CHALMERS
UNIVERSITY OF TECHNOLOGY

Optimizing Bike Sharing Systems in Gothenburg

Enhancing Multimodal Public Transport Integration

Master's thesis in Engineering Mathematics and Computational Science

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Cover: Styr & Ställ bike station in Gothenburg.

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Abstract

Rentable bike sharing systems (BSS) are an environmentally friendly way of transportation that has steadily gained popularity in cities worldwide in recent years. These micromobility vehicles provide a convenient solution to the first-mile/last-mile problem often associated with public transportation. While many studies have focused on determining the optimal placement of BSS stations to fulfill user demand, it is equally important to consider how well the BSS network integrates with other modes of public transport to encourage multi-modal travel. The aim of this thesis is to develop an optimization framework for determining the optimal placement of BSS stations to enhance multi-modal accessibility while ensuring demand fulfillment. The study focuses on the central parts of Gothenburg with demand evaluated through analysis of historical travel data. The proposed framework defines the problem as a facility location model, with the objective of maximizing a defined accessibility measure. Constraints are introduced to ensure the fulfillment of historical demand. Given the NP-hard nature of the problem, a metaheuristic optimization algorithm is employed to find an efficient solution. The resulting station placement is then compared to the current BSS station locations in Gothenburg and demonstrates that the proposed solution improves the multi-modal accessibility while successfully meeting historical demand.

Keywords: Bicycle sharing system, First-mile/last-mile problem, Facility Location Problem, Ant Colony Optimization, Multi-modal travel

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Finally, I want to express my heartfelt gratitude to my friends and family for their unwavering support, patience and encouragement throughout the writing of this thesis. I could not have done this without your support and belief in me.

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ACO	Ant Colony Optimization
BSS	Bicycle Sharing System
GIS	Geographic Information System
FLP	Facility Location Problem
NP	Non-deterministic Polynomial Time
GA	Genetic Algorithm
SA	Simulated Annealing

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1
Introduction

1.1 Background

Rentable bikes are a popular example of shared micromobility vehicles. These small, easily accessible modes of transportation can be rented for short periods to travel shorter distances and are particularly effective in addressing the first-mile/last-mile challenge commonly associated with public transport in urban areas.

In Gothenburg, Styr & Ställ has been the official provider of shared rental bikes since 2010 [1]. Users can pick up and return bikes at designated stations throughout the city, with a penalty fee applied if a bike is not returned to one of these stations [2].

As urban development progresses and the demand for environmentally friendly transportation options increases, there is a growing need to optimize bicycle-sharing systems (BSS), particularly in combination with other public transport modes. This thesis aims to develop an optimized infrastructure for a BSS in Gothenburg by leveraging historical travel data and modeling the problem as a large-scale network optimization problem. This problem will then be solved using a meta-heuristic optimization approach inspired by the foraging behavior of ant colonies in nature.

1.2 Previous work

As the use of shared micromobility continues to grow in cities worldwide, there is an increasing need to optimize these services. Consequently, numerous studies have investigated the problem of identifying the optimal locations for BSS stations using a variety of approaches.

In a systematic review by Bahadori et al. [3], a range of publications focused on the bicycle station location problem for BSS are discussed. The study identifies three key indicators of performance that should be considered when designing an effective BSS system. The first is availability, which refers to whether a station is located within a preferred distance of a given user. The second is efficiency, which captures overall customer satisfaction with the system, the third is responsiveness, which concerns how easily a station can be accessed by its users. These factors collectively play a crucial role in determining the success of a BSS.

In another study, Caggiani et al. [4] proposed a network design model with the objective of minimizing disparities in multi-modal public transport accessibility across different population groups. This approach diverged from the more traditional focus on maximizing coverage or minimizing travel distance to and from stations. Instead, Caggiani et al. imposed constraints to ensure that coverage and accessibility levels remained above a specified threshold.

The study revealed that higher coverage levels often correlate with reduced equality among population groups. These findings suggest that when designing new or expanding existing BSS systems, it is essential to consider not only demand coverage but also factors such as accessibility to other public transport modes and socio-economic disparities that could influence the need for multi-modal transport solutions.

An important aspect when addressing a location problem for BSS is the choice of solver method. Facility location problems are know to be $\mathcal{NP}$-hard [5], making exact solutions computationally impractical for large-scale systems. As a result, many studies have employed heuristic optimization techniques to identify near-optimal solutions, such as greedy algorithms and evolutionary algorithms [6]. This thesis builds upon these methods and aims to develop an optimization framework that addresses the unique challenges of BSS station placement, with a focus on multi-modal accessibility and demand fulfillment in the context of Gothenburg.

1.3 Aim & Scope

The objective of this thesis is to optimize the infrastructure of a shared micromobility service in the city of Gothenburg. The study focuses on identifying optimal locations for new rentable bike stations, with an emphasis on fulfilling travel demand and patterns while promoting multi-modal travel.

This will be achieved by collecting and analyzing relevant data to identify key factors influencing travel demand. The problem will be formulated as a facility location problem, incorporating constraints related to city planning and geospatial considerations. A metaheuristic optimization algorithm will be applied to solve the problem, and the result will be evaluated against the current station configuration.

The scope of this project includes the following:

- Collecting and analyzing historical travel data from the rentable bike system in Gothenburg.
- Formulating a facility location problem with the objective of maximizing accessibility to multi-modal travel.
- Solving the problem using a meta-heuristic optimization algorithm.
- Evaluating the result and comparing it to the existing BSS network.

2

Theory

2.1 Ant Colony Optimization

The Ant Colony Optimization (ACO) algorithm, introduced by Dorigo and Gambardella in 1997, was originally applied to the Traveling Salesman Problem [7]. Inspired by the behavior of real ants, the algorithm models their ability to discover the shortest path between their colony and a food source.

In the natural world, many ant species deposit chemical substances known as pheromones along their paths while foraging for food [8]. Initially, ants explore their surroundings randomly until they encounter a food source. Subsequent ants detect the pheromone trails left by their predecessors and are more likely to follow paths with higher pheromone concentrations. Over time, this process naturally optimizes the route for transporting food back to the colony [9]. The ACO algorithm draws heavily on this natural behavior, mimicking it to solve complex optimization problems.

The algorithm works by deploying simulated ants to explore potential solutions for the given problem. This process is repeated over multiple iterations, with each iteration influenced by the pheromone trails deposited by previous simulated ants. The algorithm also incorporates stochasticity: while path selection is random, it is biased by probabilities proportional to the pheromone concentrations along each path [10]. This approach allows the algorithm to balance exploration and exploitation, gradually converging on optimal or near-optimal solutions.

A simple version of the ACO algorithm, applied to a classical Traveling Salesman Problem, can be defined by a graph (N, E), where N represents the set of nodes and E represents the set of edges. In this scenario, we assume a colony of m ants. Each iteration of the algorithm begins with distributing the ants across the nodes. The ants then independently construct a path that fully connects the graph by traversing edges. After each iteration, the pheromone trails are updated to reflect the quality of the solutions found. Subsequent ants select their paths stochastically, with a bias towards edges that have higher pheromone concentrations [11].

The amount of pheromone deposited by ant k in iteration t is given by,

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L_k(t)} & \text{if ant } k \text{ travels along edge } (i,j) \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

Where L_k represents the travel length for ant k and Q is a pheromone deposit factor.

The total amount of pheromone deposited on an edge (i, j) by a colony of m ants is denoted as $\tau_{i,j}$, and it is updated after each iteration according to the formula,

$$\tau_{i,j}(t+1) = (1-\rho)\cdot\tau_{i,j}(t) + \sum_{k=1}^{m}\Delta\tau_{i,j}^{k}(t)$$

Where ρ is the pheromone evaporation rate.

Following the pheromone update, the probability of succeeding ants choosing edge (i, j) is calculated as

$$P_{i,j} = \frac{(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum\left((\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}\right)}, \quad \eta_{i,j} = \frac{1}{L_{i,j}} \tag{2.2}$$

Here, the first factor is the pheromone influence on the probability values and the second represents the heuristic influence, defined as the inverse of the distance of edge (i, j). The parameters α and β control the relative importance of pheromone trails and heuristic information, and can be adjusted depending on the problem.

The algorithm iterates until the solution converges or until a predefined stopping criteria is met.

2.1.1 Algorithm specific parameters

The behavior of the ACO algorithm is heavily influenced by the algorithm specific parameter values [12]. One important aspect concerns how the exploration vs exploitation importance of the algorithm is weighted, which is specifically influenced by the parameters α and β in equation 2.1. If exploration is favored, ants will be encouraged to explore new solutions and if exploitation is favored, ants will be encouraged to follow and intensify solutions with high fitness scores [13]. How exploration vs. exploitation is weighted is heavily influenced by the parameters α and β. If $\alpha = 0$, the ants will completely ignore the pheromone trails and rely on the heuristic information, resulting in a greedy approach of the algorithm. If α is given a large value, the ants will strongly favor solutions with high pheromone levels, which might lead to premature convergence. Likewise, if $\beta = 0$, ants will ignore the heuristic information and base their decisions fully on the pheromone trails, while if β is large, the ants will strongly base their decisions on the heuristic values. When applied to the TSP, this will result in ants prioritizing shorter paths even if the pheromone levels are low along these.

The parameter ρ determines the evaporation rate of the pheromones. How this parameter is set strongly impacts the global search ability and speed of convergence [14]. For large-scale problems, a too high ρ will lead to pheromone levels on not yet searched edges to approach 0, which limits the searching scope. However, a too small ρ may lead to the algorithm getting stuck in local optima by increasing the probability of choosing already searched edges [15].

The pheromone deposit factor, denoted Q, in equation 2.1 determines the total amount of pheromone left on an edge after each cycle. A large Q leads to pheromone accumulating along the edges faster and thus has an impact on the speed of convergence for the algorithm. Since the influence of Q is also dependent on the values of α and β, these parameters should all be considered in tandem to ensure an overall good performance.

The initial pheromone levels also play a crucial role in the ACO algorithm, specifically in guiding the search process and convergence [16]. It is heavily influenced by the other parameters, specifically m and ρ and should therefore be considered with these values in regard [16].

Furthermore, the performance of the ACO algorithm depends significantly on the number of ants in the colony, denoted by m above [17]. The number of ants has an impact on the rate of diversification in the solution space. This is based on the expectation that as the number of ants is increased, the number of different solutions that can be explored will increase [12]. It has however been shown that the execution time of the algorithm increases linearly as the number of ants is increased [17]. Experimental results when applying the ACO algorithm to a classical TSP has also shown the existence of a cap value after which the performance of the algorithm is not improved. In summary, it is important to set the number of ants specifically according to the problem at hand, as with the previously mentioned parameters.

3
Methodology

The methodology of the thesis is summarized in the flowchart in figure 3.1. The project was initiated by cleaning and preprocessing the raw data to ensure it was suitable for analysis. Next, an exploratory data analysis (EDA) was carried out on the processed data to identify both temporal and spatial trip patterns. Based on the insights from this analysis, the problem was formulated as a facility location problem with the objective of optimizing the multi-modal accessibility of the BSS stations within the study area. To solve the problem, an ant colony optimization algorithm was applied. The parameters of the algorithm were tuned using a grid search, and a sensitivity analysis was conducted to evaluate how each parameter influenced the algorithm's performance. Finally, the proposed station locations were compared to the existing station locations to evaluate potential improvements.

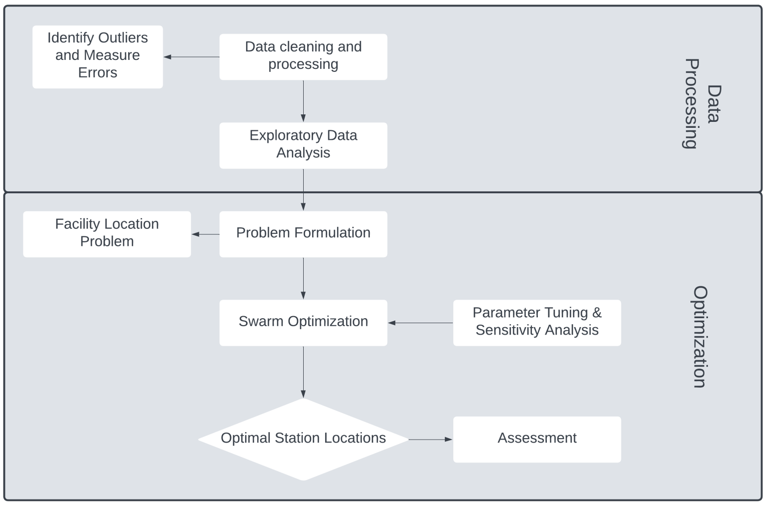


Figure 3.1: Flowchart over the methodology used throughout the thesis project.

3.1 Data Collection and Cleaning

Styr & Ställ, operated by Nextbike, is the leading provider of rentable bicycle services in Gothenburg [18]. For the purpose of this thesis, all historical travel data was obtained directly from Styr & Ställ through personal communication.

The trip data analyzed in this thesis project were recorded between August 2023 and August 2024. This dataset contained detailed information about each trip. An example entry of the dataset can be seen in Table 3.1. In addition, Styr & Ställ provided documentation of all permanent station locations that were operational during the study period. The raw dataset comprised 774,087 recorded trips within the Gothenburg and Mölndal regions.

Variable	Example Value
Start time	2023-09-01 06:08
End time	2023-09-01 06:14
Duration (s)	342
Start station ID	Svingeln (A)
End station ID	Kruthusgatan
Start latitude	57,71295674 °
Start longitude	11,99134111 °
End latitude	57,711988 °
End longitude	11,980608 °
Bike ID	113118

Table 3.1: Styr & Ställ dataset entry with example values.

The first step of the data analysis was to inspect the dataset for outliers and measurement errors. For example, trips that started or ended outside of the operational region of Styr & Ställ were identified as measuring errors and excluded from the analysis. Likewise, trips where the start and end coordinates were identical were removed, as these were assumed to represent either errors or maintenance operations.

The Styr & Ställ BSS included 136 permanent stations distributed across Gothenburg and Mölndal, as shown in Figure 3.2. Most stations are located in central Gothenburg, with a smaller number situated in the outskirts.

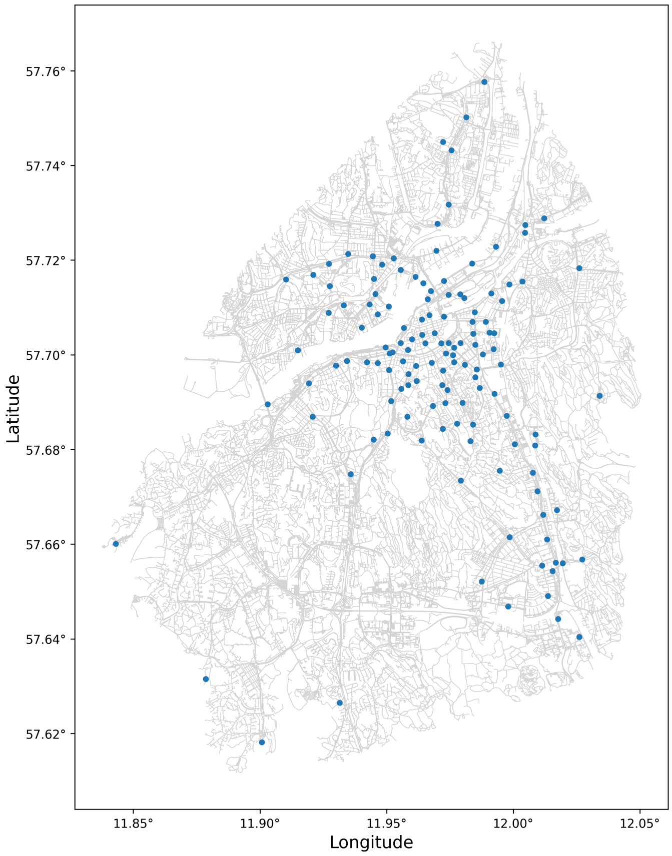


Figure 3.2: Locations of the 136 permanent Styr & Ställ bike stations in Gothenburg and Mölndal as of September 2024.

It is worth noting that a portion of the trips in the dataset involved non-permanent stations, such as summer stations that operate only during specific times of the year or temporary stations established due to road construction or other disruptions. To simplify the analysis, all trips associated with these stations were excluded, resulting in the removal of 206,670 trip records. The cleaned dataset, consisting of 567,417 trips, was then used for subsequent analysis.

After cleaning the data as described, a total of 206 670 trip records were removed. The remaining dataset consisted of 567 417 trips, which were included in subsequent analysis.

3.2 Defining the Study Area

To save computation time, a smaller study area was selected, as illustrated in Figure 3.3. This area encompasses the central parts of Gothenburg, spanning a total of 43.238 km².

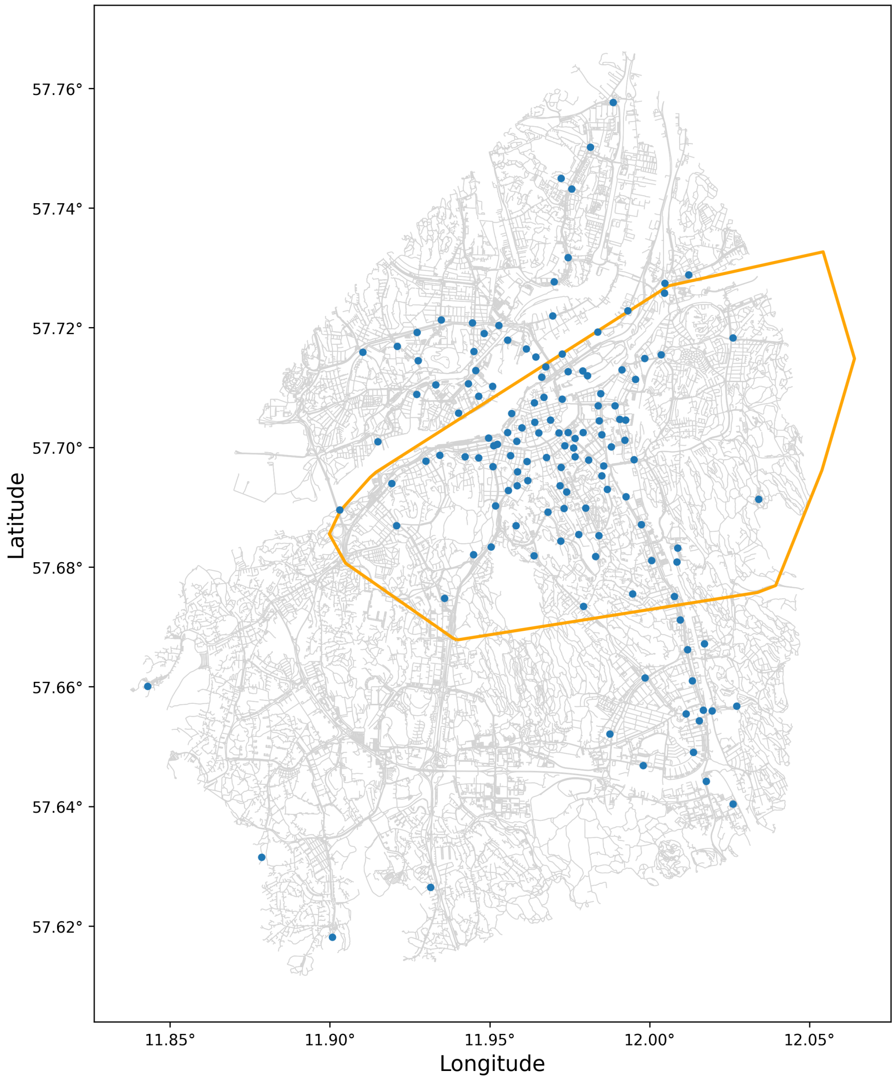


Figure 3.3: Overview of the selected study area. The orange border indicates the area that was included in the study.

Within this study area, the station configuration includes 86 permanent stations, which are shown in Figure 3.4. The stations are more densely concentrated in the city center, particularly near key transport hubs such as the train station and bus terminal. From this point onward, all data analysis was conducted exclusively within this defined area.

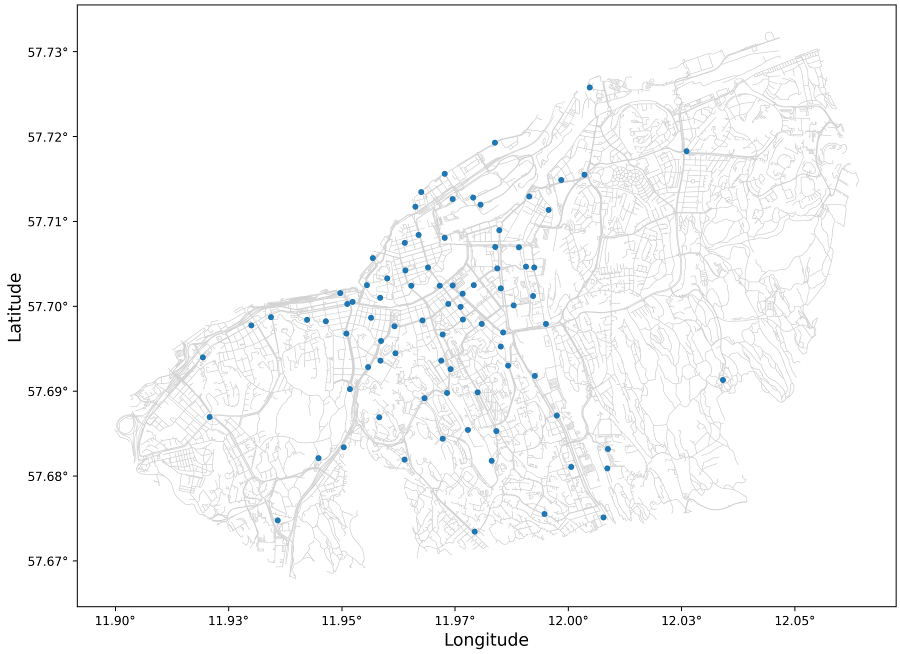


Figure 3.4: Locations of existing stations within the selected study area.

3.3 Data Analysis

In order to better understand the usage patterns of the Styr & Ställ bikes, both the temporal and spatial variations in the data were analyzed. As shown in Figure 3.5, the number of trips starting and ending was generally significantly higher during peak hours: mornings between 7 a.m. and 9 a.m., and afternoons between 4 p.m. and 5 p.m. Following 6 p.m., demand gradually declines, remaining low throughout the night before beginning to rise again around 6 a.m.

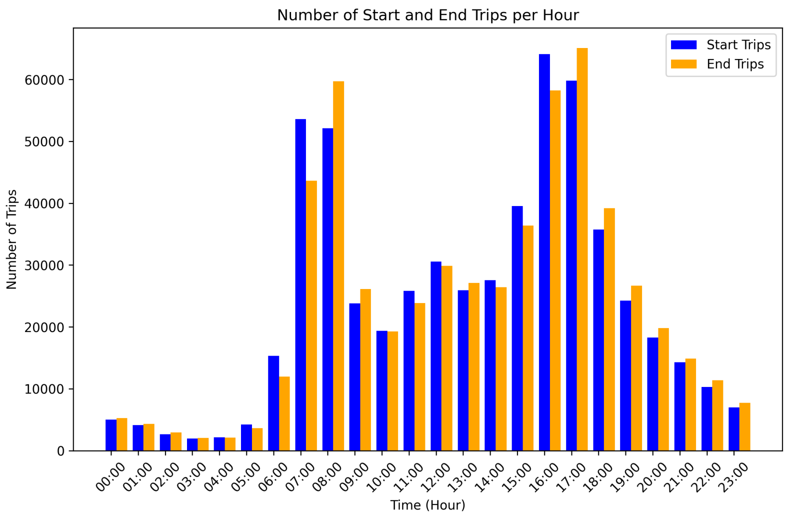


Figure 3.5: Temporal variation in the aggregated number of trip starts and trip ends throughout the day.

An analysis of the total number of trips across different days of the week, as shown in Figure 3.6, reveals substantial variations in demand. Weekday demand is significantly higher compared to weekends. Moreover, the patterns of bike usage differ between weekdays and weekends. On weekdays, there are distinct peaks in the morning and afternoon, reflecting typical commuting hours. In contrast, weekend demand gradually increases throughout the morning, peaks around midday, and then slowly declines into the evening.

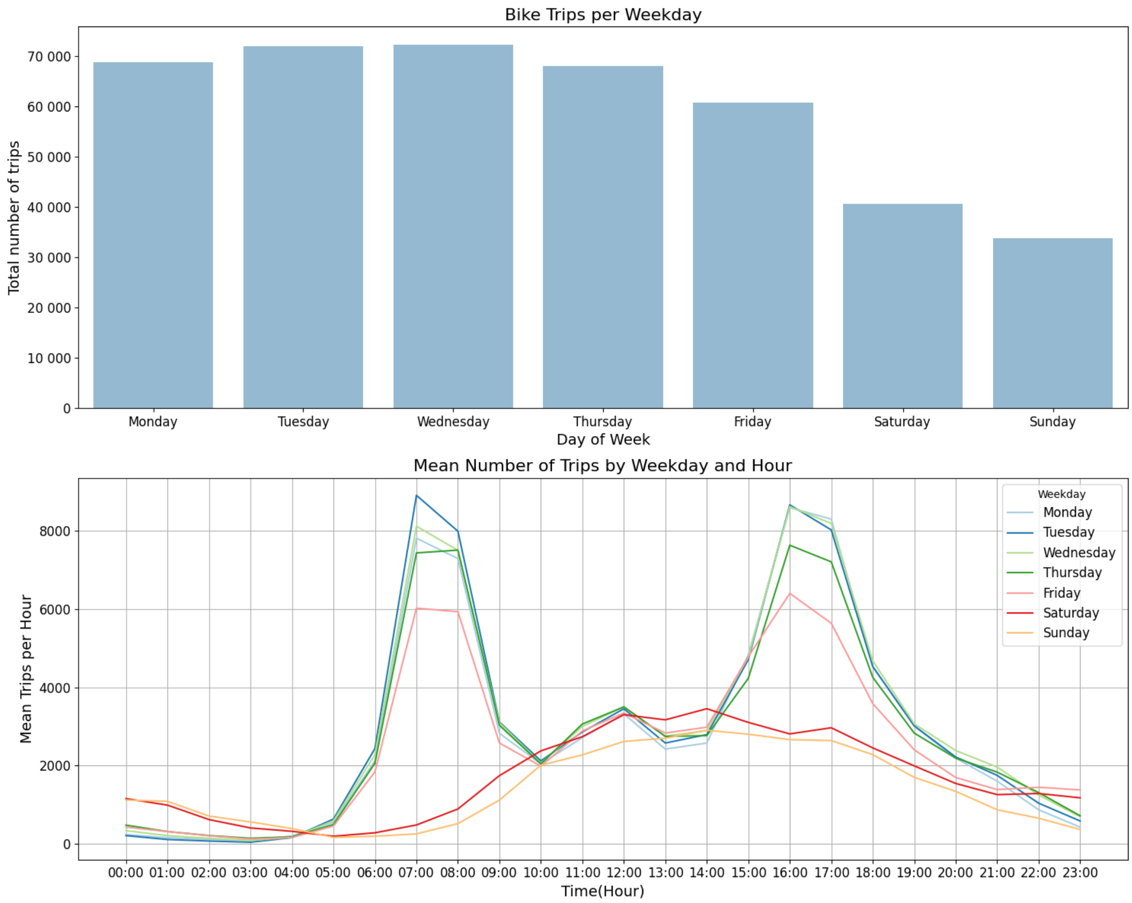


Figure 3.6: Temporal variation in the total number of individual trips depending on day of the week and hour of the day within the study area. The data represents trips recorded between August 2023 and September 2024.

Needless to say, the spatial data did not include information about the specific routes taken by the bikes (routes' actual geometry). As a result, the spatial demand was analyzed solely based on the start and end locations of the trips. To achieve this, the study area was divided into a grid with 500-meter grid cells and all trip start and end locations within each grid cell were aggregated to analyze the distribution of demand. The spatial distribution of the demand can be seen in figure 3.7. The majority of user activity can be seen in the central parts of the city, near the city core or in connection to large public transport junctions.

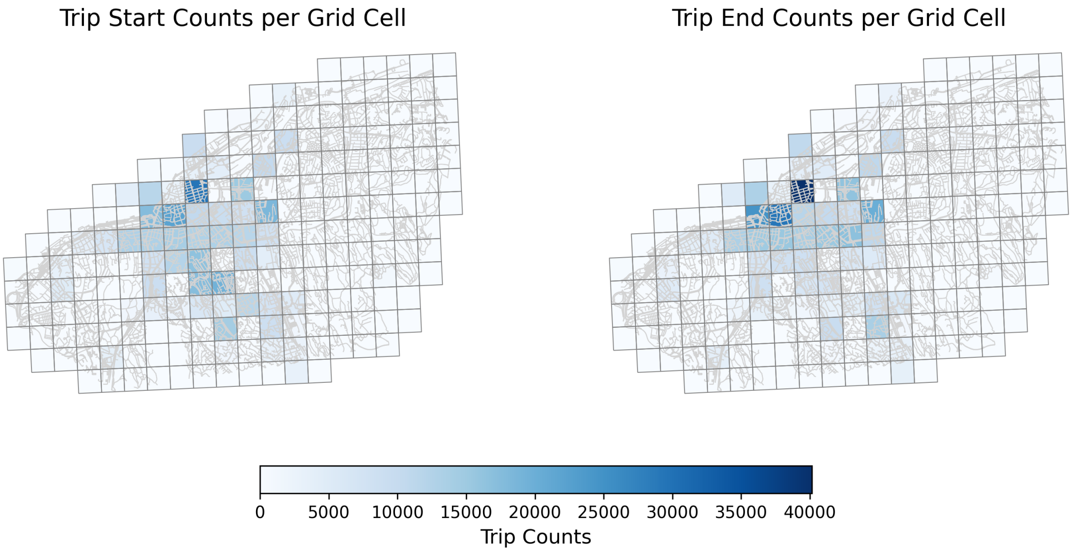


Figure 3.7: Grid of study area with a 500 meter grid size. The color intensity illustrates the historical number of individual trips that started or ended within each grid cell.

An additional analysis was conducted to examine the hourly net flow of bikes in and out of each grid cell. The operators of Styr & Ställ continuously redistribute bikes among stations throughout the day to balance supply and demand. With this operational context in mind, the trips starting and ending within each grid cell were aggregated on an hourly basis, and the net flow was calculated by subtracting the number of trips ending in a cell from the number of trips starting in that cell, according to the formula:

$$\mathrm{Flow_i(h)} = \mathrm{Start_i(h)} - \mathrm{End_i(h)}$$

where $\mathrm{Start_i(h)}$ denotes the number of trips starting in cell i during hour h and $\mathrm{End_i(h)}$ denotes the number of trips ending in the corresponding cell and hour.

To represent peak demand, the maximum net flow, $\max_{h \in H} \mathrm{Flow_i(h)}$, observed during any one-hour interval was identified for each grid cell. This maximum value was then assigned to the centroid of the grid cell to create "demand points," as shown in Figure 3.8. Given the continuous nature of bike redistribution, a one-hour interval was deemed appropriate for estimating the peak demand for bikes. The results showed significant variation in demand across the grid cells. The highest-demand point had a maximum hourly net flow of 48 bikes, while the lowest-demand point had a maximum hourly net flow of 4 bikes.

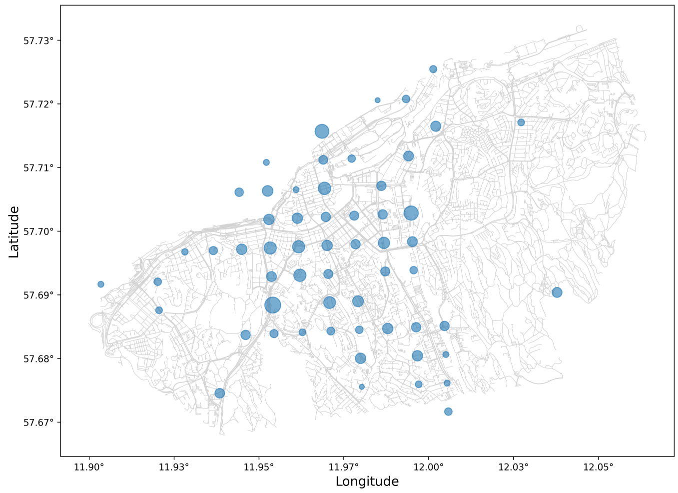


Figure 3.8: Demand point locations based on maximum hourly net flow. The size of the markers is proportional to the relative net flow. Proportions of the markers have been scaled for illustrative purposes.

Given the study's main goal of optimizing multi-modal travel in Gothenburg, public transport infrastructure was also included in the analysis. To narrow the scope, the focus was limited to bus stations within the study area, as shown in Figure 3.9.

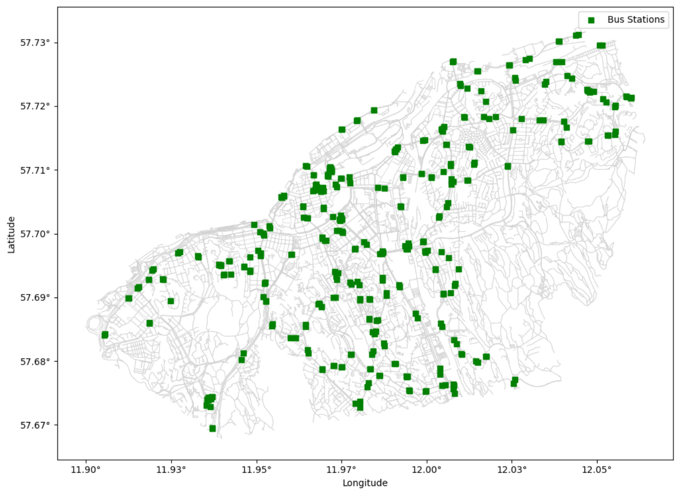


Figure 3.9: Location of Bus Stations within the study area.

3.4 Problem Formulation

The problem consists of creating a new bike station network, optimized for multi-modal travel.

We denote the set of demand points described above as $\mathcal{J}$. Furthermore, we define a set of candidate locations for BSS stations, denoted as $\mathcal{I}$. These candidate locations were defined by downloading the walking street network within the study area and assigning each street intersection as a candidate location. The street network was downloaded through the Open Street Map python extension named OSMnx, where the network is described by a graph with edges representing walking streets and nodes representing street intersections.

The accessibility to multi-modal travel was naturally defined by the proximity from each candidate station i to its nearest bus station. This value is described by the accessibility function in equation 3.1.

$$a_i = \frac{1}{L_i} \tag{3.1}$$

where L_i is the shortest walking distance from station location candidate i to its nearest bus station. To estimate this distance, the bus station locations were mapped to the nearest node in the walking network, measured by euclidean distance. The nearest bus station for candidate location i was then identified by finding the shortest path to a neighboring bus station using Dijkstra's algorithm.

The goal is to maximize the overall accessibility to the bus network for the whole BSS station network in the study area. Furthermore, a constraint was placed to ensure that the placed bike stations meet at least 90% of the historical demand, evaluated by the net flow, as described in section 3.3. The problem can now be defined as a facility location problem as follows:

We introduce a binary decision variable:

$$x_i = \begin{cases} 1 & \text{if candidate station } i \text{ is selected.} \\ 0 & \text{otherwise} \end{cases}$$

and a decision variable y_{ij} which represents the amount of demand at demand point j that is fulfilled by candidate station i.

Furthermore, we define the following parameters:

- n: Total number of candidate stations.
- m: Total number of demand points.
- p: Number of candidate stations to be selected.
- d_j: Demand at demand point j, $j = 1, 2, ..., m$
- C_i: Capacity of candidate station i
- c_{ji}: Binary coverage indicator, where:
  $c_{ij} = \begin{cases} 1 & \text{if candidate station } i \text{ covers demand point } j. \\ 0 & \text{otherwise} \end{cases}$
- a_i: Accessibility score for candidate station i.
- d_{ik}: Distance between candidate stations i and k.
- $D_{\min}$: Minimum allowable distance between two selected stations.
- $C_{\min}$: Minimum required weighted demand coverage.

The optimization problem can now be formulated as follows:

$$\max Z = \sum_{i=1}^{n} x_i \cdot a_i \tag{3.2}$$

subject to:

$$\sum_{i=1}^{n} x_i = p \tag{3.3}$$

$$x_i + x_k \leq 1 \quad \forall i, k \in \mathcal{I} \text{ such that } d_{ik} \leq D_{\min} \tag{3.4}$$

$$\sum_{j=1}^{m} y_{ij} \leq C_i \cdot x_i, \quad \forall i \in \mathcal{I} \tag{3.5}$$

$$y_{ij} \leq c_{ij} \cdot x_i \cdot C_i, \quad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.6}$$

$$\frac{\sum_{j=1}^{m} \sum_{i=1}^{n} y_{ij}}{\sum_{j=1}^{m} d_j} \geq C_{\min} \tag{3.7}$$

The objective is to maximize the total accessibility for all selected stations. Constraint 3.3 states that exactly p stations must be selected. Constraint 3.4 ensures a minimum distance, D_{min} between all selected stations, in order to avoid dense clustering of stations. Constraint 3.5 states that demand points can only be supplied from selected stations and that the total number of bikes supplied from a selected station may not exceed the maximum capacity of that station. Constraint 3.6 asserts that bikes selected from a station can only allocate bikes to demand points which are covered by the station. Here, a station is considered to cover a demand point if it lies within a radius of 500 meter from the demand point. The final constraint 3.7 ensures that a minimum demand coverage of $C_{\text{min}} = 0.90$ is fulfilled over the entire study area. The total demand is calculated as the sum of the demand over all demand points.

With these calculations, the value of a_i is thus inversely proportional to travel time and therefore candidate locations with a lower travel time will be assigned higher values for accessibility. In figure 3.10, all candidate locations are plotted, visualizing their associated accessibility values.

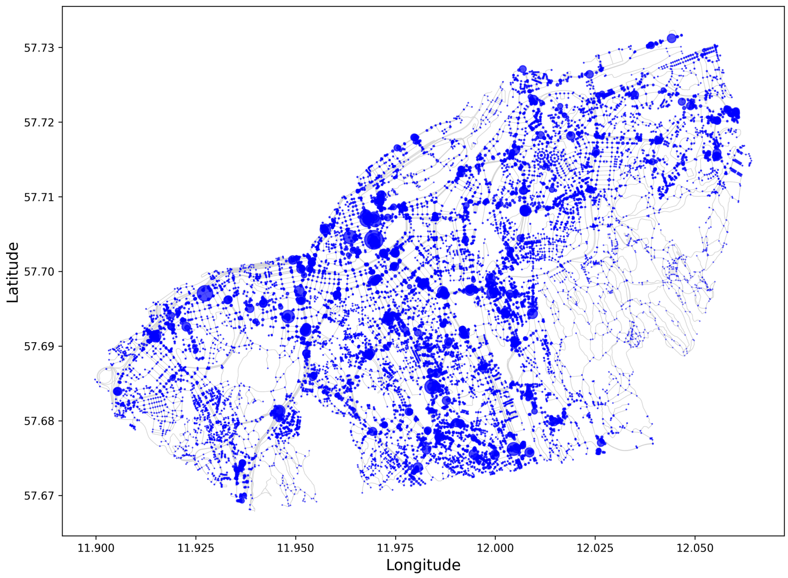


Figure 3.10: Locations of candidate stations. The size of the marker illustrates the accessibility score associated with each candidate station.

3.5 Ant Colony Optimization

The meta-heuristic algorithm used to solve the optimization problem described above is a modified ant colony optimization algorithm. The pseduo-code for the algorithm can be seen in algorithm 1

Algorithm 1 Ant Colony Optimization algorithm

```
Initialize pheromones: pheromones ← [tau_0, tau_0, ..., tau_0]
Initialize best_solution ← ∅, best_score ← 0, best_coverage ← 0
i ← 1
while i ≤ num_iterations do
    all_solutions ← ∅
    all_scores ← ∅
    all_coverages ← ∅
    heuristics ← calculate_heuristic_values()
    probabilities ← calculate_probabilities(pheromones, heuristics)
    for ant ∈ {1 ... num_ants} do
        solution ← construct_solution(probabilities)
        score, allocation, coverage ← evaluate_solution(solution)
        if coverage > min_coverage then
            if score > best_score then
                best_solution ← solution
                best_score ← score
            end if
        else
            score ← 0
        end if
    end for
    update_pheromones(all_solutions, all_scores)
    i ← i + 1
end while
return best_solution, best_score
```

The algorithm is initiated by assigning identical initial pheromone levels τ_0 to each of the candidate station locations. In each iteration, an artificial ant colony is introduced. Each ant selects a set of candidate stations in a biased stochastic way based on a heuristic value, h_i, and the pheromone levels τ_i. The heuristic value for each candidate station is calculated as the accessibility score weighted by the sum of the demand of all its covering demand points, see equation 3.8. The formula for calculating the probabilities can be seen in equation 3.9.

$$h_i = \frac{a_i}{\max(a_i)} \cdot \frac{\sum_{j=1}^{n} c_{ij} \cdot d_j}{\sum_{j=1}^{n} d_j} \tag{3.8}$$

$$P_i = \frac{(\tau_i)^\alpha (h_i)^\beta}{\sum_{i=1}^{n} \left((\tau_i)^\alpha (h_i)^\beta\right)} \tag{3.9}$$

where α is the pheromone influence factor and β is the heuristic influence factor, as described in section 2.1.

When p candidate station locations have been selected, bikes are allocated to the demand points from the selected candidate facilities sequentially according to distance and coverage as specified in equation 3.10.

$$y_{ij} = \min\left(d_j - \sum_{k \neq i} y_{kj}, C_i \cdot x_i \cdot c_{ij} \cdot d_j\right), \quad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{3.10}$$

The algorithm for allocating bikes to demand points is described in algorithm 2.

Algorithm 2 Bike Allocation Algorithm for Demand Fulfillment

Require: n candidate stations, m demand points, capacities C_i for each station, demands d_j for each demand point, coverage matrix c_{ij}, distance matrix d_{ij}, and binary selection variables x_i.
Ensure: Allocation of demand y_{ij}.

```
for each demand point j = 1, 2, ..., m do
    Initialize remaining demand r_j ← d_j.
    Identify covering stations I_j = {i : c_ij = 1 and x_i = 1}.
    Sort I_j in ascending order of distance d_ij.
    for each station i ∈ I_j do
        if r_j > 0 and C_i > 0 then
            Compute allocation y_ij = min(r_j, C_i).
            Update remaining demand r_j ← r_j − y_ij.
            Update station capacity C_i ← C_i − y_ij.
        end if
        if r_j = 0 then
            Break.
        end if
    end for
end for
return Allocation matrix [y_ij].
```

After p candidate stations have been selected and their bikes have been allocated to the demand points according to the algorithm described above, the demand coverage of the solution is computed and if it falls below 90% of historical demand it is dismissed. If the coverage threshold is reached, the fitness value is calculated according to the objective function in equation 3.2. After each iteration the pheromone levels are updated according to the formula:

$$\tau_i(n+1) = (1-\rho) \cdot \tau_i(n) + \sum_{k=1}^{n_{\text{ants}}} \Delta\tau_i^k(n)$$

$$\Delta\tau_i^k(n) = \begin{cases} \frac{Q \cdot z_k}{p} & \text{if candidate facility } i \text{ is chosen by ant } k \\ 0 & \text{otherwise} \end{cases}$$

Where ρ is the pheromone evaporation rate, Q is the pheromone deposit factor and p is the number of candidate facilities included in the solution. First the pheromones are evaporated homogeneously over all facilities. For each ant in the colony, pheromone is deposited at each candidate facility included in the solution proportionally to the fitness score z_k . Pheromones are thus reinforced for solutions with a high fitness value. After all iterations, the solution with the best fitness is identified.

3.5.1 Parameter Tuning

When defining the ACO algorithm, there are a number of parameters that need to be set. The algorithm-specific parameters include the number of ants included in the colony, initial pheromone levels, influence of the heuristic data vs. influence of pheromones, pheromone evaporation rate and pheromone deposit factor. The number of ants, n_{ants}, affects the diversification of the solutions, the higher the number of ants, the more possible solutions can be found. The influence of pheromones, α, and the influence of heuristic value, β, affects the diversity vs intensity of solutions. A higher α will encourage the ants to explore new solutions, while a higher β will encourage the ants to intensify already identified solutions with a high objective value. The parameters and the ranges considered when tuning the model are seen in table 3.2.

Table 3.2: Algorithm parameter ranges

Denotation	Parameter Type	Ranges
n_{ants}	number of ants	[10, 100]
τ_0	initial pheromone	[0.1, 10.0]
α	influence of pheromone	[0.5, 2.0]
β	influence of heuristic value	[1.0, 5.0]
ρ	pheromone evaporation rate	[0.1, 0.5]
Q	pheromone deposit factor	[50, 200]

4

Results

In this section, the results from the parameter tuning are presented. Furthermore, the results from different problem scenarios are presented and analyzed in regards to multi-modal accessibility and demand coverage. The findings are finally compared to the existing station locations.

4.1 Parameter Tuning

The parameter tuning with grid search resulted in the parameter values shown in table 4.1.

Parameter	Value
α	1.0
β	5.0
ρ	0.3
n_{ants}	100
Q	50.0
τ_0	5.0

Table 4.1: Grid search results for ACO parameter values.

This configuration of parameter values resulted in an objective value of 13.8551 when applied to the model problem. Furthermore, a sensitivity analysis was conducted based on these parameter values, where each parameter was modified individually, keeping the rest of the parameters fixed. The results from the sensitivity analysis will be discussed in the following section.

4.2 Sensitivity Analysis

This section discusses the results of the sensitivity analysis. The first parameter that was examined was *num_ants*, representing the ant colony size. Five different values were tested, and their fitness progression is shown in Figure 4.1.

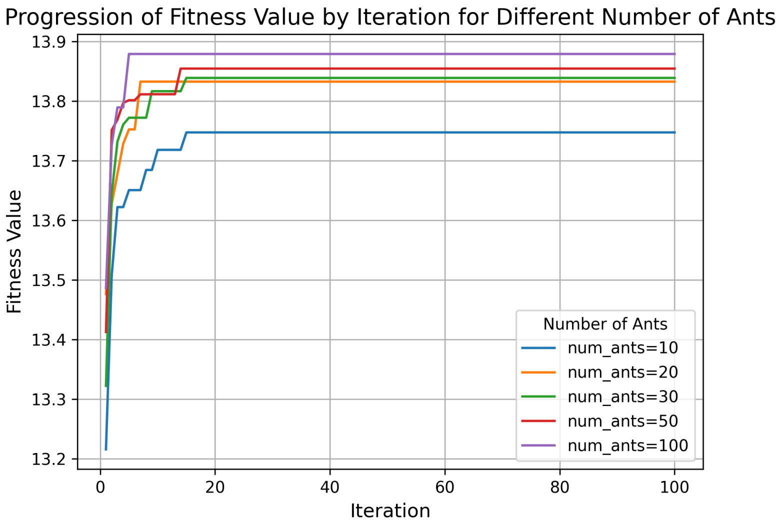
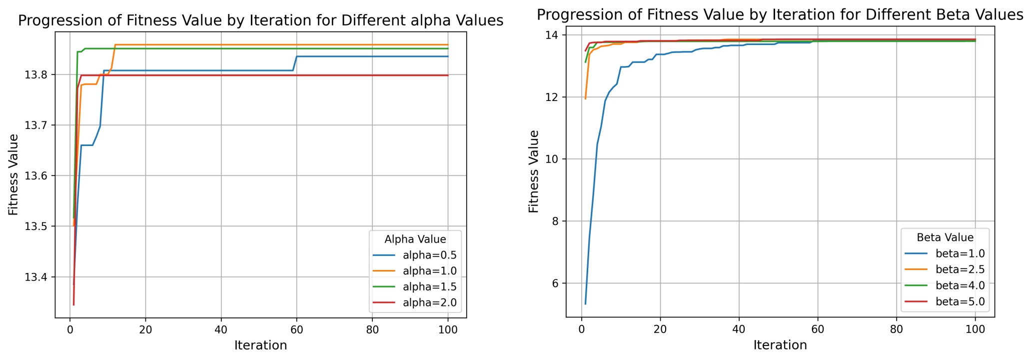


Figure 4.1: Progression of fitness value for different colony sizes.

As mention in section 2.1.1, the number of ants in the colony has a significant impact on the diversification of the solution space. A higher number of ants increases the diversity, although simultaneously increasing the execution time of the algorithm. In Figure 4.1, we see that the fitness value increases with a larger colony and the highest fitness value is obtained with the largest colony size. This is consistent with the the increasing diversification rate of the solution space. As the diversification is increased, more possible solutions can be explored with a possibly higher fitness value. It should also be noted that the largest number of ants leads to the fastest rate of convergence.

The parameters α and β represents the relative importance of pheromone trails and heuristic information respectively. Four different values where investigated for both of these parameters and the progression of fitness value can be seen in Figures 4.2a and 4.2b.



(a) Progression of fitness value for different values of α.

(b) Progression of fitness value for different values of β.

Figure 4.2: Results from sensitivity analysis conducted on parameters α and β.

In the Figure, we see that $\alpha = 1$ and $\beta = 5$ results in the highest fitness value. This is consistent with the algorithm placing a significantly higher importance on the heuristic information compared to the pheromone levels, although they are still considered. This balance between α and β suggests a greedy approach by the algorithm with some influence from pheromone trails, suitable for problems where the heuristic information is considered very reliable. Since the objective value of the FLP at hand is based directly on the proximity to bus stations, which also determines the heuristic values, this result is consistent with the characteristics of the problem.

The next parameter to be investigated was the initial pheromone levels, denoted by τ_0, which has an effect on the convergence of the algorithm. In Figure 4.3, we see that a moderate value of $\tau_0 = 5.0$ results in both the highest fitness value and the fastest convergence. We can also see that the highest value of $\tau_0 = 10.0$ is the slowest to converge. This is likely due to that high initial pheromone levels leads to a decreased importance of the heuristic information during the initial stage of the algorithm, leading to a longer phase of random exploration for the ants.

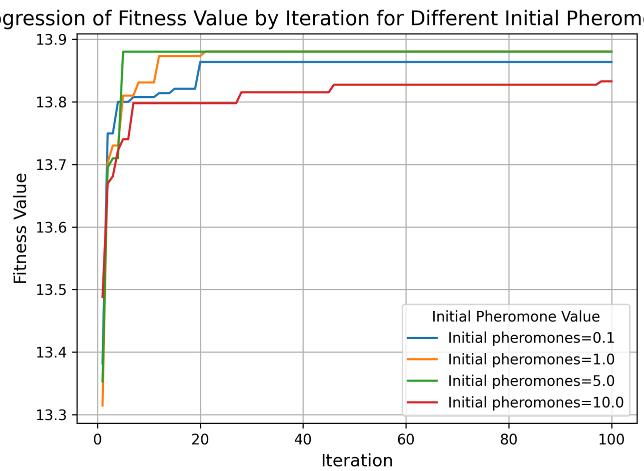


Figure 4.3: Progression of fitness value for different initial pheromone levels.

Another important parameter is ρ, the pheromone evaporation rate. As can be seen in Figure 4.4, the higher values results in better performance. A high value of ρ means that the pheromone evaporates quickly, contributing to the heuristic influence on the algorithm. As ρ is increased and the pheromone trails fade quicker, old solutions will lose their dominance more quickly, allowing for exploration of new paths.

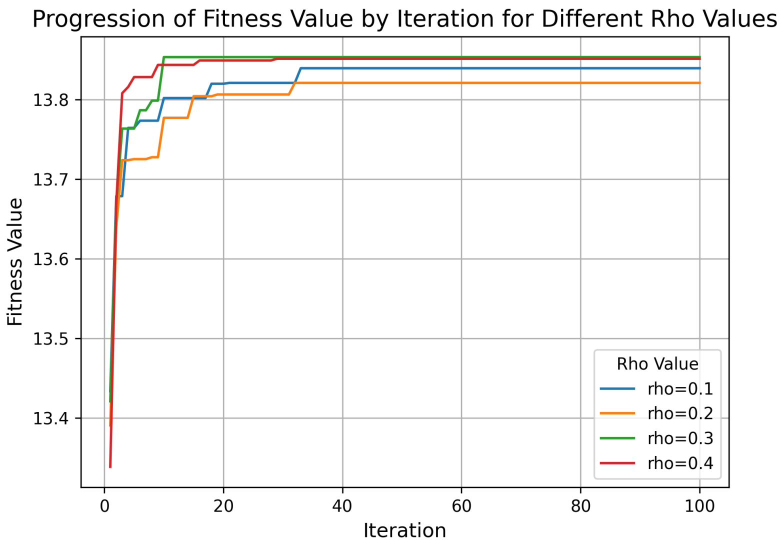


Figure 4.4: Progression of fitness value for different pheromone evaporation levels.

The last parameter considered was the pheromone deposit factor, denoted by Q. In Figure 4.5, we see that the lowest value, $Q = 50$ results in the best performance of the algorithm. This is once again an indication that a heuristic dominant approach to the ACO algorithm is favorable for the problem considered. A low value of Q leads to a lower reinforcement for good solutions, which might lead to a slower convergence, although it could also contribute to more exploration and the avoidance of getting stuck in local optima.

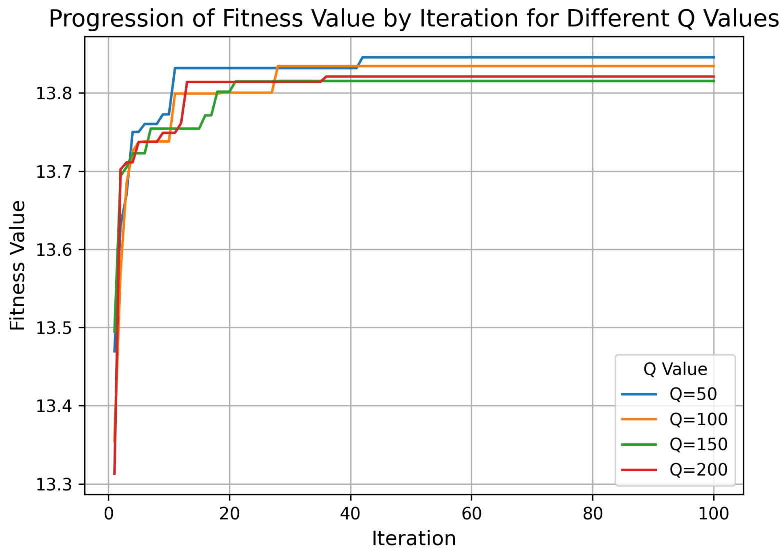


Figure 4.5: Progression of fitness value for different pheromone deposit factor values.

Overall, the sensitivity analysis shows that a heuristic dominant algorithm with a weak pheromone influence results in the highest fitness values. Since the objective value is strongly linked to the heuristic values this is a reasonable result for this specific problem. In the following section, the results when applying ACO with the best combination of parameters will be presented.

4.2.1 Final Station Configuration

After optimizing parameters via grid search, the algorithm was applied to the study area. A new station configuration with $p = 86$ stations matching the original setup was generated. The proposed solution achieved an objective score of 13.8551 with an estimated coverage of 94.37 %. When allocating bikes based on the algorithm, the estimated coverage of existing stations was 96.28%. For the original station locations, the computed objective score was 0.9073 - significantly lower than the algorithm's solution. The ACO solution is plotted next to the existing station locations in figure 4.6.

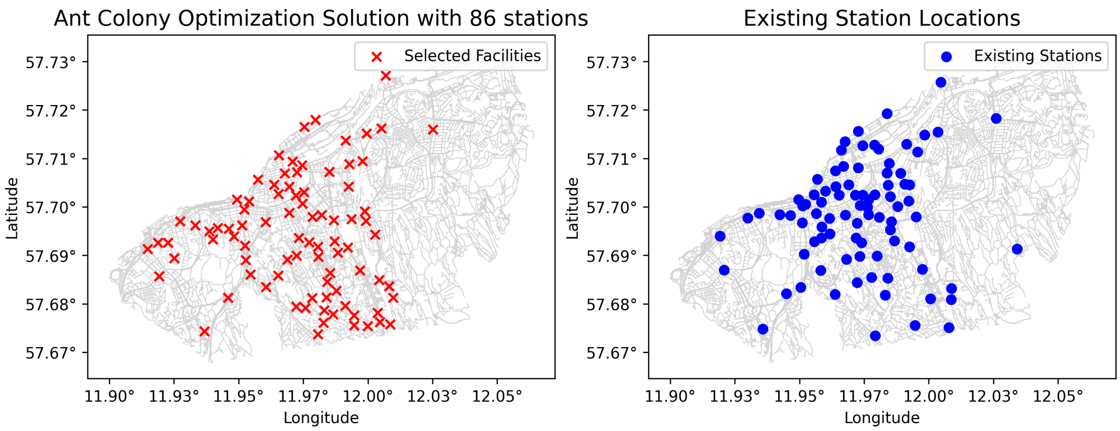


Figure 4.6: Proposed station location for 86 stations.

	Objective Value	Demand Coverage
ACO solution	13.8551	94.37%
Existing Stations	0.9073	96.28%

Table 4.2: Objective value and demand coverage for ACO solution and existing station network respectively.

The proposed solution closely matches the original in terms of overall coverage but differs in station distribution. The ACO-generated solution places a higher density of stations in the southern parts of the study area while reducing station density in central Gothenburg.

Additionally, the proposed solution was compared to the existing station layout concerning bus stop locations. As shown in Figure 4.7, bus stations are generally closer to bus stops in the ACO-generated solution than in the existing configuration.

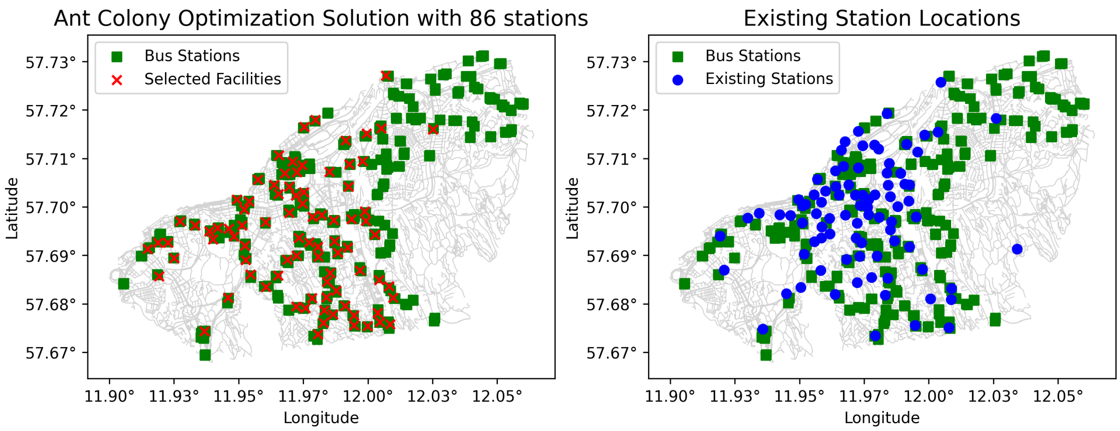


Figure 4.7: Plot comparing the station locations generated by the algorithm with the existing station locations in regards to the bus station network.

5 Discussion

This chapter discusses the results and limitations of this study, along with suggestions for future research.

While the ACO algorithm utilized in this model has been widely used in problems like network design and vehicle routing, its application to station placement for BSS is relatively new. Many previous studies has relied on optimization techniques such as linear programming, genetic algorithms (GA) or simulated annealing (SA), methods that might struggle with effectively balancing between the exploration of new solutions and the exploitations of know good solutions. The inherent nature of the ACO algorihtm allows for dynamic adjustment between exploration and exploitation, making it a novel and effective choice for solving large-scale facility location problems.

The ACO algorithm developed in this thesis generated a new bike-sharing station (BSS) network for central Gothenburg. The proposed station locations improve accessibility to the bus network while maintaining net bike flow demand, with only a 1.91% reduction compared to the existing network. Placing BSS stations in closer vicinity to bus stations can offer several benefits, especially within urban mobility and efficiency of public transport.

One key advantage is the improved multimodal connectivity. Aligning the placement of BSS stations allows for more seamless firs-mile/last-mile connections, encouraging travelers to utilize bikes for short distances before or after taking the bus. By placing BSS stations in close vicinity to stations for other modes of transportation, users might also be more inclined to choose a shared bike service for the last part of their trip, to avoid overcrowded buses and traffic congestion. Facilitating multimodal travel could also improve accessibility to destination not directly served by buses, encouraging people to choose public transport instead of private cars.

Motivating people to choose more sustainable transport options could also help decreasing the dependency on cars, with the effect of lower CO_2 emissions and less traffic congestion.

However, increasing the model's complexity could enhance its real-world accuracy. Throughout the study, several ways to refine the problem formulation were identified but excluded due to time constraints. Future research could incorporate additional geographical factors, such as transportation infrastructure (e.g., proximity to bike lanes, high-speed roads affecting safety, and parking availability). Land use data, including residential and commercial areas, could help better estimate demand. Given that most trips are for commuting, integrating data on educational institutions and large workplaces would be valuable.

Topography analysis, particularly identifying steep slopes that may deter cyclists, could further refine demand estimates. Additionally, demographic factors such as population density, employment levels, income distribution, and age groups could help assess demand in new service areas and identify locations where BSS would be most beneficial.

Furthermore, it is important to note that this thesis applied the algorithm to one specific part of the city of Gothenburg. The results can therefore be expected to reflect the unique characteristics of this area. When applying the same algorithm to other cities, or even different areas of the same city, results might differ significantly and several considerations should be taken into account. Such considerations include city characteristics and infrastructure, the availability of other types of public transport will likely influence the demand for rentable bikes. Population density and commuting patterns are additional factors that should be considered when applying the algorithm to other areas.

5.1 Further Work

This section outlines potential directions for further research on optimizing multimodal travel.

While this thesis focuses on dockable bike-sharing systems, the framework could be adapted for other micromobility services, such as rentable e-scooters. Many scooter services operate on a free-floating model, meaning they do not require docking stations. Similar net flow demand calculations could guide optimal scooter distribution, ensuring availability at key locations throughout the day. The algorithm could also be modified to optimize drop-off locations, considering both demand fulfillment and multimodal transport integration.

As mentioned in the discussion section, the algorithm discussed in this thesis would benefit from being applied to additional areas with different characteristics. The results from these applications could yield insights about additional factors that influence the demand and bike trip patterns, and could successfully be integrated into the algorithm.

Another avenue for future research is exploring alternative optimization techniques. Metaheuristic algorithms such as Genetic Algorithms (GA) and Simulated Annealing (SA), which have gained popularity in recent years , could provide alternative approaches to solving the problem efficiently.

6 Conclusion

The goal of this master's thesis was to optimize a rentable bike-sharing system (BSS) in Gothenburg to enhance accessibility to multimodal travel. This project involved collecting and analyzing historical BSS travel data to identify temporal and spatial patterns. A facility location problem was formulated to maximize accessibility by minimizing travel time between bike docking stations and public transport hubs while ensuring adequate demand fulfillment across the study area. The problem was then solved using a metaheuristic swarm optimization model inspired by the foraging behavior of ant colonies. The resulting station network significantly improved access to transit stations while meeting demand constraints.

The findings demonstrate that a BSS network can be strategically optimized to encourage multimodal travel while maintaining service efficiency. Future research could explore adapting this model to other micromobility services, such as rentable electric scooters. Additionally, alternative optimization techniques, such as genetic algorithms, could be applied to compare performance and results.

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