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The Antenna Coverage Location Problem in the context of cattle tracking in the Austrian Alps

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ABSTRACT

Alpine regions are cultural landscapes with a high level of biodiversity. They are used for multiple purposes, such as tourism, and recreation but are also home to grazing livestock over the summer. The usage of alpine regions by different user groups often results in conflicts of interest — especially between agriculture and tourism. To resolve this conflict real-time monitoring of the grazing livestock can be helpful. The start-up ViehFinder has developed a solution for cattle tracking based on Long Range Wide Area Networks. The objective of the paper is to develop a Maximal Covering Location Problem – i.e. an Antenna Location Covering Model – to optimize the locations of base stations in Alpine regions. This paper defines constraints for the demand and candidate sites that need to be considered in the context of antenna placement in the Austrian alps. In the paper, a spatial processing workflow is presented that uses a GIS-based site selection approach, resampling as a site reduction technique, and viewshed analysis for generating the service areas of the antennas. The authors go on to present an Integer Linear Program (ILP) for solving the Antenna Coverage Location Problem. The spatial optimization methodology and spatial data processing are applied to two test areas in the Austrian Alps. In addition, the paper analyzes the behavior and computational complexity of the algorithm with varying problem instances and evaluates the bottlenecks thoroughly. The results show the boundaries of ILP for spatial optimization. Further, we show the suitability of the proposed solution in the context of cattle tracking in the Austrian alps.

1. Introduction

Any Alpine region is regarded as cultural landscape whose green areas contribute to an attractive landscape. These landscapes are important for tourism, but do also ensure a high level of biodiversity (BABF and BMLFUW, 2010). In Austria alone there are about 8000 alpine green spaces with an approximate area of 311,000 ha, that are home to 301,000 cattle, 50,000 dairy cows and other livestock such as sheep, horses or goats (BMLRT, 2021) during summer. Grazing livestock is still an important branch of agriculture in Austria. It is one of the fastest growing branches of agriculture worldwide — fueled by population growth in urban centers (Robinson et al., 2014).

Particularly in highly developed societies, some problem areas arise from the agricultural and touristic use of Alpine regions. First, there are conflicts of interest between user groups (e.g. agriculture vs. tourism). These problems are increasing, particularly in tourist regions. Here, we witness attacks on tourists by grazing livestock (Wanner et al., 2021). Second, there are conflicts of cattle with large predators (Reinhardt et al., 2012). Due to the immigration of large predators, the grazing cattle is subjected to increased stress, and would require the protection of human shepherds who constantly watch over the livestock. Third, the keeping of grazing cattle requires construction of fences which is cost intensive — in both construction and maintenance. Due to the cost intensive labor, the permanent presence of shepherds in the Alpine regions is not financially realistic. Hence, monitoring the livestock in Alpine regions could help to overcome the mentioned problem areas, as smart services could help to geographically separate tourists from livestock, trace the movements (and stress) of livestock, replace physical fences with virtual ones.

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Monitoring livestock in Alpine regions requires complex technical solutions in order to overcome problems that are induced by the harsh environment and the technological shortcomings present in such areas. There are several products available on the market (ViehFinder, 2023; digitalanimal, 2023; mOOvement, 2021) that enable farmers to view the position of their grazing livestock in real-time. Most of these solutions rely on the positioning functionalities of Global Navigation Satellite Systems (GNSS) and mobile phone networks to transmit the collected position data. As mobile phone networks are not operational in most Alpine pastures, other solutions to transmit the data collected from livestock are required. The start-up ViehFinder[1] transmits the collected data via Long Range Wide Area Network (LoRaWAN) (TheThingsNetwork, 2022) to base stations that provide a secure uplink to a mobile phone network or wired Internet access.

This paper deals with the "optimal" location of these Long Range Wide Area Networks (LoRaWAN) base stations to serve a defined alpine pasture. We aim to find the "optimal" locations for base stations (antennas) as farmers can have a tight budget and no room for unnecessary expenses. In this work, optimal positioning of the antennas is achieved when a minimum number of antennas covers as much of the alp area as possible while staying within a budget.

The approach follows a spatial optimization approach, which in general uses optimization techniques to solve problems where spatial context is crucial (Tong and Murray, 2012). The proposed approach utilizes a line of sight (LoS) visibility analysis and locational problems, such as Maximal Coverage Location Problem (MCLP) and the watchtower location models (Bao et al., 2015) to find the "optimal" antenna locations for two real-world scenarios located in Austria. Locational problems require a set of demand sites (i.e. alp areas) and a set of candidate sites (i.e. potential antenna positions). They deal with finding the best locations for facilities (i.e. antennas) for the optimal coverage of demand points (i.e. alp areas). The generation of the demand and candidate sites is an important part, as they are used to solve the formulated objective function under given constraints. In this case, the objective is the maximum coverage of the alp areas with the minimum number of antennas while staying within a budget. Mathematical modeling and optimization techniques are required to find the optimal solution to the objective, which is a complex computational task. Current approaches in literature use heuristics (Porras et al., 2019; Heyns et al., 2021; Amiri, 2021) to determine close to optimal solutions for problem instances of the size of the proposed test areas. The problem at hand however requires the optimal positioning of the antennas.

The proposed approach is called Antenna Coverage Location Problem (ACLP). It uses a high-resolution (i.e. 1 m) digital elevation model (DEM) as a basis for the candidate and demand site selection. Further, we develop constraints that apply to the candidate and demand site selection in the context of cattle tracking in the Austrian alps. This GIS-based approach allows us to reduce the number of potential sites and ensure low maintenance operability of the antennas. To further reduce the computational burden we implement a resampling technique to decrease the amount of demand and candidate sites. This paper uses viewshed analysis to compute the service areas of the antennas (i.e. area covered by an antenna) as it takes terrain interference into account. Finally, the approach uses the spatial optimization tool Allagash (Pulver, 2020) and integer linear programming (ILP) to find the optimal antenna positions. This paper uses the deterministic ILP, instead of heuristics as we want to find the optimal and not close to optimal antenna positions.

The research problem addressed in this paper is focused on achieving the maximum coverage of the alp areas with a minimum number of antennas while taking the farmer's limited budget into account. Further, we check the proposed approach for potential bottlenecks.

This paper is centered around the following questions and topics:

- Can deterministic spatial optimization techniques be used for modeling the problem of optimal antenna positions in alpine regions?
- Which constraints apply to the candidate and demand site selection?
- What are the bottlenecks in terms of the computation time of the proposed approach?

In this paper our key contributions are:

1. Developing an MCLP formulation (i.e. ACLP) for optimizing antenna locations.
2. Demonstrating the suitability of the proposed approach for real-world examples.
3. Detailed understanding of the bottlenecks of the MCLP approach for optimizing antenna locations.
4. Improving the coverage generation module in the open source spatial optimization library Allagash, to make it suitable for large problem instances with complex geometries.
5. Providing detailed insights into the computational behavior for different coverage scenarios.

The paper is organized as follows. Section 2 starts with the background of this paper by introducing the ViehFinder-System, describing relevant literature on locational problems, discussing demand and candidate site selection, and the ACLP. Section 3 outlines the solution approach as well as the details of experiments carried out in this paper. Section 4 presents the mathematical model of ACLP and the implementation details of the proposed solution. Section 5 highlights the results for scaling tests of the potential bottlenecks and real-world experiments. Section 6 summarizes and concludes this paper and shows future prospects.

2. Background

2.1. ViehFinder

ViehFinder provides a holistic solution for tracking and monitoring cattle (i.e. cows) in remote areas (Welscher et al., 2021). It achieves a solution that requires the least maintenance and enables capturing high resolution (i.e. 5 m) of cattle mobility and other contextual data by utilizing robust devices and energy-self-sufficient components. One of the two hardware components (Fig. 1) of the ViehFinder setup is the ViehFinder collar. This collar is mounted around the neck of livestock and contains the ViehFinder node, a Long-Range (LoRa) based sensor unit with a GNSS module. Further, the collar contains an acceleration sensor and a temperature probe for tracking special animal behavior and environmental conditions. It is powered by a 0.5 W solar module with an attached Lithium-Polymer (LiPo) battery cell. The second hardware component is the LoRaWAN (TheThingsNetwork, 2022) antenna. Utilizing a LoRaWAN Gateway and a connected cellular router it routes the received sensor signals from collars to the data storage and processing servers. The ViehFinder solution has been designed to be cost-effective to ensure it is practical and easily adaptable by farmers. Nevertheless, the antennas are built with a unit cost of 1450 Euros each, the major part of the ViehFinder hardware setup. Achieving the objective of minimum cost is then possible by installing a minimum number of antennas for the maximum coverage of the area of interest (AoI). This also involves solving the problem of finding the optimal position of a selected number of antennas for maximization of coverage.

Fig. 2 displays the components of the ViehFinder architecture. It shows that they are all connected by the control server. It contains the essential software components to operate the system. It is based on Node.js and Node-RED and requires controller software to feature the collection and pre-processing of incoming tracking data. InfluxDB, a cloud database for handling real-time temporal data, is used to implement a time series data platform for the storage and retrieval of sensor data. Further Tago Run is used to provide the tracking data to the user.

Fig. 1. The two major components of the ViehFinder setup. The ViehFinder collar for tracking the position (left) and the LoRaWAN antenna for data transmission to the server (right). Both are solar-powered.

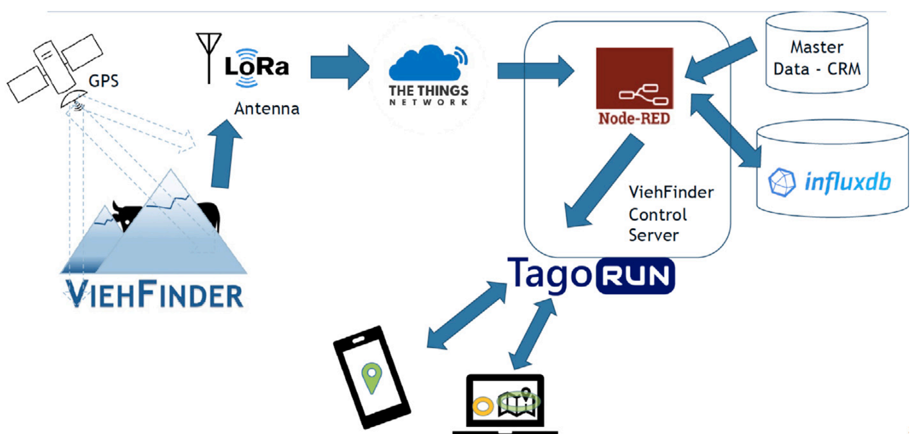

Fig. 2. The architecture of the ViehFinder-System. Consisting of the hardware site with the GPS-Collars and the LoRaWAN-Antennas, as well as the software site with the influxdb for handling the data in real-time, Node-RED, and Tago Run for providing the data to the farmer.

2.2. Locational problems

Locational problems or coverage location problems deal with finding the best locations for facilities or services for the optimal coverage of demand points (Araújo et al., 2020). Locational problems are spatial optimization problems that deal with maximizing or minimizing a spatial objective function under given constraints (mostly are also spatial). An important part of dealing with such problems is the generation of potential demand and candidate locations, which are used to solve the formulated objective function under given constraints. An example is the coverage of a city with fire stations. The objective could be minimizing the distance or the driving time to a potential fire or just maximizing the coverage of the whole city. Finding the optimal solution to these objectives is a complex computational task that requires mathematical modeling and optimization techniques.

Three different classes of locational problems are defined by Church and Murray (2018):

– Location Set Covering Problem (LSCP) (Toregas et al., 1971)

– Maximal Covering Location Problem (MCLP) (Church and ReVelle, 1974)

– Minimum Impact Location Problem (MILP) (Murray et al., 1998)

The LCSP covers a demand area completely by minimizing the number of facilities in a way that the objective of maximum driving time/distance can be achieved (Toregas et al., 1971). The MCLP is constrained by a given amount of resources. It maximizes the coverage with respect to these limited resources (Church and ReVelle, 1974). The MILP locates facilities to minimize their impact on neighboring entities (Murray et al., 1998). An example for this locational problem is the siting of nuclear power plants.

In the following sections, we briefly describe the approach for candidate and demand site selection and the formulation of the objective function of the ACLP.

2.2.1. Demand and candidate site selection

In the literature there are different approaches for generating candidate and demand sites/points (Heyns et al., 2021; Bao et al., 2015; Raisanen and Whitaker, 2005). The area containing the candidate sites is called placement zone (PZ), whereas the area containing the demand sites is called cover zone (CZ) (Heyns et al., 2021).

There are several approaches for generating the PZ. The simplest approach for generating problem instances of demand and candidate sites is random generation as done by Raisanen and Whitaker (2005). This is not suitable for real-world problems as it does not take local conditions into account. Another option is to manually select potential candidate locations by using preferable terrain such as hilltops (Zhang et al., 2019; Bao et al., 2015). However, this approach is not suitable for large real-world examples as it is time-consuming. Thus, it is mainly used for small, theoretical problem areas (Heyns et al., 2021). It is popular in the literature of location-based applications to use raster data as a basis for site selection (Heyns et al., 2021; Heyns, 2020; Kim et al., 2004). The uniformly spaced points of an elevation model represent the earth's surface and are used as a set of starting sites for further selection techniques (Heyns, 2020). A more fitting approach for real-world site selection is utilizing a GIS-based approach. Heyns et al. (2021) use such an approach for an area of 435 km^2, which is about 1.5 times the size of the largest proposed research area in this paper. They exclude difficult terrain by filtering a slope above 12° (20%) to ease access. Further they take the proximity to a street (less than 100 m) into account. To further reduce the number of candidate sites, they reduce the potential area to landforms with superior visibility, such as peaks and ridges. Eugenio et al. (2016) apply this site selection technique to an even larger area of about 46,000 km^2. They start by generating the ridges within given administrative boundaries. They proceed selecting areas with suitable land use for site installation and select the ridges within these areas. Proximity to a street was also taken into account. The final set of candidates resulted from those areas that fulfilled the three constraints, suitable land use, ridges and proximity to a street. This technique can yield problem instances that exceed a solvable range. Thus it might be necessary to apply further methods to reduce the number of potential sites.

Rana (2003) summarizes the approaches for reducing the number of potential site or observers (candidate points) to ease the computational complexity, known as the reduced observer strategy. One widespread method for reducing the number of observers is selecting sites with superior visibility such as ridges or peaks (Lee, 1994; Kim et al., 2004; Heyns, 2020). Although the correlation between visibility and elevation tends to be rather low, as a peak can be surrounded by other peaks impairing the viewshed (Kim et al., 2004; Franklin and Ray, 1994).

There are several approaches for generating the CZ. The approach by Rana (2003) generates cover zone by reducing the number of potential targets (demand points), known as the reduced target strategy. According to Heyns (2020) most literature concerning demand abstraction techniques focuses on small theoretical study areas and are not suited for real-world problems. Further many avoid the interference of terrain during the coverage computations by assuming a flat terrain (Yin and Mu, 2015; Wei and Murray, 2015; Tong et al., 2009). Heyns (2020) proposes a reduced target resolution strategy, which resamples the demand points by skipping neighboring points. A Skip-1 strategy, for example, skips one row and one column to the next demand point. This paper also implements a resampling strategy for the generation of both placement and cover zones (the candidate sites and the demand sites).

2.2.2. Antenna Coverage Location Problem

The Antenna Coverage Location Problem (ACLP) is a locational optimization problem concerned with the optimal placement of a minimum number of antennas to achieve maximum coverage. Thus the ACLP is a Maximal Coverage Location Problem (MCLP) (Church and ReVelle, 1974). There are several approaches for solving such optimization problems, ranging from Integer Linear Programming (ILP) over heuristics to evolutionary algorithms. In some literature, they have even used Machine Learning in conjunction with evolutionary algorithms to solve these problems (Mathar and Schmeink, 2001; Amiri, 2021; Dreifuerst et al., 2021; Porras et al., 2019). MCLP is an NP-hard problem (Megidd0 et al., 1983), thus ACLP is one as well. Heuristics might be necessary to solve large problem instances. Yet this work utilizes ILP, as heuristics only yield close to optimal solutions.

In the context of cattle tracking in the Austrian alps, different scenarios are possible for the ACLP. (1) LSCP is required because the farmer wants to have his alps covered completely. (2) In the scenario of antenna failure backup coverage is required. (3) A budget constraint restricts the farmer to a certain number of antennas leading to the usage of the MCLP. This last scenario is the one this paper focuses on.

Similar to other optimization approaches (Heyns et al., 2021; Eugenio et al., 2016) the ACLP defines the PZ and CZ by applying constraints such as proximity to a road or administrative boundaries. Each pixel within the CZ raster is a demand site and each pixel within the PZ raster is a candidate site. A demand site is considered covered or serviced when it is contained in the service area (i.e. viewshed) of at least one candidate site.

Computing the service area of each candidate site is an important part of the ACLP. A similar work focuses on the placement of base stations for wireless networks and utilizes radio wave propagation modeling to determine the demand sites servable from a candidate site (Raisanen and Whitaker, 2005; Mathar and Schmeink, 2001; Mathar and Niessen, 2000). However, the ViehFinder setup can only guarantee a connection in direct line of sight (LoS), thus a different approach must be chosen. As mentioned by Heyns (2020), it is important to take terrain interference into account. Thus assuming a flat terrain and using a buffer around the candidate site as a coverage area is not appropriate for this real-world application. Therefore, a more suitable approach is utilizing viewshed analysis, which uses LoS to determine all the points visible from an observer point (Sander and Manson, 2007). The LoS based viewshed certainly is a simplification compared to more complex radio wave propagation models, but it allows determining covered areas and areas of antenna shadow (Łubczonek, 2008) by considering terrain features and antenna heights.

Bao et al. (2015) use ILP to solve the MCLP for their rather small research area of 10 km^2. With 30 manually selected candidate sites and 13,886 demand sites, it takes them 101.4 s with 17,419 iterations to find the optimal solution in the worst case. As the number of maximum selected sites rises the time improves to 19 s with 2058 iterations. However, diminishing gain of coverage is observed as the number of placed towers increases.

3. Research methodology

3.1. Methodology

The approach in this paper uses ILP to solve the ACLP. The generation of the ACLP requires demand points (alp areas), candidate sites (antenna sites), and their corresponding service areas. These are calculated based on the available spatial data. We use raster as a basis for the selection of demand points and candidate sites. The centers of the raster cells are considered potential sites.

In our GIS-based selection approach we apply three constraints to the PZ and one constraint to the CZ. The PZ is restricted by (1) proximity to a street, (2) exclusion of difficult terrain and (3) reception of a mobile network to operate the antennas. The CZ is given through the areas of the alps.

To bring the problem size into a solvable range for the ILP approach, a resampling technique is applied to the demand and candidate sites. The algorithm (1) generates a grid over the area of interest, (2) computes the centroids of the grid cells and (3) clips the grid to the CZ-/PZ-constraints resulting in a new set of potential sites. These steps are repeated iteratively until a given threshold is satisfied.

The final component the ACLP requires is the service areas of the antennas (candidate sites). This paper uses LoS to determine the service areas, instead of Radio-Frequency-Modeling as currently the data connection between ViehFinder antenna and the node can only be guaranteed in direct line-of-sight (Welscher et al., 2021). With this approach, terrain interference is taken into account. The generation of a service area consists of three steps, (1) computing the viewshed using the candidate site and a raster, (2) polygonizing the viewshed and (3) converting the multiple single polygons of the viewshed into one multi-polygon.

This work uses the open-source optimization tool Allagash (Pulver, 2020) for the spatial optimization process. The generated demand

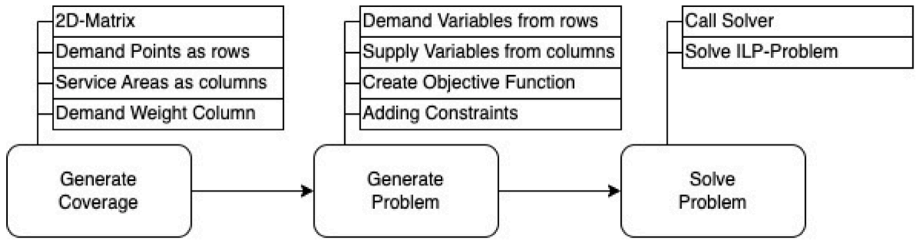

Fig. 3. The three steps of the optimization process with details.

	Demand	Service Area 1	Service Area 2	...
Demand Point 1	1	True	False	...
Demand Point 2	5	False	False	...
...	...	...	...	...

Fig. 4. Example of a coverage dataframe containing the demand points as rows, the service areas as columns and the demand column which contains the weight of each demand point.

points and service areas are processed in three steps, (1) generating the coverage, (2) generating the ILP-Problem and (3) solving it.

Fig. 3 shows the three optimization steps in detail. The first step takes the selected demand points and service areas and generates a coverage dataframe (2D matrix) by determining which demand point is contained in which service area. Fig. 4 shows an example of a coverage dataframe. It consists of the demand points as rows and the service areas as columns. The cells contain Boolean values that determine whether a demand point is covered by a service area. Additionally, a demand column is required, that contains the weight of each demand point. The weight allows us to prioritize areas, by increasing the weight of the demand points. Thus we could enforce the coverage of the alp boundaries by increasing the weight of the demand points close to the boundaries.

In the second step, this coverage dataframe is then used for the generation of the ILP problem. Creating the problem consists of three steps, (1) creating the demand variables from the rows and the supply variables from the columns of the coverage dataframe, (2) creating the objective function of the MCLP as a sum of the weights of all demand variables, (3) adding constraints to the problem, such as the maximum number of supply (service) locations.

The last step of the optimization process then solves the formulated ILP problem using python package PuLp (Mitchell et al., 2011) in conjunction with the open-source CBC-solver version 2.10.7 by Forrest et al. (2022) to determine the optimal solution.

3.2. Experimental setup

We use the raster of a DEM with a 10 m resolution as a basis for the selection of demand points and candidate sites. The center of each raster cell is considered a potential site. The potential sites are filtered by applying constraints derived from spatial data. Three constraints restrict the number of potential candidate sites. (1) Easy access for the installation and maintenance of the antennas is required, thus proximity to a street is vital. For this, we use a 200 m buffer around the streets. (2) Further difficult terrain is excluded by filtering the slope above a given threshold. This threshold is set to 20° (36.4%). (3) The reception of a mobile network is required for operating the antennas. Thus a vector grid containing the mobile network coverage of Austria as 100×100 m cells is applied as a mask. These thresholds are provided by the experts of the ViehFinder company and are based on their experience in operating and installing the antennas. Demand points are restricted by the areas of the alps, which is increased by a buffer of 200 m to enable cattle tracking even if it leaves the farmer's property.

Depending on the resolution of the raster the number of demand points and candidate sites after applying the constraints might still exceed the size of a solvable ILP Problem. This means the used CBC-solver is unable to compute a solution for the problem. Therefore, an algorithm was implemented for resampling the potential sites. The algorithm requires an initial grid cell size and step size that are chosen based on the size of the research area. In each iteration, the algorithm increases the grid cell size by the given step size. It stops when the number of potential sites is below the desired threshold.

Once the demand points and candidate sites are selected, the service areas of the candidate positions are computed. This paper uses viewshed analysis to determine the service area of the antenna, as it takes terrain interference into account. We use a DEM with 1 m resolution as a basis for the viewshed computation. Further, the area covered by a viewshed depends on the height of the antenna (observer) and collar (target) above the ground, as well as the range of the antenna. This work uses a height of 2 m for the antennas and 1.5 m for the collars. The range of the antennas is set to 8 km.

Once the generation of the demand points and service areas is complete, they are handed to the open-source optimization tool Allagash (Pulver, 2020). The optimization process consists of three steps, (1) generating the coverage, (2) generating the ILP-Problem and (3) solving it. We use PuLp in conjunction with the open-source CBC-solver version 2.10.7 by Forrest et al. (2022) to solve the well-formulated problem.

This paper takes a closer look at the performance of the three optimization steps in terms of execution time to determine possible bottlenecks of the process. Therefore, sample data are selected from the real-world data set of the upper Mölltal, a valley in Carinthia, Austria. The original data set consists of two vector data files containing 337,130 demand points and 1000 service areas as multi-polygons.

This paper compares three approaches for coverage generation, (1) the original Allagash function, (2) the original Allagash function with multiprocessing, and (3) our coverage generation function. The performance of the three functions is then measured using two kinds of service areas, complex multi-polygon geometries and simple geometries of buffered circles with a radius of 8 km. As the Allagash approach reaches its boundaries for complex geometries at small problem sizes, we further run scaling tests for larger data samples on our approach. Two major differences are separating our function from the Allagash function, (1) our approach iterates over the service areas, instead of the demand points and (2) our approach queries the spatial index of the demand points instead of checking in which service areas the current demand point is contained.

The second optimization step, the generation of the problem itself, is evaluated by sampling a coverage dataframe generated from 100,000

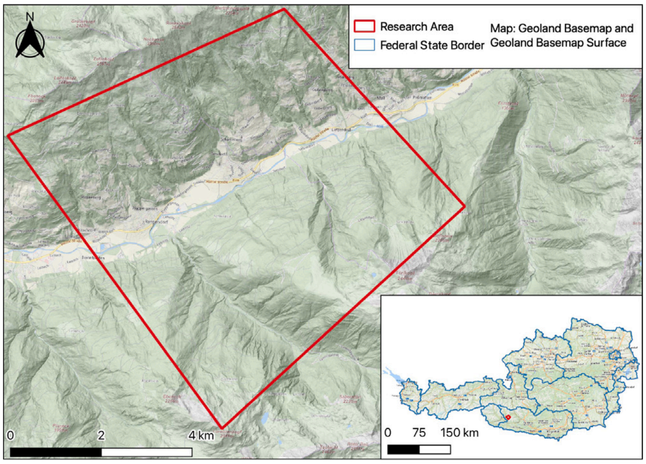

Fig. 5. An Overview map of the research area Upper Mölltal which is located in the western part of Carinthia, Austria.

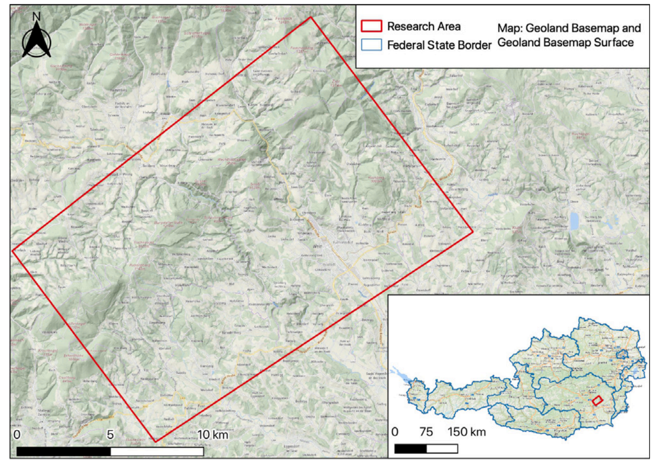

Fig. 6. An Overview map of the research area Schöckelland which is located in Styria close to the city of Graz, Austria.

demand points and 1000 service areas of the original dataset. There is just the original Allagash function to be tested and the size of the sampled coverage dataframe ranges from 10,000 to 100,000 rows and 100 to 1000 columns.

Finally, this work looks into the performance of the CBC-solver. Therefore, sample data sets are generated from the original vector-files. These are used to create coverage dataframes and the corresponding problems enabling us to trace back each problem instance to the geometries of the original data set. The sizes of the problem instances range from 10,000 to 100,000 demand points and 100 to 1000 service areas. This paper also observes the behavior of the solver for different maximum supply constraints. The investigated values area 5, 10 and 15. Originally the value 3 was also intended, but the solver shows some odd behavior for it, thus it is excluded from the tests.

Further, this paper observes the performance of the service area generation. There are two functions to be observed, (1) generating the service areas without multiprocessing and (2) with multiprocessing. There are two parameters influencing the processing time of the service area generation, (1) the maximum distance from the observer point and (2) the number of observer points. The distances used for this experiment are 500 m, 1000 m, 2500 m, 5000 m, and 8000 m. The number of observer points is 10, 25, 50, 75, and 100.

Apart from analyzing the algorithms for potential bottlenecks, the proposed solution for the ACLP is tested on two real-world examples, which are both located in, Austria. Two factors play a role in the selection of these two research areas, (1) their different sizes and (2) their physiographic properties (i.e. valleys, ridges etc.) as these influence the antenna coverage. The first one is the smaller research area of upper Mölltal (Fig. 5), a valley in the western part of Carinthia. This test area has a width of approximately 10 km and a height of approximately 9 km culminating in an area of about 47.55 km^2. It is only slightly larger than the maximum antenna range of 8 km. When using the 10 m DEM as a basis it consists of 475,365 potential demand points and candidate positions before applying any constraints. It consists of the main valley and a few smaller side valleys. The results of three different maximum supply constraints will be analyzed for this research area. The constraint is set to a maximum number of antennas of 2, 5, 8, and 10.

The second research area is called Schöckelland (Fig. 6) and is located in the northeast of the city of Graz in Styria, Austria. With a size of approx. 24.7 km by 22.8 km, it is larger than the maximum antenna range of 8 km. It has an area of about 277.34 km^2. Using the 10 m DEM as a basis for the generation of demand points and candidate positions, it provides 2,771,466 potential positions. Thus, it is more than 5 times larger than the test area Upper Mölltal. It consists of multiple valleys and ridges impairing the service areas of the antennas. Multiple maximum supply constraints will be applied to this research area. As this research area is far larger than the first one the maximum supply constraints are larger as well. The used values are 10, 20, 30, 40, 50, and 75 candidates.

4. Proposed solution

4.1. Antenna Coverage Location Problem — Computational approach

The proposed procedure to calculate the optimal base stations can be seen in Fig. 7. It is an adapted form of the previous work mentioned in Welscher et al. (2021). It generates the demand and candidate points by applying specific constraints to an elevation model. These constraints can be of different kinds such as boundaries of an area, proximity to a landmark, or a maximum slope.

In the context of cattle tracking in the Austrian alps, there is one constraint applying to the demand points, that is the area of the alps including a buffer of 200 m around it. Concerning the candidate points three constraints apply, (1) the antenna must be within 200 m of a street, (2) the slope must not exceed 20° (36.4%) for easy access for installation and maintenance and (3) the reception of a mobile network is required.

The application of these constraints to the elevation model results in the demand and candidate points. Depending on the size of the AoI and the effectiveness of the applied constraints the size of the problem might exceed the range of a solvable ILP-Problem. Thus, it might be necessary to resample the detected demand and candidate points. Once the problem size is brought into a solvable range, a service area is generated for each candidate position by computing the viewshed with the 1 m DEM, polygonizing and dissolving it.

The prepared demand points and service areas are then handed to the optimization tool Allagash, which generates a coverage dataframe, creates the ILP-Problem and hands it to the CBC-solver. As a result, it returns the optimal antenna positions and the percentage of demand covered by them.

4.2. Antenna coverage location problem — model

As described in Welscher et al. (2021) the ACLP is a MCLP, which is a non-deterministic polynomial time (NP)-hard optimization problem. MCLPs are concerned with the optimal placement of a minimum number of sites to achieve maximum coverage (Marianov and ReVelle,

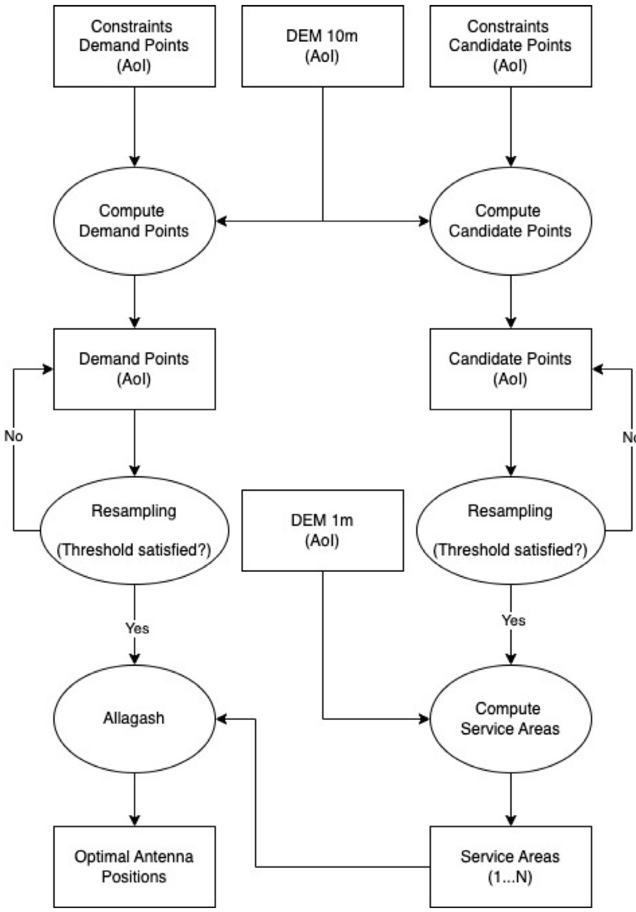

Fig. 7. Spatial Optimization approach depicting the relevant inputs and processes.

1995). Some problem instances might only be solvable using heuristic approaches, because the problem size might exceed the solvable boundaries. However, this paper focuses on finding the optimal solution to the problem instances, as farmers can have a tight budget and no room for unnecessary expenses. Thus the ILP approach is utilized as the other approaches deliver just close to optimal solutions.

Like MCLP, the mathematical model of ACLP consists of an objective function, constraints and the decision variables. The indices and constants for the ACLP are given as following:
j = Index of candidate location for building an antenna $(0 \leq j \leq M-1)$
M = Number of potential locations for building an antenna
i = Index of a demand location that needs to be covered $(0 \leq i \leq N-1)$
N = Number of demand locations that need to be covered
$w_i = 1$ (Constant demand weight of every demand location)
p = Number of candidate locations to be placed

There are two decision variables in the ACLP. One is concerning the potential candidate locations and the other one is handling the coverage of the demand locations:

$$c_j = \frac{\text{1 if an antenna is located at candidate location i}}{\text{0 otherwise}}$$

$$d_i = \frac{\text{1 if demand location i is covered by at least one antenna}}{\text{0 otherwise}}$$

According to Marianov and ReVelle (1995) the objective function for the MCLP would be defined as the following,

$$Maximize\ Z = \sum_{i \in N} a_i y_i \tag{1}$$

with a_i being the population (weight) at demand node i and y_i being the decision variable whether the node i is covered or not $(y_i \in \{0,1\}\,\forall\, i)$.

In the case of the ACLP all demand locations have the same weight w_i, thus the objective function can be written as:

$$max \sum_{i=1}^{N} d_i \tag{2}$$

This objective function tries to maximize the sum of covered demand locations, while being subject to the following constraints:

$$d_i \leq \sum_{j=1}^{M} c_j \,\forall\, i \tag{3}$$

$$\sum_{j=1}^{M} c_j \leq p \tag{4}$$

$$c_j \in \{0,1\}\,\forall\, j \tag{5}$$

$$d_i \in \{0,1\}\,\forall\, i \tag{6}$$

Constraint (3) ensures that a demand location i is only covered if it is within the service area of at least one antenna. Constraint (4) sets the maximum number of candidate positions that can be selected. Constraints (5) and (6) restrict the decision variables to be binary.

5. Results

This section demonstrates the results for the scaling tests of the potential bottlenecks, as well as the real-world examples. The experiments executed for this work, were run on a MacBook Pro with a M1 Pro chip with 3.22 GHz and 16 GB of RAM. Each experiment mentioned in this paper was executed at least 3 times to show the stability of the approaches and to flat out any singular results or outliers.

5.1. Scaling tests

This section presents the analysis of the four bottlenecks of the proposed solution. These bottlenecks evaluated are the service area, coverage, and problem generation as well as the problem solving itself.

The results of the service area generation is shown in Fig. 8. The processing time depends on the number of service areas that must be generated and on the maximum distance. There is a linear increase in the performance as the number of generated service areas increases. The approach without Multi-Core-Processing (MCP) performs better for the smaller distances 500 m and 1000 m as there is some overhead in initiating the MCP. With larger maximum distances the benefits of MCP are visible.

The MCP-approach performs about 4-times better for the largest problem instance of 100 service areas and 8000 m distance. This benefit decreases with the decreasing distance and tips over for a distance of 1000 m.

Concerning coverage generation we are considering two different approaches. On one hand side the performance with simple geometries (Circles) and on the other side the performance with complex geometries (Multi-Polygons). For simple geometries, the difference in the performance of our approach and Allagash can be neglected. Even with the overhead of the MCP the processing time for this problem size stays below 2.5 s as shown in Fig. 9.

This changes for complex geometries. While the processing time of our approach does not exceed 0.5 s, the Allagash takes more than 40 min for the largest problem instance of 30 service areas and 500 demand points. Even with MCP Allagash is not capable of performing better with a time of about 7.5 min as shown in Fig. 10.

Fig. 11 shows the performance of our approach for larger problem instances. The largest instance consists of 200 times more demand points and 33 times more service areas than the largest instance of the smaller scaling test. Yet our approach performs about 6 min better than Allagash's without MCP shown in Fig. 10.

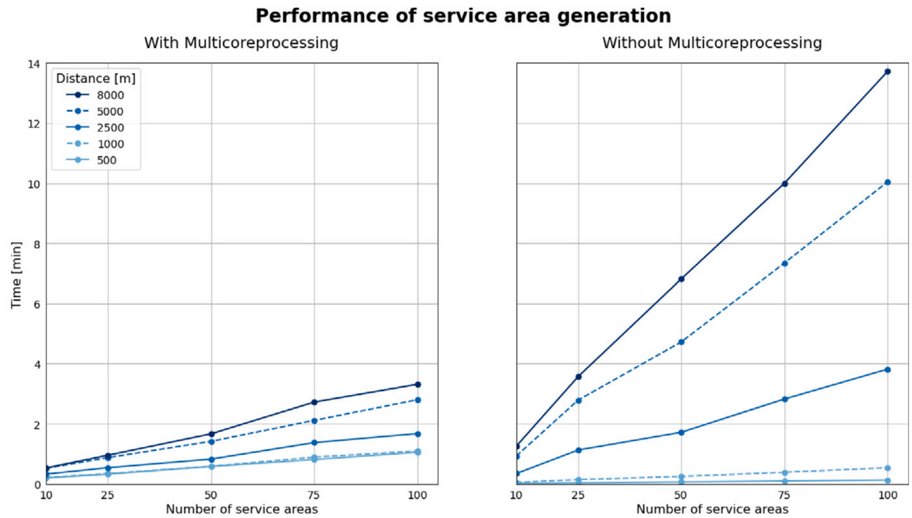

Fig. 8. Comparison of the performance of the service area generation with and without Multi-Core-Processing.

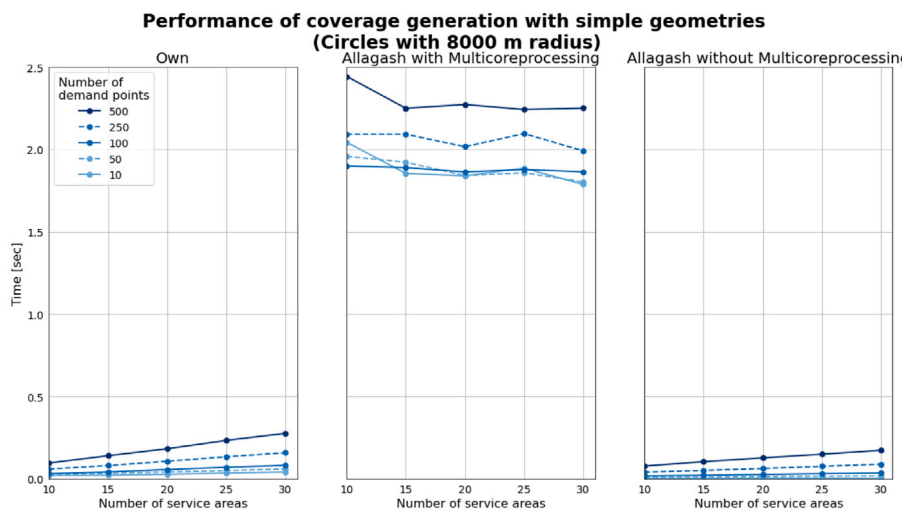

Fig. 9. Comparison of the performance of coverage generation for simple geometries (Circles). Shown is our approach (left), the Allagash approach with MCP (middle), and the Allagash approach without MCP.

There are multiple reasons for the differences in the performance of the approaches. (1) Allagash iterates over the demand points and checks if they are contained in the service areas. Our approach iterates over the service areas and queries the spatial index of the demand points to find the covered ones. (2) The complexity of the geometry has a strong influence on the performance of the contains check that Allagash uses. The querying of the spatial index however is influenced less by this.

The third potential bottleneck of the approach is the problem generation as shown in Fig. 12. As expected the scaling test results show a linear trend. It starts at 23 s for the smallest problem instance of 10,000 demand points and 100 service areas and ends with about 31 min for the largest. Thus the required time for this task lies below the time required for the coverage generation.

The potential bottlenecks discussed so far (service area, coverage and problem generation) show a stable and predictable behavior and are capable of handling large problem instances. The behavior of the last bottleneck, the performance of the used open source CBC-solver, however is problematic. Fig. 13 and Table 1 show that its performance is inconsistent. Furthermore, it showed problematic behavior such as continuing the optimization although the stop criterion (i.e. time) was reached. In addition, the CBC-solver did not return any solution until the stop time was reached. This behavior was observed especially for smaller maximum supply constraints.

As the graph in Fig. 13 shows, its behavior becomes more stable for larger maximum supply constraints. Table 1 highlights the extraordinary spikes visible in the plotted lines with 100,000 demand points. For a maximum supply of 5 the computation time drops from 16.68 min to 4.02 by a factor of 4, while the change in the number of service areas is only 100 from 400 to 500. Similar inconsistencies can be observed for a maximum supply value of 10. The computation time rises from 4.24 min to over 15 min dropping again to 8.3 min.

This unpredictability in solving time could result from multiple sources. (1) For certain problem instances the solver can apply cutting techniques. (2) The solver is unable to apply any cutting techniques. (3) The complexity of the problem overpowers the computational capacities of the hardware leading to the solver freezing.

5.2. Experiments in test areas

The experiments for the test area of the Upper Mölltal were concerned with 4 budgetary scenarios ranging from 2 to 10 Antennas. With an antenna value of 1450 Euros each, this budget ranges from 2900 Euros to 14,500 Euros. With the lowest budget of 2900 Euros

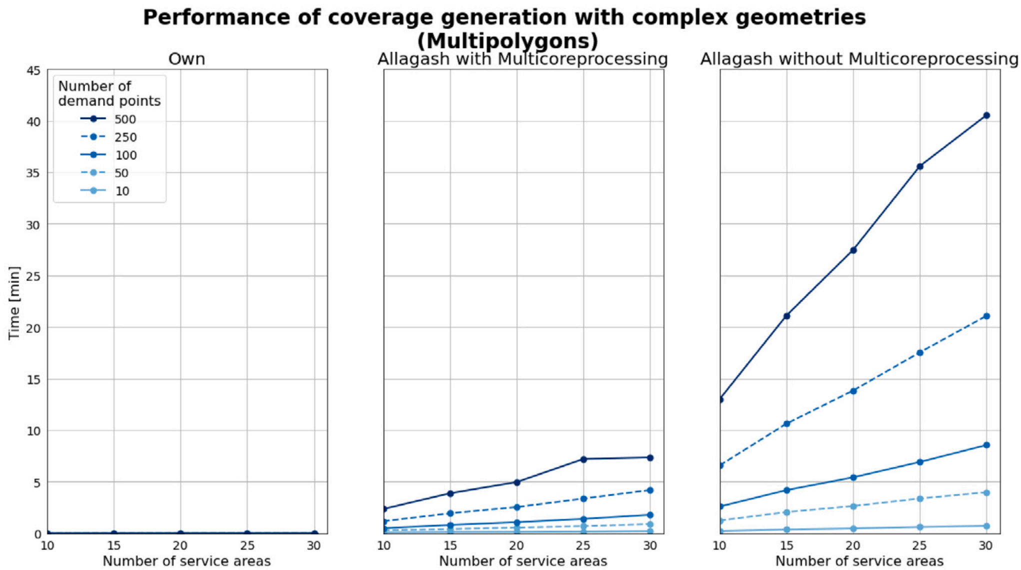

Fig. 10. Comparison of the performance of coverage generation for complex geometries (Multi-Polygons). Shown is our approach (left), the Allagash approach with MCP (middle), and the Allagash approach without MCP.

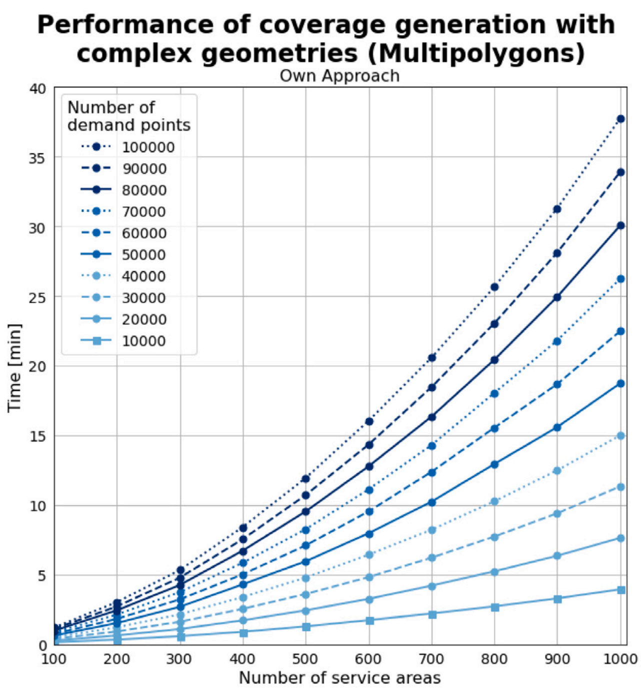

Fig. 11. Performance of our approach for generating the coverage with up to 100,000 demand points and 1000 service areas.

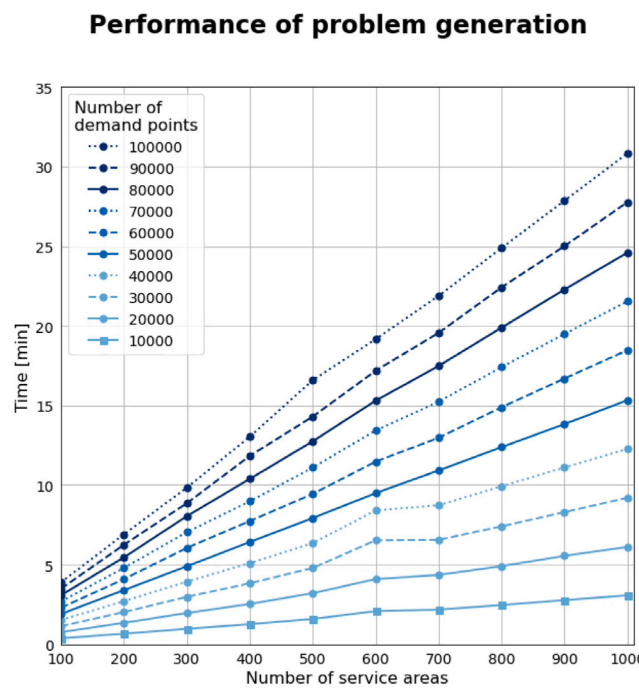

Fig. 12. Performance of the problem generation with up to 100,000 demand points and 1000 service areas.

a coverage of 86.76% can be achieved. Increasing the number of antennas increases the coverage as well as the costs. Adding 3 more antennas at a cost of 4350 Euros gains an additional 11.5% coverage. This improvement in coverage decreases to 0.58% when adding another 3 antennas at the same cost to a total of 8 antennas. Thus, it is possible to achieve a high degree of coverage with an increasing number of antennas, but the benefit per placed antenna decreases while the costs stay the same. Fig. 14 visualizes this trend, as the area covered by more than 3 antennas increases with the number of antennas placed.

With an increasing number of placed antennas, the demand points with no coverage decrease from 13.24% for 2 antennas to 0.96% for 10 antennas. But the decrease in uncovered cells comes at a cost, as the number of primarily covered demand points decreases from 78.00% to 4.44%. Backup Coverage, which means demand positions covered by two antennas, increases at first to 48.52% but then declines to 14.13%. With the number of placed antennas rising, the number of demand points with multiple coverages rise up to 80.48% for 10 antennas. Fig. 15 depicts these trends.

Bao et al. (2015) show that the computation time decreases when the number of antennas is increased. This is not always the case in this study, as the inconsistency of the solver results in a fluctuating computation time, that rises from 10.18 min to 47.20 min when the number of antennas increase from 5 to 8 respectively (as shown in Table 2).

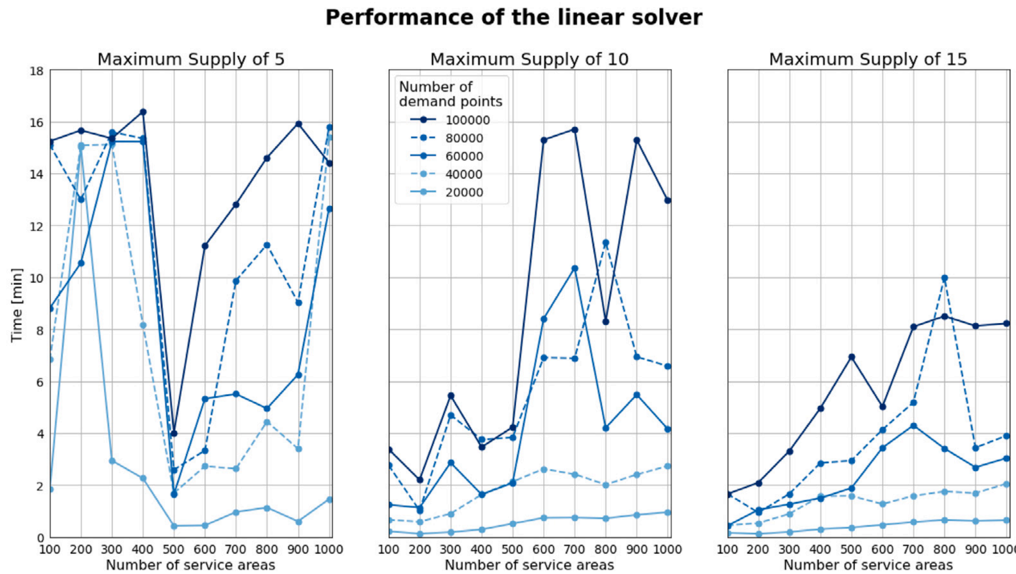

Fig. 13. Performance of the problem solving for three different maximum supply constraints. The behavior of the solver becomes more stable as the maximum supply constraint increases.

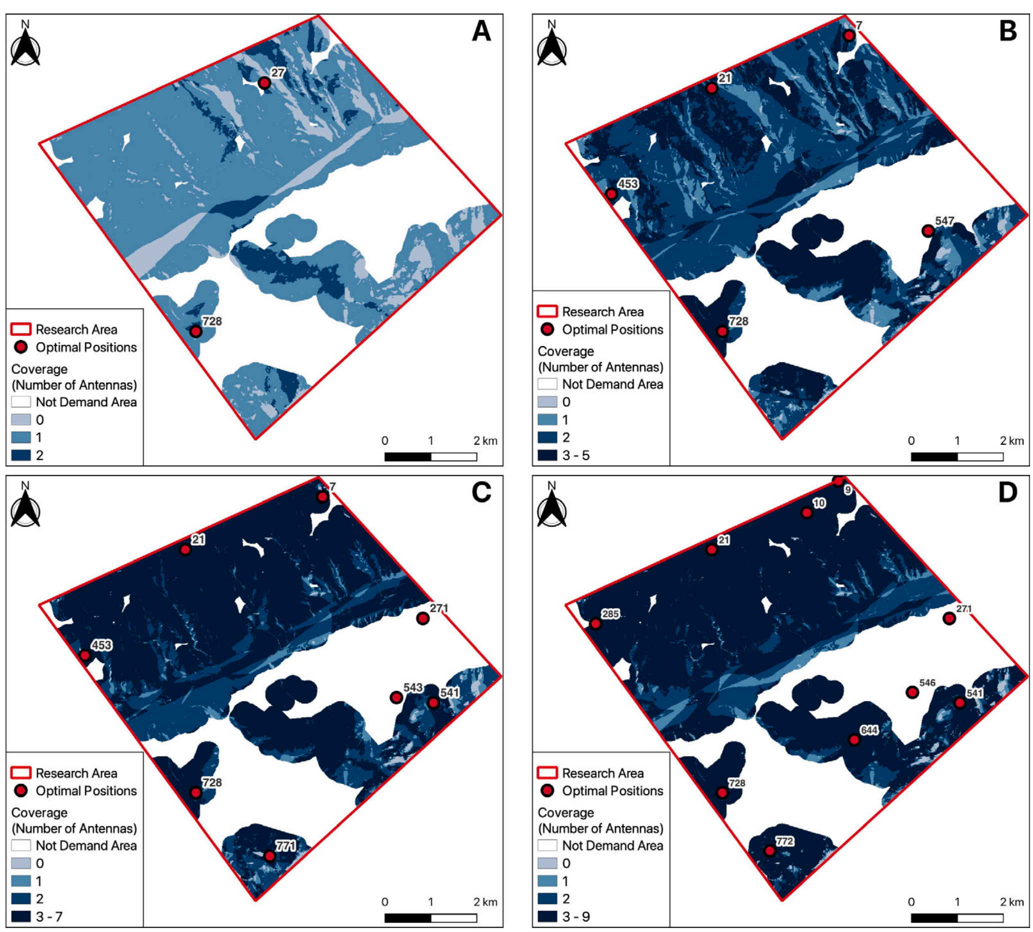

Fig. 14. Solutions for the Upper Mölltal for different supply constraints.

The second research area Schöckelland is with 277.34 km^2 about 5-times larger than the Upper Mölltal. Fig. 16 visualizes the six generated solutions. Due to the increase in size, a service area with a radius of 8 km can only cover a small portion of it. Thus the budgetary scenario had to be adjusted and ranges from 14,500 Euros for 10 antennas to 108,750 Euros for 75 antennas. On average a service area of the Upper Mölltal region covers 12.63 km^2, while a service area of the Schöckelland covers 10.22 km^2. The first solution with 10 antennas

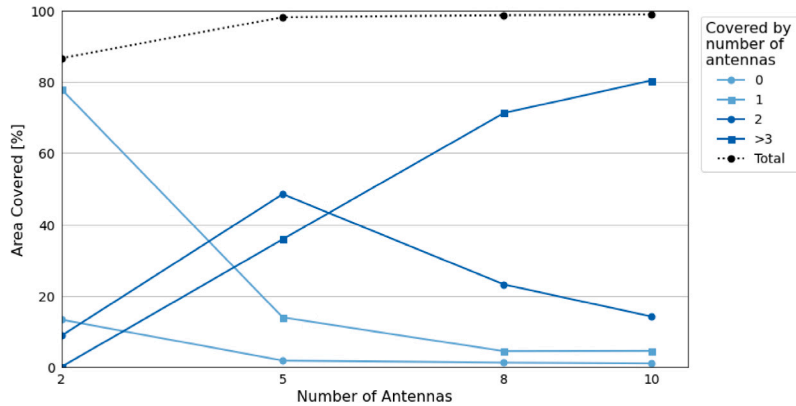

Fig. 15. No Coverage, Primary Coverage, Backup Coverage, Multiple Coverage and Total Coverage for the upper Mölltal for different supply constraints.

Table 1
Performance of the COIN-OR CBC solver with different numbers of service areas and 100,000 demand points. Extraordinary performance spikes are marked bold.

Service Areas	Max supply	Percent demand covered (%)			Solver time (min)		
		5	10	15	5	10	15
100		95.83	98.38	98.57	15.32	3.39	1.61
200		96.81	98.73	98.89	15.88	2.19	2.09
300		97.16	98.81	98.98	15.35	5.43	3.28
400		97.68	99.00	99.16	16.68	3.45	4.81
500		98.11	99.05	99.20	**4.02**	4.24	6.95
600		98.11	99.05	99.20	11.21	**15.41**	5.02
700		98.14	99.06	99.20	12.87	**15.78**	8.21
800		98.14	99.09	99.20	14.75	8.3	8.5
900		98.40	99.09	99.23	15.92	**15.28**	8.11
1000		98.40	99.15	99.29	14.96	**12.95**	8.21

covers 62.78% of the regions 110,404 demand points with a primary coverage of 39.27%. Doubling the number of antennas adds an additional 14.82% coverage to 77.60% and decreases the primary coverage by 7.08%. Similar to the Upper Mölltal region this trend continues with the gain in coverage decreasing to 2.84% for 75 antennas.

Table 3 shows the solution time for the different maximum supply constraints. Similar to the results of the Upper Mölltal the solver behaves inconsistently, rising up to 90.17 min for 30 antennas and decreasing to 24.62 min for 75 antennas.

The different sizes and physiographic properties of the research areas lead to several differences in the results. The most obvious one, being the number of antennas required to cover the same percentage of demand area. With two antennas 86.76% of the research area Upper Mölltal is covered, while in comparison 50 antennas are required to cover 88.15% of the research area Schöckelland. Further, an almost complete coverage of 99.04% can be reached with 10 antennas for the Upper Mölltal, while only 90.99% of the Schöckelland demand area are covered with 75 antennas. Thus, the size of the area, as well as the many valleys and ridges lead to a strong cost increase, while minimizing the coverage gain. But there are also similarities visible in the results. A comparison of Figs. 15 and 17 shows that similar developments concerning the no coverage, primary coverage, backup coverage and multiple coverage can be observed. (1) The gain in total coverage decreases with the number of antennas rising. (2) The areas with no coverage and primary coverage decrease with more placed antennas. (3) The backup coverage increases at first, but then starts decreasing steadily. (4) The areas with multiple coverage increase continuously.

6. Discussion and future prospects

In this paper we propose a deterministic solution for the placement of antennas for the purpose of tracking cattle in the Austrian alps. The ViehFinder system is a holistic solution for tracking and monitoring cattle in remote areas. We discuss locational problems, and in particular the ACLP. Furthermore, we discuss approaches for the selection of demand and candidate sites and defined requirements for demand and candidate sites in the context of tracking cattle in the Austrian Alps. The three constraints, (1) proximity to a street, (2) exclusion of steep terrain, and (3) mobile network coverage apply to the candidate sites. This paper defined the alp areas as constraint for the demand sites. We develop an ACLP, which is a Maximum Coverage Location Problem. It utilizes site selection techniques, resampling and LoS to generate the demand and candidate sites, as well as the service areas for the optimization process. This paper applies an ILP to solve the ACLP for two selected test areas in Austria. We investigate four potential bottlenecks of the proposed solution, which are (1) the service area generation, (2) the coverage generation, (3) the problem generation and (4) the solving of the problem with ILP. The in-depth analysis of these bottlenecks, helps to generate an improved approach for coverage generation which is suitable for large problem instances. Further, we show that the CBC-solver can be computationally unpredictable, as it shows unpredictable solution times depending on the size of the problem. This paper defines the mathematical model for the ACLP and explains the use of ILP. Finally, we demonstrate the capability of the proposed approach by monitoring the trade-off between cost and coverage, as well as the solution time for two real-world examples. We are not aware of other works applying ILP to problems of similar sizes, as mostly heuristics are used for this.

The key contributions of this paper are as follows. We highlight a detailed understanding of the bottlenecks of the proposed spatial optimization approach and demonstrate the boundaries of the ILP for spatial optimization problems. We improve the algorithm for coverage generation to make it suitable for large problem instances with complex geometries. This paper presents insights into the computational behavior of the algorithm, as well as the results concerning covering with base stations. We show that the change in coverage for zones with no coverage, primary coverage, backup coverage, and multiple coverage is dependent on the number of optimal sites. Further, we demonstrate the suitability of the proposed solution by applying it to two real-world examples.

The results show, that the methodology is applicable to both real-world examples. But there are still various future research aspects that could improve the approach, such as replacing the LoS approach for service area generation with radio wave propagation modeling. This switch from one of the simplest propagation models to a more complex model might yield more accurate results concerning service area covering. The complexity of the problems could be reduced by applying more elaborate site selection techniques. Even though the correlation between height and visibility is low (Franklin and Ray, 1994), Heyns et al. (2021) show that restricting candidate sites to certain landforms leads to a superior set of potential candidate sites

Table 2
Optimization results for the test area Upper Mölltal.

Solution	Maximum supply	Cost [€]	Selected supply	Coverage [%]	Primary covered [%]	Solver time [min]
A	2	2900	27, 728	86.76	78.00	26.39
B	5	7250	7, 21, 453, 547, 728	98.26	13.89	10.18
C	8	11 600	7, 21, 271, 453, 541, 543, 728, 771	98.84	4.44	47.20
D	10	14 500	9, 10, 21, 271, 285, 541, 546, 644, 728, 772	99.04	4.44	41.58

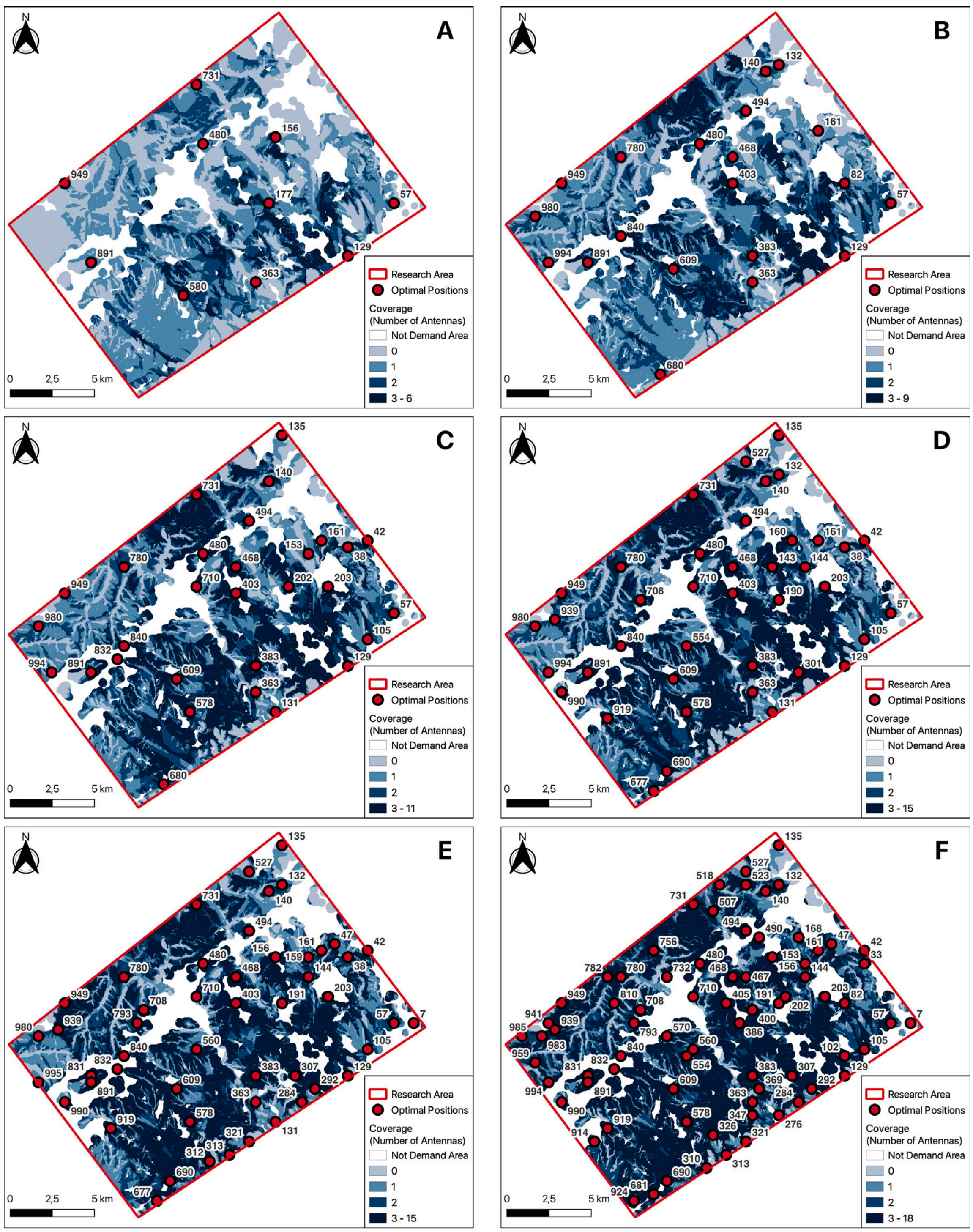

Fig. 16. Solutions for the Schöckelland for different supply constraints.

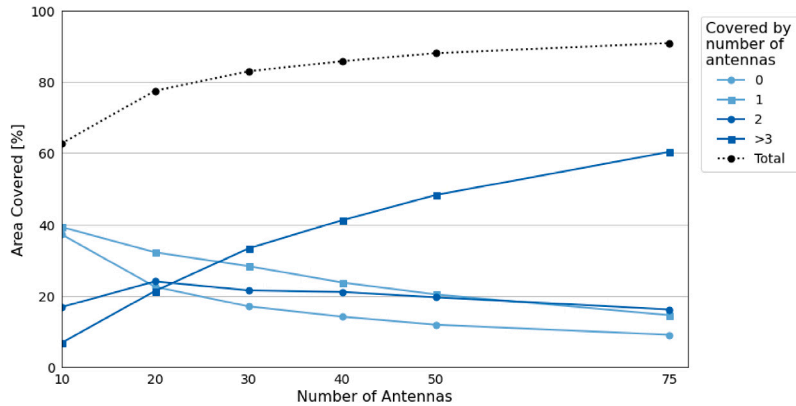

Fig. 17. No Coverage, Primary Coverage, Backup Coverage, Multiple Coverage and Total Coverage for the Schöckelland test area for different supply constraints.

Table 3
Optimization results for the test area Schöckelland.

Solution	Maximum supply	Cost [€]	Coverage [%]	Primary covered [%]	Solver time [min]
A	10	14 500	62.78	39.27	61.65
B	20	29 000	77.60	32.19	59.87
C	30	43 500	83.03	28.27	90.17
D	40	58 000	85.90	23.69	60.27
E	50	72 500	88.15	20.36	50.25
F	75	108 750	90.99	14.50	24.62

while reducing the computational complexity of the problem. Another aspect is changing the weights of the demand points depending on the objective. For example, when the farmer wants to use Geofencing it is of highest importance that the boundaries of the alp areas are covered, thus a higher weight could be applied to these zones. Our research shows that the major bottleneck for the efficiency of the proposed approach is the unpredictable computational behavior of the open-source CBC-Solver. Thus it is necessary to investigate more reliable solutions, such as commercial ILP-Solvers or heuristic approaches as applied by other works (Porras et al., 2019; Dreifuerst et al., 2021; Heyns et al., 2021). Finally, the ViehFinder-System has to secure the transmission of the tracking data to the server at all times. Thus backup coverage must be included in the model, to ensure transmission in case of an equipment failure.

CRediT authorship contribution statement

Franz Welscher: Investigation, Data curation, Methodology, Software, Experiments, Analysis, Visualization, Writing – original draft, Writing – review & editing. **Rizwan Bulbul:** Conceptualiztaion, Methodology, Supervision, Writing – review & editing. **Johannes Scholz:** Conceptualiztaion, Methodology, Project administration, Supervision, Writing – review & editing. **Peter Lederer:** Information ViehFinder-System.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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