicting, objectives. In principle, all variables are in competition with each other for the location planning, since the spatial distribution of most variables differs greatly. Location planning is further challenged by the contradicting objectives that the hubs should be strategically located near multi-modal travelers but also near car-centric travelers. The same applies to public transport, on the one hand the hubs should be closely integrated with existing public transport stations, on the other hand areas without public transport stations should be prioritized as well. These examples from Munich show that the location planning of shared mobility hubs is a complex, multi-variable dilemma.

In the case study of this research, the city of Munich is financing and implementing the shared mobility hubs. They aim to take a leading role in shaping and regulating the shared mobility ecosystem of the city, in line with their role as the responsible authority aiming for a more sustainable and efficient transportation system for the city. They have executed various pilots for shared mobility hubs in cooperation with many stakeholders and published an extensive shared mobility strategy. Therefore, this research assumes that city administrations which decide for a large-scale roll out of shared mobility hubs already went through extensive discussions with overall society, shared mobility operators and shared mobility users. When it comes to the actual location planning of shared mobility hubs, the departments of the city were then able to take into account the different perspectives in their decision making. This means, that government bodies are expected to consider the perspectives of different stakeholders in their decisions. This research therefore does not apply a MAMCA, but a MCDA with only the perspective of the mobility department of the city. This is also due to a limited time scope of this research and its focus on the extension of current approaches with network analysis methods. For future research, the benefits of a more extensive MAMCA could be explored.

For Munich, the hub types used in the policy documents were not clearly transferable into quantitatively exclusive definitions of hub types. Therefore, the typology had to be further refined in close exchange with city planners, which led to a classification of the hub types according to their respective aims.

In the Munich case study, this sequential location allocation approach for the location planning shared of mobility hubs started with a first placement of A and B nodes only along the main public transport lines. Then, areas not covered within 5 minutes were served by additional C hubs placed only at candidates defined as centres of human activity. Finally, the algorithm optimized the 3-minute accessibility with D hubs with a barely limited candidate set including locations in any street accessible by car.

The calculation of several scenarios leads to a better understanding of different placement strategies for the location planning for shared mobility hubs. Evaluating Scenario 1 based on city-wide KPIs led to an improved understanding of restrictions such as different cut-off values per hub, the general functionality of the method and the impact of local circumstances in Munich on the model. This resulted in an improved placement strategy for Scenario 2 by taking into account the lack of public transport passenger data through manual placement of A hubs and by aligning the walking time cut off for A, B and C hubs. Additionally, hub type D with a lower walking time cut off was included to increase the overall accessibility.

As a final output, the method provides a target scenario with rough location suggestions. These location suggestions are usually located at intersections and serve as a starting point for manual micro-planning. This means that a detailed micro-planning by a site planner is still required, including manual consideration of local circumstances and a more precise location selection in the area surrounding the rough location suggestions. For example, a good visibility of the location, sufficient car parking spots for a conversion and other potential factors are assessed manually via google street view and through site visits by the planner. The planner does not have to consider all the streets in a neighbourhood, but can concentrate on the suggested locations and the surrounding street space within a 100 m radius. This greatly reduces the location options and therefore manual analysis workload. In addition, the results of the service area analysis of each hub can be used in micro-planning to quickly estimate the prioritisation, offered modes and size of each hub.

Estimating the number of required hubs to achieve an accessibility within a certain walking distance seems to be a big challenge without such a methodology. In Munich, previous policy papers estimated the need of 1300 locations for a demand coverage within 5 minutes. With Scenario 2.0, around 90 % of demand can already be covered with 600 suggested locations. Such a drastic reduction in the number of required locations to achieve the goal of a policy has a strong impact on the budget and time planning for the rollout of this new infrastructure type.

Since the construction of such an infrastructure will take years in the best case and decades in the worst case, prioritisation of hubs within the infrastructure rollout is very important. The improved method enables demand-based prioritisation, for example when sites with a particularly high coverage of early adopters are implemented first. However, it is also possible to prioritise according to equity aspects: In scenario 2.1, if all 600 A, B and C hubs are implemented in a first construction phase, the vast majority of citizens, businesses, etc. are evenly supplied with a shared mobility hub within 5 minutes. In this way, an equity focused, city-wide system could be established within a few years and coverage could be ensured even in peripheral locations. Only in a second construction phase the 1000 D locations would be realised and the city-wide accessibility would be reduced to 3 minutes.

In principle, the creation of a long-term target scenario allows planners more freedom in prioritisation during the actual implementation. While all information for a data-based prioritisation is provided, the target scenario allows fast adaptions of the hub prioritisation due to political or other circumstances: Location suggestions and statistics of their service area coverage are already available for every area of the city. Data-based prioritisation is therefore always possible, but can be used in a flexible way by the implementing organisation. This flexibility in prioritisation was very relevant to the case study of Munich, as the mobility department has the general mandate from the city council to create a city-wide network of shared mobility hubs, but must coordinate the actual implementation with 25 local councils. Therefore, practical or political circumstances can easily lead to local delays and a static, city-wide implementation order calculated on the basis of data analysis is not realistic.

### 7.3. Benefits of the improved method

The improved method is able to extend the data-driven macro-level across most required steps for location planning of shared mobility hubs. As shown in Figure 60, only some steps are left for the manual micro-level, where the manual approach is beneficial to consider local circumstances and to enable the participation of local politicians and residents. As an automated location optimization is always based on simplifications of reality, the manual micro-level is also important for reviewing and adjusting the hub locations calculated in the automated macro-level.

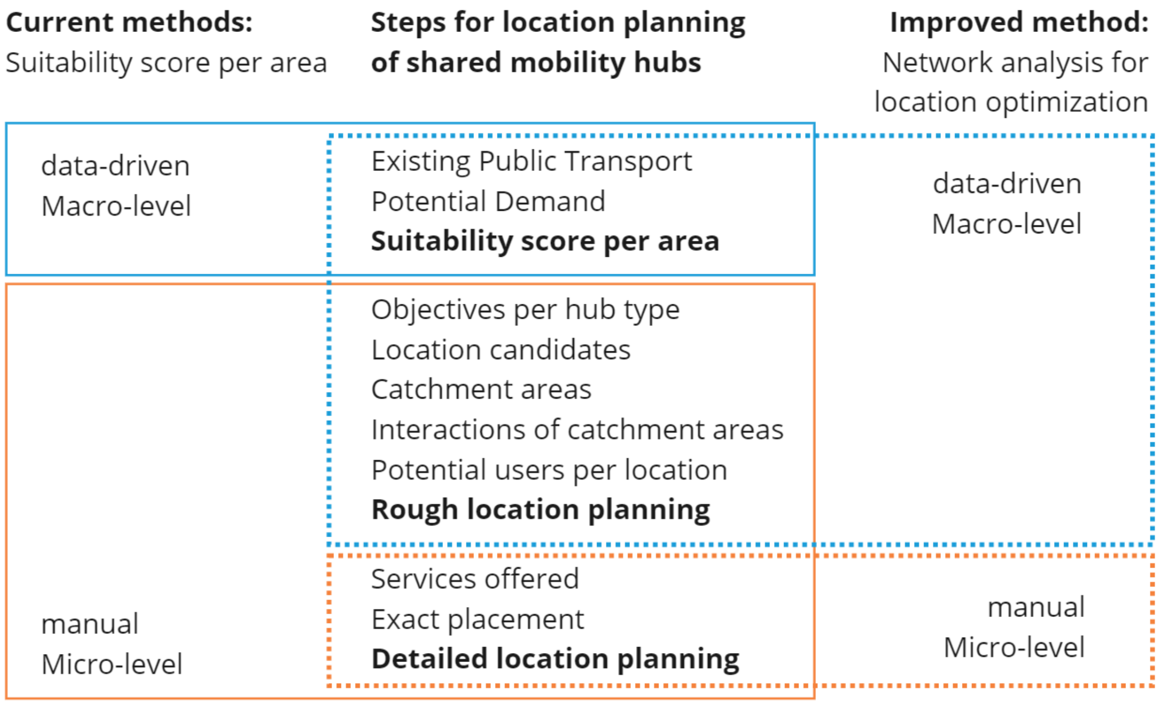


*Figure 60: Comparison of data-driven macro-level of current methods and the improved method*

The improved method minimizes the workload of the manual micro level enormously. This is achieved by four important benefits of the improved method:

**High spatial resolution of the analysis:** a 50m grid replaces the spatial analysis level of neighborhoods, traffic zones or low-resolution grids, to represent walking distances in single digit range accurately.

**Network analysis:** Catchment areas are represented by walking distances in the street network instead of Euclidean distance, since walking distances in real urban settings are strongly influenced by obstacles and street constellations.

**Automated location optimization:** The method calculates the optimal locations of a network of mobility stations instead of just showing the "suitability per area" in a heat map. The optimized location determination can consider different objectives, candidates and walking distances for each hub type. In addition, it can aim for maximized accessibility, so the hub should not only be accessible within a fixed maximum value (e.g. 5 min), but the algorithm places the hub as close as possible to the demand points with particularly high weight. This automated location optimization can reduce the required time and cost for location planning of shared mobility hubs immensely, by eliminating many and simplifying the remaining steps of the manual micro analysis. By focusing on the rough locations identified by the optimization algorithm, the workload of remaining manual steps can be reduced.

**Statistical results:** The concrete location of the hubs enables the calculation of further beneficial figures. A clear target vision with scenario KPIs (e.g. Scenario A results in city-wide hub accessibility within 3 minutes walking time for 63% of residents, 55% of retail m2, ...), thereby factualizing political and site-specific discussions. Statistics per hub catchment area (Hub 418 serves within 5 minutes 806 early adopters, 383 private cars, 430 individual households, 303 households with children, ...), thereby reducing the workload for the remaining steps of the manual microanalysis.

## 7.4. Limitations of the improved method

The method has very high requirements for data availability and data processing. Cities might not have access to criteria datasets at the required spatial resolution or lack experience in processing high-resolution spatial data. A very high spatial resolution of the input datasets to calculate the MCDA score per grid cell is a precondition for the integration of the network analysis, as it later serves as demand points for location optimization with the ArcGIS location allocation tool. This method is only useful if the spatial MCDA score is available with a very high spatial resolution, because the location planning of shared mobility hubs requires an optimization of catchment areas of very short walking distances. If the spatial MCDA score is not available in high spatial resolution, a network analysis based on the street network is not meaningful due to an error-prone assignment of the grid cell centroids within the road network.

In a city-wide location allocation, there is always a direct competition between the city centre and the outskirts for locations. An algorithm optimising for demand coverage will always first place hubs in high demand areas, and thus in the city centre. Only when these high demand areas are saturated the medium to low demand areas in peripheral areas are covered. This means that in a location optimization for a small number of hub locations (e.g. 100), most of the locations will be placed in the city centre. This is correct in the sense of the optimization algorithm, but does not correspond to the city's placement strategy. The city is rather aiming for an even distribution of hubs across the city area, also in the sense of equity aspects in infrastructure development. This challenge was addressed by using the methodology solely to calculate the target scenario. In this way, the algorithm can first place hubs in the city centre, before starting to cover medium to low demand areas in the peripheral areas.

For an infrastructure development of this size, such a long-term target scenario helps to have a clear vision during the implementation. The prioritisation of the hubs in the implementation can thus be answered in a data-driven way, for example the hubs with the largest number of early adopters in the catchment area, or can be adjusted to take into account local political circumstances.

ArcGIS location allocation only allows optimization according to one objective - in this study maximize coverage was applied. With the help of targeted restrictions of the candidate set and the sequential location allocation approach, further aspects of the strategic location planning for shared mobility hubs could be implemented in the model. However, no further restrictions can be incorporated with this approach, for example a minimum distance of 5 stops in the public transport network between two A hubs, to avoid a concentration in the city centre. Using the ArcGIS location allocation tool, the method can only optimise according to the walking time in the street network and one problem type. Other mathematical models allow for a multi-faceted constraint definition for optimization and can be further explored to improve the functionalities of the method.

Within this research, the Maximize Coverage problem type is applied for location optimization, which only allows for a linear distance decay function. For the case study in Munich, this choice was made due to the equity focused location planning objective to achieve a city-wide maximum walking time of 5 minutes to a hub. If the improved method is applied with different location planning objectives, for example from the perspective of profitability for an operator, the maximize attendance problem with an adapted distance decay function can be a powerful tool to place hubs e.g. in the hotspots of early adopters.

Since it can be assumed that changes will occur continuously in the course of the detailed planning and implementation of the shared mobility hubs over the years or even decades, it would be advantageous to provide the target scenario in an interactive software. For example, a simplified WebGIS application that displays the optimized location suggestions as a baseline scenario. Over the course of manual microplanning, hub locations are moved by a few intersections and it would be very beneficial to use a software solution that constantly adjusts the changing catchment areas and effects on the overall KPIs. In this way, the impact of manual changes and possibly the placement of additional nodes on coverage can be evaluated in a data-driven manner. This would enable data-driven decision-making of the location planners throughout the actual implementation period.

For this research, the processing of spatial data, especially with the integration of network analysis, is complex and difficult to automate as a whole. Furthermore, the model implementation will differ from city to city, as each city has individual circumstances, data availability and objectives for such an analysis. It can be assumed that such detailed and in-depth analyses will not be available as an automated software solution, but for larger cities rather an individual multi-month consultancy service is required. Alternatively, it might be possible to accept certain compromises for accuracy and quality of the method to achieve a simplified and generalizable method.

Data-driven location optimization techniques need to be well-explained, well-structured and transparent to be acceptable to decision-makers and the public. This condition is challenging because processing high-resolution spatial data in a method that integrates MCDA and network analysis is difficult to communicate to the general public. According to Malczewski & Ogryczak (1995), this requires the researcher to strongly communicate while working with decision-makers and various stakeholders, as this is the only way to convince them of the credibility and usefulness of the results of the analysis. Only then, the results produced by a data-driven location optimization technique may be accepted for implementation.

Malczewski & Ogryczak (1995) concluded at the time that many public sector location planning decisions are ill structured because of diverse or even conflicting stakeholder perspectives and difficulties in measuring and evaluating the impacts associated with alternative location decisions. While there have been major advances in digitalization and data-based decision-making methods in the past decades, also in today's public sector the execution of location planning decisions can still be untransparent, solely based on the personal judgment of planners and political agendas. This lack of consideration of transparent and data-driven methods in planning practice can be seen as a major challenge for the implementation of location planning tools, not only for Shared Mobility Hubs.

# Conclusion

# 8. Conclusion

To tackle challenges such as climate change, air pollution, traffic accidents and lack of space in cities, our urban transportation system must become sustainable, emission-free, safer and more efficient. The introduction of shared mobility is seen as an important ingredient to facilitate a mobility transition in large cities. With the introduction of Mobility-as-a-Service (MaaS) and a strong integration with existing public transport, shared mobility can promote multimodal travel behavior, leading to a reduced ownership and usage of the private car. This can contribute to less greenhouse gas emissions, less air pollution and less pressure on the traffic system as well as public spaces (ITF, 2017, 2021a, 2021b).

Shared mobility itself requires charging solutions, parking space in the existing urban fabric as well as digital and physical integration into existing transportation systems. These requirements should be jointly addressed within the concept of shared mobility hubs. Shared mobility hubs have been a concept explored in various pilots around the world. Recently, cities have moved from testing standalone shared mobility hubs to the scaling of these hubs to city-wide networks. Within Germany, multiple cities are planning to build hundreds of shared mobility hubs over the next few years and are challenged with the required location planning.

## 8.1. Main findings of research questions

To investigate the main research question "How can network analysis methods improve location planning of shared mobility hubs?", more detailed research questions (RQ 1-4) are introduced.

For RQ 1 "What methods are currently applied for location planning of shared mobility hubs?", a literature review is conducted. This has shown, that the existing literature on location finding of shared mobility hubs provides different typologies for shared mobility hubs, frameworks to categorize a large number of indicators as well as methods to weight indicators according to (multiple) stakeholders using AHP and MCDA. Most sources perform spatial analysis based on different datasets aggregated in polygons (raster cells or administrative areas) and Euclidean distance, leading to a shared mobility station suitability per area. Spatial analysis using network theories is less common and allows for the calculation of specific location suggestions for shared mobility hubs. Some studies calculate multiple placement strategies. Only studies that use a network analysis to calculate the catchment area can provide specific location proposals. This enables a comparison of different scenarios with performance metrics on the catchment area coverage. From the research on RQ 1, it can be concluded that many of the reviewed studies on location planning for shared mobility hubs have used spatial MCDA to account for the complexity of the location planning problem, but none of the reviewed studies that used network analysis techniques employed a prior MCDA. Spatial MCDA based on a high-resolution grid cell has a great potential to translate the location planning objectives for shared mobility hubs into quantitative input for network analysis. Network analysis allows for a suggestion of specific locations and a comparison of different scenarios based on performance metrics.

To answer RQ 2 "What network analysis techniques could be applied for location planning of shared mobility hubs?" another literature review is provided. The hub location problem (HLP) can be described as a new extension of classical facility location analysis. In general, facility location problems aim to determine the position of a set of facilities in a given location space, for example a network, to provide a service to actors within the location space. Integrating MCDA and network analysis for location planning by converting multiple criteria problems into single criterion problems is very beneficial, as many network analysis methods for facility location analysis accept only one demand criterion. Using this approach, the multi-criteria decision problems can be solved using single-criteria optimization techniques. This means that the wide range of algorithms, software, and experience that currently exist for single-criteria optimization can be directly applied to solving multi-criteria facility location problems. For this study, the ArcGIS location allocation solver is seen as the most suitable tool to perform a location optimization for shared mobility hubs based on network analysis. As the location allocation solver only optimizes according to one criterion, the possibility to apply a prior spatial MCDA to convert the multiple-criteria optimization problem into a single-criterion optimization problem is highly relevant to the suggested method.

For RQ 3 “How can network analysis techniques be integrated into an improved location planning method for shared mobility hubs?”, the previous findings of RQ 1 and RQ 2 were synthesized to design an improved location planning method. As a result, a combination MCDA and Network Analysis is used to represent complex location planning problems for shared mobility hubs. Different prioritizations at the decision-maker level can be translated into placement strategies through MCDA and, if necessary, multiple stakeholders can be involved through a MAMCA analysis. The resulting MCDA score for each spatial unit converts a multivariate into a single variable location optimization problem. In this way, single variable location optimization tools, such as ArcGIS location allocation, can compute specific location suggestions and their respective catchment areas. This also allows a comparison of different placement strategies based on city-wide KPIs. This enables decision-makers to compare different placement strategies in terms of potential impacts on their objectives and to accelerate micro-planning processes through a defined target scenario and data-based insights per hub location.

To answer RQ 4 “What are the results and learnings from applying the improved method to the Munich case study?” the improved method is implemented with the Mobility Department of Munich. It became clear, that even if only the city administration is involved, the location planning for shared mobility hubs is interwoven with various other infrastructures and comes with diverse, sometimes even conflicting, objectives. These examples from Munich show that the location planning of shared mobility hubs is a complex and multi-variable dilemma. For the case study, the mobility department was expected to consider the perspectives of different stakeholders of mobility hubs in their decisions. This research therefore did not apply a MAMCA, but a MCDA with only the perspective of the mobility department of the city. Within the method application, the calculation of several scenarios leads to a better understanding of different placement strategies for the location planning for shared mobility hubs. Evaluating Scenario 1 based on city-wide KPIs led to an improved understanding of restrictions such as different cut-off values per hub, the general functionality of the method and the impact of local circumstances in Munich on the model. This resulted in an improved placement strategy for Scenario 2. With Scenario 2.0, around 90 % of demand can already be covered with 600 suggested locations. In Munich, previous policy papers estimated the need of 1300 locations for a demand coverage within 5 minutes. Such a drastic reduction in the number of required locations to achieve the goal of a policy has a strong impact on the budget and time planning for the rollout of this new infrastructure type. The improved method was able to extend the data-driven macro-level across most required steps for location planning of shared mobility hubs in Munich. Only some steps are left for the manual micro-level, where the manual approach is beneficial to consider local circumstances and to enable the participation of local politicians and residents.

The main research question "How can network analysis methods improve location planning of shared mobility hubs?", was answered through the RQ 1-4, leading to the design and testing of an improved method using network analysis methods. By conducting the research along the Munich case study, the method has also proven its practical applicability.

## 8.2. Scientific and societal relevance

Research on the placement of shared mobility hubs often applies MCDA and results in heat maps that show the location suitability per area. The scientific relevance of this research lies in the extension of existing MCDA approaches with location optimization using network analysis and high-resolution spatial data. This leads to a better understanding of different placement strategies in location planning and of shared mobility hubs in general.

A major transformation of the transport system is one of the greatest metropolitan challenges of our time. Improved methods for locating large networks of mobility hubs are of high societal relevance as they could enhance the quality and speed of implementation of this new infrastructure type, whilst reducing planning cost. This could support cities in achieving their policy goals for shared mobility and mobility hubs, which have very high societal relevance: Improving public space, achieving a sustainable and liveable environment, reducing the usage and ownership of cars, as well as improving accessibility in cities.

## 8.3. Recommendations for future research

Existing research did not yet agree on a definition and typology of shared mobility hubs. This can be seen as a prerequisite for the development of generalizable tools for the location planning of a new infrastructure. Therefore, further research is required to better understand the different perspectives on shared mobility hubs and harmonize the definitions and typologies.

Within the case study, the spatial MCDA was only based on the input of one stakeholder, the city of Munich. As various stakeholders can be considered when planning locations of shared mobility hubs, a spatial MAMCA could translate different prioritizations into agreements on potential placement strategies and scenarios. Research of a more advanced or multi-actor analysis within the MCDA component of the improved method can increase the method's ability to mediate conflicting perspectives on this new infrastructure prior to its implementation.

Within the case study, the Maximize Coverage problem type of the ArcGIS location allocation tool was applied, which only allowed for a linear distance decay function. For the case study in Munich, this choice was made due to the equity focused location planning objective to achieve a city-wide maximum walking time of 5 minutes to a hub. If the improved method is applied with different location planning objectives, for example from the perspective of profitability for an operator, the maximize attendance problem with an adapted distance decay function can be a powerful tool to place hubs e.g. in the hotspots of early adopters. Research on the effect of the combination of a spatial MCDA with different network analysis approaches can lead to a refinement of the method to represent other placement objectives.

Whilst distance decay functions are well-researched for established facility types, e.g. public transport stations, there is no available research on distance decay functions for shared mobility hubs. In transportation planning, it is generally assumed that people are willing to walk longer to public transport stations for longer average trip distances, for example 400 m for bus stops and 800 m for subway stations. In the case of bike-sharing, the average trip distance is rather short and the maximum walking distance for access to bike-sharing stations should be lower than that for public transport stations. For shared modes with longer average trip distances, e.g. car-sharing, the maximum walking distance is expected to be higher. Following this reasoning, it can be assumed that the distance decay functions for shared mobility hubs will differ from the modes offered at the hub. If further research results in a better understanding of distance decay functions for different shared mobility modes and therefore shared mobility hubs, these insights can be used to improve location allocation models by using adapted distance decay functions.

## 8.4. Recommendations for policy makers

Larger transport projects require evaluation methods and science has already provided many different types of evaluation methods for this purpose. Therefore, it is recommended to perform location planning decisions for shared mobility hubs by using data-based decision-making methods which are transparent and consider the interests of all stakeholders.

The recommendation to use data-based decision-making methods is to be understood not only as a recommendation for the planning of shared mobility hubs, but for all important location planning decisions in the public sector. Consequently, numerous data-based decision-making methods in the public sector will face similar challenges as this research, namely obtaining high-resolution spatial data for e.g., a city. Improving the general accessibility of high-resolution spatial data can therefore have a positive impact on various location planning decisions in a city. This can be achieved through the creation or the further expansion of internal data sharing platforms or, in the best case, public open data platforms.

When choosing a data-based decision-making method for the location planning of shared mobility hubs, the short-time investment into an in-depth analysis such as automated location optimization methods using network analysis techniques could bring enormous long-term benefits. The implementation speed, cost efficiency and location quality for networks of shared mobility hubs are assumed to be substantially improved in comparison to current methods without location optimization.

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# Appendix

## Appendix A: Detailed review of network analysis tools

### Space Syntax

Space syntax is a theory and method for analyzing spatial relationships, especially for measuring configurational spatial relationships in the built environment. It can be described as a mathematical street network model for calculating topological spatial relationships. Space syntax was developed in the 1970s by Bill Hillier and colleagues at the Bartlett, University College London. The initial calculations were done by hand, and only later automated computations could extend the analysis to the street networks of entire cities (van Nes & Yamu, 2021). In general, space syntax aims to measure the build environment by the spaces or connection between objects rather than their physical shape. On one hand, spatial syntax measures the "to-movement potential" or the closeness of each street segment to all others. On the other hand, spatial syntax measures the "through-movement potential" or the betweenness of each street segment relative to all others. In this way, space syntax provides a set of tools to quantify connectivity, accessibility, walkability or socioeconomic activities in an urban area (van Nes & Yamu, 2021). According to scholars such as Jane Jacobs (Jacobs, 1961), these measurements are crucial indicators for creating vital and lively neighborhoods. Many space syntax measures can be calculated using the depthmapX software, which is also available via a QGIS plug-in (UCL, 2022). In the following, selected space syntax measurements are presented according to van Nes & Yamu (2021):

Global Integration Analysis: When performing such analysis, the selected radius is set to the total extent of the research area. The more integrated a street in a Global Integration Analysis is, the shorter is its topological distance to all other streets in the urban system. This analysis type normally indicates car-based distances and accessibility on a city-wide scale. Illustration (a) on the next page shows a global integration analysis of Oslo, indicating the inner and outer ring roads (van Nes & Yamu, 2021).

Local integration analysis: When performing such analysis, the selected radius is smaller than the global extent. A Local Integration Analysis calculates the average mean depth value of all streets within a certain syntactic radius, for example, a radius of three topological steps or a metric distance of 500m. This analysis type normally indicates walking distances and accessibility on the local scale. Illustration (b) on the next page shows a local integration analysis of Oslo, indicating the local centers of Oslo with pedestrian friendly and vital shopping streets (van Nes & Yamu, 2021).

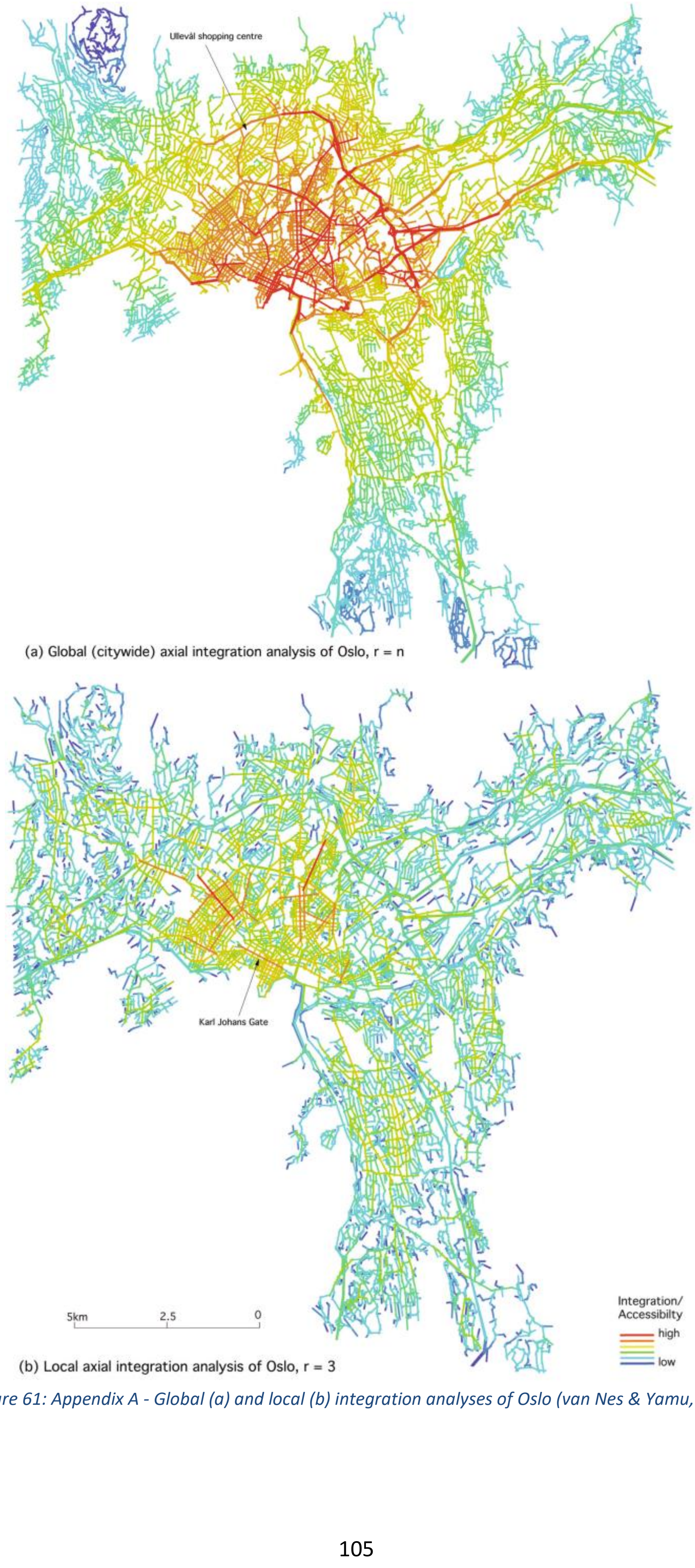


*Figure 61: Appendix A - Global (a) and local (b) integration analyses of Oslo (van Nes & Yamu, 2021)*

Angular Segment Analysis incorporates the assumption that human routing decisions aim to maintain both linearity in direction and minimum angles for turns. This way, the angular segment analysis computes the number of trips passing each street segment, considering all possible combinations of origin and destinations within a certain radius. For Angular Segment Analysis, the radius can be defined in a  topological, geometric, and metric way (van Nes & Yamu, 2021).

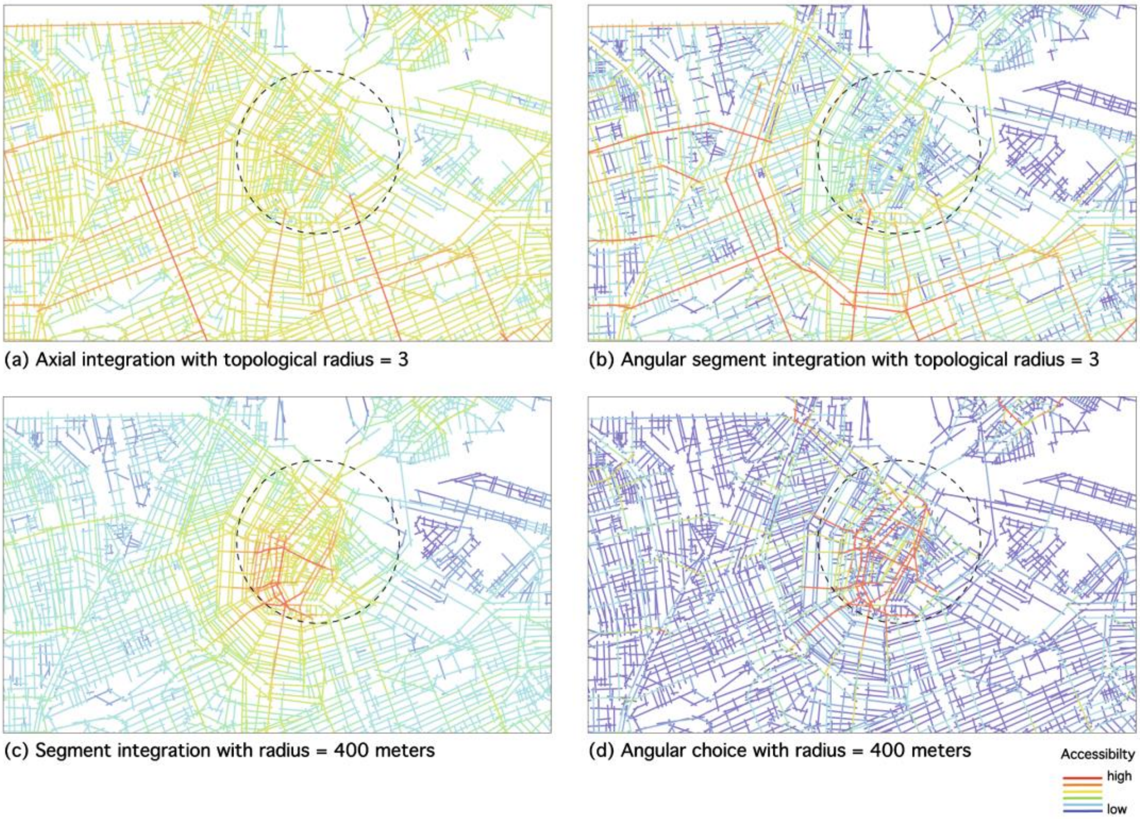


*Figure 62: Appendix A - Various local measurements of Amsterdam, with the location of the oldest center of Amsterdam around the old Berlage stock exchange indicated in the black circle (van Nes & Yamu, 2021)*

Above, an Angular Segment Analysis with the old Amsterdam city center (dotted circle) is shown. Image (c) displays the results of an angular integration analysis with a metric radius of 400 m. Image (d) displays the results of an angular choice analysis with a metric radius of 400 m. This shows that the pedestrian-friendly city center of Amsterdam was categorized accordingly using the angular segment analysis with metric radius. A metric distance of 400-800 m applies for pedestrian accessibility, while a distance of 5000-8000 m is suitable for centers for car accessibility (van Nes & Yamu, 2021, p. 64).

**UNA Toolbox**

The Urban Network Analysis (UNA) toolbox provides methods to describe the spatial patterns of cities using mathematical network analysis methods. The UNA toolbox computes graph analysis measures for spatial networks and extends existing network analysis methods to address a number of shortcomings, e.g. the use of only nodes and edges as network elements, as well as the importance of buildings to the understanding of the interaction of streets. It was released by the City Form Research

Group at MIT in 2011 and is aimed at researchers and practitioners concerned with the spatial configuration of cities (Sevtsuk & Mekonnen, 2012).

To better represent the built environment within a network, the UNA toolbox introduces 1) buildings as a new network element besides nodes and edges, 2) weighted representation of the network elements. This expands the possibilities of network analysis in urban areas, as the analysis can now be performed at the building level, which are interacting with each other via a street network. The analysis can include various characteristics of the urban space through the attributes of the individual buildings, which allow for weighting. If the focus is on the network itself, the tool can also, instead of buildings, use nodes in the road network as input. The UNA Toolbox is implemented as a freely available add-on to the ArcGIS software, requiring a license for the network analyst extension of ArcGIS (Sevtsuk & Mekonnen, 2012).

The UNA toolbox allows for the computation of the following relevant centrality metrics, which are defined based on Sevtsuk & Mekonnen (2012): Reach, Gravity Index, Betweenness and Closeness.

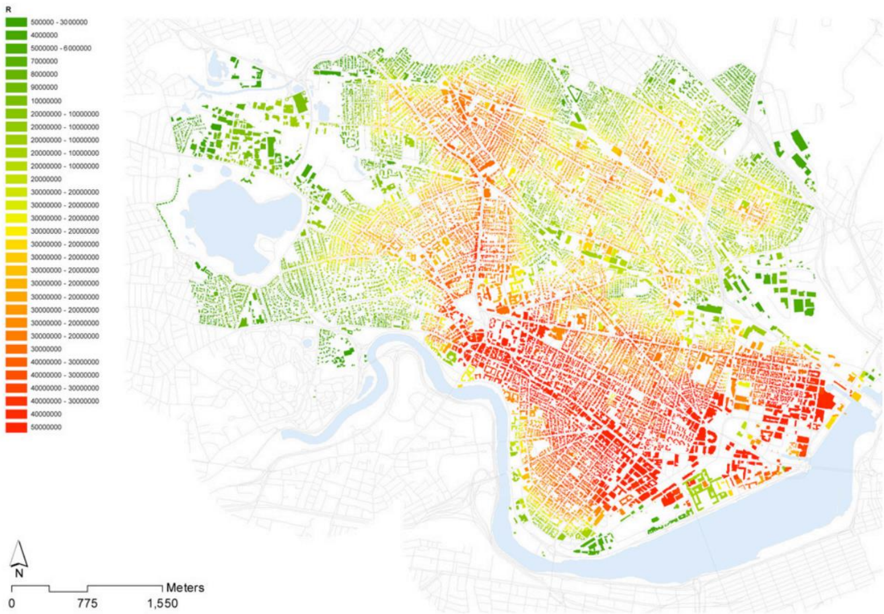


*Figure 63: Appendix A - Reach to build volume within a 600-meter network radius from each building in Cambridge & Somerville, MA (Sevtsuk & Mekonnen, 2012)*

The Reach measure (Sevtsuk, 2010) counts the number of buildings each building can reach within a certain search radius on the street network. The reach measure can also explore the access to any other destination type or include weights per building attribute.

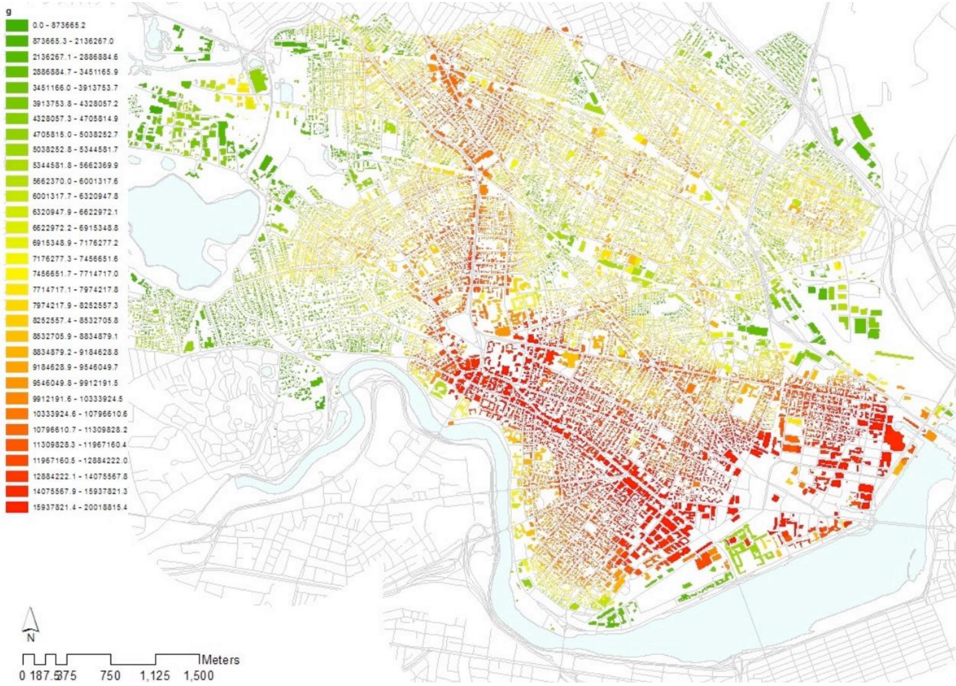


*Figure 64: Appendix A - Gravity Index measured to build volume within a 600-meter network radius from each building to every other building in Cambridge & Somerville, MA (Sevtsuk & Mekonnen, 2012)*

The Gravity measure (Hansen, 1959) also counts the number of buildings each building can reach within a certain search radius on the street network, but additionally considers the spatial impedance between the building and each destination.

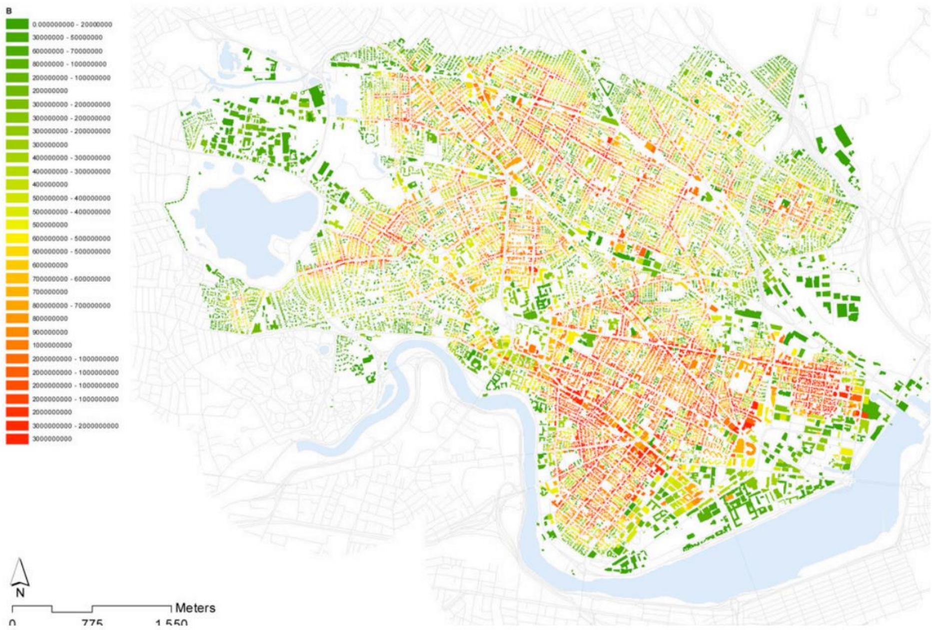


*Figure 65: Appendix A - Betweenness centrality in a 600-meter network radius, weighted by building volume in Cambridge & Somerville, MA (Sevtsuk & Mekonnen, 2012).*

The Betweenness measure (Freeman, 1977) describes the portion of the shortest paths between pairs of other buildings that pass by the particular building. It estimates the amount of passersby traffic for each building and the passerby traffic can also be weighted with e.g. demographic attributes.

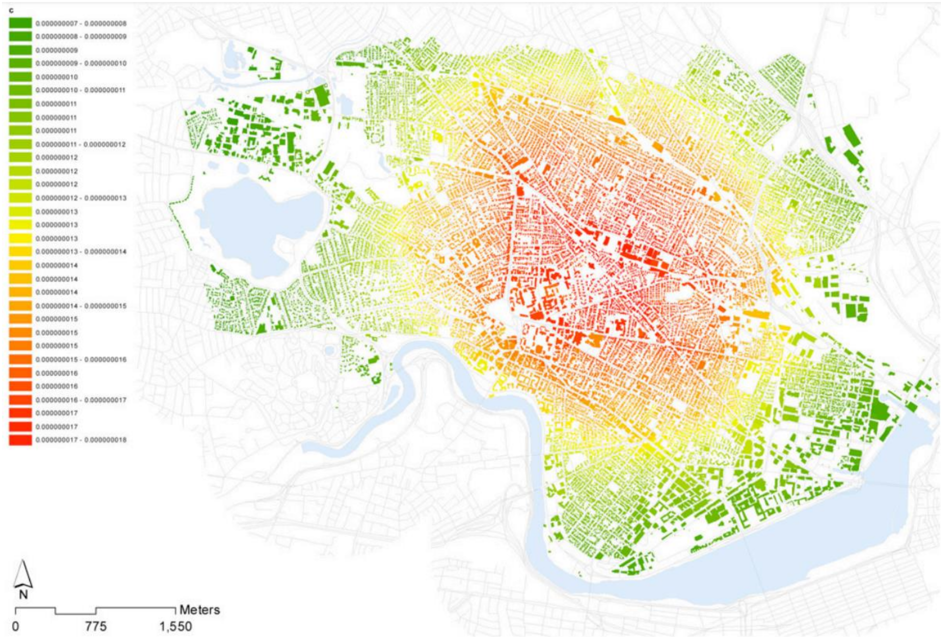


*Figure 66: Appendix A - Closeness centrality to surrounding buildings with no limiting radius and no weights in Cambridge & Somerville, MA (Sevtsuk & Mekonnen, 2012)*

The Closeness measure (Sabidussi, 1966) indicates how close a building is to all other surrounding buildings within a given distance threshold. It is defined as the inverse of cumulative distance required to reach from that building to all other buildings with the shortest paths within the Search Radius.

**QGIS Network Analysis**

QGIS is a free and open source GIS software, which is developed by a volunteer community. In the processing menu of QGIS, two network analysis algorithms are offered: The Service Area algorithm returns only the part of a network which can be reached within a set cost, e.g. time or distance, from a starting point. The Shortest Path algorithm computes the shortest or fastest route from one or multiple start locations to another end location (QGIS, 2022). There are Plug-ins, which allow computation of further measures, e.g. an Origin-Destination-Matrix (Raffler, 2018). Currently, there is no algorithm available in QGIS to optimize facility locations in a network based on weighted demand points, travel time or competition effects (Open Door Logistics, 2019).

**ArcGIS Network Analyst**

ArcGIS Pro is a GIS software, which requires licensing from esri (esri, 2022b). It offers a network analysis extension. The network analysis extension allows importing network datasets, transforming them into an ArcGIS network analysis layer, which is the basis to run different solvers. The network analysis extension has multiple functionalities relevant to this research:

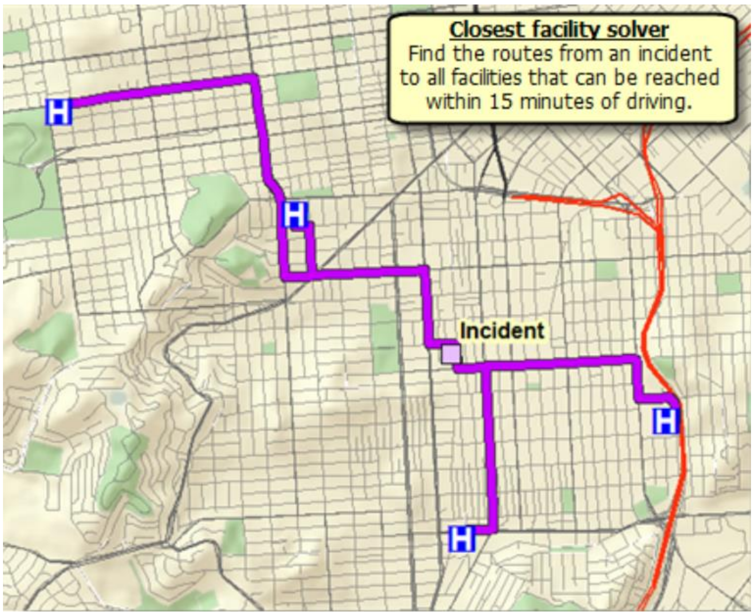

*Figure 67: Appendix A - Closest Facility Solver (esri, 2022b)*

The closest facility solver calculates the travel costs between a set of incidents and facilities. A threshold defines the maximum travel cost in time or distance. The results include the best route from a facility to an incident and the associated travel costs (esri, 2022b).

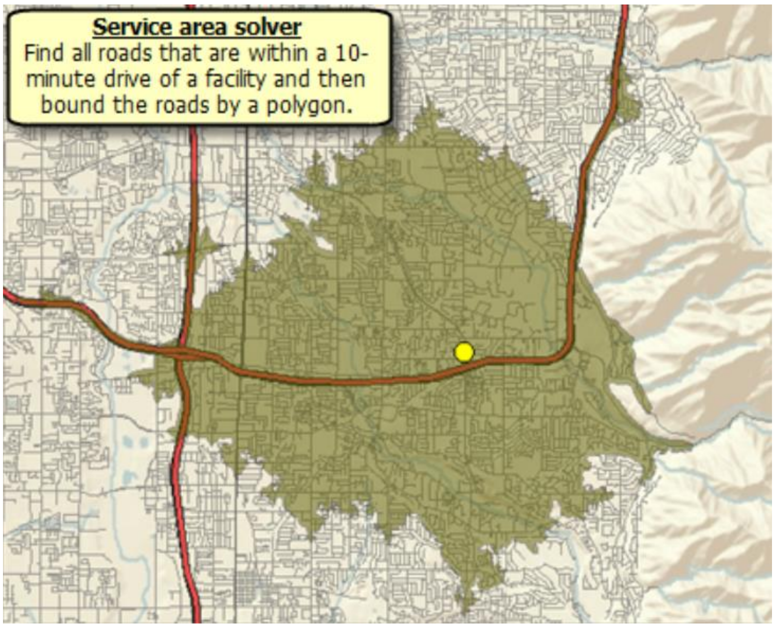

*Figure 68: Appendix A - Service Area Solver (esri, 2022b)*

The service area solver computes the area which can be reached from a set of facilities via a street network within a certain impedance value. Impedance is defined as time or distance and can be adapted for each facility individually. The tool allows calculations of overlapping or non-overlapping service areas of competing facilities. The results include the individual service area for each facility (esri, 2022b).

*Figure 69: Appendix A - Location Allocation Solver (esri, 2022b)*

The location allocation solver chooses locations from a set of location candidates based on the potential interactions of each location with demand points. The location allocation problem is a combinatorial optimization problem, which means that the number of possible solutions increases rapidly with the number of candidate and demand points, leading to very high computational effort. To reduce the computational effort and achieve reasonable search times, the network assignment tool applies heuristics (esri, 2022a)..

The location allocation solver can select locations with different objectives to solve different types of problems. The following problem types could be relevant for this research:

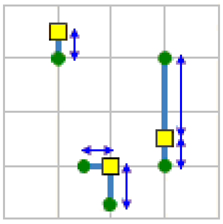

*Figure 70: Appendix A - Minimize Impedance chooses facilities such that the sum of weighted impedances (demand allocated to a facility multiplied by the impedance to the facility) is minimized (esri, 2022a).*

Minimize Impedance problem type - Facilities are located such that the sum of all weighted costs between demand points and solution facilities is minimized. The allocation is based on distance among all demand points for a facility (esri, 2022a).

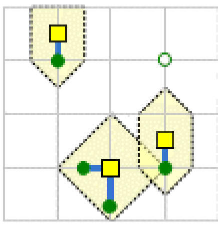

*Figure 71: Appendix A - Maximize Coverage chooses facilities such that as much demand as possible is covered by the impedance cutoff of facilities. In this graphic, the solver was directed to choose three facilities (esri, 2022a)*

Maximize Coverage problem type - Facilities are located such that as many demand points as possible are allocated to solution facilities within the impedance cutoff (esri, 2022a).

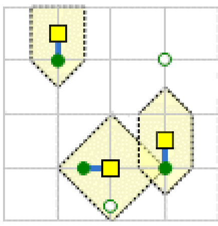

*Figure 72: Appendix A - Maximize Capacitated Coverage chooses facilities such that all or the greatest amount of demand can be served without exceeding the capacity of any facility (esri, 2022a)*

Maximize Capacitated Coverage problem type - Facilities are located such that as many demand points as possible are allocated to solution facilities within the impedance cutoff; additionally, the weighted demand allocated to a facility can't exceed the facility's capacity (esri, 2022a).

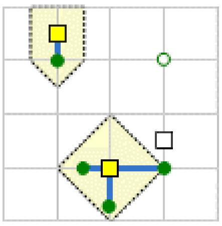

*Figure 73: Appendix A - Maximize Coverage and Minimize Facilities problem type chooses facilities such that as many demand points as possible are within the impedance cutoff of facilities. Additionally, the number of facilities required to cover all demand points is minimized. In this graphic, the solver was able to cover all demand points with only two facilities. (esri, 2022a).*

Maximize Coverage and Minimize Facilities problem type problem type - Facilities are located such that as many demand points as possible are allocated to solution facilities within the impedance cutoff; additionally, the number of facilities required to cover demand points is minimized (esri, 2022a).

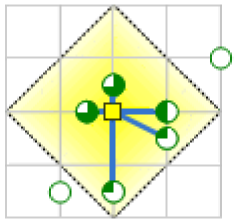

*Figure 74: Appendix A - Maximize Attendance chooses facilities such that as much demand weight as possible is allocated to facilities while assuming the demand weight decreases with distance. The demand points, represented by pie charts in this graphic, show how much of their total demand is captured by the facility (esri, 2022a).*

Maximize Attendance problem type - Facilities are chosen such that as much demand weight as possible is allocated to facilities while assuming the demand weight decreases in relation to the distance between the facility and the demand point. Therefore, the tool provides an impedance transformation, which allows manipulating the effect of the distance between the facility and the demand point on the respective demand point weight allocation. The impedance transformation determines the equation for transforming the network cost between facilities and demand points, thereby calibrating how severely the network impedance between facilities and demand points influences the solver's choice of facilities (esri, 2022a).

The approach of the "Maximize Attendance" problem type in ArcGIS is described in theory as a distance decay function. As demand for services declines with distance, which means that locating facilities as close as possible to potential demand is an important consideration to maximize the served demand (Farhan & Murray, 2006). Within ArcGIS, the distance decay function can be included as linear, power or exponential function. If a five-minute impedance cutoff and a linear impedance transformation is selected, the probability of visiting a store decays at 20 percent per minute. Therefore, a store within 1 minute walking distance of a demand point has an 80 percent visit probability and a store four minutes away only has a 20 percent visit probability (esri, 2019). Using power or exponential functions, the decay function can be adapted to existing knowledge of user travel behavior of the investigated facility type. The graph below is an example from the RATP, the public transport operator of Paris, for the use of distance decay functions for location planning of public transport stations (Manout et al., 2018).

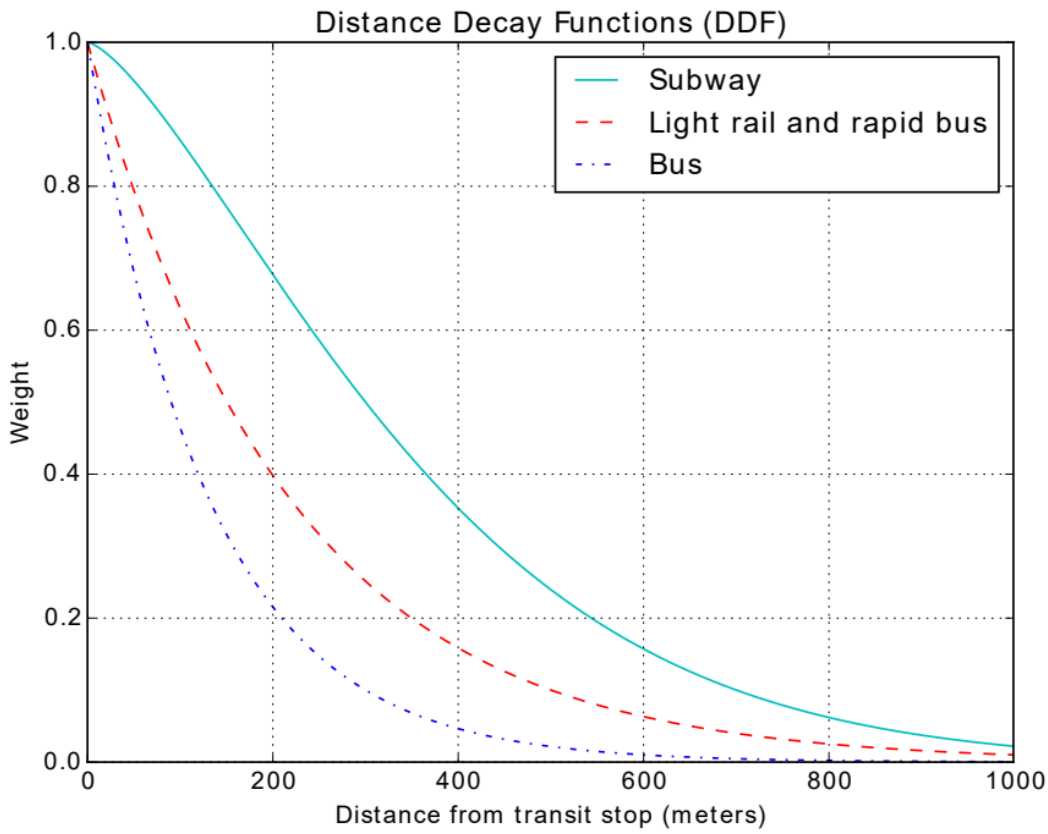


*Figure 75: Appendix A - Distance decay functions by transit mode from RATP data (Manout et al., 2018)*

Whilst this knowledge on distance decay exists for established facility types, e.g. public transport stations, there is no available research on distance decay functions of for shared mobility hubs. For shared mobility hubs, distance decay functions can currently only be roughly estimated and in the longer term the modelling of accessibility can be improved by distance decay research based on usage data of shared mobility hubs.

Murray et al. (2019) evaluates, besides other software solutions, the general performance of the location allocation solver of ArcGIS. Specifically, the solution performance and quality of the use of heuristic techniques to solve location coverage problems are analyzed. Therefore, three case studies with more than 1000 planning problem instances were solved in different commercial software and the results are compared. The results for the GIS software are described as encouraging and of high quality, whereas their heuristically computed solutions never varied more than 7% from the optimum in the problem instances. Therefore, the research underlines the fact that heuristics can find optimal results in certain cases, but it cannot be guaranteed that the heuristics solver always achieves the exact optimal result. It is important to be aware of this limitation of heuristic approaches to location allocation and communicate them clearly when presenting the results.