FACULTY OF ENGINEERING
AND ARCHITECTURE

Optimal location of UAV base stations to serve demand in an urban environment for emergency services

Niels Maes
Student number: 01704590

Supervisors: Prof. dr. Ivana Semanjski, Prof. dr. ir. Sidharta Gautama
Counsellor: Ir. Casper Van Gheluwe

Master's dissertation submitted in order to obtain the academic degree of
Master of Science in Industrial Engineering and Operations Research

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Preface

On the road to obtaining a master's degree, writing a master thesis is an essential part. In this master thesis, I had the opportunity to work out an optimization about the optimal placement of Urban Air Vehicle (UAV) base stations for emergency services.
There are multiple reasons why I chose this subject. First of all, I'm fascinated by today's mobility limitations, such as traffic congestion and air pollution. Electric urban air mobility offers a chance to better cope with these problems. It introduces an additional dimension to today's mobility landscape and due to its electric character, air pollution can be reduced resulting in a healthier city landscape to live in.
Additionally, I wanted to study a topic related to healthcare or emergency services. In this sense, this master thesis allowed me to investigate an optimization problem with a focus on emergency services. This is something I deem to be very relevant for the community.

The master thesis is the final stage in this five-year education at the University. This last stage is different from everything that has been seen before. In the theory courses, you gain insight into the most essential theory and learn to study problems from a theoretical point of view. In project work then, theoretical information is put into practice to solve clear, well-defined problems.
A master thesis puts all of this together, from the very beginning to the end: You search for a subject yourself and explore it on your own. The discovered theoretical knowledge is then used to clearly define a problem you want to tackle. After this, experiments are conducted to make observations and eventually draw conclusions about the subject under study.
Of course, this wouldn't be an engineering thesis, if it didn't come with the necessary amount of iterations: Some perspectives that seemed interesting in the beginning turn out not to be as promising as you thought they would be or some extra unforeseen problems occur on the road. It is then the art of not letting it come to you and continue, each time trying to come up with new, interesting solutions.
Luckily, during a master thesis, you do not stand alone. Therefore, I, first of all, want to thank prof. dr. Ivana Semanjski. During the execution of this master thesis, I could always direct my questions toward you and you were there to clear out ambiguities. When I needed some extra guidance in navigating myself through the research stages, you were always ready to offer some extra insights and perspectives to me. For all of that, I am grateful.

I also want to thank prof. dr. ir. Sidharta Gautama for giving me the first taste of more advanced solution methods during the course on 'Heuristics and Search Methods' and being ready to answer my questions. Additionally, I want to thank ir. Casper Van Gheluwe for giving me some very good remarks about the perspectives I presented during the intermediate thesis presentation.

Finally, I want to thank my parents for supporting me during the execution of this master thesis. During the most difficult moments, they were always there to support me and offer the mental support I needed.

Niels Maes

Ghent, June 10, 2022

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Abstract In tackling major traffic and transportation issues in an urban environment, electric urban air mobility (eUAM) offers a chance to efficiently address these issues. EUAM creates an extra dimension in the current mobility landscape and due to its electric character, it reduces the emission of fine particles. Even though eUAM certainly has a lot of potentials, there are still quite some questions that remain unanswered. One of these questions is how an optimal location of the urban air vehicle (UAV) base stations can be obtained to minimize the associated response time for emergency services. This study proposes a solution method for the location-allocation problem of UAV base stations in an urban environment, which will be the city of Ghent in this study. In this research, clustering will be used to solve the location-allocation problem. In doing this, a clustering method that combines bottom-up or agglomerative hierarchical clustering with Fuzzy C-Means (FCM) clustering is designed. The proposed method is then applied to the real-life case of Ghent. In the initial approach, the problem is simplified a lot. Only 1 UAV type is considered, no initial infrastructure is present and no specific decision criterion is used. Step by step, the relaxations are lifted which results in the problem being more complex and better resembling the real-life case. The eventual problem that is solved is then the one that includes all important aspects that have a substantial effect on the actual situation. In the final proposed solution to the location-allocation problem, 3 UAV types are considered, each offering a different type of emergency service application. It can be concluded that the final solution includes a clever combination of initial and new infrastructure. This allows the UAVs to serve the demand in the whole of Ghent in a worst-case response time of about 3 minutes, which is sufficiently low for emergency service applications.

Keywords Electric urban air mobility, emergency services, response time, clustering, location-allocation

Optimal location of UAV base stations to serve demand in an urban environment for emergency services

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Abstract – **Cities nowadays are increasingly exposed to traffic issues and fine particle emissions. Electric urban air mobility (eUAM) offers an additional dimension to the mobility landscape and helps reduce particle emissions. One of the most promising application areas of eUAM is emergency services. In those applications, determining the optimal location of urban air vehicle (UAV) base stations to minimize the associated response time is very important. This study proposes a solution method for the location-allocation problem of UAV base stations in an urban environment, which will be the city of Ghent in this study. This location-allocation problem will be solved using a clustering method. This clustering method combines bottom-up or agglomerative hierarchical clustering with Fuzzy C-means (FCM) clustering. The proposed method is then applied to the real-life case. In the initial approach, only 1 UAV type is considered, no initial infrastructure is present and no specific decision criterion is used. Step by step, the relaxations are lifted which results in the problem being more complex and better resembling the real-life case. The problem that is eventually solved is the one that includes all important aspects that have a substantial effect on the actual situation. In the final proposed solution to the location-allocation problem, 3 UAV types are considered, each offering a different type of emergency service application. It can be concluded that this final solution includes a clever combination of initial and new infrastructure. This allows the UAVs to serve the demand in the whole city in a worst-case response time of about 3 minutes, which is sufficiently low for emergency service applications.**

Keywords – **Electric Urban Air Mobility, Emergency services, Response time, Clustering, Location-Allocation**

I. Introduction

Cities nowadays grow larger and larger, increasing problems caused by transport and traffic. Traffic congestion alone costs U.S. cities more than 2 billion dollars annually [1] while exposing many people to harmful fine particles, causing a serious health hazard. To cope with these problems, cities try to produce smart mobility plans to increase the quality of life in these urban environments and enhance economic growth.
To achieve this in urban environments, Electric Urban Air Mobility (eUAM) comes into play [2]. EUAM offers many possibilities to battle these issues in a more efficient way by offering an additional dimension to the urban mobility landscape. Even though eUAM seems to be very promising, there are still many questions, such as environmental or technological issues, that will need to be answered [3].
An application area in which the use of eUAM seems to be very promising is the area of emergency services. In these types of services, the response time will play a crucial role. Urban Air Vehicles (UAVs) have a clear advantage compared to ground vehicles. They can fly everywhere and are therefore not limited by the existence of streets, they are not hindered by other traffic and they can enhance the mobility of first-aid devices such as automated external defibrillators (AEDs).
However, to guarantee a sufficiently low response time, a good location of the UAV base stations and allocation of demand to these base stations is necessary. This research aims to design a good location-allocation strategy for UAV base stations trying to minimize the associated response time.

Location-allocation problems [4] have already been studied extensively in literature. Several types of solution methods are designed to solve these problems. Some of the most often used strategies are traditional approaches [5], meta-heuristics [6] [7] and clustering methods [8].
It seems to be the case that traditional approaches and meta-heuristics already have been studied more in their applications to location-allocation problems than clustering approaches. Additionally, clustering methods have some potentially very interesting properties that could certainly be useful to better solve location-allocation problems. Fuzzy clustering [9] allows demand points to be allocated partially to different UAV base stations and hierarchical clustering [10] introduces the ability to implement some hierarchy in the data, making it possible to work in different clustering levels.

II. Methodology

In the research, it is the objective to design a good location-allocation approach based on clustering methods. During the course of this research, the problem complexity is gradually increased in order to make the modeled problem better resemble the real-life situation that is tried to be solved.

A. Data

To assess the performance of the designed clustering methods, it is applied to the case of the city of Ghent. Ghent is a Belgian city that can be divided into 202 sectors in which in total 264 676 people live [11]. For each sector, it is assumed that the population is centralized in its center of gravity. Then, these 202 sectors represent the demand points that are used as inputs for the model.
In serving these demand points, 3 UAV types are considered, as is shown in table I. These 3 UAV types are used for different applications and in this research, the main focus is directed toward the multicopter-type UAV. This is the slowest UAV type and therefore, well-positioned locations will certainly be necessary to achieve a low response time.

Size	Type	Cruise speed ($\frac{km}{h}$)	Endurance (h)
Small	Multicopter-type	40	0.5
Medium	Rotorcraft-type	100	1.5
Large	Optionally-Piloted VLR	150	3.5

Table I: Specifications UAV types [12]

In case initial infrastructure would be used as starting point for UAV base stations, several options can be considered in Ghent. For the multicopter-type UAV, already present electric vehicle (EV) charging stations are considered as initial infrastructure. For the rotorcraft-type UAV, only large already existing parking lots are considered. In these locations, enough open space is present for the take-off and landing of these UAVs. Finally, for the Optionally-Piloted VLRs, only helipads are considered as initial infrastructure. This is because this type of UAV will mostly be used for ambulance services and is preferably positioned close to hospitals.

B. Used clustering methods

Clustering methods can be divided into two major categories: hierarchical and partitional clustering methods.
The hierarchical clustering method that is considered is bottom-up or agglomerative hierarchical clustering. This clustering method starts from each data point separately and groups them based on a certain linkage criterion. This way, several hierarchical levels can be introduced in the clustering.
Alternatively, the partitional clustering method that is considered is Fuzzy C-Means (FCM) clustering. This clustering method partitions data points in different clusters by minimizing the dissimilarity in the clusters. In this method, data points can be partially allocated to different clusters, which explains the fuzzy component of this algorithm.
These methods can be used on their own, as will be the case in the first part of the research, but it is certainly also possible to combine them in a more advanced clustering technique. A very useful property of FCM clustering is that it works with partial allocations. However, applying it to a large data set can result in worst-case response times being too high. Therefore, it can certainly be a promising idea to first apply agglomerative hierarchical clustering to the full data set. This method introduces a first hierarchical level in the data, after which FCM is applied to the resulting sub-clusters.
In the more advanced research stages, this compound method is used as a clustering framework. More generally, including the worst-case response time as a decision criterion, this multi-level clustering approach is schematically presented in figure 1. In this approach, it is allowed to reiterate the first step in case the first partitioning that resulted from the agglomerative hierarchical clustering was not sufficient to enable the FCM algorithm in the second step to return sufficiently low response times.

C. Problem structure

In tackling the location-allocation problem for Ghent, several steps are followed. Initially, the problem is simplified a lot. The first problem that is considered is quite basic. No initial infrastructure is considered and population weights are not yet included in the research. Additionally, the clustering performance is assessed by traditional cluster performance measures (Xie-Beni index [13] for FCM, dendrogram for agglomerative hierarchical clustering). These measures are also used as a decision criterion to determine the optimal number of clusters. As these performance measures do not yet look at the obtained response times, they will not be able to assess the performance well enough for this application.

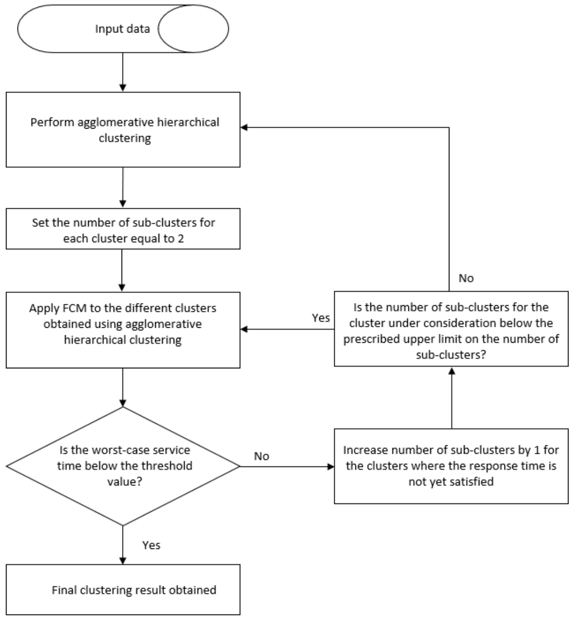


Fig. 1: Compound clustering framework

Afterward, each step, one relaxation is reconsidered and the problem that is tackled becomes more and more complete. The different steps that are followed can be presented in a flowchart, which is shown in figure 2.

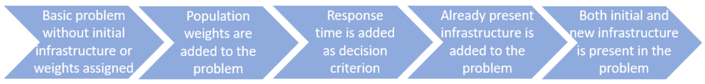


Fig. 2: Visualisation steps increasing problem complexity

Some of the steps presented in figure 2 were studied in quite some detail. The exact methods that are considered and worked out during the research are the following:

- To add the effects of the actual population distribution to the model, a new approach is suggested that takes into account the actual population of all different sectors in Ghent. In the general clustering framework, the FCM step is adjusted so that it uses a weighted cluster center calculation method instead of the initial cluster center calculation method. The weighted cluster center calculation method shifts the cluster centers closer to sectors that are more densely populated, resulting in those areas being served more efficiently. However, some other complications can arise using this alternative cluster center calculation method.
- In case only initial infrastructure is considered as a possible location for the UAV base stations, the FCM step of the clustering method can be adjusted in several ways. First of all, the cluster centers can be shifted to infrastructure points on the go, meaning that this happens each iteration in the FCM step. To overcome too many cluster centers being assigned to the same initial infrastructure point, a constraint can be added that would restrict more than one cluster center from being shifted to the same initial infrastructure point. The third and final proposition would be to

perform all iterations of the FCM step and only assign the cluster centers afterward to the initial infrastructure point.
- In case both new and initial infrastructure are present, two hybrid approaches are proposed. These hybrid approaches have the objective of eventually selecting a clever combination of new and initial infrastructure. A first hybrid approach is a distance-based approach. When the obtained cluster center is sufficiently close to an initial infrastructure point, the cluster center is shifted to this initial infrastructure point. When this is not the case, a new infrastructure point is set up. One of the main challenges in this method is to determine a good threshold value for the maximum distance at which cluster centers are shifted to the initial infrastructure.
  The second approach is based on the region in which respectively a lot or almost no initial infrastructure is present. In the regions where a lot of initial infrastructure is present, only initial infrastructure will be selected. On the contrary, in the regions where almost no initial infrastructure is present, only new infrastructure points are set up. In this approach, the difficulty lies in identifying those regions.

Afterward, the results for all 3 UAV types are combined and put together in a general solution.
Finally, a cost-based approach is briefly touched upon to check if the results obtained using the previous approaches lay in line with the ones obtained from a cost perspective.

III. Results and discussion

The major results obtained during the different research steps are reported and discussed in this section. For most steps, the results are obtained using the multicopter-type UAV. Only in the step where all 3 UAVs are considered, this is not the case. The reason for this is that the multicopter-type UAV has the lowest cruise speed and for this UAV, it is, therefore, most important to select suitable UAV base stations.

A. *FCM and agglomerative hierarchical clustering*

In the first research step, the performance of FCM and hierarchical clustering applied separately to the case of Ghent is observed. In selecting the optimal number of clusters, the Xie-Beni index is used for FCM and the dendrogram of the agglomerative hierarchical clustering method is used to determine its optimal number of clusters. Combining these findings with the corresponding worst-case response time results in table II.

Clustering method	Optimal # clusters	Worst-case response time (in min)
FCM	6	5.89
Agglomerative hierarchical clustering	2	14.56

Table II: Initial clustering results

The worst-case response times shown in table II are not acceptable for emergency services. Therefore, some improvements will have to be made.

B. *Multi-level clustering approach*

As the results obtained using FCM and agglomerative hierarchical clustering separately were not acceptable, the improved approach shown in figure 1 is implemented here. As opposed to that approach, the optimal number of clusters is obtained here using the Xie-Beni index.

During the further course of this study, the obtained results in the first step, using agglomerative hierarchical clustering, will remain the same. The two clusters shown in figure 3 are obtained using this first step. These two main clusters will then serve as inputs for further clustering.

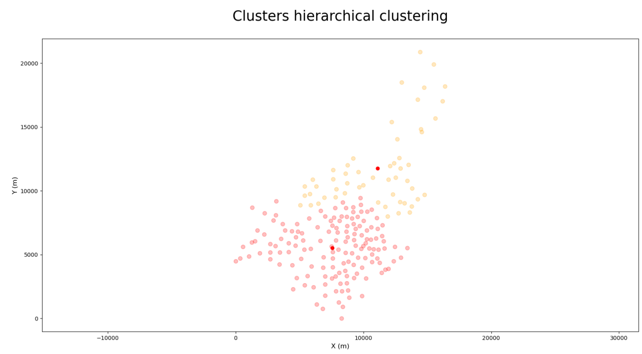


Fig. 3: Clustering result agglomerative hierarchical clustering

In the second step, the FCM algorithm is applied to these main two clusters. The number of sub-clusters and the worst-case response times obtained by applying FCM to these two clusters are given in table III.

Cluster	Optimal # sub-clusters	Worst-case response time (in min)
Cluster 1	11	4.78
Cluster 2	3	5.80

Table III: Initial results multi-level clustering approach

The worst-case response times obtained here are already quite a bit lower than in case both methods were used separately. This is mainly due to the fact that more clusters are present. However, the initial sub-partitioning certainly helps explore the full search space better, which is certainly useful for rather large data sets.

C. *Weighted cluster center calculation*

In this part, an attempt is made to include the actual population distribution over the different sectors in Ghent in the model. The influence of the population distribution is twofold. First of all, allocating comparable amounts of people to each cluster will result in an even distribution of the population over the clusters. This will prevent clusters from having too much demand while other clusters would have almost no demand. Secondly, larger sectors could be served more efficiently by placing the cluster centers closer to these sectors. As was described in the methodology section, an alternative approach to include this influence will be examined in this section.

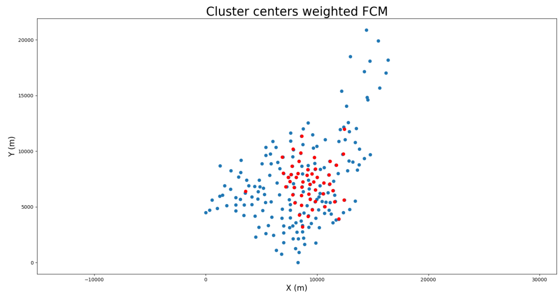
Comparing the average population per cluster and the standard deviation from the mean cluster population obtained by either FCM, weighted or unweighted multi-level clustering results in the values shown in table IV.

The weighted clustering method results in worse population distribution over the different clusters compared with pure FCM or the unweighted clustering method. Therefore, the weighted clustering method does not succeed in more evenly spreading the population over the different clusters.

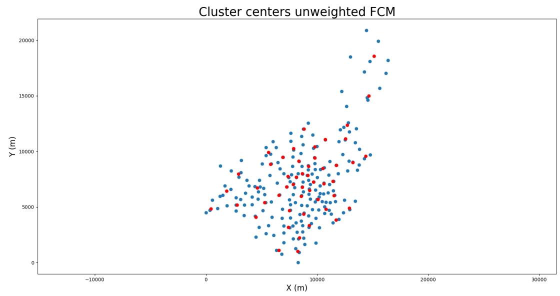
In case 50 clusters are present, the distribution of cluster centers over the city of Ghent resulting from applying weighted and unweighted FCM is shown in figure 4.

Clustering method	Average population per (sub-)cluster	Standard deviation from mean cluster population
FCM clustering algorithm	18 905	2277
Weighted multi-level clustering approach	18 905	3152
Unweighted multi-level clustering approach	18 905	1867

Table IV: Standard deviation from mean cluster population for different clustering methods. In each scenario, 14 clusters are present



(a) Cluster center location result weighted FCM for 50 cluster centers



(b) Cluster center location result unweighted FCM for 50 cluster centers

Fig. 4: Comparison cluster center locations using weighted and unweighted FCM for 50 clusters

From the observations made in this section, it follows that the unweighted clustering method performs quite well in evenly distributing the population over the different clusters. The observed bad performance of the method using weighted cluster center calculation can be explained by the fact that more densely populated sectors are located at the center of Ghent. The more densely populated sectors attract the cluster centers rather hard, which makes it very hard for the FCM algorithm to explore the full region of Ghent. As this method does not succeed in exploring the full search space sufficiently, no acceptable solution for the location-allocation problem is obtained. An adjusted version in which weights are added to the cluster center calculation in the final stage of the FCM algorithm won't return good results either because they again discriminate less populated sectors, thereby increasing the worst-case response time.

D. Clustering approach for initial infrastructure

In this section, only initial infrastructure is considered. Here, it is not possible to construct new UAV base stations starting from scratch. This way, the influence of initial infrastructure on the problem can be studied in more detail and without external influences. In the general case, only EV charging stations are considered as initial infrastructure. By applying the 3 methods presented in the methodology part, the number of sub-clusters necessary to guarantee a worst-case response time below certain threshold values is given in table V. Notice that these results are obtained by applying these methods to main cluster 1.

Clustering Method	# clusters for response time under 9 min	# clusters for response time under 8 min	# clusters for response time under 7 min
Shift cluster centers to Initial infrastructure during iterations	16	-	-
Shift cluster centers to Initial infrastructure at the end	3	4	5
At most 1 cluster center shifted to initial infrastructure point	6	6	54

Table V: Worst-case response time per amount of clusters by applying different clustering methods for main cluster 1. In this case, only EV charging stations are considered as initial infrastructure

From table V, it follows that selecting the best-suited method is crucial to obtaining good results. However, even for the best method (which is the method in which the cluster centers are shifted at the end of the clustering method) from table V, it seems to be the case that adding more clusters does not lead to a further decrease in worst-case response time. When a certain number of clusters are present, the response time stalls and reaches a plateau. This is visually shown in figure 5.

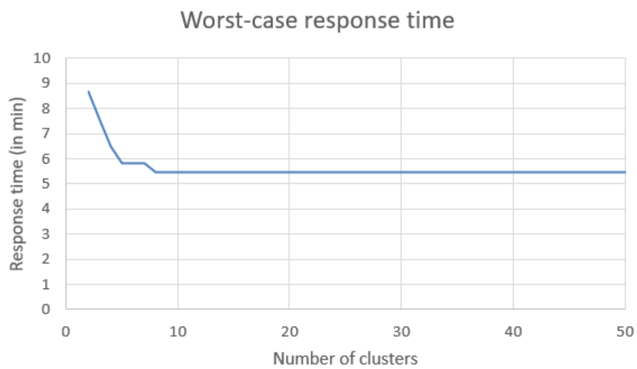


Fig. 5: Worst-case response time for clustering cluster 1 in case EV charging stations are already present and the cluster centers are shifted toward initial infrastructure at the end of the algorithm

A possible explanation for this behavior is the fact that the initial infrastructure is not well-spread over the city of Ghent. Even though more than 200 EV charging stations are present in Ghent, it is the case that these are mostly located in the center of Ghent. The more remote areas could be left behind, which is why the initial infrastructure might be a limiting factor. To investigate the influence of initial infrastructure on the eventually obtained results, a simulation in which initial infrastructure points are randomly generated is performed. This simulation is shown in figure 6. In case 40 random infrastructure points are simulated, the obtained worst-case response time goes well below 4 minutes in case cluster 1 is clustered in 15 or more clusters. As there are more than 200 EV charging stations in Ghent, it is fair to state they are not optimally distributed over the full area of Ghent.

It can be concluded that considering only present initial infrastructure is not sufficient to obtain acceptable worst-case response times for the deployment of emergency services in Ghent. Therefore, a hybrid strategy, that considers both initial and new infrastructure points, is needed.

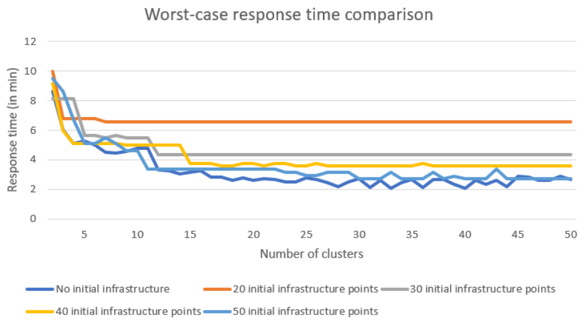


Fig. 6: Worst-case response time for clustering cluster 1 with different randomly generated options for the initial infrastructure

E. Hybrid clustering method

In this section, the result obtained using both hybrid clustering methods are reported and discussed. Using new and initial infrastructure, these hybrid methods are able to obtain response times that are well below 3 minutes. However, the two considered methods select a different amount of clusters to obtain this worst-case response time below 3 minutes, together with a different composition of old and new infrastructure. These results are shown in table VI.

Clustering Method	Number of clusters (New infrastructure / initial infrastructure)
Distance-based	36 (11/25)
Initial infrastructure-based	40 (21/19)

Table VI: Number of clusters using a combination of new and initial infrastructure necessary to obtain a worst-case response time below 3 minutes. This is reported for both hybrid clustering methods

Using a clever combination of initial and new infrastructure, sufficiently low worst-case response times can be obtained. As the distance-based method requires fewer clusters to obtain a worst-case response time below 3 minutes, combined with selecting a lot of initial infrastructure, this method is clearly the best hybrid method to use.

F. All 3 UAV types considered

Combining the results from the previous sections, a network of UAV base stations can be obtained, combining all 3 UAV types. In this network, the two largest UAV types will only use initial infrastructure, as their cruise speed is high enough to obtain sufficiently low worst-case response times using only this initial infrastructure. For the smallest UAV type, the distance-based hybrid method is used to obtain the optimal set of UAV base stations, consisting of both new and initial infrastructure. Newly constructed UAV base stations will be called multicopter base stations, while the other types of infrastructure are referred to by their original name.

Combining the findings for all 3 UAV types, the network of UAV base stations shown in figure 7 is obtained, with the associated worst-case response times for each type of UAV base station shown in table VII.

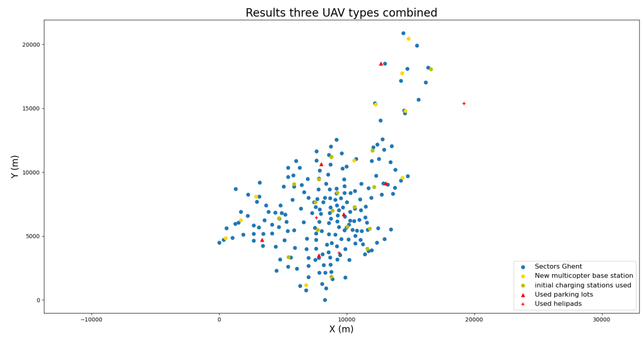


Fig. 7: Visualisation of infrastructure used in case all 3 UAV types are considered

Type of UAV base station	Worst-case response time (in min)
New multicopter base stations	2.32
Used EV charging stations	2.81
Used parking lots	2.70
Used helipads	3.15

Table VII: Worst-case response times achieved for each type of UAV base station

Combining the 3 types of UAV base stations, a total of 39 base stations are present. These base stations are well-distributed over the city of Ghent. With a reasonable amount of UAV base stations, it seems to be the case that the city of Ghent can be served efficiently by UAVs in different emergency applications, ranging from AED deliveries to ambulance services.

G. Cost optimization analysis

Taking into account all relevant costs, an alternative way to assess the previously obtained results can be found in the cost optimization analysis. In case the UAV system in which only the multicopter-type UAV is considered and using the averaged response time as a decision criterion, the quantified cost as a function of the number of clusters is shown in figure 8. In this figure, the results for both clusters 1 and 2 are shown.

In this figure, the adjusted averaged response time is used instead of the classic averaged response time. In this adjusted version, it is assumed that lowering the averaged response time below 2 minutes does not result in higher chances of survival, therefore not lowering the incurred cost anymore.

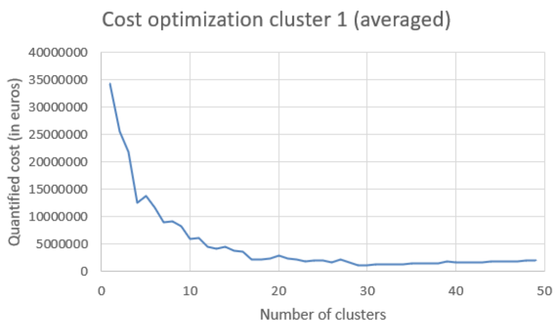
The clustering results obtained by minimizing the quantified costs are shown in figure VIII.

Cluster	Averaged response time (in min)	Infrastructure (new/initial)
Cluster 1	1.97	29 (6/23)
Cluster 2	1.86	8 (2/6)

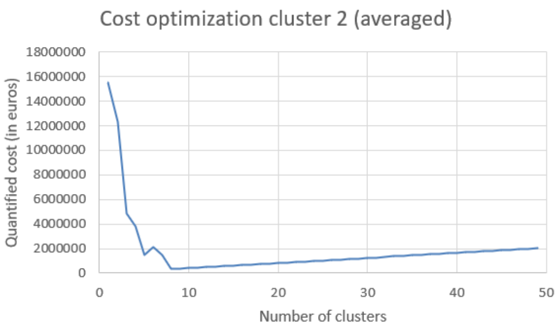
Table VIII: Optimal solution adjusted averaged response time-based cost optimization analysis

In total, 37 infrastructure locations are used, of which 29 were initially present. When these results are compared with the ones obtained using the distance-based hybrid clustering approach, it follows that almost the same number of infrastructure locations are selected. In both cases, the majority of the infrastructure locations are the ones that are initially present.

As the results obtained using both methods are clearly in line with each other, it seems to be the case that both solutions are certainly acceptable.



(a) Adjusted averaged response time-based cost optimization cluster 1



(b) Adjusted averaged response time-based cost optimization cluster 2

Fig. 8: Adjusted averaged response time-based cost optimization for cluster 1 and cluster 2

IV. Conclusion

Using a well-designed combination of clustering techniques, each having its main strengths, the location-allocation problem for UAV base stations can be solved efficiently. In doing this, selecting the right decision criterion is essential. For emergency services, the major decision criterion is the worst-case response time. Using a reasonable amount of UAV base stations, the whole city of Ghent can be covered by all 3 UAV types in about 3 minutes. Compared to ground-based emergency services, UAVs seem to offer a clear advantage in terms of worst-case response time.

In designing a good clustering strategy, it is noted that sufficient attention should be paid to the execution of all different complicating steps. Relaxing initial assumptions often result in unexpected turns, which is why each step should be handled with care. Therefore, a critical look is necessary for assessing results. Future research could apply the designed methods here to other urban environments that have other characteristics (larger population, less initial infrastructure, etc.) and evaluate if the clustering methods return equally satisfying results for these other cases.

Finally, it can be concluded that clustering has promising features regarding its usage in solving location-allocation problems of UAV base stations in urban environments for emergency services. Even though quite some questions remain unanswered in the area of eUAM, it is not unthinkable that soon, eUAM will be deployed in the first urban environments.

References

[1] N. McCarthy, "Traffic congestion costs u.s. cities billions of dollars every year [infographic]," Mar 2020.

[2] A. Milić, A. Randjelovic, and M. Radovanović, "Use of drones in operations in the urban environment," 10 2019.

[3] S. Watkins, J. Burry, A. Mohamed, M. Marino, S. Prudden, A. Fisher, N. Kloet, T. Jakobi, and R. Clothier, "Ten questions concerning the use of drones in urban environments," *Building and Environment*, vol. 167, p. 106458, 2020.

[4] L. Cooper, "Location-allocation problems," *Operations Research*, vol. 11, no. 3, p. 331–343, 1963.

[5] R. L. Church and C. S. ReVelle, "Theoretical and computational links between the p-median, location set-covering, and the maximal covering location problem," *Geographical Analysis*, vol. 8, pp. 406–415, Sept. 2010.

[6] S. Salhi and M. Gamal *Annals of Operations Research*, vol. 123, no. 1/4, pp. 203–222, 2003.

[7] A. Ghodratnama, "Comparing three proposed meta-heuristics to solve a new p-hub location-allocation problem," *International Journal of Engineering*, vol. 26, Sept. 2013.

[8] Ş. Esnaf, T. Küçükdeniz, and N. Tunçbilek, *Fuzzy C-Means Algorithm with Fixed Cluster Centers for Uncapacitated Facility Location Problems: Turkish Case Study*, pp. 489–516. Berlin, Heidelberg: Springer Berlin Heidelberg, 2014.

[9] J. C. Bezdek, *Pattern recognition with fuzzy objective function algorithms*. Springer Science & Business Media, 2013.

[10] F. Murtagh and P. Contreras, "Algorithms for hierarchical clustering: an overview," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 2, pp. 86–97, Jan. 2012.

[11] I. Heyndrickx, "Meer gentenaars, minder overlijdens en minder scheidingen," 2022. Last accessed 22 April 2022, url=https://stad.gent/nl/over-gent-stadsbestuur/nieuws-evenementen/meer-gentenaars-minder-overlijdens-en-minder-scheidingen.

[12] Aurora consortium, *Technical Specifications (D 2.2)*, 2021. Version 1.0.

[13] X. Xie and G. Beni, "A validity measure for fuzzy clustering," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, no. 8, p. 841–847, 1991.

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Acronyms

ABC Artificial Bee Colony. 8, 9

ACO Ant Colony Optimization. 8, 9

AED automated external defibrillator. XII, 1, 21, 23–25, 39, 40, 42, 44, 49, 51, 72, 73, 81

eUAM Electric Urban Air Mobility. 1–3, 18, 27, 86–88

EV Electric Vehicle. XII, XIV, XVII, 21, 23–25, 39, 40, 63–74, 77, 79, 82

FCM Fuzzy C-Means. X, XI, XIII, XIV, XVI, 13–16, 28, 30–34, 36–40, 46–49, 52–57, 59–62, 79

GA Genetic Algorithm. 8, 9

LSCP Location Set Covering Problem. 7, 8

MCLP Maximal Covering Location Problem. 7

NP-hard non-deterministic polynomial-time hard. 5, 6, 8, 14

PC Partition Coefficient. 31, 47, 48

PSO Particle Swarm Optimization. 8, 9

SA Simulated Annealing. 8, 9

SSE Sum of Squared Errors. 17, 31, 47, 48

TS Tabu Search. 8, 9

UAM Urban Air Mobility. 1

UAV Urban Air Vehicle. I, X–XII, XV–XVII, 1, 18, 20–25, 27–29, 32, 35, 36, 40–44, 49–51, 60, 67, 72, 75, 76, 81, 82, 85–88

UFLP Uncapacitated Facility Location Problem. 6

VLR Very Light Rotorcraft. XVII, 21, 41, 42, 76

VOL Value of Life per Minute Response Time. 43, 44

VTOL Vertical Take-Off and Landing. 20

1

Introduction

Cities nowadays grow larger and larger, increasing problems caused by transport and traffic. Traffic congestion alone costs U.S. cities more than 2 billion dollars annually [3] while exposing many people to harmful fine particles, causing a serious health hazard. To cope with these problems, cities try to produce smart mobility plans to increase the quality of life in these urban environments and enhance economic growth.
To achieve this in urban environments, Electric Urban Air Mobility (eUAM) comes into play [4]. eUAM offers many possibilities to battle these issues in a more efficient way by offering an additional dimension to the urban mobility landscape. Even though eUAM seems to be very promising, there are still many questions, such as environmental or technological issues, that will need to be answered [5]. Addressing these problems and designing an effective way of implementing such a eUAM system is also the objective of the AURORA project. This is a project led by the ISyE team of UGent, in collaboration with industry leaders, SMEs, NGOs, and other research institutions, in which research is performed towards fully automated aircraft and integrated Urban Air Mobility (UAM) services.
eUAM offers a high potential over different application areas. The area of emergency services is certainly one of the most promising ones, which is why the attention of this thesis is directed towards the application of eUAM to emergency services. In these types of services, the response time will play a crucial role. In case of an emergency, such as a cardiac arrest, the first minutes are crucial. To guarantee a low response time, UAVs have a clear advantage compared to ground vehicles. They can fly everywhere and are therefore not limited by the existence of streets, they are not hindered by other traffic and they can enhance the mobility of first-aid devices such as AEDs [6].

To guarantee a low response time, it will be crucial to locate the UAV base stations at appropriate locations. A good placement of UAV base station can sometimes really make the difference between life and death. Designing a good approach to optimally locate several UAV base stations and assign them to their region of service will therefore be the subject of this master thesis.
Along with these main research questions, some other questions will be tried to be answered during this master thesis. In locating the UAV base stations and allocating the demand to the different base stations, it will also be important to determine the associated response time and coverage. These are important performance measures in scoring the performance of emergency services. Together with that, the optimal number of UAV base stations will have to be determined as well. In urban environments, it is often possible that already existing infrastructure is present, which could be adapted to be part of the integrated UAM system. It will therefore be important as well to assess the already present infrastructure and examine

if it could be integrated into the system as well.

To help answer the aforementioned questions cleverly, a case study will be performed for the city of Ghent. The city of Ghent is a great test case as it is an urban region from which sufficient data can be collected online. This data can then be used as input for the used models while trying to formulate answers to the formulated research questions.
In the present literature, quite some research has been performed in trying to answer problems in which locations have to be determined, together with the allocation of a certain demand to these locations. These problems are called location-allocation problems. A lot of research into classical solution methods and heuristics to solve location-allocation problems has already been performed. Clustering methods, usually used to seek patterns in data, seem not to have yet been studied extensively for location-allocation problems. This is certainly not the case for these types of problems in the context of eUAM and minimization of the response time. Following this, the application possibilities of clustering methods to the location-allocation problem of the type described above will extensively be studied in this master thesis research.
In this master thesis, first of all, a literature review of relevant topics will be performed. In this research, it will be reported which areas are already studied and more insight into location-allocation type of problems is given. Then, the data that will be used is presented clearly. Following this, the used methods are taken into the spotlight, in which the focus lays on the structure of the actual research. By applying these methods, the obtained results are reported and commented on. To wrap up the thesis, potentially interesting topics for future work are highlighted, followed by a brief conclusion of the obtained results to complete this thesis.

2

Literature Review

During the literature review, a broad background on location-allocation problems is given. At first, some more insight into location-allocation problems is given and something will be said about their complexity. Afterward, the most well-known solution methods for these types of problems are presented. In doing this, traditional approaches, such as median problems, heuristic methods, and machine learning techniques, more specifically clustering methods, are included. In this literature search, the focus is on clustering techniques as these are the techniques that will mainly be used during this master thesis. To conclude the literature review, the phenomenon of data aggregation is observed as well. This will turn out to be interesting, as input data will also influence the eventual results of the location-allocation problem.
By performing this literature review, more insight into the already present methods for these problems will be provided. This will later serve as a basis for the application of the location-allocation problem to the case of eUAM.

2.1 Location-Allocation Problems

During the last century, Location-Allocation Problems have been researched quite extensively. One quite primitive discussion about this type of problem is given by Cooper [7]. He presented the location-allocation problem in a quite general manner, as this was one of the first times it was studied in the literature. In solving these types of problems, one tries to allocate several facilities and decides which customers are going to be served by which facilities. In doing this, the total cost that comes with setting up the system as a whole should be minimized, which is the main objective here.
Typically, some information is already known which will help solve these problems. In the original formulation, the input data that is used for solving the location-allocation problem is the following:

- The location of each destination (Demand locations)
- The requirements at each destination (Demand requirements)
- A set of shipping costs for the region of interest (Unit shipping cost)

Using these input data, the other types of information are tried to be determined. The unknowns that should be determined in the general location-allocation problem are the following ones:

- The number of sources (How many facilities to locate)
- The location of each source (Where to locate the facilities)
- The capacity of each source (Facility capacity)

This general formulation can be applied to a large variety of problems covering a very broad range of applications. Here, it will be important to make several assumptions, such as non-increasing unit shipment costs. These assumptions will help reduce the complexity of the problem, whilst making sure that the simplification is still a very good representation of the problem that is tried to be solved in reality.
An attempt to split up location-allocation problems into two smaller problems that should be solved simultaneously is made by Scott [8]. He described location-allocation problems as problems in which it is the purpose to locate the central facilities (e.g. suppliers) whilst assigning the different output flows from these facilities to the corresponding demand locations (e.g. customers). These two actions need to happen at the same time, as optimizing one of them will not necessarily optimize the other one, nor the combination of both parts. In doing this, the goal is again to minimize the total operation cost of the system. The operation cost of the system can be viewed in a quite general manner: this cost typically includes tangible components, such as the facility cost and the variable cost of item delivery, and less tangible components such as noise disturbance for residents.

Apart from formulating location-allocation problems in a descriptive way, they can also be formulated more mathematically.
Suppose that a set of n facilities (suppliers) with infinite capacity is available (n or fewer facilities will be used in practice), then this specific location-allocation problem can be translated to the following mathematical programming formulation:

$$Minimize \sum_{i=1}^{n}\sum_{j=1}^{m} s_{ij} f_{ij} d_{ij} X_{ij} + \sum_{i=1}^{n} FC_i Y_i \tag{2.1}$$

Subject to:

$$\sum_{i=1}^{n} f_{ij} X_{ij} = D_j \qquad \forall j \in \{1...m\} \tag{2.2}$$

$$X_{ij} \in \{0,1\} \quad \forall i \in \{1...n\} \cap j \in \{1...m\} \tag{2.3}$$

$$Y_i \in \{0,1\} \quad \forall i \in \{1...n\} \tag{2.4}$$

$$f_{ij} \in R^+ \tag{2.5}$$

In this notation, m is the number of demand locations (customers), each with demand D_j, that need to be served from the facilities that are chosen from the set of candidate locations. Additionally, s_{ij} is the unit shipping cost, d_{ij} is the distance between facility i and demand location j and FC_i is the operating cost that comes with using facility i.
Given all these input data, it is the purpose to determine the decision variables, which are also included in the mathematical formulation. X_{ij} is used to allocate demand locations to the facilities. X_{ij} equals 1 if demand location j is (partly) served

from facility i and 0 otherwise.
Y_i is the decision variable associated with locating the facilities at some of the candidate locations. Y_i equals 1 if there is a facility operated at location i and 0 if no facility is operated at location i. Finally, f_{ij} stands for the (material) flow from facility i to demand location j. f_{ij} takes on the value of the flow stream between these two locations.
In this mathematical formulation, the goal is to minimize the objective function, which is given in equation 2.1. In essence, this comes down to minimizing the total operating cost. This total cost is split up into two different parts:

- A variable cost, which represents the transportation cost. This is the cost that comes with moving f_{ij} items over a distance d_{ij} at a cost of s_{ij} per item from i to j.
- A fixed cost, which represents the facility location cost. This is the cost of locating the facility at candidate location i at a cost of FC_i.

Although the mathematical formulation that is given here relies on quite a few assumptions, it is certainly useful to get a better understanding of location-allocation problems. There exist quite a few more complex location-allocation problems. However, in most cases, the basic idea remains the same, such as the basis represented here. Often, assumptions are relaxed or additional complications are added to the model to make it a better representation of the real-life situation under study. For more advanced mathematical formulations of location-allocation problems, more tailored literature should be looked into, but this is beyond the scope of this study. For example, Mestre Oliveira [9] presented a more advanced mathematical formulation that takes into account different demand scenarios for the optimal planning of a hospital network.

Going back to the general study of location-allocation problems, it can be stated that a location-allocation problem is a combination of a transportation problem (Assigning the flow) and a pure location problem (Locating the central facilities). Often, these two problems are easily solvable alone, but they are much harder to solve when they are solved simultaneously. Especially when problems become larger, specialized solution methods will be necessary to make sure a (sub-)optimal solution can be obtained in a reasonable amount of time.
This observation is confirmed by Sherali [10]. In his work, it was proven that location-allocation problems are non-deterministic polynomial-time hard (NP-hard). NP-hard problems are problems for which no efficient algorithm has been found yet. This means that solving these types of problems is not possible in polynomial time. From this, it follows that an exact solution to a pure location-allocation problem can't be found in a reasonable amount of time. As classical solution methods won't be able to solve these problems efficiently, there is a need for more specialized solution methods to find a (sub-)optimal solution in a reasonable amount of time.

One way to counter the complexity of these NP-hard problems would be to use solution methods such as heuristics. However, the usage of heuristics can only be justified if the region around its achieved optimum is robust: this means that around the optimum value, other solution values can be obtained that are quite close to the optimal solution value. Fortunately, in location-allocation problems, this will often be the case. Cooper [11] concluded that a well-constructed heuristic will achieve a sub-optimal solution that is rather close to the optimal solution with a reasonably high probability. In many cases, the heuristic can be constructed in a way that a sub-optimal solution is only 2 to 3 % off from the optimal solution, which is an acceptable bias. Often, it will cost more to achieve the perfect optimum than the benefit that would come with achieving this optimum. Therefore, it is important to always keep in mind the trade-off between accuracy and efficiency.

2.2 Traditional approaches for location-allocation problems

For location-allocation problems, some very common models have been proposed. These models typically can be classified into two categories: median and coverage problems. Both types are designed to find the most suitable location for facilities, but they differ in the way their objective function is constructed. In what follows, the present literature on these methods is studied, followed by a brief conclusion about these methods.

2.2.1 Median problems

Median problems, more specifically the p-median problem, are very useful to model real-life location-allocation problems. This problem also resembles the Uncapacitated Facility Location Problem (UFLP), but there are some clear differences between these two problems. First of all, in the p-median problem, there are no costs to open facilities. Secondly, in the p-median problem, it is known how many facilities will need to be opened, which is not the case in the UFLP. From this, the name p-median follows evidently, as exactly p facilities will need to be located.
P-median methods can be used as a location-allocation method for different types of services: Locating emergency services (fire stations, ambulances ...) [12][13], locating schools [14], warehouse location [15], public service center locations [16] and so on. From a more theoretical perspective, the p-median problem can be formulated in its mathematical formulation [17], which is formulated as follows :

$$Minimize \sum_{i=1}^{n}\sum_{j=1}^{n} a_i d_{ij} x_{ij} \tag{2.6}$$

Subject to

$$\sum_{j=1}^{n} x_{ij} = 1 \;\; \forall i \tag{2.7}$$

$$\sum_{j=1}^{n} x_{ij} = p \tag{2.8}$$

$$x_{ij} \leq x_{jj} \;\; \forall i, j \tag{2.9}$$

$$x_{ij} \in \{0,1\} \, \forall i, j \tag{2.10}$$

In this mathematical formulation, n is the number of demand points, a_i is the population of demand point i, d_{ij} is the (shortest) distance between i and j and p is the number of facilities that have to be located.
Next to the input variables, the decision variables have to be defined as well. x_{ij} equals 1 if the demand of j is fulfilled by j and 0 otherwise.
This problem is an integer programming problem, which has n^2 decision variables, taking on values of 0 and 1. From this, it can also be shown that the p-median problem is NP-hard [18], independent of the network structure used. The high number of decision variables makes this a large problem, but the number of candidate sites for facilities can often be reduced

(restricted areas, only consider appropriate locations ...) which makes the problem size smaller. Resulting from the smaller problem size, the time in which the problem can be solved will be reduced as well.
As p-median problems have shown their usefulness in solving location-allocation problems, they have been studied extensively. Researchers have come up with a lot of different methods to solve them. Branch-and-bound algorithms [19][20] and meta-heuristic approaches to the p-median problem [21] [22] are only some of the possible procedures that have been proposed by researches to solve the p-median problem. From this, it can be concluded that the p-median problem is already a well-studied topic in literature.

2.2.2 Coverage problems

An issue with p-median problems is that they do not take into account the 'worst-case' situation, therefore resulting in unacceptable solutions in terms of service [23]. The total obtained traveling distance in the p-median problem can be minimized, however, it does not take into account the maximum travel distance for one user. For this, p-median problems will not give the best solution for emergency service location problems, as all users should be reachable in a predetermined amount of time. For this reason, it would be advantageous for the location of emergency services, to consider maximum distance or maximum time constraints as well. For these reasons, the Location Set Covering Problem (LSCP) is proposed. Here, the minimum number of facilities should be determined, making sure that each user is served in the prescribed time. This results in the following mathematical formulation [24]:

$$Minimize \sum_{j=1}^{n} x_j \tag{2.11}$$

Subject to

$$\sum_{j \in N_i} x_j \geq 1 \quad \forall i \tag{2.12}$$

$$x_j \in \{0, 1\} \quad \forall j \tag{2.13}$$

In this formulation, N_i is the set of facilities that can provide cover to demand i, which can be reformulated as $N_i = \{j | d_{ij} \leq S\}$, where S is the defined as the maximal service distance. The variable n is again defined as the number of demand points and d_{ij} is the (shortest) distance between i and j.
In the LSCP, the sole decision variable is x_j, which equals 1 if a facility is located at j and 0 otherwise. It can be noticed that the number of decision variables is quite limited, as only n x_j's can take on values of 0 or 1. This makes this formulation rather suitable for large problems. However, n inequality constraints are present so solving this type can still be computationally difficult.

Alternatively, it could be the case that not all demand should or could be covered. This can be because several users are too far away to serve them in a good manner or when not enough resources are disposable. In this case, not all users will be served, but it will be the goal to serve as many users as possible. To these people, service of a sufficiently high service level should be given. In this problem, a fixed number of facilities will be located, while trying to cover as much demand as possible, for users who are located at feasible distances from a service perspective. This problem is called the Maximal

Covering Location Problem (MCLP). For this problem, the mathematical formulation is as follows [25]:

$$Maximize \sum_{i=1}^{n} a_i y_i \tag{2.14}$$

$$\sum_{j \in N_i} x_j \geq y_i \quad 1 \leq i \leq n \tag{2.15}$$

$$\sum_{j=1}^{n} x_j = p \tag{2.16}$$

$$x_j \in \{0,1\} \quad \forall j \tag{2.17}$$

$$y_i \in \{0,1\} \quad \forall i \tag{2.18}$$

In this formulation, x_j is defined in the same way as in the formulation of the LSCP, while a_i and p are defined in the same way as in the formulation of the p-median problem. The decision variable y_i here is the allocation variable. If the demand of user i is covered by any facility, then y_i will be equal to 1. If the demand of user i is not covered by any facility, then y_i will be equal to 0. This problem has 2n binary decision variables, which makes this problem more suitable than for example p-median problems, in which n^2 decision variables are present.
Variations for both these types of coverage problems have been come up with [26], so that it is possible to deal with all types of variants of these types of problems. However, these variations won't be discussed as they would go into too much detail. Both of these methods can also be used as location-allocation problems for different types of service, such as locating bus stops [27], locating dialysis facilities [28], habitat reserve site selection [29], emergency services [30] and so on.

Following the literature review of the classical approaches, it can be seen that these methods have already been discussed in the literature. Additionally, nowadays, approaches that seem more promising are present. This is why the discussion of traditional approaches is limited to this (short) review and it won't be discussed further in this thesis. However, a good understanding of these methods is important to get more insight into location-allocation problems.

2.3 Meta-heuristic solution methods

An alternative to the traditional solution techniques for location-allocation problems can be found in the use of meta-heuristics. These meta-heuristics are a better fit to efficiently find a sub-optimal solution in case problems are very hard to solve using traditional approaches. As location-allocation problems are NP-hard, the usage of meta-heuristics is certainly justified for solving these types of problems.
In the literature, meta-heuristics have extensively been applied to location-allocation problems. Here, the main focus will be directed towards Genetic Algorithm (GA), Simulated Annealing (SA), Tabu Search (TS) and population-based optimization algorithms (Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC)). These meta-heuristics are very popular and therefore already well-studied. A summary of some literature regarding these techniques applied to location-allocation problems is given in table 2.1.

Authors	Problem type	Used meta-heuristic
Saeidian et al. [31]	Location-Allocation	PSO & ACO
Righini [32]	Location-Allocation	Double annealing
Murray and Church [33]	Location Planning	SA
Lin et al. [34]	Facility Location-Allocation	Improved ABC
Sahli and Gamal [35]	Continuous Location-Allocation	GA
Ohlemüller [36]	Location-Allocation	TS
Brimberg and Mladenovic [37]	Multisource Weber Problem	TS & GA
Ghodratnama et al. [38]	Location-Allocation	GA, PSO & SA

Table 2.1: Summary of some literature regarding meta-heuristic solution procedures for Location-Allocation problems

Notice that between these meta-heuristics differences are present as well. From the literature presented in table 2.1, it follows that GA is less effective compared to the other meta-heuristic approaches. However, GA is a quite simple and easy-to-understand approach, which is an asset as well.

Even though the performance of GA seems to be a bit worse compared to the other meta-heuristics, the performance of all meta-heuristics is better compared to the performance of traditional approaches. Because these meta-heuristics perform really well, they have been studied and used extensively in solving location-allocation problems. This however makes it a bit less interesting to consider meta-heuristics again in a new study as most of these properties have already been explored quite thoroughly.

2.4 Machine learning techniques

Another approach that could be used to find a feasible solution to the location-allocation problem lies in the area of machine learning. Machine learning techniques can be used to find patterns in input data that are used to represent a real-life case. By doing this, it is attempted to find out which data points belong together and then assign these data points to the same hub. The demand from the data points that are grouped will then be fulfilled from the same location. In doing this, the location-allocation problem is solved. It seems to be the case that the usage of these types of problems is less well-studied in the literature compared to the traditional approaches and heuristic solution methods. This is why a more detailed look is directed towards the usage of machine learning techniques.
Generally speaking, problems in pattern and machine learning can be categorized in three main categories that are most relevant to this research. These three broad categories are the following ones [39]:

- Supervised learning: This approach would require to have some example inputs that come with their optimal outputs as well. This (input, output)-set would be needed as the objective is to learn how a certain set of inputs should be translated into a set of outputs that would result in good performance of the method. In the case of location-allocation problems, the algorithm should be fed with the demand point (inputs) and their optimal, well-positioned hubs, to learn the algorithm how the inputs and outputs are linked together. However, this would not be optimal in this application as the set of well-positioned hubs has to be determined in advance by another solution method. This approach can only be used in case good results are already achieved, which is not always the case. Additionally, achieving good results using another method and then training this model would be quite cumbersome. Therefore, supervised learning techniques are not optimal to use in the application under consideration here, despite their excellent characteristics and their superior performance in case the algorithm is well-trained.

- Unsupervised learning: In this approach, the algorithm is left on its own to find a structure in the input data that is fed to it. As opposed to supervised learning and reinforcement learning, no initial (input, output)-set has to be fed to the algorithm to make the algorithm perform well. This can be seen as an advantage, however, the data should be well-labeled and therefore, some pre-processing of the data will certainly be necessary. Unsupervised learning is a broad topic in the domain of machine learning, with quite some sub-disciplines such as dimension reduction, clustering, and anomaly detection [40]. Of these sub-disciplines, clustering will be the most relevant for this research. Clustering will be an important topic for this master thesis, so this topic will be studied in more detail later on in this report.

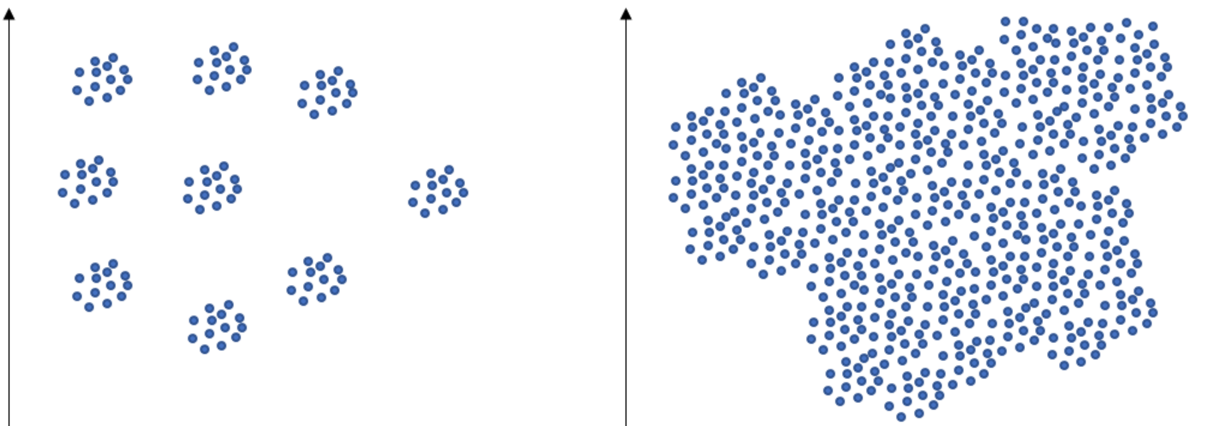
- Reinforcement learning: In reinforcement learning, the agent faces a problem by learning behavior through trial-and-error interactions with a dynamic environment [41]. Here, feedback is provided to the system as it navigates the problem space. Feedback is given in terms of either reward or punishment here. Kaelbling and Littman found out that reinforcement learning techniques work effectively on a lot of small problems. However, issues are incurred when these techniques are tried to scale to larger problems. This is because arbitrary problems are very hard to solve in the general case. Due to these drawbacks, this method won't be considered further.

Apart from these machine learning algorithms, there are still some other algorithms, such as transduction, that are already used in machine learning applications. However, these are less relevant to the topic under consideration and are therefore left behind in this literature review.
Between supervised and unsupervised learning there is also another hybrid method, called semi-supervised learning [42]. This is a mixture of the before mentioned methods, in which an incomplete (input, output)-set is fed to the algorithm as a training signal. In this set, this number of missing target outputs can range from a few to many missing outputs.

Because of the aforementioned reasons, it is decided to further focus on unsupervised learning methods in the next section, and more specifically to focus on clustering.
In clustering, similar objects are grouped into different groups. Another way of describing the clustering process is by saying that the input data set is partitioned into subsets. The data in each subset should be similar, which means that they are close enough together as defined by some distance measure.
Clustering seems to have a great potential in solving location-allocation problems. Efficiently clustering the demand locations in distinct clusters can make sure demand locations that are close to each other and therefore belong together, are serviced by the same facilities. Eventually, these will form efficient sets of facility locations and demand locations, resulting in a demand that is fulfilled in an efficient and effective way.
However, this is just an initial hypothesis and more insight into clustering, as well as more experimental results, should be executed to draw meaningful conclusions.

2.5 Clustering methods

As mentioned before, the goal of clustering will be to make sure that similar objects belong to the same group, while dissimilar objects should belong to different clusters. Questions that could arise are how two objects can be considered to be 'similar' or how they can be considered 'dissimilar'.
To answer these questions, more specialized algorithms have been designed. However, distance-based clustering is a rather basic concept on how to partition data. This can be done either internally or externally. The former states that distances between members in a cluster should be small (members of the same cluster are close together), while the latter states that distances between members of different clusters should be large (Members of different clusters are far away from each other). However, this definition will not always be sufficient, as can be seen in figure 2.1. In figure 2.1a, the clusters are quite clear and the two distance-based clustering definitions will be applicable unambiguously. However, in figure 2.1b the partitions of the data are not clear at all and therefore, distance-based clustering will not be applicable in an unambiguous way. For cases such as figure 2.1b, more advanced approaches will therefore be necessary to guarantee good data clustering. Also, different measures can be considered to partition the data into clusters, which will not necessarily give the result. Therefore, the performance measure should be tailored to the specific application, because different applications could require different performance measures.



(a) Data grouped in clear clusters

(b) Data not partitioned in clear clusters

Figure 2.1: Comparison of scenarios in which data is respectively clustered in a clear way and not in a clear way

Different approaches on how to cluster data can be used. Jain [1] proposed a clear overview of different clustering approaches is given in figure 2.2. Notice that the figure proposed by Jain does not contain all clustering details. Approaches such as hierarchical clustering also have other linkage criteria, but more will be stated about it later on.

At the top level in this taxonomy tree, a split is made between hierarchical and partitional approaches:

- In hierarchical clustering algorithms, the data set is divided or merged in a sequence of nested partitions [43]. Here, the successive clusters are found using previously established clusters. Hierarchical clustering methods can be either agglomerative (bottom-up) or divisive (top-down) [44]. Agglomerative algorithms depart from elements as separate clusters and then merge them into successively larger clusters, while divisive algorithms do it the other way around (start from the whole set and divide them into successively smaller clusters).

- In partitional clustering [45], data points are iteratively relocated between an optimal partition is achieved, according to a certain clustering criterion. This clustering criterion is an objective function that is optimized according to a certain partitioning criterion such as maximizing the similarity between items in a cluster. [43]

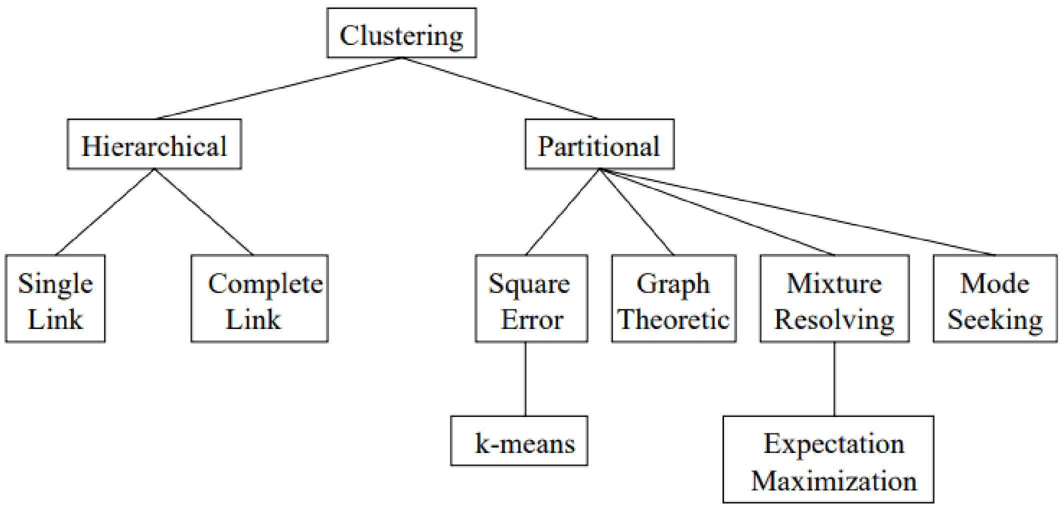


Figure 2.2: Taxonomy of clustering approaches [1]

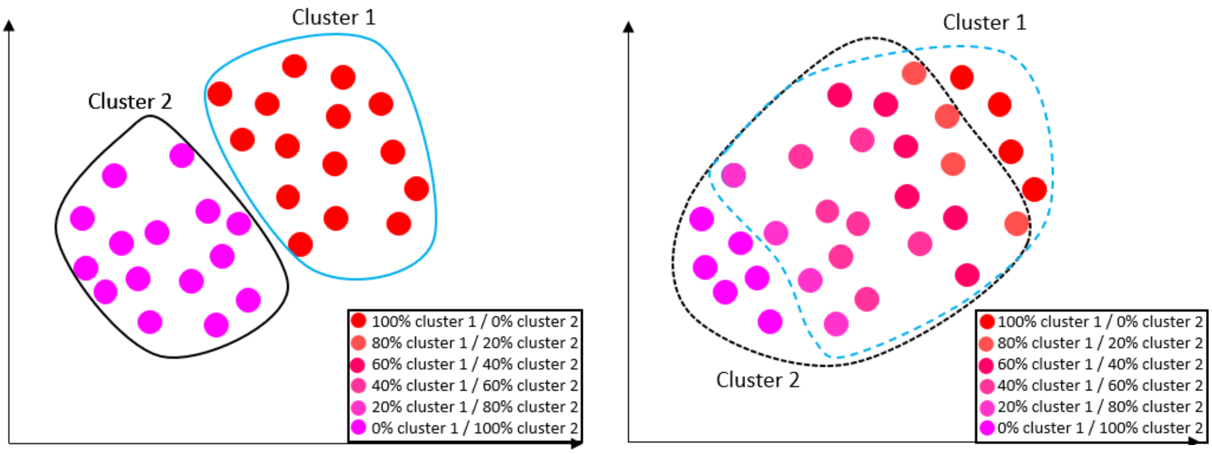
Additional to the tree structure presented in figure 2.2, other issues could affect all of the approaches in the tree, regardless of their place in the tree structure. These other aspects won't be discussed in too much detail, because this is out of the scope of this thesis. However, one aspect will be discussed in more depth: Hard clustering compared with soft clustering. Observing these two, the distinction between the two is quite straightforward:

- In hard clustering, data is grouped and each item can only be assigned to one cluster. Therefore, the probability of a data point belonging to a certain cluster always takes on binary values, either 1 if the item belongs to the cluster and 0 if the item does not belong to the cluster under consideration. In hard clustering, the cluster boundary is determined unambiguously.

- On the contrary, in soft clustering, data is grouped and items can belong to multiple clusters. Therefore, the probability of a data point belonging to a certain cluster is not binary anymore, as the item under consideration can appear in multiple clusters at once.

In figure 2.3, the difference between hard and soft clustering is visualized in a clear example. In figure 2.3a, it is clear that each data point only belongs to one cluster, as both clusters are separated with a full line. This is also indicated by the colors in the figure.
However, in figure 2.3b, this is not the case. Points can belong to both clusters and both clusters are circled with dotted

lines, indicating that points can belong to both clusters here. This is also indicated with the different coloring of the dots, indicating the percentage of each data point that belongs to each of the clusters.



(a) Hard clustering

(b) Soft clustering

Figure 2.3: Example of hard and soft clustering

In his research, Bora [46] made a comparison between soft and hard clustering methods as well. It is concluded that the choice of the clustering algorithm depends heavily on the purpose of the clustering applications. Hard clustering will be more appropriate for exclusive clustering tasks, while soft clustering will be more appropriate for overlapping clustering tasks. As the logic behind soft clustering methods is more complicated than that behind hard clustering methods, it is obvious that the computation time of soft clustering methods will be larger.

As both of these methods exhibit interesting characteristics, a possible implementation of both of them will be discussed in what follows. The K-means method is a popular example of a hard clustering method, whereas the FCM method is a good example of a soft (or fuzzy) clustering method. Both methods are cluster-centric algorithms [47]. This means that, based on distance as the measure of similarity or dissimilarity, these algorithms calculate the centers of groups of data points.
In the more recent years, clustering methods have been used to solve location-allocation problems as well [48] [49] [50]. From those researches, it followed that clustering methods exhibit quite a bit of potential in solving location-allocation problems. This is why in what follows, a deeper look is directed toward these clustering techniques. As in literature, most attention seems to be paid to K-means and FCM clustering, which is why these clustering methods will be mainly considered.

2.5.1 K-means clustering algorithm

The K-means clustering algorithm is one of the most popular hard clustering algorithms. It is a quite simple algorithm and is an often-used algorithm with a squared error function as an objective to minimize [51]. The goals of the K-Means algorithm is quite straightforward: Partition a set of n object in k clusters and meanwhile calculate the centers of these clusters. In doing this, it should be made sure the intra-cluster similarity is high, while the inter-cluster similarity should be low [46]. Initially, random cluster centers are chosen and data points are initially allocated to clusters randomly. Afterward, the data points are reassigned to clusters, trying to maximize the similarity between data points in a cluster and their cluster centers. This process is repeated until a stopping criterion is met. This stopping criterion could be a predetermined number of iterations or the squared error that does not change anymore. One problem with the K-means algorithm is that it is sensitive to the initial choice of randomly selected cluster centers. Selecting a different initial solution can therefore affect the eventual outcome of the algorithm. Therefore, in the literature, methods for selecting better initial solutions have been proposed [52]. Another way of coping with this is to run the algorithm several times on different initial solutions. This way, the effect of these initial solutions will eventually die out. Another drawback of the K-means method is its time complexity. It can be shown that, even for k equal to 2, the K-means method is NP-hard [53]. Additionally, there is no guarantee that the algorithm will converge to a global optimum [54].

In practice, the K-means algorithm [55] can be expressed in its pseudo-code, which is expressed in algorithm 1 [56].

Algorithm 1 The K-means Algorithm

```
Input: a data set containing n points: {(x_1, y_1), ..., (x_n, y_n)}
Output: Cluster centers C^(t) with their assigned data point sets A^(t)

Fix k, 2 < k < n
Fix MaxIterations
Randomly select k initial centers C^(0) = {c_1, ..., c_j, ..., c_k}
while t ≤ MaxIterations do
    for i = 1 to n do
        Find the closest center c_j^(t-1) to data point (x_i, y_i)
        Assign data point (x_i, y_i) to the cluster A_j^(t) with current center c_j^(t-1)
    end for
    for i = 1 to |A_j^(t)| do
        Set c_i^(t) to be the center of mass of all points in A_j^(t)
    end for
end while
```

2.5.2 FCM clustering algorithm

The FCM clustering algorithm was first proposed in by Bezdek [57] and by Dunn [58], who presented the special case for which the fuzzifier exponent (m) was assumed to be equal to. Inspiration for this algorithm came from the K-means algorithm. However, the main reason for the design of this algorithm is to introduce the effect of soft or fuzzy clustering, as it can have some nice applications.

Due to the introduction of the fuzzy character, FCM is more complicated than K-means. This also means that more parameters are used for this algorithm and the parameters specific for this algorithm are represented in table 2.2.

Furthermore, some specific parameters are used for the representation of the data set, and those are given in table 2.3.

As was the case for K-means clustering, the goal in FCM clustering is to minimize the dissimilarity between points (partially) belonging to a cluster and the cluster center. Several performance measures, such as the partition coefficient [59] and the Xie-Beni index [60] can be used, but these will be explained in more detail in one of the next chapters.

Parameter	Explanation
m	Fuzzifier exponent
μ_{ij}	Membership matrix
c / c_i	number of clusters and i^{th} cluster

Table 2.2: FCM parameters

data set parameter	Explanation
n	Total number of objects in the data set
x_i	i^{th} data point
D	dimension of the object under consideration

Table 2.3: Parameters data set

In FCM however, the goal is to minimize the objective function given in equation 2.19.

$$J_m = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m ||x_i - c_i||^2 \tag{2.19}$$

Notice that in this formula, the Euclidean distance metric is used to calculate the distance between the data point x_i and the cluster center c_i. Other distance measures such as the Manhattan distance metric could have been used. However, Euclidean distance metrics are very effective for a small amount of quality data. This is also why they favor squared error methods with greater efficiency [61]. In the chapter about data, the choice of distance metric will be covered in detail.
A fundamental concept in the FCM concept is the membership matrix, with values μ_{ij}. As the name suggests, this matrix indicates the probability of data point i belonging to cluster j, indicated with value μ_{ij}. Opposite to hard clustering methods, the values are not binary in soft clustering methods, however, the criterion in equation 2.20 should always be satisfied. This criterion states that the probability of each data point belonging to any of the clusters is always equal to 1.

$$\sum_{j=1}^{c} \mu_{ij} = 1, \quad 0 \leq \mu_{ij} \leq 1 \tag{2.20}$$

Then, the formula used to update the membership values on the go is given equation 2.21. The exact place of this step in the algorithm will be indicated later on.

$$\mu_{ijnew} = \frac{1}{\sum_{j=1}^{c} (\frac{||x_i - c_i||}{||x_j - c_k||})^(2/(m-1))} \tag{2.21}$$

The last important equation of which the FCM algorithm makes use of is the one to calculate the cluster center. This is indicated in equation 2.22.

$$c_i = \frac{\sum_{j=1}^{N} \mu_{ij}^m x_j}{\sum_{j=1}^{N} \mu_{ij}^m} \tag{2.22}$$

Putting all of this together, then FCM algorithm can be written in pseudo-code, as is illustrated in algorithm 2 [62].

Algorithm 2 The FCM Algorithm

Input: a data set containing n points: {(x_1, y_1), ..., (x_n, y_n)}
Output: Final membership matrix $U^{(t)}$ and final cluster centers $C^{(t)}$

```
Fix c, 2 < c < n
Fix m, 1 < m < ∞
Fix ϵ, MaxIterations
Choose an appropriate distance metric
Randomly initialize membership matrix U^(0) ← μ_ij^(0)
while t ≤ MaxIterations do
    Update membership matrix: U^(t) ← μ_ij^(t)
    Compute cluster centers C^(t) = {c_0, ..., c_i, ..., c_{c-1}} using equation 2.22
    Calculate objective function J_m^(t) using equation 2.19
    if |J_m^(t) − J_m^(t−1)| < epsilon then
        Break
    else
        J_m^(t−1) ← J_m^(t)
        Increase t by 1
    end if
end while
```

Fuzzifier exponent

In table2.2, the fuzzifier exponent m was already introduced. This will be an important parameter for the FCM method. This parameter corresponds to the degree of fuzziness of the obtained solution. If m is close to one, then the result obtained by the FCM algorithm is similar to that obtained using K-means, if the other parameters are kept equal. If m is large, the obtained clusters will be blurred and elements will tend to belong to all clusters. Because of this, values of m close to one or very large won't be used. Generally speaking, m is typically between one and two [63**?**].

The fuzzifier exponent m can also have other undesired side-effects, such as the tendency of all data points to influence all clusters in fuzzy clustering [64]. As the selection of a good value for m will be important for the eventual outcome of the algorithm, this parameter has been well-studied in the literature. For sake of convergence of the algorithm, it was proposed that $m > \frac{n}{n-2}$, with n the total number of data points [65]. Another experimental approach to determine the range of m, is obtained by observing some cluster validity indices [66]. It is suggested that m should lie between 1.5 and 2.5. Because of this, most researchers prefer to work with a value of two for the parameter m. However, more theoretical approaches to determine the value of m are researched as well [67]. A satisfying result is that the obtained ranges are more or less similar, independent of the used approach. Schwämmle and Jensen [68] proposed a formula to find the optimal value of the fuzzifier exponent. This formula is displayed in equation 2.23. Schwämmle and Jensen also showed that the proposed formula is a good fit for large data sets.

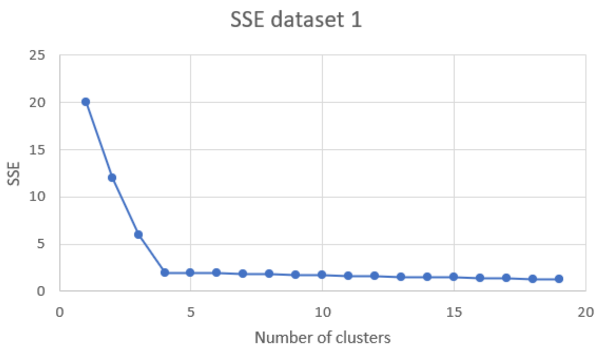
$$f(C,N) = 1 + (\frac{1418}{N} + 22.05)C^{-2} + (\frac{12.33}{N} + 0.243)C^{-0.0406\,ln(N)-0.1134} \tag{2.23}$$

In the further course of this master thesis, m will be assumed to be equal to 2. This is the case because the main objective of this thesis is to design a good approach for a clustering-based location-allocation method, not to analyze the influence of the fuzzifier exponent on the eventual results.

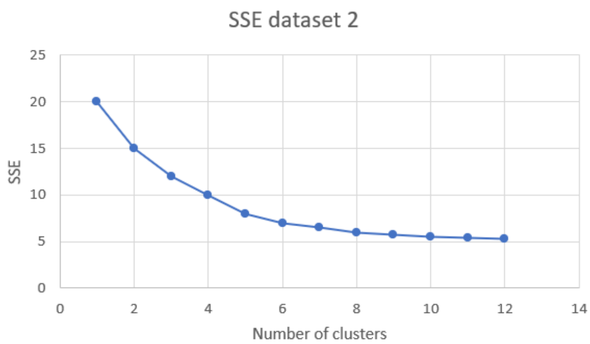
Optimal number of clusters

One of the most interesting questions in clustering is how to determine the optimal number of clusters. In clustering methods, the number of clusters is mostly used as an input for the model. However, it is not obvious at all to determine in how many clusters the data should be partitioned optimally. The most basic criteria to estimate the optimal number of clusters c is based on a simple rule of thumb [69]: $c = \sqrt{\frac{n}{2}}$, where n represents the number of data points in the data set.

Alternatively, an often-used method to determine the number of clusters is called the elbow method [70][71]. In the elbow method, the Sum of Squared Errors (SSE) value is calculated for each value of the number of clusters in a predetermined range. Then, the values should be compared with each other and it is started from a number of clusters equal to 2, which is then increased one by one. From the moment that no significant decrease of the SSE value occurs anymore, it can be stated that the elbow point is reached. According to the elbow method, this will be the optimal number of clusters for the considered problems. One problem with the elbow method is that the elbow point is not always easily detected, which would result in a solution that is not certainly optimal. This problem is illustrated in figure 2.4.



(a) data set for which the elbow method gives a clear result visually



(b) data set for which the elbow method does not give an ambiguous result visually

Figure 2.4: Comparison of two data sets for which the elbow methods respectively gives an unambiguous (figure 2.4a) and an unambiguous result (figure 2.4b)

Other methods, relative to the elbow method, have been proposed as well in the years afterward [72], but the elbow method is the most important one and for the others, reference is made to more specialized literature. Notice that these methods are mainly used for hard clustering methods, but could also give an indicative result for their soft counterparts.
In soft clustering, cluster validity indices can be used to determine the optimal number of clusters. A Good overview and comment for the different cluster validity indices are given by Kim Lee [73]. These measures can then be used to determine the theoretical optimal number of clusters. Notice that the optimal number of clusters can also depend on the structure of the input data that is used.

Another interesting observation about the number of clusters is that it decreases when the fuzzifier exponent m increases

[68]. Intuitively, this is what could be expected, as with increasing m, the fuzziness increases as well.

Finally, some more advanced algorithms have been designed to calculate the optimal number of clusters [74][75]. However note that these algorithms are often tailored to a specific type of problem, which results in limited applicability to other types of problems.
In the actual thesis research, the already studied literature will certainly be kept in mind. However, the methods discussed here to find the optimal number of clusters are mainly theoretical, which will sometimes result in limited applicability in reality. In reality, some other measures deem to be more important, which then requires a more specialized approach.

2.6 Data aggregation

To solve real-life location-allocation problems, sufficient data should be gathered to use as inputs for the solutions models. As this thesis concerns finding the optimal location of UAV base stations from which a certain demand should be fulfilled, a good representation of this demand will be a crucial element for this thesis. For certain applications of eUAM, the population distribution across a given urban environment can be a good representation of the demand that should be served by those UAVs.
In an urban environment, many people live closely together. In Belgium, cities count thousands of inhabitants, and globally, certain metropolises count even more than a million inhabitants. As this thesis focuses on urban environments, data concerning the inhabitants of this kind of city will be crucial as input data.
Formulating a model with hundreds of thousands or even a million demand points will be very hard to solve. This level of detail is too large and will not even be necessary to make sure the proposed model is a sufficiently good representation of reality. In addition, the housing locations of every single inhabitant of such cities are not publicly available.
For the reasons stated above, it will be important to trade off accuracy with efficiency here. More aggregated data will probably require less computation time, but it is possible that it would result in less accurate results. On the contrary, for more disaggregated data, the results will be more accurate. This better performance comes at a cost, namely in the increase in computation time.
An illustration of data aggregation is given in figure 2.5. In this figure, a simple example of data aggregation is given. In the first part, raw data is given which is not yet processed in a further way. This data will then be aggregated in different zones and the density will be centered in the center of gravity of the zones. Finally, the data is aggregated even further in single points which do not depend on the borders of the individual zones. The complexity of the data has reduced a lot, but its level of details as well.

In the literature, the use of aggregated data has already been studied for certain types of location-allocation models. Fotheringham [76] conducted a study to observe the aggregation effects of the p-median procedure. In p-median problems, three types of errors are defined as A-, B- and C-type errors [77]. These errors respectively represent the error that comes from clustering zonal demand in a single point instead of a series of points, the error that comes with inter-zonal demands that are set to zero, and the error that comes with the fact that zones can only be served from a single facility, even if a part of the zone is closer to another facility. The outcome of the study for p-median procedures is that the outcome is optimal only for a particular definition of spatial units. Changing the definitions of these spatial units can cause large deviations in

optimal facility location. Even though some solution sites are quite stable, it can be shown that other solution states can easily be changed by manipulating how data is aggregated.
However, Goodchild [78] concluded that the effects of using aggregate data on location are much more dramatic than on the values of the objective function. Also, how to evaluate or minimize the severity of the aggregation effects depends on the way the input data is gathered. In case the data is aggregated to reduce the problem to a manageable size, then care should be taken on how this data aggregation is performed. Some ways of aggregating data results in greater errors. Aggregating data should therefore only be done while paying sufficient attention to the effects of this data aggregation.
In other cases, where the data is gathered in aggregate form, often no access to the initial, disaggregated data is possible. In these cases, fewer measures can be taken to ensure the data is aggregated appropriately. Always observe the obtained results critically or if there is another way to gather data, this would be more appropriate.

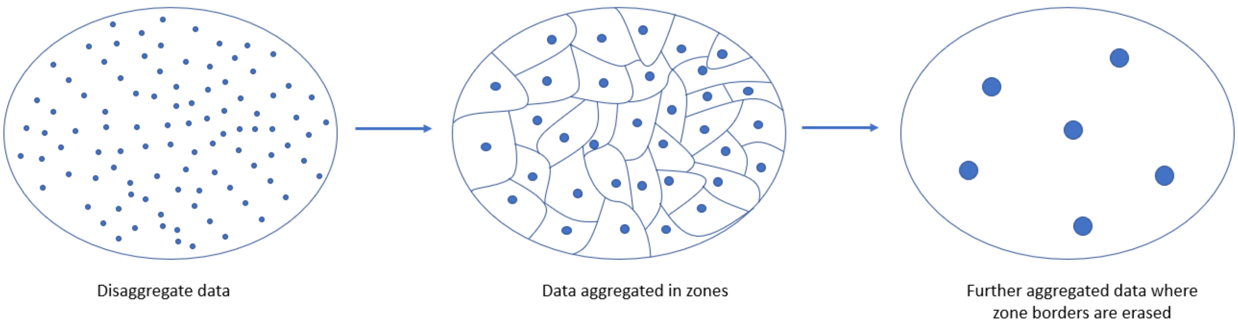


Figure 2.5: Illustration of data aggregation

Apart from aggregation effects in the p-median type of problems, the effect of aggregation is also studied for maximum covering models [79]. This is another traditional approach to solving location-allocation problems.
In the study for aggregation effects in maximum covering models, two types of objective function errors are identified. These were respectively optimality errors and coverage errors. In the study conducted by Daskin [79], three different aggregation schemes were tested to see in which case the biggest effect occurs.
The results obtained from that study are in line with the results for the p-median method. It is observed that demand and candidate location can be aggregated significantly, without increasing the optimality or coverage error a lot, if the right aggregation schemes are used. On the other hand, location errors will be large, regardless of the used aggregation scheme.

From literature, it can therefore be concluded that data aggregation is not something one can do without the risk of introducing errors. Therefore, if possible, it is beneficial to use data in a quite disaggregated level of detail if this is computationally possible. Often, the level of aggregation will be limited by the available data, as publicly available data is always aggregated in some way.
Therefore, to get the best results possible, data will not be aggregated in this thesis, unless it would be necessary for computational reasons. If the available data would be aggregated in a further way during this thesis, it will explicitly be mentioned. However, attention should always be paid to the possibility of the introduction of errors.

3

Data

The purpose of the data chapter is to present all input data that will eventually be used in the study concerned with finding the optimal location-allocation of UAV base stations.
The main data that is discussed here are the ones related to the different UAV types, the population of the city of Ghent, and initial infrastructure. To work with this data appropriately, the used distance metric is presented and justified. Finally, some major model assumptions are presented. This is done to clear up potential ambiguities.

3.1 UAV types

The UAVs that will be considered in this thesis research are the same ones as those that will be deployed in the AURORA project. This project can best be described as "a cross-disciplinary project aiming at linking aeronautical, smart mobility, intelligent systems, urban planning, and citizens' engagement with industry, authorities and citizens perspectives to foster the adoption of urban air mobility" [80], with a focus on emergency services. In this project, three UAV types of different sizes are considered. These are respectively small, medium and large UAVs. The technical specifications can be found in table 3.1 [2]. In this table, the cruise speed is defined as the maximum speed that the UAV can achieve during flight. However, for the remainder of this study, it will be assumed that the cruise speed is equal to the average speed of the UAV under consideration.

Size	Type	weight (kg)	Cruise speed ($\frac{km}{h}$)	Endurance (h)	Landing area requirement (m x m)
Small	Multicopter-type	$\leq$25	40	0.5	21.6 x 21.6
Medium	Rotorcraft-type	$\leq$80	100	1.5	7.2 x 7.2
Large	Optionally-Piloted VLR	$\leq$600	150	3.5	2 x 2

Table 3.1: Specifications UAV types [2]

A bit more clarification about the different UAV types might be necessary. The first UAV type is the multicopter-type UAV. This UAV is a type of helicopter that has at least three propellers. Additionally, the multicopter has the ability of Vertical Take-Off and Landing (VTOL) [81]. This means that the UAV can take off and land respectively straight up or down. This means that the UAV does not require a lot of space around it, which is certainly handy in an urban environment. Generally, this type of UAV is not able to carry a lot of weight and can therefore only be used to transport small goods. In emergency services, this

means that the applicability of these types of UAVs will be directed towards the distribution of AEDs.
The second UAV type is the multicopter-type UAV. This type of UAV is typically larger than the multicopter-type UAV and will therefore be able to handle a heavier payload. As this type of UAV is larger, it can also travel at a higher cruise speed and will have a larger endurance.
Finally, the third and largest UAV type are the optionally-piloted VLRs. Their endurance and cruise speed are the largest of all three UAV types and they can transport the heaviest payloads. This type of UAV is also the only one that can be used to transport persons as passengers, with ambulance services as a potential application.

In the context of location-allocation problems, the most important property will be how far each UAV type can range without running out of power and how fast this can be done. These abilities respectively correspond to the coverage and the response time of the UAVs. As this won't be the same for each type, this is something that should be investigated in further research. Therefore, the optimal placement of the UAV base stations may differ depending on the type of UAV that is considered.

3.2 Input data

3.2.1 Data Ghent

In this master thesis, a case study will be performed to observe the performance of the proposed approach. The real-life case that will be considered is that of the city of Ghent.
For this city, it is known that in total, it counted 264 676 inhabitants between its borders at the end of 2021 [82]. To apply the location-allocation problem to the case of the city of Ghent, it is not sufficient to only know the total population. Additionally, it will be necessary to know how the population is distributed across the entire city. This is because the population will be used to represent the demand for emergency services here. This is quite intuitive, as regions that are more densely populated will also require more emergency interventions.
Fortunately, the city of Ghent has a public data tool that enables people to consult all types of information, ranging from population distribution to EV charging points and so on. From this tool, it can be seen that the city of Ghent can be subdivided into 25 neighborhoods and even into 202 sectors. The subdivision in sectors will be the most disaggregated level of data. As this level of detail is the most detailed level of data available, this will be used as input data in the remainder of this thesis. For each sector in Ghent, its name, its sector code, its coordinates (initially latitude and longitude), and the total population in the sector is available[83][84].
As the most disaggregated level of detail is used, this means that the data for 202 sectors will be present. Assuming that each sector is represented by its center of gravity and that the weight given to each sector is the same, this results in the visualization shown in figure 3.1.

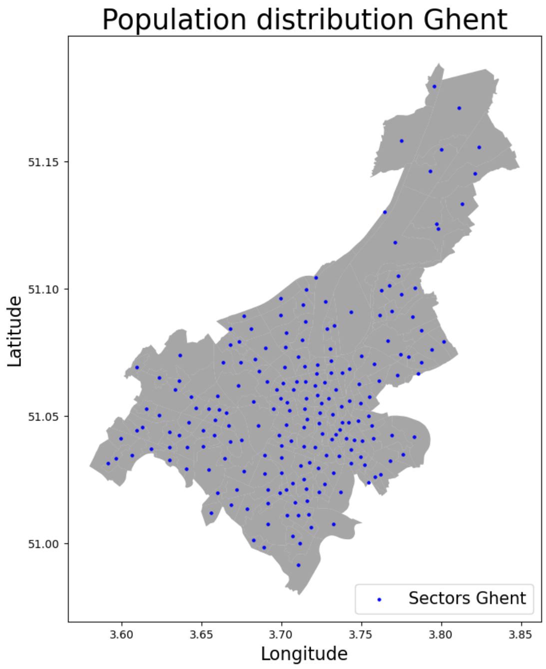


Figure 3.1: Visualisation sectors Ghent indicated with their corresponding (unweighted) center of mass

3.2.2 Data type

Typically, geographical data is given in a geographic coordinate system, which is also the case for the data available for the city of Ghent. This means that for each data point, their longitude and latitude are given as a tuple. However, to make the data easier to understand, it would be better to convert the data to a two-dimensional x-y-coordinate system, which is expressed in terms of meters or kilometers. Distances in meters or kilometers are generally easier to comprehend. Also, it is better to use data in meters or kilometers when other calculations will be performed such as calculating the time it takes to reach a certain destination. In the emergency UAV location-allocation problem, the response time is a crucial factor and is easier to calculate for data sets already expressed in meters.

Making the conversion from the tuple (longitude, latitude) to the tuple (x, y) can be done using projected coordinate systems. In QGIS, it is possible to load the data in the right initial reference frame. As the data is initially expressed in (longitude, latitude), it should be loaded using EPSG:4326 - WSG 84. Then, the projected coordinate system that is going to be used, should be tailored to the case of Belgium. The most often used and most known projected coordinate system for Belgium is the Lambert projection [85]. For example, Lambert 72 can be used, which only gives an error of 1 meter. This type of error is certainly small enough for an application such as the one of location hubs for emergency UAV usage.
When this conversion is performed, it is also possible to shift the current coordinate system to a more obvious coordinate system. For example, a great coordinate system would be one in which the data point below on the left is placed in the origin. Then, this local coordinate system is most illustrative and user-friendly. This conversion is performed in Excel, after which the data can easily be loaded into python, where it can be used as input for the eventual model.
In practice, the coordinate system is shifted 96 227.05 meters to the left and 187 020.5 meters shifted down. It is important

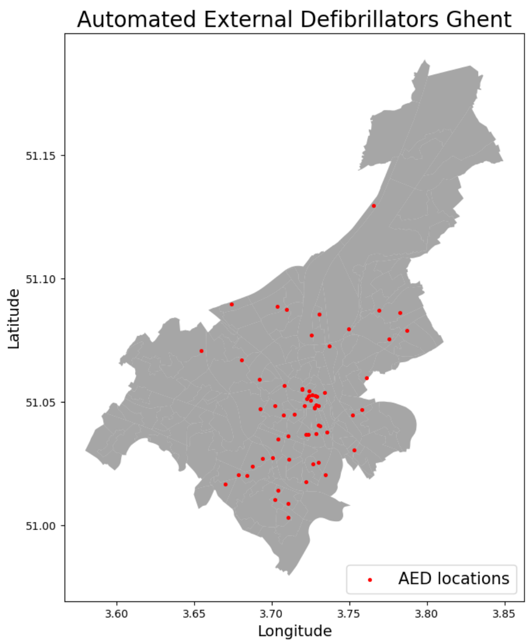
that all types of data undergo the same shift. Otherwise, the coordinate systems would not be compatible with each other. The shift that is performed here makes sure that the uppermost left demand point has an x-coordinate equal to 0, while the lowest demand point has a y-coordinate equal to 0.

3.3 Initial infrastructure

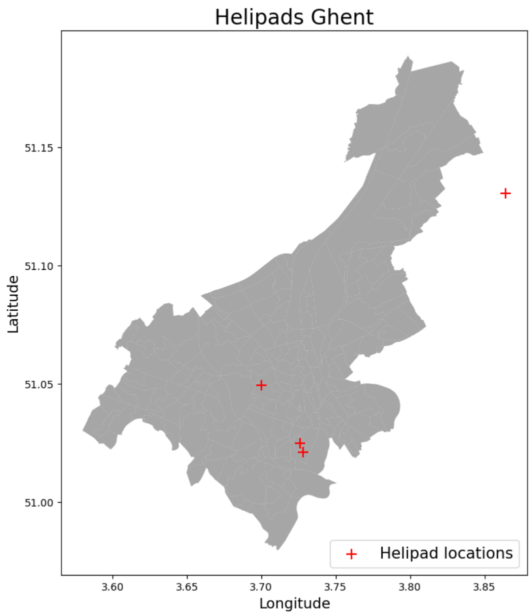
3.3.1 Initial infrastructure present in Ghent

For locating the UAV base stations, it is not necessary to start from scratch to build a new UAV base station. Sometimes, it is possible to start from some already existing infrastructure and then build further on it by making a few improvements or adjustments to the initial infrastructure.
As a starting point, different possibilities are possible.
First of all, it is possible to start by looking at the locations in Ghent where AEDs are located. As AEDs are very important as first aid for people with a cardiac arrest, these locations are certainly relevant, as this thesis also focuses on the application for emergency services. In Ghent, about 60 AEDs are already present. The locations of the AEDs, plotted on the map of Ghent, are displayed in figure 3.2a [86].
Another possibility to consider as initial infrastructure for UAVs, would be to use already existing helipads. Usually, they are near hospitals, and there, helicopters can land. Therefore, helipads will certainly be able to be used as base stations for all three UAV types. However, they will probably be most relevant for the largest type of UAV. An overview of the helipads in and close to Ghent is shown in figure 3.2b. Note that one of these four helipads (the most right one) is just outside Ghent, but still quite close to Ghent so that it could be used as a base station as well.

Additionally, infrastructure that is not yet deployed for emergency services can be used as a starting point for UAV base stations. As the UAVs that will be used are going to be electric ones, a great point of departure would be to use the charging stations that are already present for EVs in Ghent. These can then be used as well to charge the electric UAVs that will be deployed. In the city of Ghent, already a quite extensive network of EV charging stations is present. This network is shown in figure 3.3a[87].
For the multicopter-type UAV, the areas around EV charging stations will be sufficient to efficiently take off as an area of 2 meters by 2 meters is sufficient, which is more or less comparable with the size of a car. However, for the larger UAV types, this area will not be large enough. Therefore in reality, for the largest type of UAV, which requires an area of 21.6 meters by 21.6 meters, only helipads will be large enough. For the medium type of UAV, there are still other possibilities. They require an area of about 7.2 meters by 7.2 meters. As this is already a quite large area, for these UAV types, parking lots will be considered as initial infrastructure. In figure 3.3b, both public car parks and public truck parks will be considered. In total, there are 32 candidate locations, which is quite a bit less than the initial EV charging stations. However, as the medium size UAV can travel at a higher cruise speed than the smallest UAV type, this is not necessarily a problem.

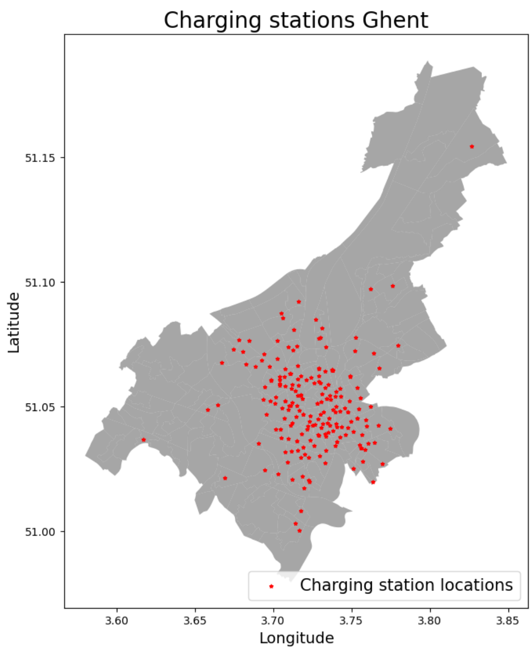


(a) Visualisation of existing AED locations across Ghent

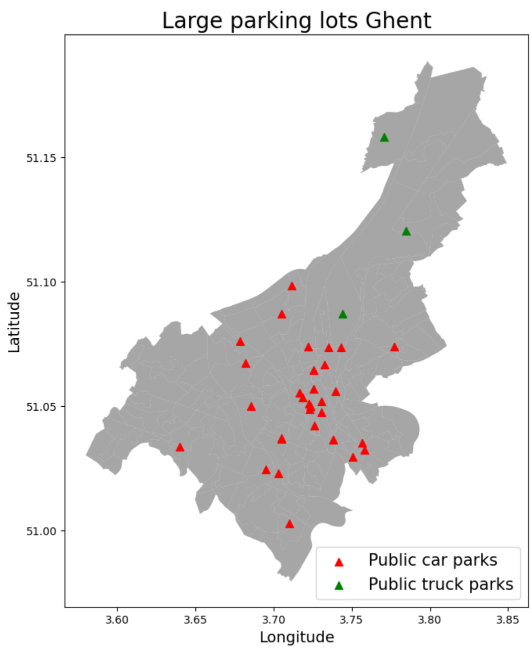


(b) Visualisation of existing helipad location in and near Ghent

Figure 3.2: Initial emergency service infrastructure



(a) Visualisation of existing EV charging stations across Ghent



(b) Visualisation of large parking lots Ghent

Figure 3.3: Non-medical initial infrastructure

In further research, the focus will be directed toward the multicopter-type UAV. For these UAVs, the AED locations and EV charging stations are considered as initial infrastructure. For the data sets of these initial infrastructure possibilities, some observations can be made. For both AED and EV charging station locations, it can be seen in figures 3.2a and 3.3a that these locations are dense in the center of Ghent, while not a lot of initial infrastructure is present farther away from the center. Therefore, it could be possible that just starting from initial infrastructure won't result in an acceptable service time in the more remote areas of Ghent. However, this will be studied in the further course of this master thesis.

3.3.2 Conversion cost initial infrastructure

To convert the initial infrastructure to suitable Landing and charging stations for UAVs, making some adjustments is necessary. Making these adjustments comes at a cost, which is here referred to as the conversion cost. Next to converting initial infrastructure, it is also possible to construct new UAV base stations from scratch. As both situations will come with different types of costs, it will be explicitly stated which costs are incurred in which scenario. The total costs incurred with setting up new UAV base stations and converting initial infrastructure to suitable UAV base stations are shown in table 3.2. In this table, all costs are also expressed on an annual basis, which will turn out to be useful for further cost optimization. It is assumed that the lifetime of AEDs, UAVs, and charging stations span over 10 years. For both charging stations and AEDs, the total cost shown in table 3.2 contains the purchasing, installation, and maintenance costs. The UAV and data link prices obtained follow from an approximation/estimation based on the market analysis within the project [2].

Equipment	Used where	Total cost (in euros)	Annual cost (in euros)
Surface area 2m x 2m [88]	Only in new infrastructure	1 368	136.8
Charging station [89] [90]	Only in new infrastructure	5 400	540
AED device [91]	Both initial and new infrastructure	2 500	250
UAV + data link [2]	Both initial and new infrastructure	410 000	41 000

Table 3.2: Cost overview used equipment and infrastructure multicopter-type UAV base station

3.4 Distance metric

In clustering, it is important to select the right distance metric. The distance metric has a big influence on measuring similarity in patterns. Therefore, using an appropriate distance metric is crucial to obtain good clustering results.
Some distance metrics have already been proposed, but here the most appropriate ones will be discussed in more detail to finally select the most suitable one. Notice that the problem is two-dimensional, which will also have some implications on the possible distance metrics.
As the initial coordinates for the data points in the city of Ghent were given as a couple (latitude, longitude), an obvious approach would be to use the Haversine formula to calculate distances between two points. This distance metric calculates the distance between two points in spherical coordinates, ignoring the fact that the earth is not a real sphere. The two points which we want to calculate are given as follows:

$$(lat_i,\, long_i) = (\phi_i,\, \lambda_i), \quad \forall\, i\, \in \{1, 2\} \tag{3.1}$$

Then, expressing the Haversine formula for which all angles are expressed in radians and the radius of the earth r is assumed to be 6371 km, the following formula for the Haversine distance D is obtained. [92]:

$$D = 2r\,arcsin\sqrt{sin^2(\frac{\phi_2 - \phi_1}{2}) + cos(\phi_1)cos(\phi_2)sin^2(\frac{\lambda_2 - \lambda_1}{2})} \tag{3.2}$$

Even though the Haversine distance succeeds in successfully calculating the spherical distance, it is not as intuitive as methods that use metric coordinates instead of spherical coordinates. As there are good projected coordinate systems available (see section 3.2.2), the conversion from spherical coordinates to metric coordinates happens easily. This is why the focus is redirected towards more intuitive methods now.

For the more intuitive methods, the two distance metrics that will be discussed are the Euclidean distance and the Manhattan distance, as these seem most promising right now.

Consider here that both coordinates have already been projected in a metric coordinate system, then the coordinates are expressed in meters, as follows:

$$(x - coordinate_i,\ y - coordinate_i) = (x_i,\ y_i), \quad \forall\, i\ \in \{1, 2\} \tag{3.3}$$

Then, the Euclidean distance D_e in two dimensions can be expressed as follows [93]:

$$D_e = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{3.4}$$

and the Manhattan distance D_m in two dimensions can be expressed as [93]

$$D_m = |x_2 - x_1| + |y_2 - y_1| \tag{3.5}$$

Visually, the difference between these two metric is shown in figure 3.4. Notice that the Manhattan distance in yellow and grey is the same, which is why the Manhattan distance is not uniquely determined.

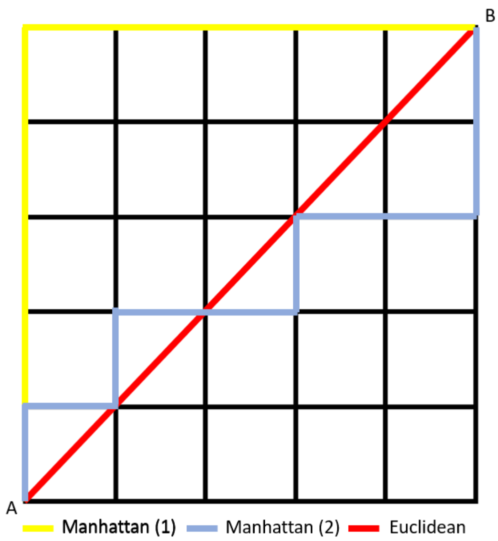


Figure 3.4: Visual comparison of Euclidean and Manhattan distance metric

From this figure, it can also be seen that the Manhattan distance is always greater or equal to the Euclidean distance.
For the application of eUAM, in which the UAVs can travel without restrictions of predetermined streets, it follows that the Euclidean distance metric will be appropriate. For cities where vehicles travel on streets and where the street pattern is by approximation equal to a checkerboard pattern, the Manhattan distance will be more appropriate.
In the remainder of this thesis, the Euclidean distance metric will be used as a reference metric.

3.5 Major model assumptions

Each model tries to represent reality as well as possible. However, it is important to make sure these models are not overly complex as that could render the models infeasible or very hard to solve. This is why it will be necessary to make some appropriate simplifications and assumptions before feeding the input data to the models under consideration. In this master thesis, the major model assumptions are the following:

1. In between interventions, UAVs have plenty of time to charge their batteries to make sure they are fully charged before pulling out for the next intervention.

2. The considered initial infrastructure is assumed to be convertible and suitable for eUAM. Note that these adjustments can come at a cost, but the basis of the initial infrastructure is considered to be fit for eventual use as UAV base station.

3. Each UAV base station is considered to have sufficient capacity to serve the demand that is allocated to it in a smooth and efficient way.

4. UAV are allowed to fly everywhere in the considered urban environment. New UAV base stations can be located at their optimal locations, even though in reality this would not be the case. Therefore, in this model, no forbidden regions are included.

5. In each sector, the population is assumed to be located in its center of gravity. Additionally, the population characteristics (age, lifestyle, etc.) are the same for each sector in Ghent.

4

Methods

In the chapter about methods, the used approach in this research will be highlighted. This is done from a high-level point of view, as this mainly includes a general view of the used approach. The more detailed approach that is used and decisions that are made during this master thesis are discussed in the chapter on applied methods.

More concrete, the general approach can be split up into two main parts: The used methods and the problem structure. These two parts will constitute the remainder of this brief chapter.

4.0.1 Used clustering methods

From the literature review, it is quite clear that the focus here is directed toward clustering techniques. It seems to be the case that these techniques currently aren't the most-used methods, even though they have really interesting properties, which are mainly studied in research on image and pattern recognition.
In this research, A look will be given at both hierarchical and partitional algorithms. More precisely, the focus will be directed toward agglomerative (bottom-up) hierarchical clustering and FCM clustering.
There are several reasons why these two methods are chosen. First of all, hierarchical methods have some really interesting properties concerning the introduction of different levels, thus the hierarchy. This is an interesting point of departure and this will be looked into in more detail in what follows.
Then, the reason why FCM clustering is selected is mainly due to its soft clustering properties. This means that demand points can belong partially to different clusters and they can therefore be allocated to different UAV base stations. In practical situations, this makes the system more prone to disruptions such as outages or maintenance. Also, when several interventions need to happen in a cluster at the same time, the soft clustering can help decide which intervention should be responded to by which cluster, based on the fraction in which the demand locations belong to the different clusters.

In the research, the performance of these methods will be observed and reported. In case further steps can be taken to increase the performance of the clustering methods, these are reported clearly and worked out in detail. However, these methods will be discussed more concretely in the further course of this master thesis.

4.0.2 Problem structure

In tackling the location-allocation problem, several steps should be taken to eventually be able to efficiently find a solution to the problem. Often, large problems are first simplified to a rather simple problem, after which more complexity is added. In approaching the location-allocation problem for emergency services for the case of Ghent, this will be no different. Initially, the problem is presented quite simply, assuming no initial infrastructure is present and no specific decision criteria are present. afterward, more complexity is added to the problem to finally come to a problem that is a quite good representation of reality. In summary, the main steps that are taken to increase the complexity of the problem are presented in the flowchart shown in figure 4.1.

Figure 4.1: Visualisation steps increasing problem complexity

In the main part of the research, when UAVs are included, the focus lies on the multicopter-type UAV. This is the UAV with the smallest endurance and speed and will therefore also have the highest response time. This will therefore result in the most conservative response times of the system and also in the most interesting cases.
In the end, the final results for joint implementation of the three UAV types will be shown and discussed.
Finally, the research is concluded with a brief cost optimization analysis that can be used to determine the optimal number of clusters from a cost-based perspective.

5

Applied methods

In the chapter concerning applied methods, the used methods are highlighted in more detail. In this chapter, the exact steps followed in this research are shown and explained thoroughly. These steps are the exact methods that will eventually be used to obtain results that will eventually be reported and discussed in chapter 6. The current chapter and chapter 6 are closely related, as the framework given here will be used in the next chapter to obtain the actual research results.
The steps will follow each other in order of increasing complexity. Therefore at first, basic algorithms (FCM and agglomerative hierarchical clustering) are presented. These will form the foundation for all further research steps and extensions.

5.1 Basic FCM algorithm

Now that the input data for the city of Ghent is known and represented clearly, the first clustering method can be applied to it. In this first stage, a general FCM algorithm will be applied to the input data to observe patterns in this data. As was described in the literature review, the initial choice of the membership matrix in FCM can influence the eventual results.
In this first exploratory application of FCM to the data set of Ghent, the purpose is to already observe some patterns in the data set.
In applying FCM to data sets, it was already discussed in the literature review that the initial choice of the membership matrix can influence the eventual results. Therefore, to not bias the algorithm initially, the initial membership matrix is generated randomly. In doing this, it will however be important to respect the boundary conditions. For each row of the membership matrix, the elements should sum up to 1 and each element is non-negative.
There are multiple ways to generate this membership matrix randomly, but here it is chosen to use the Dirichlet distribution. In numpy, the function numpy.random.dirichlet allows us to build n samples, each of length k. For the city of Ghent, this corresponds to n equal to 202, which is the number of data points, and k equal to the predetermined number of clusters.

5.1.1 Cluster performance measures

To be able to judge the performance of the FCM algorithm, there will be a need for some well-defined performance measures. These performance measures mainly have something to do with the optimal number of clusters that are present. The explanation for this is that in case too many clusters are present, the data points are split up too far. In case not enough clusters are present, data points that are too dissimilar to each other can still belong to the same cluster. Additionally, visually observing the optimal number of clusters can be very hard in case the clusters that are formed are not too clear. Therefore, there is a need for some more advanced performance measures.

A first but very naive way of estimating the optimal number of clusters is by using a very simple rule of thumb, which is shown in equation 5.1.

$$c \approx \sqrt{\frac{n}{2}} \tag{5.1}$$

However, this rule of thumb does not take into account the structure of the data itself and purely looks at the total number of data points. This will therefore be too simple to result in good and reliable estimates.

Therefore, some more advanced performance measures can and should be used to determine the optimal number of clusters. In the following, a few very important performance measures are given. More performance measures are present in literature as well, but these are left out for now as they would go too far.
Mainly in hard clustering, the elbow method is a commonly used technique. This method was already partially explained in the literature review, which is mainly based on the SSE.

Adjusting this method to the case of the FCM algorithm, the weighted SSE can be calculated as illustrated in equation 5.2. In this equation, the used parameters are the same as defined before. Notice that this SSE is the same for FCM as its objective function J_m.

$$SSE_m(c) = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{m} ||x_i - c_i||^2 \tag{5.2}$$

Another performance validation measure that could be used is the Partition Coefficient (PC) [94]. The value of the PC ranges between 0 and 1, with the best values being those closest to 1. To optimize this performance measure, the number of clusters resulting in the maximum value of PC should be selected. In observing the PC, the number of clusters ranges between 2 and n, with n being the total number of data points. Mathematically, the PC is calculated as is shown in equation 5.3

$$PC(c) = \frac{1}{n} \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^{2} \tag{5.3}$$

A validity measure related to the PC is the partition entropy. This validity measure mostly returns similar results as the PC, which is why the partition entropy is left out from this research. For further information about this, the reader can consult specialized literature.

The last validity measure that is used to determine the optimal number of clusters, is the Xie and Beni index [60].
The Xie and Beni index is an internal cluster validation index that is used to determine the optimal number of clusters in fuzzy clustering approaches such as FCM. The nominator of the Xie-Beni index is calculated in the same way as the weighted SSE, which computes the intra-cluster compactness. To calculate the Xie-Beni index, this term is then divided by an inter-cluster separation index. This separation index is calculated as the minimum square distance between cluster centers, being the distance between the two cluster centers that are closest together. The Xie-Beni index can then be formulated more mathematically as shown in equation 5.4.

$$XB(c) = \frac{\sum_{i=1} c \sum_{j=1}^{n} \mu_{ij}^2 ||v_i - x_j||^2}{n \min_{i,j,i\neq j} ||v_i - v_j||^2} \tag{5.4}$$

Minimizing the Xie-Beni index with respect to the number of clusters eventually results in the optimal number of clusters. The number of clusters for which the Xie-Beni index is minimal is then the optimal number of clusters.

5.2 Hierarchical clustering

From the initial results obtained using FCM, it is observed that the FCM algorithm will certainly have its added value. The fuzzy part of this clustering method clearly shows some interesting properties, as some hubs won't be operated all the time or some hubs can temporarily be out for maintenance or other unforeseen circumstances. Even though this fuzzy clustering method is very useful on a small scale, problems can arise when fuzzy clustering is applied on a large scale. For example, the actual worst-case service time can be really large if a point on the other side of the map is allocated partially to a UAV base station on the other side. This would be a problem in terms of quality of service.
Additionally, on this large scale, it is often not easy to determine the optimal number of clusters using the cluster validity measures. Therefore, it might be useful to implement some different layers or levels in the clustering hierarchy which can serve as a first partitioning.
To respond to the shortcoming of the FCM method, hierarchical clustering is introduced. This is a type of clustering method that introduces different stages or levels in the clustering hierarchy. Hierarchical clustering can be used on its own to determine the optimal number of clusters or it can be used for a first hard sub-partitioning after which another clustering method can be applied further. For now, hierarchical clustering will be considered on its own, but it is kept in mind that it could eventually be combined with other clustering methods as well.

In hierarchical clustering, different approaches to clustering the data can be used. For example, there is a distinction between bottom-up and top-down hierarchical clustering. In the research considered here, bottom-up clustering, also called agglomerative hierarchical clustering, will be used. This clustering method starts from all data points on their own and then groups them step by step until eventually, only one group remains. This final group then contains all data points that were present in the initial set.
In practice, the steps in hierarchical clustering can be summarized as follows:

1. Initially, there is no structure in the data points. In this first step, each data point is converted into a cluster on its own. This results in a set of n singletons.
2. Then, the two clusters that are closest together are selected and they are merged to form one cluster. The selection of these closest clusters is based on a certain linkage criterion.
3. Repeat step 2 until only one group remains in the end. Then, the clustering method can be terminated and the agglomerative hierarchical clustering method has succeeded in grouping all data points together, following a certain sequence.

In this procedure, it is stated that the two clusters that are closest together should be grouped. However, the notion of 'closest' can be interpreted in multiple ways. In clustering, determining the distance between clusters can happen based on several criteria, called linkage criteria. The most often used linkage criteria are the following ones [95]:

- Single linkage: The distance between two clusters is equal to the distance between the points of each cluster that are closest together, which is the shortest distance.
- Complete linkage: The distance between two clusters is equal to the distance between the points of each cluster that are the farthest away from each other, which is the longest distance.
- Average linkage: The distance between two clusters is equal to the average distance between all the points of each cluster. For two clusters containing n points, this will be the average of n^2 distances, which will be computationally intensive.
- Ward linkage: This linkage criterion calculates the total within-cluster variance, thus the variance between the data points in each cluster itself.

To observe in which order clusters are formed, it would be very useful to visualize this process sequential process in a clear way Dendrograms visually display in which sequence clusters are formed and they can be used to help determine the optimum number of clusters. To determine the latter, a rather simple but powerful procedure can be followed, which is shown in the following enumeration:

1. At first, the dendrogram is constructed. Starting from the full dendrogram, the longest uninterrupted vertical distance in the dendrogram is determined. This is the longest distance during which no new clusters are formed. For the dendrogram, this means that during this distance, the dendrogram does not branch out any further. To highlight this distance, two horizontal lines are drawn, one at each extreme of this longest vertical distance.
2. For one of these lines, count how many vertical lines of the dendrogram intersect with the horizontal line under consideration. This number of intersections then equals the optimal number of clusters.

Implementing agglomerative hierarchical clustering can easily be done in python. In python, a package called sklearn makes it possible to easily perform agglomerative clustering and visualize the dendrogram, using the preferred linkage criterion. In the actual implementation of this clustering procedure, the Ward linkage is used as linkage criterion. This linkage criterion is chosen over the other linking criteria as it is one of the more advanced linkage criteria and it mostly performs better on clusters that are not well-separated initially [96]. However, in the results chapter, the influence of the linkage criterion on the eventual result will be observed as well.

5.3 Design multi-level clustering approach

As both FCM and agglomerative hierarchical clustering do not return results on their own that would be feasible in real-life applications, it could be a good idea to combine the strengths of both clustering approaches to form a more advanced

clustering approach. In this new clustering approach, some level of depth could be introduced in the hierarchy of the solution. In this new approach, it would be the idea to first perform the agglomerative hierarchical clustering, followed by FCM. The reason that it is performed in this order is that the FCM works with partial memberships, while the agglomerative hierarchical clustering does not do this. If the highest level of initial clustering would already be structured in a way that certain demand points can belong to different clusters, this would complicate the further clustering steps. Next to that, clusters could be too large, with partial belongings ranging over the full demand space. In that case, the worst-case service time with a small part belonging to one cluster would be way too large. It could be the case that a point on one side of the map belongs for a small fraction to a cluster on the other side of the map, which would result in a very large response time. Therefore, some initial filtering using a hard clustering technique would be a clever choice as the chance that such kinds of bad behavior occur is then reduced to zero.
Schematically, the proposed procedure is displayed in figure 5.1.

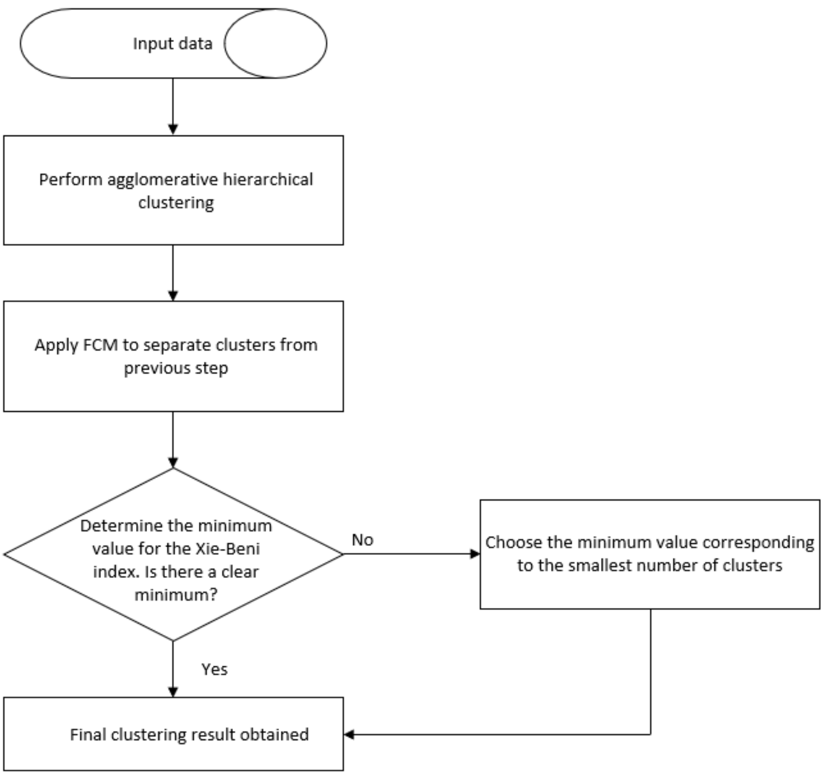


Figure 5.1: Flowchart of proposed alternative clustering approach

In this newly proposed clustering approach, it is chosen to work with the Xie-Beni clustering method because this is one of the most often used performance measures in fuzzy clustering. As the evaluation here happens for results from the FCM algorithm, it seems to be a good choice as an initial evaluation function.

5.4 Population distribution in city of Ghent

Until now, it is assumed that each sector in Ghent is represented by a single point mass and that each sector in Ghent has the same mass, or stated otherwise the same importance. In reality, however, the number of inhabitants in the different sectors of Ghent is not the same for each sector. This is indicated in figure 5.2. In this figure, each blue dot represents the center of gravity of each sector. The weight (or size of each sector center) of each center of gravity is proportional to the number of inhabitants in the corresponding sector. The scale for the weights of each data point is indicated below on the left of figure 5.2.

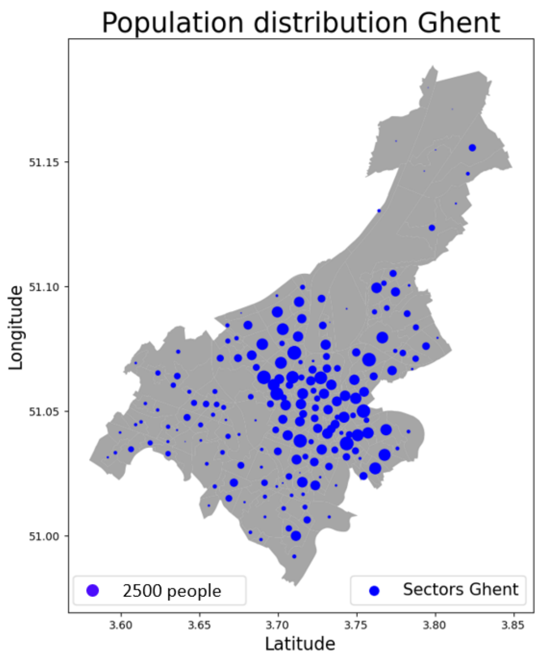


Figure 5.2: Population distribution for the city of Ghent

The complication of adding weights to the different data points could also affect the eventual obtained result of solving the location-allocation problem under consideration: Sectors where more people live will demand more service than the less populated sectors. Therefore, this is something that should be considered as well, as it might not have a negligible effect on the results. More concrete, the population distribution will affect the results in two ways:

- As more populated areas demand more service, it will be beneficial to locate the UAV hubs closer to the high-demand points than to the low-demand points. However, problems can occur concerning the response time when the position of UAV hubs is favored too much to the larger data points.
- If a lot of demand has to be served, the hubs will have to be able to efficiently serve this amount of demand. This can be done by locating larger facilities in the high-demand areas or by introducing more facilities in these areas.

However, before concluding, the current population distribution over the different sub-sectors should be observed to propose meaningful improvements to the used approach. These results are shown in section 6.4

5.5 Weighted center calculation

In section 6.4, it will be shown that using the approach from section 5.3, the population is already spread out quite well over the different sub-clusters under consideration and this is already a quite satisfying result. Therefore, no further actions are conducted to better distribute the population over the different possible sub-clusters.
A possible improvement regarding the population distribution would be to consider the fact that some sectors are assumed to be more important than others, based on the number of inhabitants in the sector. Sectors containing more inhabitants will also have a higher demand than others, which is something that should be looked into as well.
To serve the demand in a cost-efficient way, it will be beneficial to place the UAV base stations close to the largest demand points. However, by introducing the weights to the different points, the optimal solution can change. A reasonable attempt to take these weights into account as well is to adjust the formula to calculate the cluster centers in the FCM algorithm. In this calculation, the weights of each demand point can be included as well and this will favor locations closer to large demand points over locations farther away from large demand points. To include this in the calculations, a new variable pop_j is added to equation 2.22, an equation that was initialized in the literature review before. Each term pop_j represents the population in demand point j, for a total of n demand points. The new cluster center calculation equation is then shown in equation 5.5.

$$c_i = \frac{\sum_{j=1}^{n} \mu_{ij}^{m} pop_j x_j}{\sum_{j=1}^{n} \mu_{ij}^{m} pop_j} \tag{5.5}$$

5.6 Improved clustering approach using response time as decision criterion

The response time will be a crucial factor in the location-allocation of UAV hubs for emergency services. To quantify the response time, two possible approaches are possible:

- Quantify how costly a minute lost in responding to an emergency is and then include this in an objective function. When a person suffers a cardiac arrest, time is crucial. Each minute that passes by without getting help will decrease the chances of survival and will increase the chances of serious injuries.

- All demand (or a high portion of the demand) should be served within a predetermined response time. This predetermined response time can be used as a parameter in the clustering model and can be varied to observe its influence on the eventual results.

At first, the second approach will be studied. The first approach depends on other cost factors and is therefore not considered now. In a final research stage, this however will be included as well.
In emergency services, it is specifically the case that all (or almost all) demand has to be satisfied within a predetermined response time. Therefore, a hard constraint on the response time could be the way to go.

5.6.1 General approach

To achieve response times below a certain threshold value, the procedure in figure 5.1 will be adjusted. Here, the minimization of the Xie-Beni index won't be used as the selection method anymore, as the focus is directed toward the response time. Instead, a threshold value will be defined for the response time and iterations are performed until this threshold value is reached.
The adjusted clustering procedure, based on the response time, is now shown in figure 5.3.

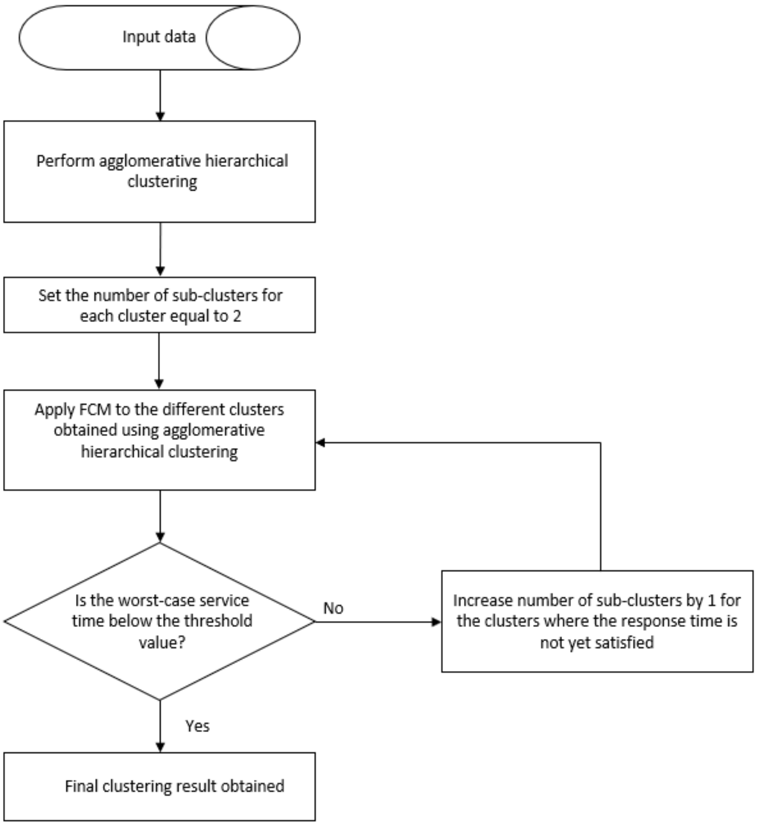


Figure 5.3: Clustering procedure with response time as decision criterion

With this procedure, it is possible to determine the number of clusters that will be needed to serve the demand within a certain response time threshold value. In this procedure, it is not yet specified if the FCM algorithm with weighted or unweighted cluster center calculation will be used. Therefore, both weighted and unweighted methods will still be considered here.

5.6.2 Approach on large data sets

The general approach that was presented can be subject to disturbances or unwanted behavior. For example, when the initial agglomerative hierarchical clustering does not perform well, this can cause problems in further stages of the approach. In

the chapter about results, more precisely in section 6.6, it is observed in table 6.11 that the initial partitioning helps to reduce the number of clusters that are necessary to guarantee a worst-case response time below a predetermined threshold value. From this, it can be deduced that the FCM algorithm works better on smaller data sets. Otherwise, even if the FCM algorithm does not behave as expected, generally speaking, lower response times are obtained for smaller data sets, assuming their structure is the same as the one of their larger counterparts.
However, if the initial partitioning does not result in a clear sub-partitioning, the chances at eventual bad results increase. This can be the case in several circumstances, such as the ones that are mentioned here:

- The city of Ghent has about 250 000 inhabitants and when we look at a bigger scale, many cities are a lot larger than Ghent. When this type of problem would be considered on a larger scale, it could be the case that one of the sub-partitioned clusters is similar to the initial data set of Ghent. As is already shown in table 6.11 in results section 6.6, some further sub-clustering gives much better results (less than one-half of the clusters for the whole data set would be needed). Therefore, it will be important to sub-partition the data enough before fully relying on the FCM step.

- It can be the case that an input data set is of the same size as the one for Ghent, but that there are two, really uneven clusters returned by the agglomerative hierarchical clustering step. For example, it could be the case that one of the clusters contains 95 % of all data points. This can substantially complicate the second step and result in bad results that are be obtained in the second step, due to bad initial sub-partitioning. In this case, too many clusters could be required to obtain a feasible response time and it may be recommended to further sub-partition the largest sub-cluster before relying on the second step of the procedure.

To take these remarks into account, a new approach will be designed that will be aimed at efficiently solving larger or more complicated problems.
The newly designed approach will be based on the approach in figure 5.3. However, an improvement will be made in the part in which the number of sub-clusters gets improved and then fed back to the FCM algorithm. Until now, it has not been possible to go back more than one step in the procedure and further partition a particular sub-cluster that would still be too large or would not yet be sub-partitioned in a sufficient way. Therefore, this newly adjusted procedure adds a new twist, in which the number of sub-clusters per cluster can be increased until a certain threshold value is reached. If this value is reached, the considered cluster is fed back to the first major step in the procedure and then, agglomerative hierarchical clustering is applied to this cluster as well. Afterward, the same procedure is repeated until a feasible clustering solution is obtained. This new, improved procedure is schematically shown in figure 5.4.

The performance of this procedure could be applied in future works on larger data sets. Probably, a good choice of a maximum number of clusters that are considered before further partitioning happens is necessary as the whole algorithm would otherwise run for a real long time.

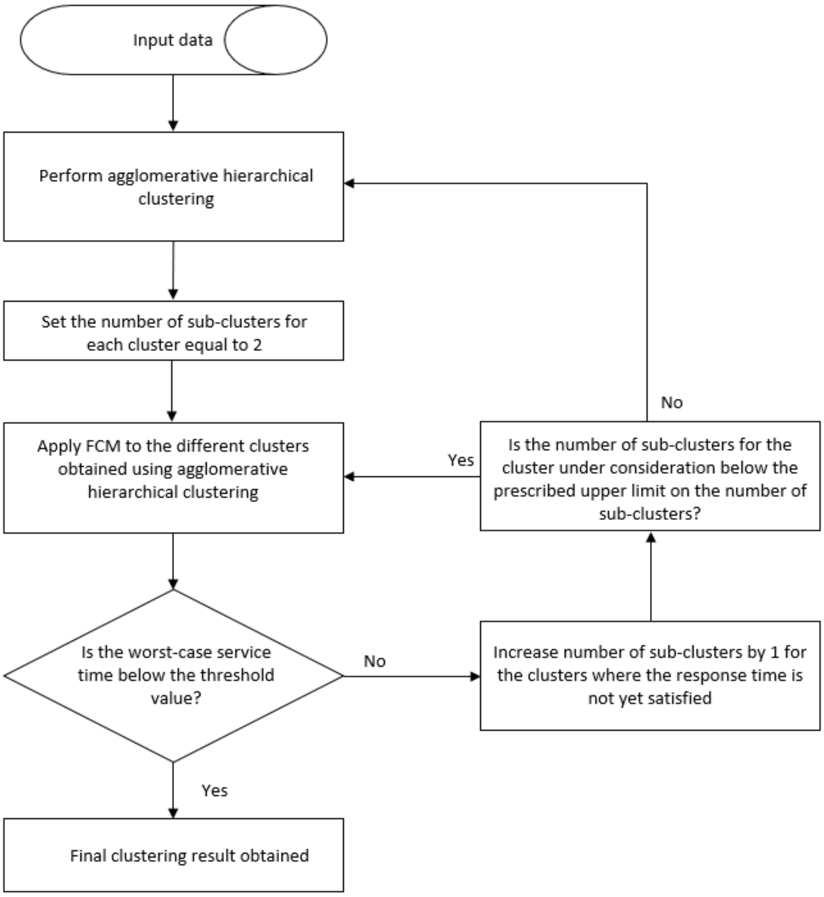


Figure 5.4: Clustering procedure to overcome initial partitioning issues

5.7 Introduce the presence of initial infrastructure

Previously, it has always been assumed that no initial infrastructure was present. This assumption will now be reconsidered. As was already introduced in the chapter 3, three types of initial infrastructure will be considered: EV charging stations, AED locations, and helipads.
Currently, the main steps followed are the same as for the approach shown in figure 5.3. This is the same approach as the one that was proposed in section 5.6. Some small steps will be changed, but the main part remains the same. These small adjustments will be presented in subsection 5.7.1.

5.7.1 Implementation initial infrastructure in clustering procedure

To implement the presence of initial infrastructure, two methods will be considered first.
As was already discussed before, the agglomerative hierarchical clustering is performed in the first step of the procedure. This step is left untouched.
The two major possibilities that are considered here are to implement the presence of initial infrastructure in the FCM step

or at the end of the procedure. These two approaches are the following:

- In the second large step of the procedure, the FCM algorithm is performed. Instead of just calculating the cluster centers and then using these further on, the distances between each cluster center and the already initial infrastructure points are calculated. Then, each cluster center is replaced by the infrastructure point that is closest to it and the demand that was initially allocated to the cluster center will be allocated to the infrastructure point with which the cluster center is replaced. In the iterations that follow the current one, these selected infrastructure points are used as inputs (thus cluster centers) for further calculations.
- Perform the whole clustering procedure and then consider the final set of cluster centers. Calculate the distances between the cluster centers and the initial infrastructure points. Replace each cluster center with the infrastructure point that is closest to it and similarly as in the other considered option, all the demand that was initially allocated to the cluster center will now be allocated to the infrastructure point with which the cluster center is replaced.

Initially, no constraints are introduced on the fact that multiple clusters could be allocated to a single initial infrastructure point. However, this is subject to further analysis and could still be reconsidered in further research stages.
In the experiments, the focus for initial infrastructure will be on the EV charging stations. This type of infrastructure allows drones to charge their batteries and therefore seems to be a logical initial choice. Also, this is the most elaborate network of initial infrastructure, which is why it seems to be most promising at first sight. However, further, in the research, the other types of initial infrastructure are going to be looked at as well.
In the experiments, the first-mentioned possibility to implement initial infrastructure will be considered first. Secondly, in an attempt to improve the performance of the clustering method, the second method is considered as well. Comparing these methods will certainly result in more insight into the limitations of these models.

The experiments that will be conducted are mainly focused on the multicopter-type UAV, using either only EV charging stations as initial infrastructure or also helipads and AED locations.
For the larger UAV types, only the tailored initial infrastructure is considered briefly. These are larger and require more space, therefore respectively being stationed at large parking lots or helipads.

5.8 Hybrid clustering approach

In reality, it is often the case that the already present infrastructure is not sufficient. It can be the case that not enough initial infrastructure is present or that the initial infrastructure is not spread well over the full demand area, therefore resulting in a worst-case response time being too high.
On the other hand, only focusing on new infrastructure is really costly. If in certain areas, a good network of initial infrastructure is present, it is certainly better to also make use of that network, as it makes implementing the newly designed system a lot easier.
During the literature review, it was stated that location-allocation problems are quite robust to the placement of optimal locations. In general, small deviations in these locations will not result in a big increase in costs or response time.
In cases that initial infrastructure is present in the near neighborhood of an the optimal solution that is obtained, it will

therefore be a good idea to shift the obtained locations to the most nearby initial infrastructure point. It is expected that in those cases, shifting the optimal location to an initial infrastructure point will not affect the response time dramatically, but it will drastically lower the implementation barrier. However, if no initial infrastructure is close to the optimal solution, shifting this optimal solution would result in the worst-case response time being too high.

In what follows, two hybrid clustering approaches are suggested. These two hybrid approaches both have another point of departure, which is why both of them would be really interesting to observe. In both approaches, assigning of cluster centers to initial infrastructure points happens when the algorithm has performed all its iterations.

5.8.1 Distance-based hybrid clustering approach

The first hybrid clustering approach is a distance-based approach. In this adjusted approach, the choice if a cluster center is assigned to an initial infrastructure point or not is based on the maximum distance between the obtained cluster center and its closest initial infrastructure point. If this maximum distance is above a defined threshold value, then the cluster center is not shifted and a new infrastructure point is set up. If the maximum distance is below this threshold value, then the cluster center is shifted toward its closest initial infrastructure point.

Evidently, the threshold value for the maximum distance will have a substantial effect on the solution that is eventually obtained. In case the maximum allowed distance is very low, almost all infrastructure will be new. On the contrary, if the maximum allowed distance is very high, almost all infrastructure will already have been present initially.

5.8.2 Initial infrastructure-based hybrid clustering approach

The second hybrid clustering approach is an approach based on the already present initial infrastructure. In this approach, a clear distinction is made between two regions: the region in which a lot of initial infrastructure is already present and the region where no or limited initial infrastructure is present. In the areas where already a lot of initial infrastructure is present, no new infrastructure will be introduced and all used infrastructure is infrastructure that was already present. The cluster centers are calculated here as before and in the end of the algorithm, they are shifted to the initial infrastructure points.
In the area where no or limited initial infrastructure is present, no initial infrastructure is used and all used infrastructure will be new infrastructure. In this area, the clustering approach in case no initial infrastructure is present is used.

A clear disadvantage of this hybrid clustering method is that it requires quite some pre-processing: The data should be filtered based on the presence of initial infrastructure close to the demand points and making the distinction between the two types of area is not after easy. Doing this is a profound way will therefore take quite some time.

5.9 Clustering approach including all three UAV types

Combining the approaches presented in the previous sections, it is possible to come to a representation in which several approaches are used and where three different types of UAV base systems are used. These types are UAV base station for respectively multicopter-type UAVs, rotorcraft-type UAVs and Optionally-Piloted VLRs.

In this combined scenario, the base stations for rotorcraft-type UAVs and Optionally-Piloted VLRs are obtained using the optimal approach in case only initial infrastructure is present. For the base stations for multicopter-type UAV, the distance-base hybrid approach is used. Here, both initial and new infrastructure is used.

Finally, the obtained solutions are put together and observed further. In some cases, two UAV base stations could be located closely together. In those cases, it might be more cost-efficient to put the two solutions together such that only one instead of two station is operated.

5.10 Integrated cost optimization analysis

Another way of determining the optimal number of clusters would be by making an integrated cost optimization. The purpose is to select the number of clusters for which the incurred cost is minimal. In the previous cases, the objective was to minimize the worst-case response times, with the worst-case response time as a decision criterion. The cost of adding more clusters and infrastructure was not considered as it was not important back then. However, when such an integrated system is implemented on a large scale such as is the case for the city of Ghent, it will also be necessary to estimate the costs that come with the system. For this integrated cost optimization, it is assumed that only UAVs that distribute AEDs will be studied. For this case, only the smallest UAV type is used and only people suffering a cardiac arrest will be responded to. In case other emergencies are considered as well, more data needs to be studied and this would lees us too far.
Going back to the system under consideration, there will be two important cost categories, which are the following:

1. Material costs: The costs come with the used infrastructure and equipment. For UAV base stations, the most important material costs are summarized in section 3.3.2 of chapter 3. As these are material costs, these are tangible costs.

2. Immaterial costs: These costs are less tangible. The immaterial cost is mainly focused on quantifying the cost of the response time. This cost quantifies the length it takes before the emergency service arrives at it the location where help is needed. This cost can be expressed in a cost per minute of a larger response time. Notice that the immaterial cost can include both physical and emotional damage to the person in need.

The used reasoning to determine the immaterial cost is given in subsection 5.10.1. This is included here as it does not fit in other chapters as well, but this immaterial cost is of major importance in the reasoning that is presented later on.

5.10.1 Immaterial costs

In emergency services, the response time has a big influence on the chances of survival of the person in need. In the case of emergency services associated with cardiac arrests, this becomes even more important. According to a study performed in the United Kingdom [97], the chances of survival are correlated with the response time. In case 90 % of the emergency calls are served within 14 minutes, only 6 % of the people survive their cardiac arrest. In case the response time is lowered to 8 minutes, 8 % manage to survive, and when the response time equals 5 minutes, even 10 to 11 % manage to survive. From this, it follows that achieving a lower response time pays off.

Another important aspect in quantifying the response time is the value of statistical life. This value represents the trade-off between the chance of fatality and the value of money [98]. In 2017, the value of statistical life was equal to 10 million dollars in the United States. Between countries, differences occur as well [99]. Assuming the ratio between the United States and Belgium remained the same over the last 20 years, the value of statistical life in Belgium should be equal to about 8.2 million euros.

In the previous parts of this master thesis, it was assumed that the response time should be as low as possible. In this application, the range of response times between 5 and 8 minutes will be used here. In case the response time is equal to 5 minutes, 10 % of the people suffering a cardiac arrest manage to survive. The value of life that is saved there then equals (8.2 million euros) * 10 % = 820 000 euros. In case the response time is equal to 8 minutes, the value of life saved is (8.2 million euros)*8 % = 656 000 euros. In this range, the value of life saved per minute of lower response time, abbreviated by Value of Life per Minute Response Time (VOL), is calculated as follows:

$$VOL = \frac{value\, of\, life}{minute\, response\, time} = \frac{(820000 - 656000)\, euros}{3\, minutes} = \frac{54667\, euros}{min} \tag{5.6}$$

From this, it follows that in the first model that will be proposed, each minute of response time that is lost will be penalized with a cost of 54 667 euros. This is a quite rough calculation but can be useful here for some first indicative purposes. To construct a more detailed and more precise model, further research concerning the value of life will be necessary as well. Probably, a more dynamic evolution of the value of life per minute response time is close to reality, but this is beyond the scope of this master thesis.

To use the quantified response time, it will be essential to know how often emergencies occur. In case more emergencies occur, the UAVs will have to travel more often, putting more weight on the response time in the cost optimization analysis. In case the UAVs only have to go for an emergency a few times, the weight of the infrastructure cost will be heavier.

It will be essential to know how many people suffer a cardiac arrest every year in Ghent. For Belgium, it is estimated that about 15 000 people suffer a cardiac arrest each year [100]. As was mentioned in a chapter 3, in Ghent, 264 676 people live, compared to 11 521 238 people who lived in Belgium in 2020 [101]. Comparing these two results in the fact that 2.30 % of the total Belgian population lives in Ghent.

Rescaling the number of cardiac arrests in Belgium to the case of Ghent, it follows that about 345 people suffer a cardiac arrest in Ghent each year.

5.10.2 Integrated cost optimization model

Starting from the material and immaterial costs, the actual cost optimization can be constructed. In this part, two different cost optimization approaches are proposed:

1. In the first approach, for each data point, the response time from the cluster to which it mainly belongs is considered. Then, the closest cluster is selected for all these points. From all these response times, the largest is selected and it is assumed this one is the global, worst-case response time. Then, the response time is scored based on this worst-case value and the cost of the response time only gets lower when the worst-case response time is lowered. The reason why this one is used is that in general, emergency services have to satisfy all or almost all demand within a specified time. If some of the other response times would be low, these could mask the fact that the actual worst-case response

time is high. This influence is worthwhile investigating.

2. In the second approach, the considered response time is the one that is completely weighted according to the population present in the different sectors in Ghent. This response time includes effects from the membership matrix and the population distribution into account, which is not the case for the worst-case response time. Unlike the first approach, all response times are included, even the ones that are really high or really low. This is done additionally to the first approach, as it would not be correct as well to give all weights to the worst-case response time and not consider the better performing response times.

In the following, the two cost optimization approaches are worked out in more detail and mathematical expressions are given there as well.

Worst-case response time-based cost optimization

Observing the worst-case response time is quite straightforward.
Assuming that for each data point, the response time to its main allocated cluster is selected, the response time from data point i to its main cluster center j can be expressed as follows:

$$RT_i = RT_{i,argmax_j(\mu_{ij})} \quad \forall\, i \in \{1...n\} \tag{5.7}$$

In this equation, the membership matrix is defined as μ, with elements μ_{ij}. To obtain the worst-case response time, the largest response time is selected, resulting in the worst-case response time.

$$RT = max_i(RT_i) \tag{5.8}$$

Further on, the actual objective function is designed. In this objective function, quite some variables will be used, which is why they are listed and abbreviated in table 5.1. Notice that the concept of response time is not specified here, as it can be used in several ways, such as the worst-case or averaged response time.

Number of new infrastructure locations	NI	UAV cost	UAV
Number of initial infrastructure locations	II	Charging station cost	CHS
AED cost	AED	Surface area cost	SAC
Value of life per response time minute	VOL	Response time	RT

Table 5.1: Abbreviations objective function variables

Putting all of this together in an objective function, including all relevant costs, the result is shown in equation 5.9.

$$Total\, cost\, UAV\ system = (NI + II) * (AED + UAV) + NI * (CHS + SAC) + RT * VOL \tag{5.9}$$

Averaged response time-based cost optimization

To analyze the averaged response time-based cost optimization, it is important to determine the averaged response time in a clear way.
Assume that the membership matrix is again defined as μ, with elements μ_{ij}. The response time from cluster center j to data point i is given by RT_{ij}. The weighted response time for each data point, with the corresponding weights that are given to each response time indicated by the membership matrix, is shown in equation 5.10.

$$RT_i = \sum_j \mu_{ij} RT_{ij} \quad \forall\, i \in \{1...n\} \tag{5.10}$$

Further on, a combination of all these RT_is is made to obtain the global averaged response time. As in each sector of Ghent, a different number of people live, it is important to take the population distribution into account. More populated sectors will in general require more emergency interventions and therefore, these sectors will be assigned a higher weight than less populated sectors. To do this fairly, the RT_is will be rescaled according to the population of each sector. As previously defined, pop_i represents the total population in sector i. Putting this together, the averaged response time is calculated in what follows:

$$RT = \frac{\sum_i RT_i\, pop_i}{\sum_i pop_i} \tag{5.11}$$

Substituting the obtained averaged response time in equation 5.9 eventually gives the objective function for the averaged response time-based cost optimization.

6

Results

In this chapter, the methods proposed in section 5 are put into practice and the obtained results are reported. These results are thoroughly discussed and based on the observations here, the methods from chapter 5 are further tailored to improve the performance of the used approaches. The sections that are reported here are in line with those used in chapter 5. This is done to be consistent and for ease of understanding for the reader.

6.1 Basic FCM algorithm applied to data city of Ghent

Applying the FCM algorithm to the data set of Ghent, a first indicative solution can be observed. Suppose the number of clusters is equal to 4, then the eventual clustering is visualized in figure 6.1. In figure 6.1, the data points belonging to different clusters are colored in blue, purple, green and yellow. For each cluster, the cluster center is indicated in red. For illustrative purposes, it is assumed that a data point belongs to a cluster if the FCM algorithm allocated more than 50 % of the data point to the corresponding cluster.

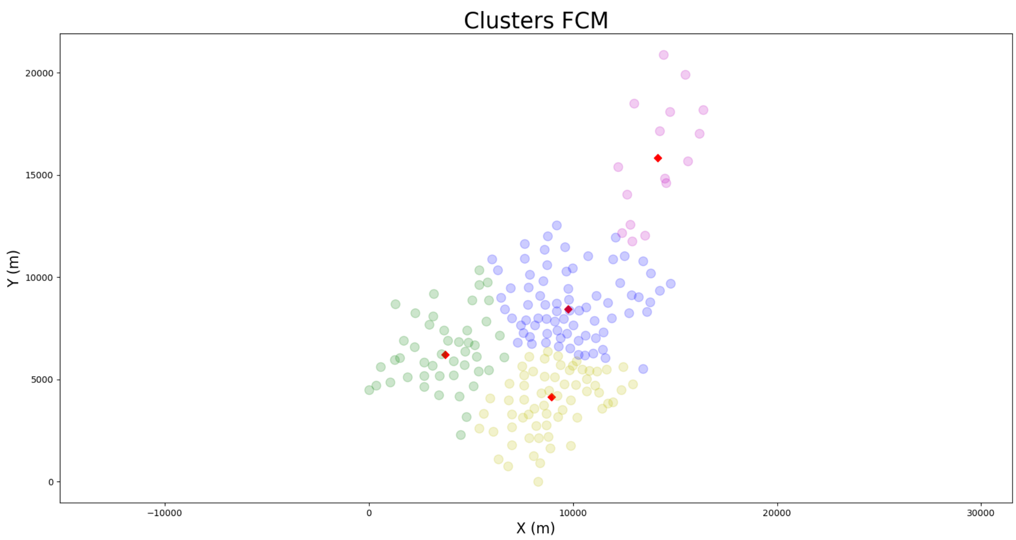


Figure 6.1: FCM result for the city of Ghent in case there are 4 clusters

From figure 6.1, it is observed that some clusters contain more data points and that some clusters are denser than others. This is mainly due to the fact that the FCM algorithm looks at patterns between the data points and focuses on the correlation between the different data points. If a constraint would have been added to the algorithm stating that the number of data points per cluster should be equal, then the algorithm would have to sacrifice some of the clustering quality. In that case, some of the clusters can't fully be formed as they are too big according to the limiting constraint. As the main objective of this section is to observe initial results, this constraint will be left behind.

6.1.1 Cluster performance measures

Using the cluster performance measures, a good estimate of the optimal number of clusters can be made. In this section, the results from applying those to the case of Ghent are reported and discussed.

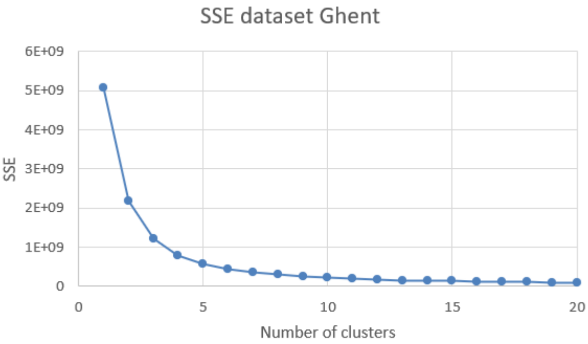
The first and most intuitive result for the optimal number of clusters is obtained using the simple rule of thumb. As there are a total of 202 data points present, the optimal number of clusters is calculated in equation 6.1

$$c \approx \sqrt{\frac{n}{2}} = \sqrt{\frac{202}{2}} = 10.05 \approx 10 \tag{6.1}$$

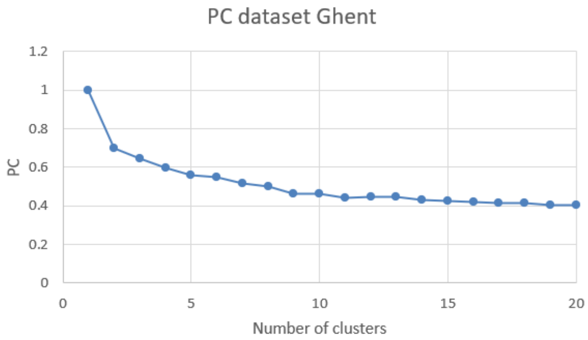
Thus, a first initial guess for the optimal number of clusters is equal to 10.

Further on, a look will be directed toward the more advanced cluster performance measures. Letting the number of clusters range from 2 to 20 clusters, the resulting performance measures for the initial data set of Ghent obtained using the FCM algorithm are shown in figure 6.2. Figure 6.2 consists of three sub-figures, each showing another performance measure. In figure 6.2a, the weighted SSE curve is shown, which will later be used as input for the elbow method. The other sub-figures are respectively figures 6.2b and 6.2c, which represent the PC and Xie-Beni index as a function of the number of clusters. All of these figures are obtained after running the FCM algorithm for a total of 100 iterations per number of clusters. This number of iterations is chosen to make sure convergence is obtained in each case.

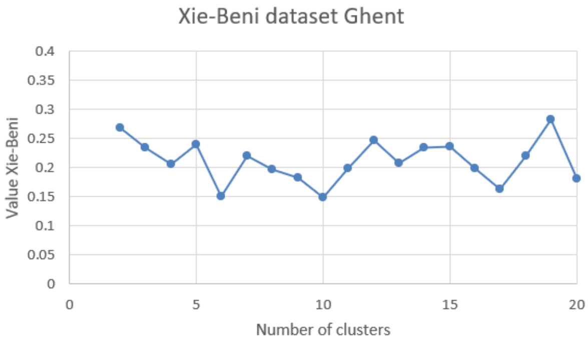
To get an acceptable solution from the elbow method, there should be a clear elbow point in the plot of the weighted SSEs. However, in figure 6.2a, no clear elbow point can be observed, which is why the elbow method can't be applied here in an unambiguous way. Therefore, it is impossible to return the exact solution for the optimal number of clusters precisely.
In figure 6.2b, it is observed that the value of PC decreases with an increasing number of clusters. This is what could be expected intuitively as a lower value for PC indicates a lower level of compactness of the clusters. In these cases, more overlap between different clusters will occur. As it is the objective to maximize the PC, the optimal number of clusters according to this method would be equal to 2. For the last performance measure, minimizing the Xie-Beni index, the optimal number of clusters is equal to 6, which can be seen in figure 6.2c. However, the values of the Xie-Beni index obtained for the number of clusters equal to 6 and 10 are close to this optimum value. Choosing the number of clusters equal to 10 will therefore also return quite good results.
For now, we assume the optimal number of clusters to be equal to 6. Executing the FCM algorithm for this optimal number of clusters results in the clusters shown in figure 6.3.



(a) SSE for FCM on Ghent data set



(b) PC for FCM on Ghent data set



(c) Xie-Beni index for FCM on Ghent data set

Figure 6.2: Cluster performance measures on the data set for Ghent

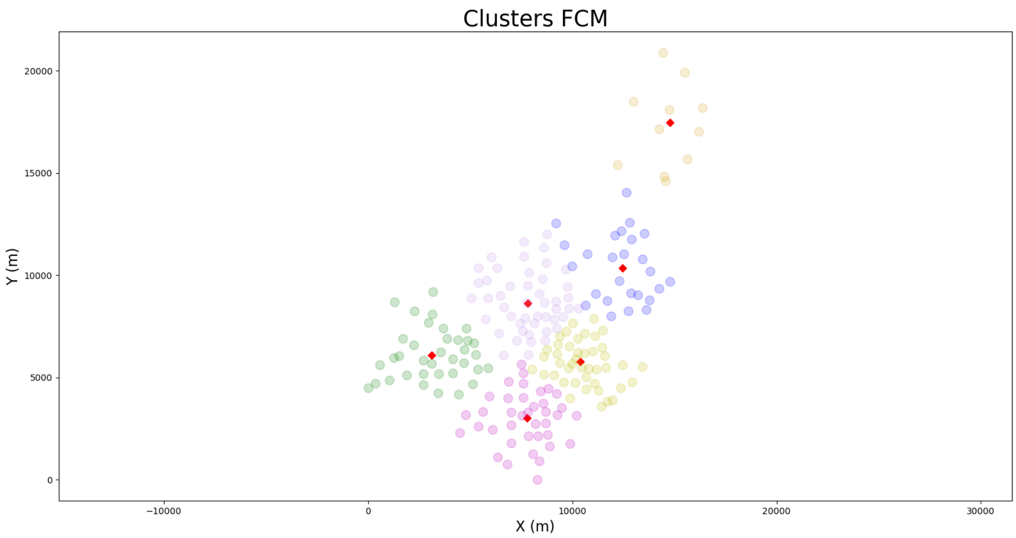


Figure 6.3: Result from FCM for the number of clusters equal to seven

The results obtained here mainly serve as a benchmark for the future stages of the research. The model proposed here is rather basic and will therefore not be sufficient to represent real-life cases. It however could be interesting to see what influence will be observed when more complexity is added to the model. However, it certainly is interesting to analyze the solutions obtained here.

Following the obtained results from the Xie-Beni index, some interesting results are shown in table 6.1. In table 6.1, the respective cluster centers (x-coordinate, y-coordinate), the distance between each cluster center and the point in its cluster that is farthest away (in meters) and the worst-case response times are shown. The response time here is calculated for the smallest UAV type, which has a cruise speed of $40\frac{km}{h}$. The choice for this UAV type can be justified because this UAV will give the worst-case response time as the two other UAV types have a higher cruise speed and will be able to cover a larger area in the same time.
For the results shown in table 6.1, it is again assumed that a point fully belongs to a cluster if the FCM algorithm allocates more than 50 % of the point to the cluster under consideration.

Cluster	Cluster center	Distance (in meters)	Worst-case Response time (in min)
Cluster 1	[10373.71, 5782.78]	3081.51	4.62
Cluster 2	[7815.82, 8611.12]	3531.60	5.30
Cluster 3	[12442.81, 10344.10]	3924.92	5.89
Cluster 4	[7795.37, 3009.74]	3373.61	5.06
Cluster 5	[3126.13, 6072.42]	3498.28	5.25
Cluster 6	[14767.44, 17458.11]	3430.26	5.15

Table 6.1: Distance and response time obtained by FCM in case of three clusters

In table 6.1, it is observed that there is indeed some variation in the worst-case service time per cluster. The worst-case response time in cluster 3 is equal to 5.89 minutes, while the worst-case response time is 4.62 minutes in cluster 1. The response time in cluster 3 is, therefore, more than 25 % higher than the response time of cluster 1, which is a rather significant difference.
In emergency cases such as cardiac arrests, the first few minutes are crucial and the worst-case response time should be sufficiently small here. Each minute that is lost increases the chances of serious injury or mortality. Certainly, for the deployment of AEDs, it is crucial to deliver the device in just a few minutes.
In the future course of this research, it will be attempted to lower this worst-case service time significantly.

6.2 Agglomerative hierarchical clustering

Executing the agglomerative hierarchical clustering procedure on the given data set results in the dendrogram shown in figure 6.4. On this dendrogram, the procedure to obtain the optimal number of clusters is already applied. The maximum distance, which is the vertical distance between the two red lines, is already shown in figure 6.4. According to agglomerative hierarchical clustering using the Ward linkage criterion, the optimal number of clusters is equal to 2. Note that correct labeling of the data is very important to show which points belong to the different obtained clusters.

To observe the influence of the used linkage criterion on the obtained results, the case in which an alternative linkage criterion is used is considered as well. In figure 6.5, the dendrogram for the single linkage is displayed. Comparing figure 6.5 with figure 6.4, it follows that the clustering, in case single linkage is used, results in less optimal and less structured results than in case the Ward linkage is used. Therefore, the hypothesis that the used linkage criterion has a substantial effect on the obtained results is definitely true.

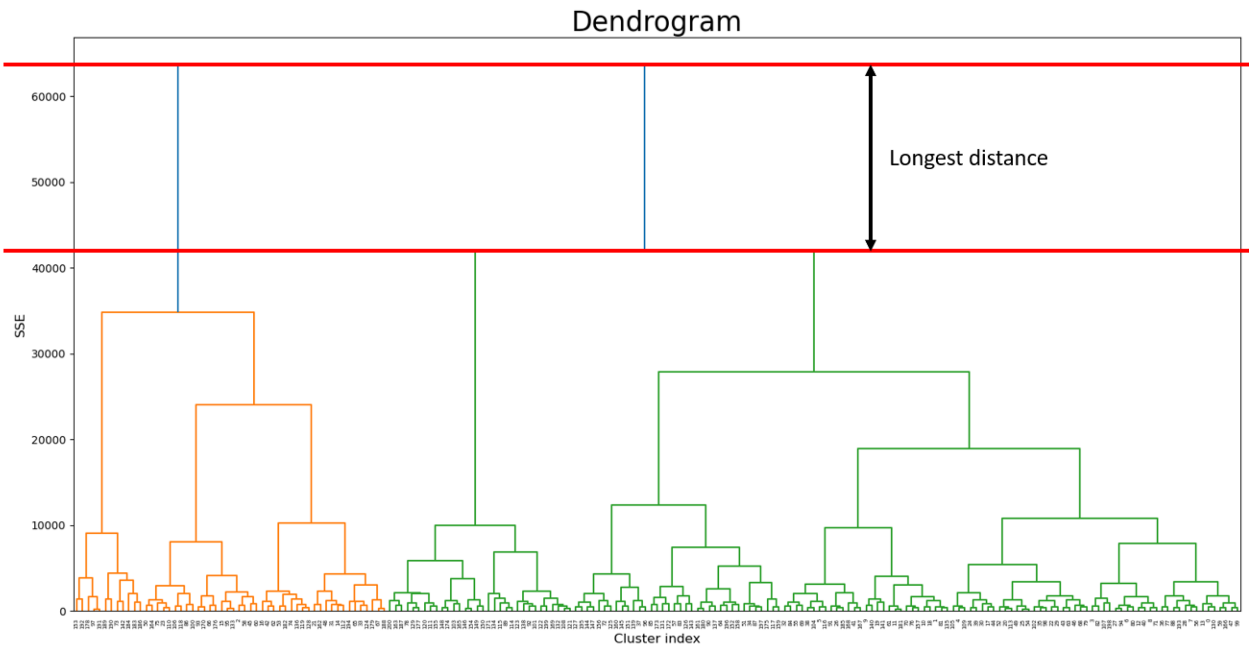


Figure 6.4: Dendrogram agglomerative hierarchical clustering (Ward linkage)

From this figure, it is clear that the clustering obtained by applying the single linkage criterion on the data set results in less optimal clustering results compared to the results using the Ward linkage criterion. Other linkage criteria, such as complete and average linkage, gave results comparable with the ones obtained using the Ward linkage, but in those cases, one of the two clusters was a lot larger than the other one, which is not the best clustering result either.

The two clusters that are determined using the hierarchical clustering method will form the highest level in the hierarchy and the respective clusters are shown in figure 6.6. The obtained clusters are visualized in orange and red (transparent) and their cluster centers are indicated in red. These cluster centers are calculated as the points of gravity of the clusters, assuming the weight of each data point is equal. In this section, it was already shown that according to the agglomerative hierarchical clustering method, the optimal number of clusters is equal to two.
However, in real-life applications, the maximum distance between the cluster centers and the point farthest away from them can't be too large. Otherwise, the obtained service level will not be sufficiently high, certainly not for emergency services. Additionally, it would be appreciated if the worst-case service time is more or less equal in each cluster, as this would not discriminate against people based on where they are located. For the case of two clusters, the cluster centers, the worst-case distances between the cluster centers and the point that is the farthest away from it, and the worst-case response time are displayed in table 6.2. Here again, the worst-case response time is calculated based on the multicopter-type UAV.

Cluster	Cluster center	Distance (in meters)	Worst-case response time (in min)
Cluster 1	[7554.63, 5534.74]	7624.85	11.44
Cluster 2	[11109.02, 11757.23]	9705.53	14.56

Table 6.2: Distance and response time obtained by agglomerative hierarchical clustering in two clusters

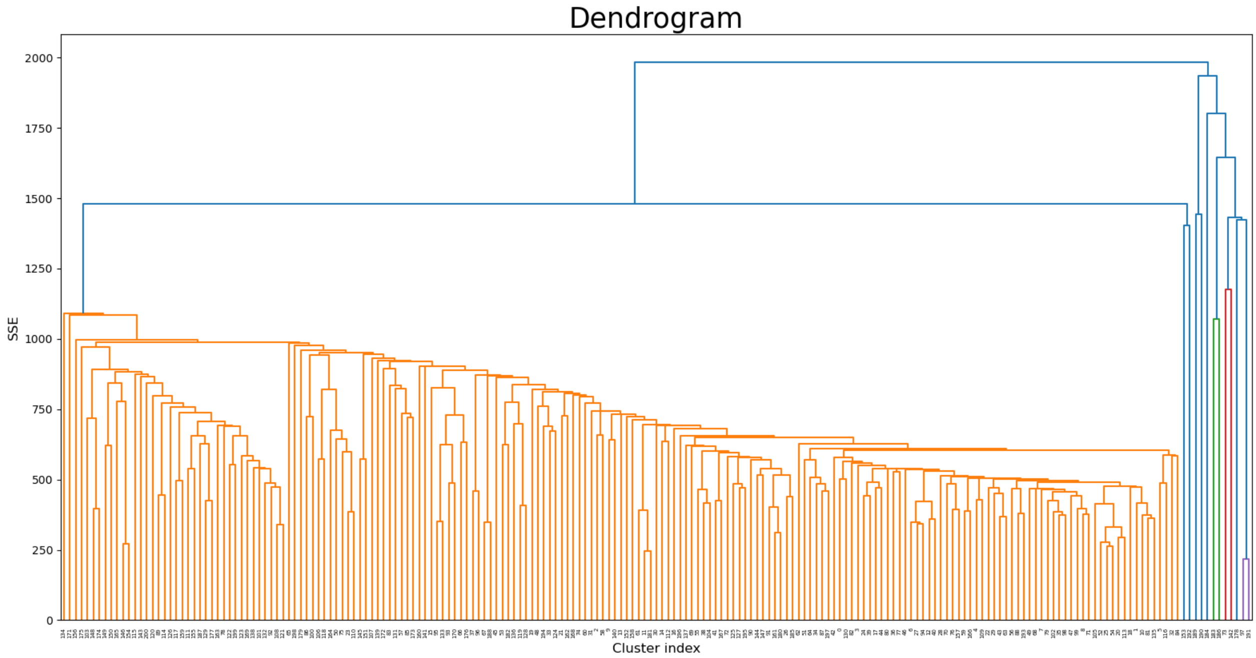


Figure 6.5: Dendrogram agglomerative hierarchical clustering (Single linkage)

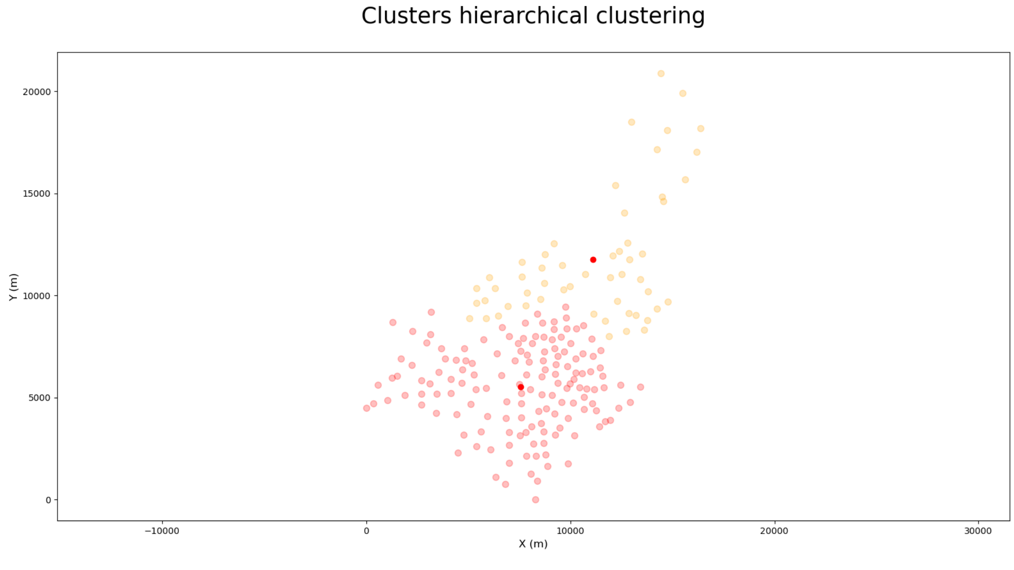


Figure 6.6: Clustering result agglomerative hierarchical clustering

In table 6.2, it is observed that the maximum distance is still quite large, with a worst-case response time of 14.56 minutes. This is not acceptable for the application of emergency services such as the delivery of AEDs, as was already mentioned before [102]. In the united states, the average response time for emergency service is 7 minutes in an urban environment, compared with 14 minutes in a rural environment. However, to implement the usage of UAVs in emergency services, they should be able to improve the response time compared with ground-based emergency services. Therefore, the goal will be to be at least as fast as the average response time of the classical emergency services discussed in the article.

Comparing the results obtained using the FCM algorithm and the results obtained using agglomerative hierarchical clustering, it is observed that the worst-case response time obtained by hierarchical clustering is higher than the worst-case response time obtained by FCM. This is an intuitive result as more clusters are present in the FCM solution than in the hierarchical clustering solution. However, in both cases, the worst-case response time is not yet satisfying, which is why further research will need to be conducted.

6.3 Performance multi-level clustering approach

The newly designed approach, as shown in figure 5.1, is now applied to the data of Ghent.
As is reported, the first step is to perform the agglomerative hierarchical clustering algorithm. However, the clustering results that will be obtained are the same as the ones obtained in section 6.2. Therefore, these initial results will be used again.
The two clusters that are obtained will be further referred to as cluster 1 and cluster 2. In figure 6.6, cluster 1 is colored red and contains 147 data points. In the same figure, cluster 2 is colored orange and contains 54 data points. In the following steps, these two clusters will again be referred to as cluster 1 and cluster 2.
In the further solution process, 100 iterations for each number of clusters will be performed in the FCM algorithm. This arbitrarily high number is again chosen to make sure convergence occurs in the end.
In what follows, the results for both clusters will be obtained and further discussed.

Results cluster 1

As mentioned before, the first cluster under consideration is the largest one. In this part, the second large step of the newly designed approach is applied to cluster 1, which is the application of the FCM algorithm.
Here, the number of clusters ranges from 2 to 50, and for each number of clusters, the Xie-Beni index is calculated. Visually, the Xie-Beni values for the different observed numbers of clusters are shown in figure 6.7.

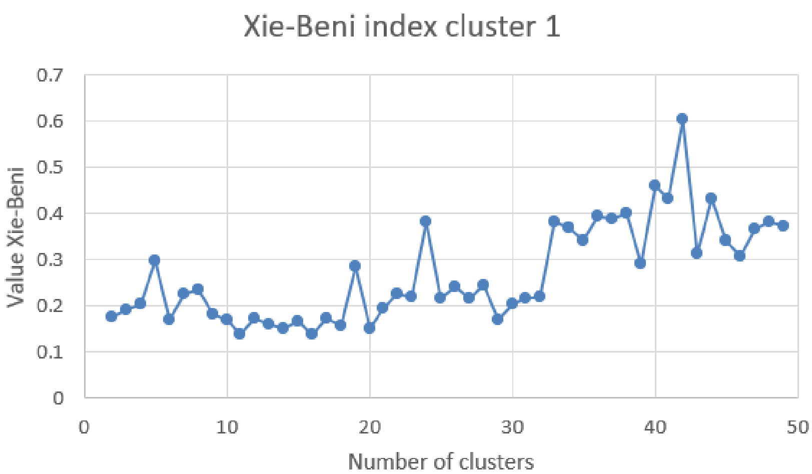


Figure 6.7: Xie-Beni index using FCM applied on cluster 1

In figure 6.7, the minimum value for the Xie-Beni index is observed for the number of clusters equal to 11. From this, it follows that the first cluster should be sub-partitioned into 11 sub-clusters.
The further sub-partitioning for cluster 1 is displayed in figure 6.8, with the points belonging to the different sub-clusters colored in different colors. Here again, the corresponding cluster centers are indicated in red. For simplicity of the visualization, it is again assumed that a data point belongs to a cluster if more than 50 % of this point is allocated to the corresponding cluster.

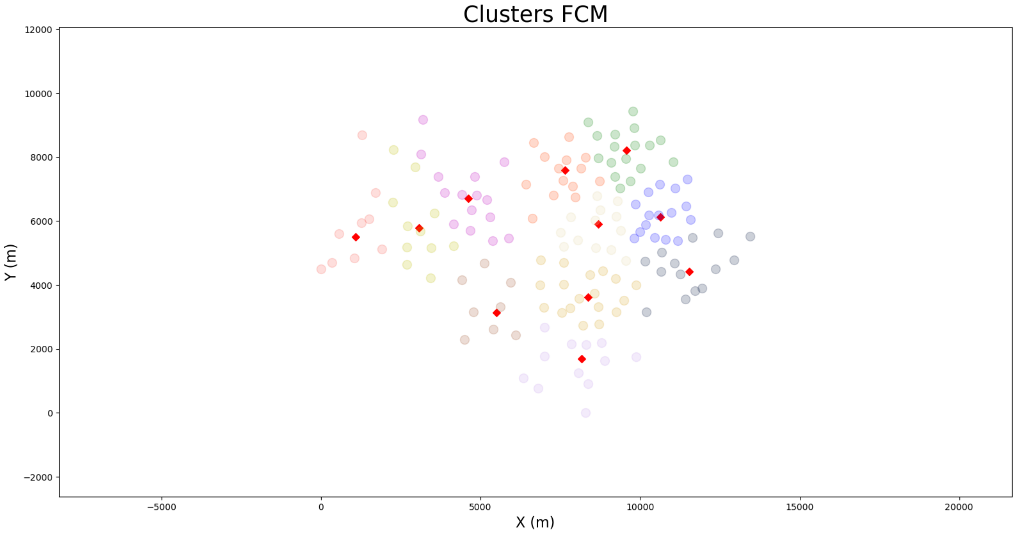


Figure 6.8: Further partitioning results of cluster 1 using FCM

In these sub-clusters, the distances between the cluster centers and the points farthest away from them are still important in terms of the response time for emergency service applications. For the sub-clustering of cluster 1, the most important information is shown in table 6.3. In table 6.3, it is observed that the worst-case response time is a bit below five minutes.

Sub-cluster	Sub-cluster center	Distance (in meters)	Worst-case response time (in min)
Sub-cluster 1.1	[3077.25, 5787.28]	2583.45	3.88
Sub-cluster 1.2	[9577.57, 8219.90]	1510.08	2.27
Sub-cluster 1.3	[4615.41, 6707.04]	2858.88	4.29
Sub-cluster 1.4	[10637.66, 6118.05]	1463.71	2.20
Sub-cluster 1.5	[8167.77, 1687.83]	1919.90	2.88
Sub-cluster 1.6	[8376.02, 3626.72]	1893.89	2.84
Sub-cluster 1.7	[5497.90, 3144.50]	1573.51	2.36
Sub-cluster 1.8	[7646.01, 7584.06]	1814.65	2.72
Sub-cluster 1.9	[1088.41, 5508.28]	3196.56	4.79
Sub-cluster 1.10	[8685.31, 5916.15]	1448.49	2.17
Sub-cluster 1.11	[11537.92, 4421.14]	2206.64	3.31

Table 6.3: Distances and worst-case responses time for different sub-clusters obtained by sub-clustering of cluster 1

This result is already substantially better than the results obtained in the previous sections, but more clusters are present here as well. However, the spread in response time between the different sub-clusters is still quite large and there is also still room for improvement concerning the response time. This is something that will certainly be addressed in one of the following sections.

Results cluster 2

Similar calculations as the ones for cluster 1 can be performed for cluster 2. Plotting the values for the Xie-Beni index in terms of the number of clusters is shown in figure 6.9.

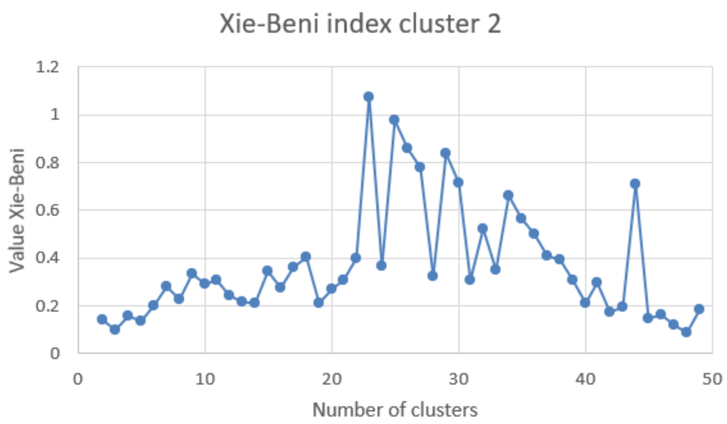


Figure 6.9: Xie-Beni index using FCM applied on cluster 2

From figure 6.9, it is observed that the value initially increases with the number of clusters and decreases afterward again. However, the higher values for the Xie-Beni index won't be considered here as there are only 54 data points in cluster 2. It would therefore not make any sense (due to economical reasons) to consider a solution consisting of more than 40 clusters. Taking this observation into account, it follows that the optimum number of sub-clusters for cluster 2 is equal to 3. Compared to the 11 sub-clusters that are present in cluster 1, the number of sub-clusters for cluster 2 is quite a bit lower. This is a quite evident result, as cluster 1 contains 3 times more data points than cluster 2 as well.
Furthermore, the different sub-clusters for cluster 2 can also be visualized. This is shown in figure 6.10. In this figure, the same conventions are used as in the plot for cluster 1.

Calculating the maximum distances and worst-case response times for the sub-clusters of cluster 2 then results in the values shown in table 6.4.

Sub-cluster	Sub-cluster center	Distance (in meters)	Response time (in min)
Sub-cluster 2.1	[7230.47, 10245.81]	3031.95	4.55
Sub-cluster 2.2	[12726.83, 10201.01]	3864.01	5.80
Sub-cluster 2.3	[14745.95, 17429.09]	3457.19	5.19

Table 6.4: Distances and worst-case responses time for different sub-clusters obtained by sub-clustering of cluster 2

From table 6.4, it is clear that the worst-case service time is well below 6 minutes. However, this worst-case response time is higher than the worst-case response time for the first cluster. Even though the ratio of sub-clusters per number of data points seems to be the same for both clusters, it can be observed that cluster 1 is denser than cluster 2. In cluster 2, the distances between the different data points are a lot higher, which will make it harder to efficiently serve all these data points while assuring a low worst-case response time.

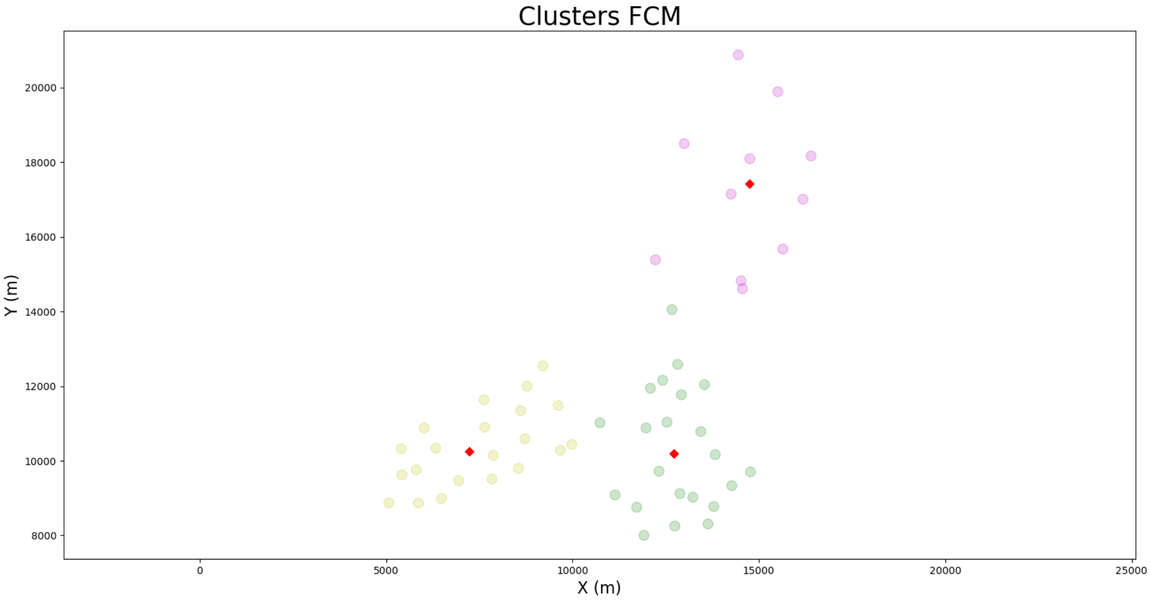


Figure 6.10: Further partitioning cluster 2 using FCM

Finally, in cluster 2, the difference between the lowest and the highest value for the response time is not too large. The highest worst-case response time in cluster 2 is 27 percent higher than the lowest, while for cluster 1, the highest worst-case response time is more than double of the lowest worst-case response time.

6.4 Population dispersion over sub-clusters

When observing the different clusters and sub-clusters, it is interesting to observe how the total population that has to be served is distributed over the different sub-clusters. The corresponding allocation of the population of Ghent over the different sub-clusters obtained in section 6.3, is then shown in table 6.5.
In this table, the distinction is made between two ways of calculating the assigned population per cluster. In the third column, the population is allocated to the sub-clusters based on the majority principle. In this principle, it is assumed that a data point fully belongs to the corresponding sub-cluster if 50 % or more of this data point is allocated to the sub-cluster. In the fourth column, the population is allocated to the sub-clusters based on the membership values obtained from the FCM step of the new approach. This is the actual allocation obtained using the new approach. The reason that both takeaways are given is to be able to observe the influence of how the population is allocated to the clusters.

When table 6.5 is observed, two clear observations can be made:

- Overall, the spread in demand allocated to the different sub-clusters using the membership value allocations is not too large. The largest population allocated to a single sub-cluster is 23073 people, while the smallest population allocated to a sub-cluster equals 16449 people. This difference is already reasonably small, but not that the largest sub-cluster does contain about 40 percent more people than the smallest one.

- The difference in population spread is larger in case the majority principle is used than in case the membership values of FCM are used to calculate the population allocated to the different sub-clusters. From this outcome, it can be concluded that FCM helps to spread the total served population over the different clusters and sub-clusters in a more even way. This is a nice feature here and will therefore also be one of the advantages of using the FCM algorithm. This way, it is the case that fuzzy clustering methods better distribute demand than hard clustering methods, due to their fuzzy character.
  Additionally, the more dispersed population over the cluster will result in a lower peak demand per cluster, making it easier to cope with these demands from an operational point of view.

Sub-cluster	Sub-cluster center	Population allocated (major stakes)	Population allocated (membership)
Sub-cluster 1.1	[3077.25, 5787.28]	39383	19119
Sub-cluster 1.2	[9577.57, 8219.90]	3368	18170
Sub-cluster 1.3	[4615.41, 6707.04]	7165	20151
Sub-cluster 1.4	[10637.66, 6118.05]	3228	20322
Sub-cluster 1.5	[8167.77, 1687.83]	15134	16039
Sub-cluster 1.6	[8376.02, 3626.72]	37275	18244
Sub-cluster 1.7	[5497.90, 3144.50]	24141	20212
Sub-cluster 1.8	[7646.01, 7584.06]	6563	16449
Sub-cluster 1.9	[1088.41, 5508.28]	26561	16986
Sub-cluster 1.10	[8685.31, 5916.15]	32443	17082
Sub-cluster 1.11	[11537.92, 4421.14]	5111	18597
Sub-cluster 2.1	[7230.47, 10245.81]	31619	23073
Sub-cluster 2.2	[12726.83, 10201.01]	29078	20778
Sub-cluster 2.3	[14745.95, 17429.09]	2607	19453

Table 6.5: Population allocated to the different clusters and sub-clusters

Comparing the population distribution obtained using the new approach with the case of applying the pure FCM algorithm to the raw data set of Ghent, an interesting observation can be made. In both cases, when the number of cluster/sub-clusters is kept equal to 14, the average population per sub-cluster equals 18905.36 people. However, the standard deviation in the case of applying the pure FCM algorithm to the full data set is equal to 2277, while for the adjusted procedure proposed in this section, the standard deviation is 1867. From this, it can be stated that the population is more evenly spread over the different sub-clusters in case this new approach is used compared to the pure FCM algorithm.

6.5 Weighted cluster center calculation results

Replacing the cluster center calculation formula with the weighted cluster center calculation formula presented in section 5.5 in the FCM algorithm and then applying it to cluster 1 that was obtained using the agglomerative hierarchical clustering method, the sub-clustering of cluster 1 is shown in figure 6.11.

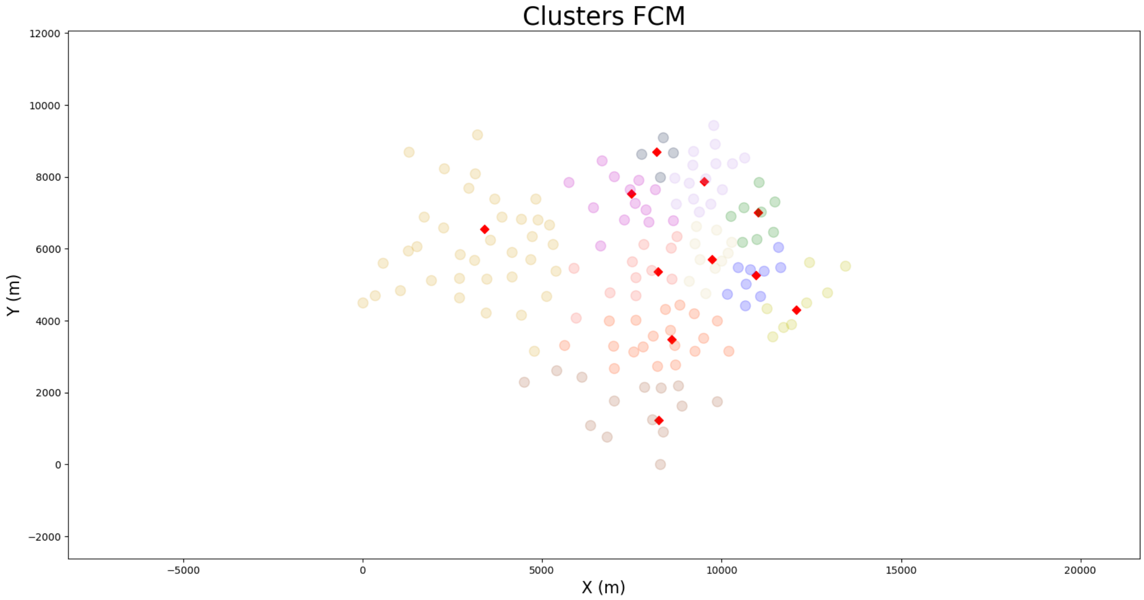


Figure 6.11: Further partitioning cluster 1 using FCM with weighted cluster center calculation

Comparing the results from figure 6.11 with the results displayed in figure 6.8, it can be seen that not only do the cluster centers change by adding the population weights to the cluster center calculation but also the clusters themselves change by making this adjustment. This can intuitively be explained as the distance between the points belonging to the clusters and the cluster centers are being used to update the membership matrix. Other distances will result in different membership matrices, which in turn influence the further iterations in the FCM algorithm, thereby influencing the whole outcome of the algorithm.
Again, the maximum distances from the cluster center to the point that is farthest away from the cluster center and the worst-case response times are given in table 6.6, this time using the weighted cluster center calculations.

Comparing table 6.6 with tables 6.3 and 6.4 for the results without weights, it can be seen that the worst-case response time increases when the weighted calculations are used instead of the unweighted. This can intuitively be explained as the cluster center will be closer to the more densely populated demand points. As the more remote areas are in general less populated than the sectors in the center of the city, it is a logical consequence that these zones now have to wait longer than before to receive service. As a result, the worst-case response time increases.

Another important aspect that should be observed is how the total served population is now distributed over the different sub-clusters. Using the weighted cluster center calculation, this results in table 6.7.

Comparing table 6.7 with table 6.5, it can be seen that spread in allocated population per sub-cluster is larger when the weighted calculation is used. The standard deviation for the population distribution over the sub-clusters increases from 1867 in case of unweighted calculation to 3152 when weighted cluster calculation is used. Therefore, the distribution of the population over the clusters is worse in the case of weighted center calculation here.

Sub-cluster	Sub-cluster center	Distance (in meters)	Worst-case response time (in min)
Sub-cluster 1.1	[12081.80, 4294.72]	1840.48	2.76
Sub-cluster 1.2	[11015.17, 7008.83]	929.76	1.39
Sub-cluster 1.3	[7488.40, 7525.09]	1781.42	2.67
Sub-cluster 1.4	[10958.89, 5259.28]	1005.29	1.51
Sub-cluster 1.5	[9508.96, 7871.06]	1587.68	2.38
Sub-cluster 1.6	[3395.26, 6542.95]	3961.31	5.94
Sub-cluster 1.7	[8246.63, 1240.49]	3898.04	5.85
Sub-cluster 1.8	[8618.07, 3483.23]	3000.34	4.50
Sub-cluster 1.9	[8226.70, 5358.92]	2614.05	3.92
Sub-cluster 1.10	[9730.41, 5698.47]	1021.61	1.53
Sub-cluster 1.11	[8178.28, 8694.35]	706.58	1.06
Sub-cluster 2.1	[12248.86, 9086.17]	2597.39	3.90
Sub-cluster 2.2	[7426.56, 10061.35]	3056.88	4.59
Sub-cluster 2.3	[12787.99, 12309.18]	8721.75	13.08

Table 6.6: Distances and worst-case response times obtained by sub-clustering method for the different clusters using weighted cluster center calculations

Sub-cluster	Sub-cluster center	Population allocated (major stakes)	Population allocated (membership)
Sub-cluster 1.1	[12081.80, 4294.72]	13787	18605
Sub-cluster 1.2	[11015.17, 7008.83]	25253	19652
Sub-cluster 1.3	[7488.40, 7525.09]	21936	18833
Sub-cluster 1.4	[10958.89, 5259.28]	25278	14030
Sub-cluster 1.5	[9508.96, 7871.06]	21993	19469
Sub-cluster 1.6	[3395.26, 6542.95]	14040	20183
Sub-cluster 1.7	[8246.63, 1240.49]	8063	17179
Sub-cluster 1.8	[8618.07, 3483.23]	13845	23393
Sub-cluster 1.9	[8226.70, 5358.92]	21219	15415
Sub-cluster 1.10	[9730.41, 5698.47]	20978	17898
Sub-cluster 1.11	[8178.28, 8694.35]	14980	16714
Sub-cluster 2.1	[12248.86, 9086.17]	19471	26750
Sub-cluster 2.2	[7426.56, 10061.35]	31619	16105
Sub-cluster 2.3	[12787.99, 12309.18]	12214	20449

Table 6.7: Population allocated to the different clusters and its sub-clusters using weights in cluster center calculation

From the results in tables 6.6 and 6.7, it follows that the addition of weights in the cluster center calculation does not result in better solutions at all.

First of all, the worst-case response times get a lot worse and the spread in response time between the sub-clusters increases, which is also an unwanted result. A larger spread in service times means that the service level for different people differs a lot and therefore discriminates against people living in the more remote areas.

Secondly, the population distribution over the different sub-clusters does not get more evenly distributed in case weighted cluster center calculation is used. This is seen by comparing the standard deviations calculated based on the 14 sub-clusters.

As both complications are unwanted results and result in the worse performance of the procedure, it seems to be the case that the weighted calculations are inferior to the unweighted. However, in the calculation performed in the following section, they are still to observe the behavior in case adaptations are made.

6.6 Results improved clustering approach using response time as decision criterion

In this section, the results that can be obtained using the new clustering approach based on the response time decision criterion are reported.
Running the procedure for both unweighted and weighted cluster center calculation in the FCM algorithm, the number of sub-clusters necessary for each of the two main clusters to obtain response times from a predefined set of response times are shown in tables 6.8 and 6.9. In both tables, the set of response times that should be obtained are respectively 6, 5, 4, and 3 minutes. For each case, the number of sub-clusters for which the worst-case response time gets below the threshold value will be reported.

Cluster Number	# sub-clusters for response time under 6 minutes	# sub-clusters for response time under 5 minutes	# sub-clusters for response time under 4 minutes	#sub-clusters for response time under 3 minutes
Cluster 1	6	22	26	43
Cluster 2	5	32	49	49

Table 6.8: Worst-case response time per amount of sub-clusters by weighted (original) FCM for the two main clusters obtained by agglomerative hierarchical clustering

Cluster Number	# sub-clusters for response time under 6 minutes	# sub-clusters for response time under 5 minutes	# sub-clusters for response time under 4 minutes	#sub-clusters for response time under 3 minutes
Cluster 1	4	7	11	20
Cluster 2	4	7	10	16

Table 6.9: Worst-case response time per amount of sub-clusters by unweighted FCM for the two main clusters obtained by agglomerative hierarchical clustering

Similarly as was being shown in the previous section, it can be seen by comparing tables 6.8 and 6.9 that in terms of response time, the weighted calculation exhibits inferior performance compared to the unweighted cluster center calculation. For both cases, it is however possible to achieve service times below three minutes. In terms of obtainable response times, there is no real difference between the weighted and unweighted cases.

The number of sub-clusters necessary to obtain worst-case response times below certain thresholds is different in both cases. For example, for cluster 1, 43 sub-clusters would be needed to obtain a response time below 3 minutes in the case of weighted cluster center calculation. For the case of unweighted cluster calculation, only 20 sub-clusters would be needed. This is a big difference and for the second cluster, the difference between both methods is even larger.
In table 6.8, it can be seen that response times below 4 and 3 minutes for cluster 2 are only obtained for the number of sub-clusters equal to 49. This is not a reasonable value as in cluster 2, only 54 data points are present and therefore, this

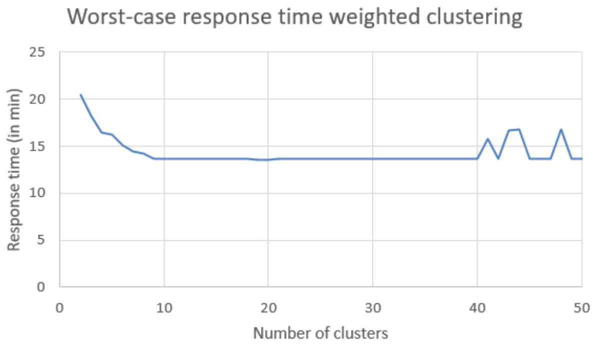
clustering result could even be worse than just placing 49 data points randomly in the solution space.
It can be noted that cluster 1 initially exists of 147 data points, while cluster 2 only contains 54 data points. However, the number of sub-clusters per data point is a lot larger for cluster 2 than for cluster 1. From this, it seems to be the case that the clustering method performs worse on this type of data set. This can be the case because it is more difficult to identify patterns in smaller data sets or because the data in cluster 2 is less dense and less structured than the data in cluster 1.
To examine the hypotheses that it could be the case that observing patterns for smaller data sets is more complicated, the FCM algorithm will be applied to the initial data set for the city of Ghent. Here again, both weighted and unweighted cluster center calculation methods will be considered. In table 6.10, the necessary number of sub-clusters for the response time to be below respectively 3, 4, 5, and 6 minutes is given. Afterward, these results will be compared with each other and with the previously obtained results.

Cluster Number	# clusters for response time under 6 minutes	# clusters for response time under 5 minutes	# clusters for response time under 4 minutes	# clusters for response time under 3 minutes
Weighted cluster center calculation	98	123	\	\
Unweighted cluster center calculation	6	12	22	\

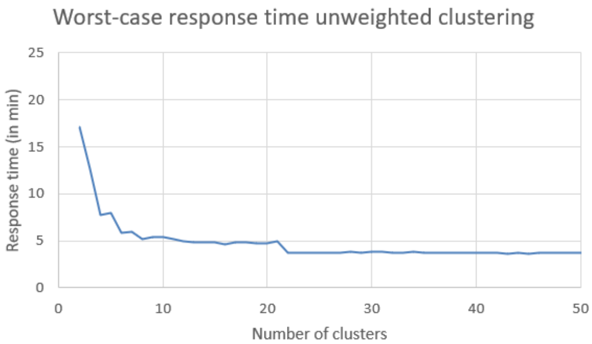
Table 6.10: Number of clusters necessary for the response time to be below the specified threshold values, using either weighted or unweighted FCM

From table 6.10, it can be seen that for both weighted and unweighted cluster center calculations for the full data set of Ghent, no results can be obtained in case the response time threshold is set below 3 minutes. However, with the alternative clustering procedure, it was possible to obtain values for the response time below 3 minutes. In table 6.10 the maximum number of clusters was limited to 125 clusters. The reason for this is that in case even more clusters are present, more than one UAV base station should be located per two sectors. This would render the proposed solution expensive, which is why those solutions are considered infeasible.
As can be seen in table 6.10, for unweighted cluster center calculation, the last improvement happens for the number of clusters equal to 22. For the 100 clusters that are added afterward, there is no drop in response time of more than one minute anymore. For this reason, the course of the function for the number of clusters between 2 and 50 will be studied in further detail. afterward, no real improvements seem to happen anymore for the unweighted method.
For the weighted method, it follows from table 6.10 that the first time a response time below 6 minutes is achieved when 98 clusters are present. afterward, the worst-case response time drops below 5 minutes when 123 clusters are present. Again, only the course of the function for the number of clusters between 2 and 50 will be considered, as for larger values, an actual implementation would become too costly. For the considered values here, it seems to be the case that a plateau is reached, which can be observed in figure 6.12a
For the FCM algorithm with unweighted cluster center calculation, a plateau is reached as well. For this case, the plateau is formed at a response time that is lower than the plateau that was reached in case weighted cluster center calculations were used. The plateau for the unweighted case can then be observed in figure 6.12b
In figure 6.12, these two plots are shown next to each other to make the comparison even more clear. From this comparison, it follows that there is a large difference in results between the weighted and unweighted methods, especially on a large

scale. For the number of clusters ranging between 2 and 50, the difference in worst-case response time here is more than 5 minutes. In emergency services, a difference of 5 minutes is huge.
Combining these findings with previously made observations, it follows that the hypothesis that FCM clustering gets worse on a small scale is not confirmed. On the contrary, results seem to get worse when larger data sets are used.



(a) Worst-case response time using weighted clustering on full data set



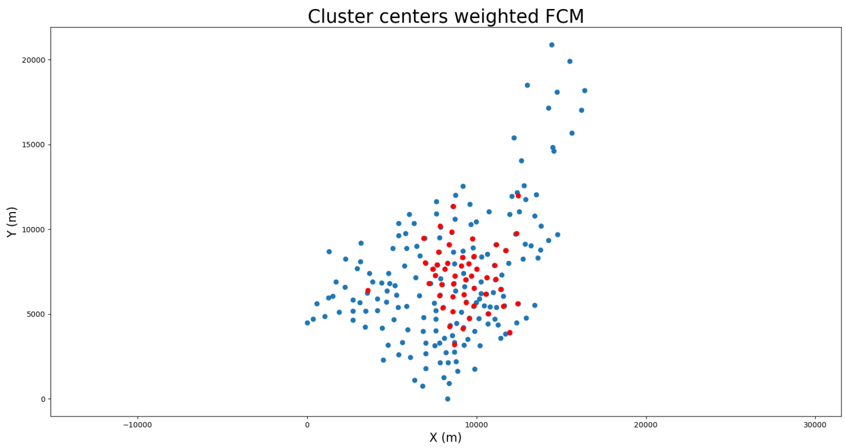
(b) Worst-case response time using unweighted clustering on full data set

Figure 6.12: Evolution of the worst-case response time as a function of the number of clusters for weighted and unweighted clustering on the full data set

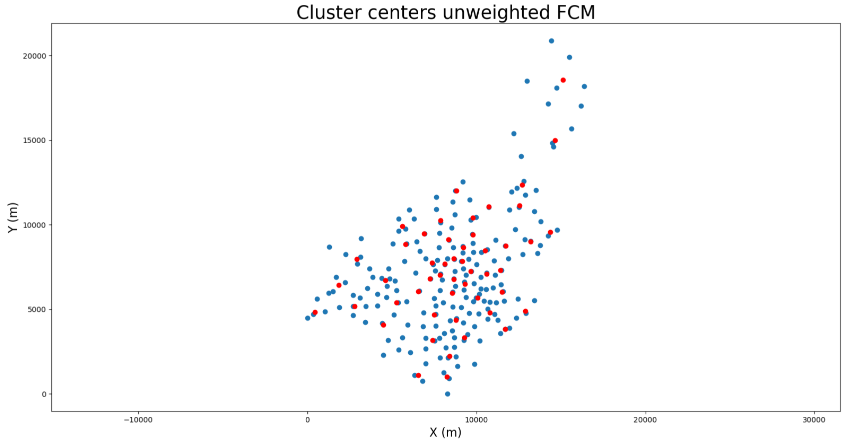
The cluster centers obtained by both methods can be visualized as well. For the number of clusters equal to 50, the resulting cluster centers are shown in figures 6.13a and 6.13b. These two figures together form figure 6.13. Note that the upper value of 50 for the number of clusters is chosen because this value is arbitrarily high and is very illustrative to visually indicate the differences between the two methods under study.

In figure 6.13, it is observed that the unweighted method performs better in exploring the whole map and in identifying clusters in the more remote areas. In the weighted case, this is much less the case. Because in this case the exploration is worse, the worst-case response time gets stuck at a plateau and does not improve anymore afterward, unless for unreasonably high values for the number of clusters. This is probably the case because the city of Ghent is most densely populated in the center, while fewer people live near the borders. In the weighted method, the more densely populated sectors are preferred over less densely populated sectors and thus, the dense sectors tend to attract most of the obtained cluster centers. For the cluster centers, it is difficult to 'escape' from the most densely populated sectors, resulting in only a few cluster centers being successful in progressing to the more remote areas.
Even though the results obtained using the unweighted method on the whole data set are better than those obtained by applying the weighted method, these results are not great as well.
First of all, the worst-case response time always remains above 3 minutes, even if the amount of clusters present is really high. This is not the case when the data is sub-partitioned first using the agglomerative hierarchical clustering method, before applying the FCM algorithm to the resulting clusters. In that case, the unweighted method easily manages to return results making sure the worst-case response time is well below 3 minutes.
Another comparison that can be made between these two methods is about the total number of clusters that are eventually present, without making the distinction between sub-clusters anymore. An overview of these results is given in table 6.11.

From table 6.11, it is clear that when response times are considered to be important, initial pre-clustering will be necessary.



(a) Cluster center location result weighted FCM for 50 cluster centers



(b) Cluster center location result unweighted FCM for 50 cluster centers

Figure 6.13: Comparison of cluster center location using either weighted or unweighted FCM for 50 clusters

Clustering Method	Total # clusters for response time under 6 minutes	Total # clusters for response time under 5 minutes	Total # clusters for response time under 4 minutes	Total # clusters for response time under 3 minutes
Weighted clustering without partitioning	98	123	\	\
Weighted clustering with initial partitioning	11	54	75	92
Unweighted clustering without partitioning	6	12	22	\
Unweighted clustering with initial partitioning	8	14	21	36

Table 6.11: Total number of clusters necessary for the response time to be below four possible threshold response times for different clustering methods

However, the unweighted methods always perform better than their weighted counterparts. For these types of applications, it will certainly be beneficial to work with unweighted clustering methods as these methods tend to partition the data in a more structured way.

6.7 Results in case initial infrastructure is present

In this section, the results and key takeaways will be reported in case initial infrastructure is present from the beginning. In this section, the methods that were presented in section 5.7 are put in practice for the case of the city of Ghent. Several options for initial infrastructure that is present are considered. At first, it is assumed only EV charging stations are present as initial infrastructure, but later on, the other initial infrastructure options are considered as well.

6.7.1 EV charging stations as initial infrastructure

In this part, it is assumed that the only considered initial infrastructure are the EV charging stations as described in chapter 3. Applying the procedure from figure 5.3 to the case of Ghent again results in two main clusters that will then be sub-partitioned further. Until further notice, here, the method that shifts the cluster centers to initial infrastructure point in each iteration is used.
Determining how many sub-clusters are needed to obtain a worst-case response time below certain specified threshold values then gives the results shown in table 6.12.

Cluster Number	# sub-clusters for response time under 8 minutes	# sub-clusters for response time under 7 minutes	# sub-clusters for response time under 6 minutes	#sub-clusters for response time under 5 minutes
Cluster 1	16	\	\	\
Cluster 2	\	\	\	\

Table 6.12: Worst-case response time per amount of sub-clusters by applying the clustering procedure for the cases in which EV charging stations are present as initial infrastructure

In table 6.12, it is observed that only for cluster 1, a response time below 8 minutes is achieved here. Response times below 7 minutes are not achieved here, so further investigation will be needed. Is this decreased performance fully accountable to the fact that now, only initial infrastructure is present? Or does the currently proposed approach result in a bad performance?
Intuitively, it is clear that the response times increase in case a deviation from the optimal location is made. This would indeed be the case in which initial infrastructure is present. However, in this case, the response time increases quite a bit and therefore, further examination will be advised. This is because it would be too short-sighted to directly come to this conclusion.
To examine the observed results further, two observations will be discussed in more detail. These two observations are the seemingly limited exploration in dense areas (cluster 1) and limited infrastructure in remote areas.

6.7.1.1 Limited exploration in dense areas

When the further clustering of cluster 1 is observed using the procedure for cases where initial infrastructure is present, it is observed in figure 6.14 that the response time initially improves a bit when clusters are added. However, this improvement is not really significant and only in some peak moments, values for a worst-case response time below 8 minutes are achieved. Previously, without initial infrastructure, response times even below 3 minutes could be achieved. The response times obtained here are not acceptable at all. Therefore, what is happening in the clustering procedure should be looked at in more detail.

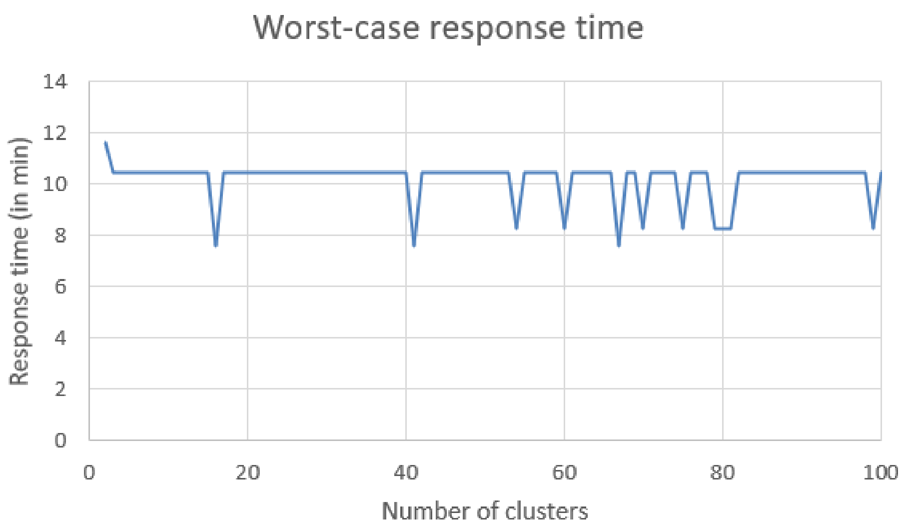


Figure 6.14: Worst-case response time for clustering cluster 1 in case EV charging stations are already present

To visually observe what happens during the clustering, a simulation is performed. In this simulation, the number of clusters is increased from 0 to 19 and for each number of clusters, the data points are plotted in blue, together with the corresponding cluster centers in red. This simulation is visualized in figure 6.15.

In this figure, it seems to be the case that the number of clusters does not increase as would be expected. Seemingly, focusing on the range of clusters between 0 and 19 clusters, the maximum number of clusters that is observed is equal to 6. This is a counter-intuitive result, as the maximum number of clusters would be expected to be 19.
Another observation that can be made is that in some of the simulated cases, the cluster centers are close together. All or most of these cluster centers are located near the center of the data points.
As the data points in this cluster are quite densely distributed, it could be the case that the algorithm doesn't succeed in exploring the full search space sufficiently. AT some point, the algorithm gets stuck in certain locally optimal solutions with the initial infrastructure under consideration. afterward, the algorithm does not seem to move further to other candidate solutions to explore the full search space. As a consequence, some cluster centers lay closely together or they even come together in the same initial infrastructure point. This could be an explanation for the fact that there are only 6 cluster centers that can be distinguished from each other in the case that 19 clusters should be present.

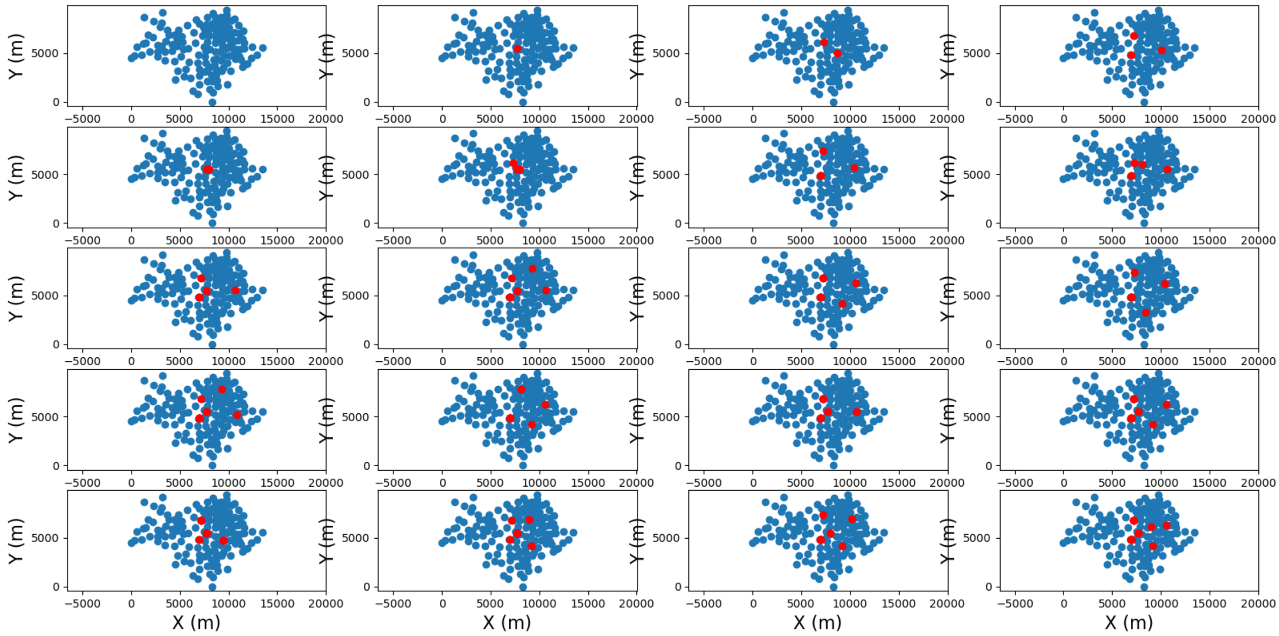


Figure 6.15: visualization of evolution application procedure to data set Ghent for the number of clusters increasing from 0 to 19

Another explanation for this observation could be that not enough EV charging stations are initially present. In figure 6.16, the data points of cluster 1 are colored in blue, together with the EV charging stations that are colored in red. From this figure, it seems to be the case that enough charging stations are present on the right side of cluster 1 to fulfill the demand there in a satisfactory way. On the left side of cluster 1 however, few EV charging stations are present, which could make sure that even adjusting the procedure doesn't suffice to obtain acceptable results. However, on the right-hand side of cluster 1, the more remote initial infrastructure seems not to be selected by the algorithm as well. For the left-hand side, it can also be observed that the obvious EV charging stations located there are left untouched.
From this, it follows that, next to the limited presence of initial infrastructure, there will be another limiting factor that stands in the way of selecting the globally optimal solution.

Taking into account the observation that was made above and the observation about figure 6.15, it can be concluded that the adjusted procedure doesn't succeed in finding the best solutions possible, as it gets trapped in a local solution. When the number of clusters increases, more and more clusters will be centered in the same points, making it useless to further increase the number of clusters using this method. However, it could be worthwhile examining other solution methods and comparing their performance with the initial proposal.

A possible solution to overcome this problem would be to only assign the cluster centers to the initial infrastructure at the very end of the algorithm when all iterations have already been executed. This could overcome the problem that cluster centers get stuck in initial infrastructure points and that it does not get to better solutions. This is a method that was also suggested in chapter 5.

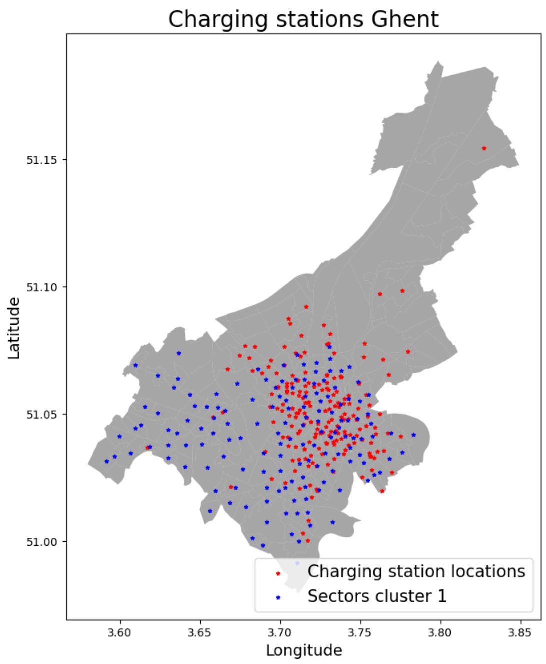


Figure 6.16: visualization of data points cluster 1 and the initial EV charging stations in the city of Ghent

Another possible solution that is suggested places a constraint on the number of cluster centers that can be located in a certain initial infrastructure point. This would mean that in each initially present infrastructure point, only one cluster center can be placed, instead of multiple ones. This is a phenomenon that was observed in the previous results and could easily be overcome by this alternative constraint. This constraint then forces the algorithm to further examine the search space than it would have done without the constraint.

The application of the two suggested improvements is analyzed in what follows. By analyzing their performance, a reasonable conclusion could be drawn about the observed bad performance of the initial suggested approach.

6.7.1.1.1 Assign clusters centers to initial infrastructure points at the end of algorithm execution The first alternative method to deal with the presence of initial infrastructure is analyzed in this section. In this method, the clustering method is executed as was done in the case no initial infrastructure is present. In the end, the distance between each obtained cluster center and initial infrastructure point is calculated. The cluster centers are then shifted toward their closest initial infrastructure point, with the demands allocated to the cluster centers shifted toward the initial infrastructure as well.
For this new approach, an overview of the number of clusters needed to reach a response time below a certain threshold value is shown in table 6.13. In this table, only the results for cluster 1 are included as in this cluster. This is the largest cluster containing most initial infrastructure points and will therefore render the best results.

In table 6.13, it is immediately observed that the number of clusters needed to achieve a certain time threshold is a lot lower than was the case in table 6.12. In table 6.13 it can be seen that no improvements happen anymore when the number of clusters increases above 5. This is in line with the results from figure 6.17 where it is observed that a plateau is reached when the number of clusters is equal to about 10. The plateau here is reached for a worst-case response time of about 5 and a half minutes.

Cluster Number	# sub-clusters for response time under 8 minutes	# sub-clusters for response time under 7 minutes	# sub-clusters for response time under 6 minutes	#sub-clusters for response time under 5 minutes
Cluster 1	3	4	5	\

Table 6.13: Worst-case response time per number of sub-clusters by applying the clustering procedure in which the cluster centers are shifted at the end for the cases in which EV charging stations are present as initial infrastructure

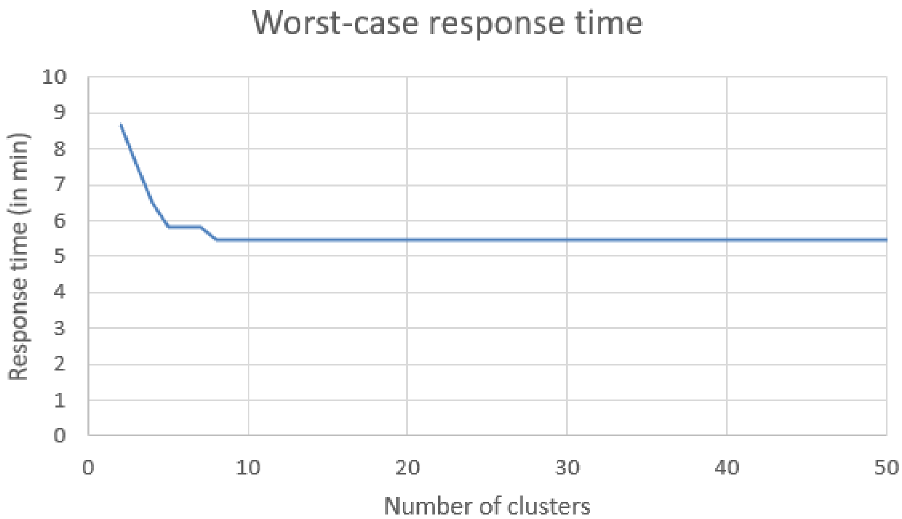


Figure 6.17: Worst-case response time for clustering cluster 1 in case EV charging stations are already present and the cluster centers are shifted toward initial infrastructure at the end of the algorithm

To observe the cluster centers that are explored by the algorithm, the evolution of the cluster center placement is again simulated for the number of clusters increasing from 0 to 19. This is shown in figure 6.18. In this figure, it is clear that the search space gets explored well and that the cluster centers are not too closely located to each other.

In this method, however, it can be the case that a lot of the demand is allocated to a certain demand point, while others would have to serve no or almost no demand. This can still happen as multiple cluster centers can still be allocated to the same initial infrastructure point.
This is certainly something to keep in mind and this can be overcome using a constraint on the amount of demand to specific UAV base stations. For example, in the following, a constraint is added to ensure only 1 cluster center can get shifted toward each initial infrastructure point, therefore preventing allocating too much demand to a single initial infrastructure point.

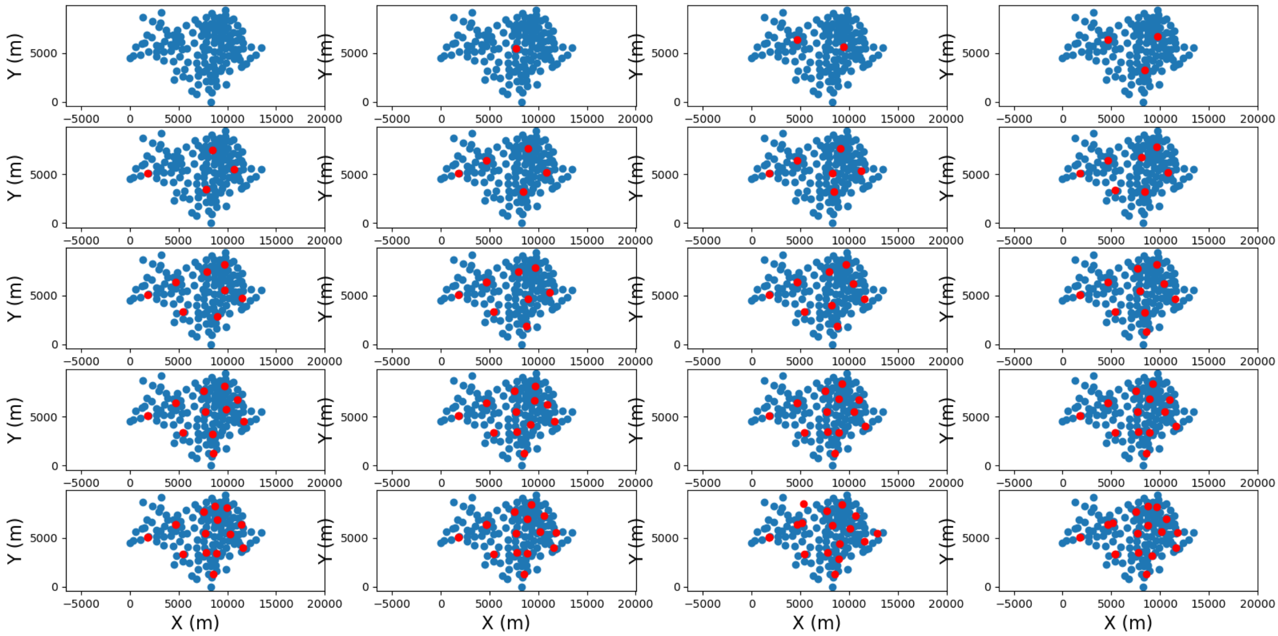


Figure 6.18: visualization of data points cluster 1 and the initial EV charging stations in the city of Ghent in case cluster centers are shifted to initial infrastructure at the end

6.7.1.1.2 Allocate at most one cluster center to each initial infrastructure point In this solution method, the approach is similar to the initial proposed approach to include initial infrastructure. The difference here again appears in the cluster calculation step. Each time a cluster center is calculated, it is assigned to the initial infrastructure point that is closest to it. Unlike the initial case, the set of possible infrastructure points is updated each time a cluster center is assigned to an initial infrastructure point. The infrastructure point to which the cluster center is assigned is then removed from the candidate list of this iteration. For the next cluster center, the same happens until all cluster centers are allocated to initial infrastructure points. In the following iteration, the candidate list again contains all initial EV charging stations, and the same steps are repeated until the eventual stopping criterion is reached. Then, the optimal solution is obtained.

Applying this adjusted solution method to the first cluster and then identifying how many clusters are needed to get a response time below a certain threshold, the results are shown in table 6.14. Comparing these results with the ones initially obtained for cluster 1 in table 6.12, it can be seen that the ones obtained using the adjusted method proposed here are better solutions.

Notice that the reported response time threshold values here differ from the ones in the previous tables.

Cluster Number	# sub-clusters for response time under 9 minutes	# sub-clusters for response time under 8 minutes	# sub-clusters for response time under 7 minutes	#sub-clusters for response time under 6 minutes
Cluster 1	6	6	54	54

Table 6.14: Worst-case response time per amount of sub-clusters by applying the clustering procedure for cluster 1 in which EV charging stations are present as initial infrastructure, with adjusted method

Visualising the evolution of the response time as a function of the number of clusters then results in figure 6.19. In this figure, it is seen that the response time gets stuck on a plateau for the number of clusters ranging from about 10 to 50. afterward, another plateau is reached, at a response time that is about 2 minutes lower than the first plateau. Compared with figure 6.14, it can be seen that the first plateau obtained here is higher than the one obtained previously.

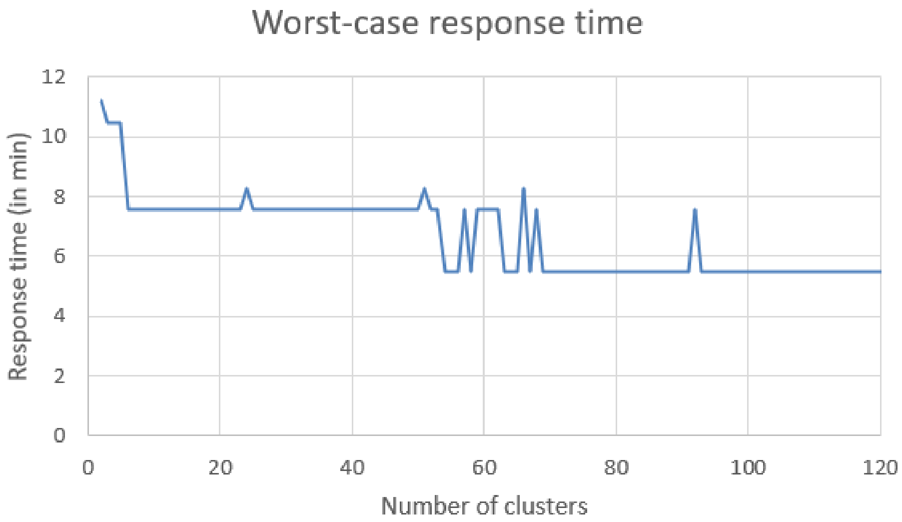


Figure 6.19: Worst-case response time for clustering cluster 1 in case EV charging stations are already present and each cluster center can only be assigned to one initial infrastructure point

Finally, as was done for the initial method, a visualization of what happens in the clustering process in case the number of clusters is gradually increased from 0 to 19 is shown in figure 6.20. Comparing this figure with figure 6.15, it is observed that in the new procedure, the search space is explored more profoundly and that more candidate points are consulted than in the initial method. Also, the number of clusters does not seem to get stuck in the new method. It can also visually be observed that in each step, one new cluster is added.

The newly proposed method achieves better results than the initial, naive method for solving instances where initial infrastructure is present. It should also be noted that the number of clusters necessary to reach certain threshold values for the worst-case response time is higher than the case where the cluster centers are shifted to the initial infrastructure in the end. In this sense, this method performs worse than the second proposed solution method.
From the observation made in this section and the one before, it can be concluded that the newly proposed method is quite a bit better than the initial method. However, the lowest achieved response time, which is a bit higher than 5 minutes, is still a lot higher than the obtained worst-case response time in case no initial infrastructure is present. This is why in the following, a look will be directed toward the limited presence of initial infrastructure. The influence of limited initial infrastructure will be most clearly present in cluster 2. Therefore, the focus in that part is directed toward cluster 2.

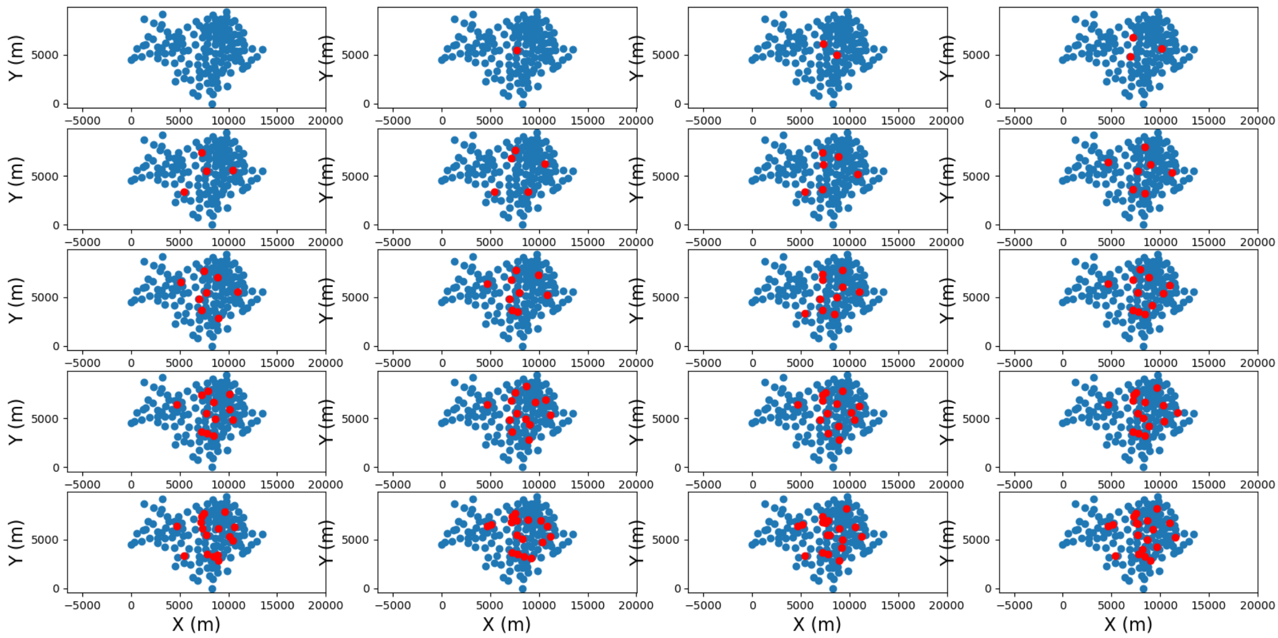


Figure 6.20: visualization of evolution application procedure to data set Ghent for the number of clusters increasing from 0 to 19 in case of the newly proposed procedure

6.7.1.2 Limited initial infrastructure in remote areas

Another problem that could arise would be that not enough initial infrastructure is present to make sure a feasible or acceptable solution can be obtained. In cluster 2, it is initially observed that the obtained worst-case response times are very bad in case initial infrastructure is present. This is something that should be looked into.

Using the initial proposed method in case initial algorithm is present for cluster 2, the evolution of the response time as a function of the number of clusters is visually shown in figure 6.21. The best solution for the worst-case response time that is obtained here is equal to 13.72 minutes. This response time is four times higher than the worst-case response time that can be obtained for cluster 2 in case no initial infrastructure is present.

Additionally, when the number of sub-clusters is increased above three here, no improvements seem to happen anymore.

Visualising the data points of cluster 2 together with the initial EV charging stations in Ghent, figure 6.22 is obtained. In this figure, the same color convention is used as before.

Compared to figure 6.16, it is observed that cluster 2 is covered less by initial infrastructure than cluster 1. From this, it seems obvious that this will put some restrictions on the eventual results that can be obtained. Previously, two improvements were proposed for the initial approach in case initial infrastructure is present. The proposal in which the cluster centers are allocated to initial infrastructure points at the end of the iterations will be applied here as well.

Applying this method to the case of cluster 2 is mainly done to see how big the obtained solution is influenced by the lack of sufficient initial infrastructure. Also, note that the last proposed method won't be used here. As there does not seem to be a lot of initial infrastructure present, assigning each cluster center to a different initial infrastructure point could result in very large distances between the cluster centers and their corresponding initial infrastructure. In that case, the results could even become worst by applying this method.

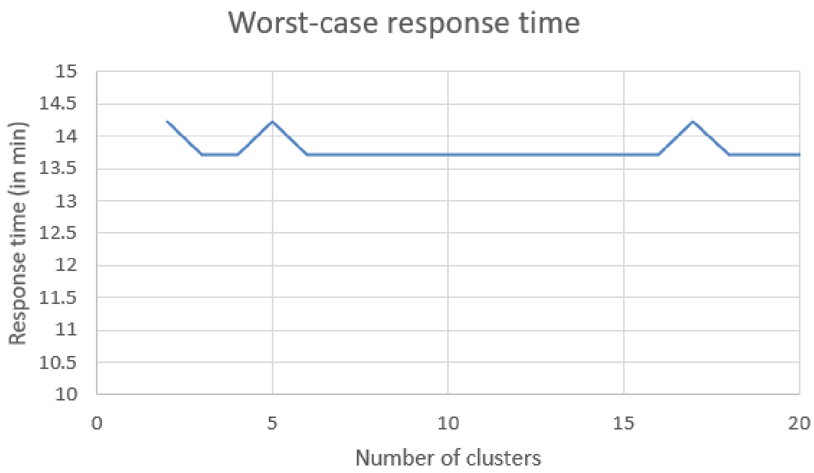


Figure 6.21: Worst-case response time for clustering cluster 2 in case EV charging stations are already present

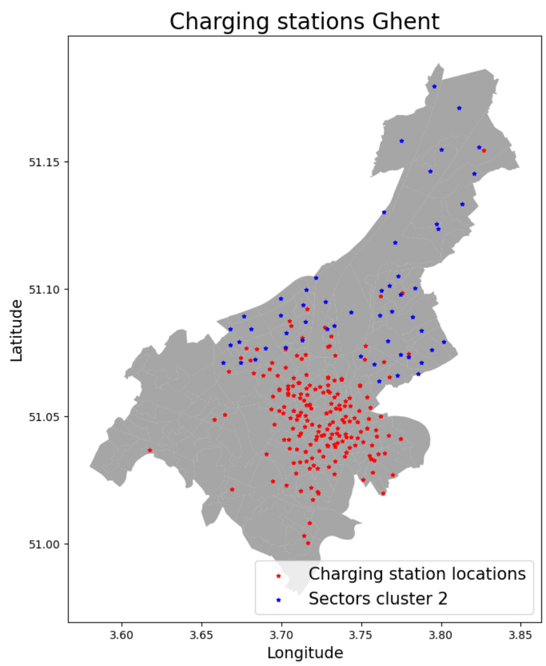


Figure 6.22: visualization of data points cluster 2 and the initial EV charging stations in the city of Ghent

Plotting the worst-case response time for the improved strategy for cluster 2 results in figure 6.23.

Here again, a plateau that is higher than in case no initial infrastructure is observed. However, the results in figure 6.23 are much better compared to the results in figure 6.21. Comparing the results when 20 clusters are present for both methods, the visualization of clusters that are present is shown in figure 6.24.
It seems that the naive initial method does not succeed in selecting the cluster center on the upper right, which makes sure the most remote areas can also be served in a reasonable (but high) response time. The newly proposed approach in which the cluster centers are shifted after the algorithm has been performed does succeed in selecting the upper right initial infrastructure point but also looking at figure 6.22, it can be concluded that better solutions are not obtainable with this set

of initial infrastructure.

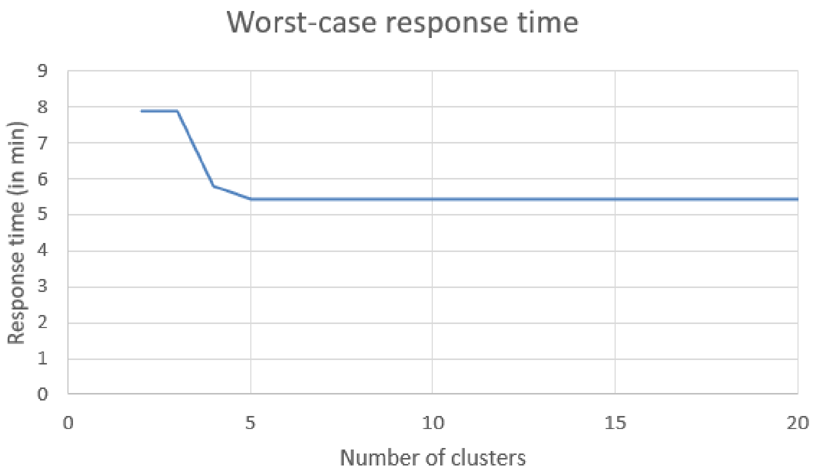
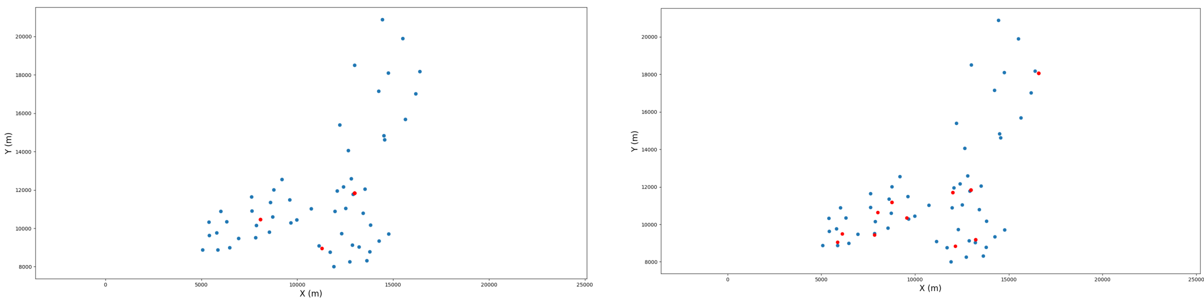


Figure 6.23: Worst-case response time for clustering cluster 2 in case EV charging stations are already present when cluster centers are shifted after the initial procedure is executed



(a) visualization of cluster center initial clustering method initial infrastructure for 20 clusters

(b) visualization of cluster center new (shifted) clustering method initial infrastructure for 20 clusters

Figure 6.24: Comparison clustering methods for cluster 2 with initial infrastructure

Concluding this, knowing that about 200 initial EV charging stations are present, it can be stated that these stations are not well-spread over the city of Ghent at all. Only working with these locations won't result in acceptable response times for the smallest type of UAV.
Therefore, other initial infrastructure should be looked into as well or the possibility to introduce new infrastructure as well should be combined with the already present infrastructure.

6.7.2 EV charging stations, AED locations and helipads considered as initial infrastructure

In chapter 3, also initial AED locations and helipads were proposed as initial present infrastructure. As only EV charging stations were not sufficient to set up a good UAV emergency system, the combination of these three types will be considered here.
Again using the procedure for initial infrastructure in which cluster centers are shifted to initial infrastructure points at the end of the algorithm, the resulting worst-case response times and the number of clusters needed to achieve this worst-case

response time are shown in table 6.15.

Cluster	Present infrastructure	lowest response time (in min)	number of clusters
Cluster 1	Only EV charging stations	5.47	8
Cluster 1	All three types	5.47	6
Cluster 2	Only EV charging stations	5.46	5
Cluster 2	All three types	5.46	5

Table 6.15: Lowest observed worst-case response time for the two main clusters in case either only EV charging station or all three types of initial infrastructure are considered

From this table, it can be seen that adding the initial AED locations and the helipads to the candidate list, does not change the worst-case response time obtained by the adjusted algorithm for initial infrastructure. This can be explained by the fact that in the more remote areas, not enough initial infrastructure is present. As the worst-case response time is mostly observed in remote areas, this worst-case behavior is not improved significantly.
It could be the case that this bad response time is an inherent characteristic for cases in which only initial infrastructure is present. To examine if this is the case or not, the next part will handle a randomly generated case and the performance observed there will be compared with the one observed in case the three previously discussed infrastructure types are present.

6.7.3 Randomly generated initial infrastructure points

In the previous sections, it was observed that there were quite some limitations in case the initial EV charging stations are used as initial infrastructure. For the case in which all three types of initial infrastructure were present, the same was observed. To extract a meaningful observation about the clustering performance in case of the presence of initial infrastructure, some other things should be looked into as well. As the observed performance in the previous sections was not too great, the hypothesis that this is due to the insufficient distribution of initial infrastructure should be looked into in more detail.
In this section, the influence of the seemingly bad distribution of initial infrastructure will be filtered out. It was observed that most of the EV charging stations were located at the center of Ghent. Therefore, the more remote regions were left relatively untouched. To minimize the influence of the bad placement of initial infrastructure, another experiment is proposed in this section.
Observe the location of all data points for the city of Ghent. These can all be included in a rectangle, which has its boundaries at respectively the minimum and maximum x- and y-components. Note that in this case, data points can be located quite far away from the actual data points. This is because the data points for the city of Ghent are not distributed in a rectangle. An additional constraint on these random locations is imposed. For each candidate random point, it is checked if the distance from this random point to the closest data point for the city of Ghent does not exceed a certain threshold value. However, if this is the case, the data point is replaced by another randomly generated data point that meets the additional requirements. The threshold value can be adjusted and the effect of this value can be observed, together with the number of initial data points.

In what follows, the clustering procedure is applied to different cases with initial infrastructure present. In this case, the

number of initial random infrastructure points is varied from 20 to 50, in steps of 10. For each case, the maximum distance between a random initial infrastructure point and its closest data point is either 1 000 or 5 000 meters.
As was observed in a previous section, the best results in the presence of initial infrastructure were obtained when the original clustering method is performed as was presented, after which the cluster centers were shifted to the initial infrastructure point. For the results that will be obtained here, this method is used as well.
Executing this gives the results shown in table 6.16.

Number of random infrastructure points	Maximum distance (m)	lowest response time (in min)	number of clusters
20	1 000	6.56	7
20	5 000	7.61	7
30	1 000	4.34	12
30	5 000	7.65	5
40	1 000	3.61	18
40	5 000	4.76	9
50	1 000	2.73	31
50	5 000	3.75	26

Table 6.16: Worst-case response time for cluster 1 in case different numbers of random initial infrastructure points are present. For each number of initial data points, the maximum distance between the randomly generated infrastructure point and the closest data point is equal to either 1 000 m or 5 000 m

It follows that evidently, the obtained worst-case response time decreases when more random initial data points are present. The worst-case response time is lower when the maximum distance is equal to 1 000 meters compared to the case where it is 5 000 meters. This is the case because the deviation of 5 000 meters is quite large in case the total map is only about 20 000 by 20 000 meters. It is reasonable to state that the maximum distance is equal to 1 000 meters, as the maximum distance between two points of the Ghent data set is never more than 1 000 meters.
Another question that could be asked is how well the performance of the algorithm is in case initial infrastructure is present compared to the case where no initial infrastructure is present. A comparison for several cases for a maximum distance of 1 000 meters is shown in figure 6.25.
In figure 6.25, it is clear that the more initial infrastructure possibilities are present, the lower the observed worst-case response time is. Also, as the number of initial infrastructure points increases, the worst-case response time gets closer and closer to the one achieved in case no initial infrastructure points were present initially. Therefore, no significant difference is observed anymore between the case where 50 random infrastructure points are present and the case where no initial infrastructure was present.
This observation allows us to conclude that the adjusted clustering method for cases where initial infrastructure is present performs well. Additionally, the bad distribution of EV charging stations in the previous sections is the main cause for the worst-case response time being too high.
In reality, it will be the case that it is possible to choose between setting up a new location or adapting an initial infrastructure location. Previously, the two distinct cases were observed separately, stating that either all infrastructure is new or all infrastructure was already present. Therefore, it could be really interesting to design a hybrid approach that trades off the pros and cons of having initial infrastructure with the pros and cons of having to construct new locations. This will be addressed in one of the following sections.

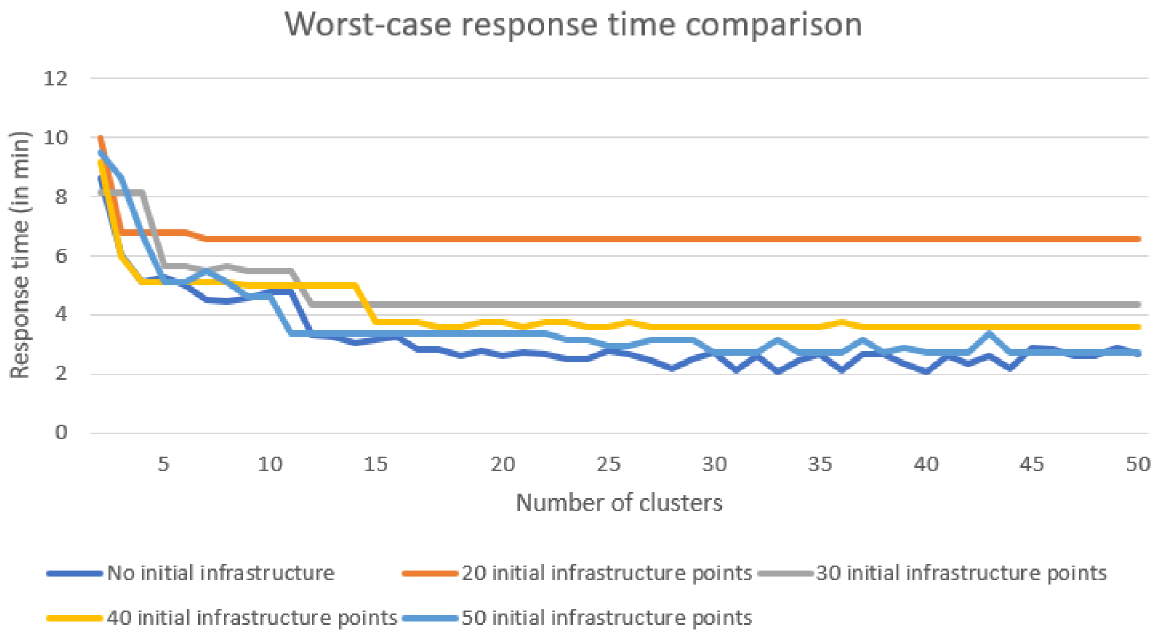


Figure 6.25: Worst-case response time for clustering cluster 1 with different options for the initial infrastructure present with the number of clusters ranging from 2 to 50

6.7.4 Large parking lots as initial infrastructure for rotorcraft-type UAV

In the previous sections, it was assumed that the used UAV is the multicopter-type UAV. This changes here. In this section, the Rotorcraft-type UAV is considered, which has a cruise speed of $100\ \frac{km}{h}$, which is more than twice as fast as the cruise speed of the multicopter-type UAV. Considering only the large parking lots shown in figure 3.3b, the number of clusters necessary to obtain a response time below 3 minutes and the actual worst-case response time for cluster 1 and cluster 2 is shown in table 6.17. In this table, the results obtained in case no initial infrastructure is present for the same amount of clusters are shown as well.

Cluster	Worst-case response time only parking lots present (in min)	Worst-case response time no initial infrastructure (in min)	Number of sub-clusters
Cluster 1	2.70	2.41	3
Cluster 2	2.66	2.32	3

Table 6.17: Worst-case response time for cluster 1 and 2 for the rotorcraft-type UAV. In this case, both no initial infrastructure and only parking lots as initial infrastructure are considered. For the obtained results, the number of sub-clusters per cluster is reported as well

In total, using parking lots as initial infrastructure, 6 locations are set up to serve all demand using the rotorcraft-type UAV within 3 minutes. As expected, the number of UAV of this type necessary to cover all demand in Ghent within 3 minutes is a lot less than for the multicopter-type UAV. The results obtained here also show that using the parking lots only, enough initial infrastructure is present to serve all demand without having to introduce new locations. Therefore, no further improvements are needed here.

6.7.5 Helipads as initial infrastructure for Optionally-Piloted VLR

To consider the application of ambulance services, the Optionally-Piloted VLR is the UAV type that should be used. This UAV type has a cruise speed of $150\ \frac{km}{h}$, which is almost 4 times as high as the cruise speed of the multicopter-type UAV. Applying the optimal clustering method on both clusters 1 and 2 then returns the results in table 6.18. For both clusters 1 and 2, the number of clusters that can be present is equal to 2. However, they share 1 UAV base station, thus in total, 3 base stations are used in reality.

Cluster	Worst-case response time no initial infrastructure (in min)	Worst-case response time only helipads present (in min)
Cluster 1	2.30	3.15
Cluster 2	2.13	2.98

Table 6.18: Worst-case response time for cluster 1 and 2 for the Optionally-Piloted VLR as UAV type. In this case, both no initial infrastructure and only helipads as initial infrastructure are considered. For both cases, the number of clusters is equal to two

It is observed that for both clusters, the worst-case response time of the Optionally-Piloted VLR is close to 3 minutes when only helipads are considered as initial infrastructure. These response times are not as low as the cases where no initial infrastructure is present, but it is often not possible to construct new locations in an urban environment for such large UAV types. Also, introducing more UAV base stations here would not be feasible because for such large UAVs it would become costly. From this, it leads us to be satisfied with the obtained results, which are quite good. Response times lower than the ones shown in table 6.18 are not obtained, which is why no worst-case response time below 3 minutes is given for cluster 1. However, for ambulance services, a worst-case response time of close to 3 minutes is certainly acceptable.
It follows that the faster the UAV can travel, the less important the performance of the clustering algorithm will be. Even if a bad solution is obtained, the worst-case response time will still be quite low. Putting in extra effort becomes inefficient and costly very fast. Naturally, it follows that in the remainder, the focus will be redirected toward the smallest UAV type again, as the results for this UAV type are more sensitive to changes.

Using only the initial infrastructure considered for Rotorcraft-type UAVs and Optionally-Piloted VLRs, acceptable solutions are obtained. Evidently, for these UAV types, only initial infrastructure is used to start from. However, for the Multicopter-type UAVs, only initial infrastructure does not result in acceptable results. Therefore, further research is performed to address this issue.

6.8 Results hybrid clustering approach

As was discussed in section 5.8 of chapter 5, two possible ways of considering both initial and new infrastructure are considered. In the following parts, these two approaches are applied to the case of Ghent, and the obtained will be reported and compared for the two methods.

6.8.1 Results distance-based hybrid clustering approach

In this part, the approach proposed in section 5.8.1 will be put into practice.
As was discussed previously, the considered threshold value for the maximum distance between the obtained cluster centers and their closest initial infrastructure point will play a crucial role in obtaining good results.
Because of this, an experiment is conducted in which the threshold distance is from 100 to 10 000 meters, in general steps. For each distance, the worst-case response time obtained for sub-partitioning cluster 1 and cluster 2 (as were obtained using agglomerative hierarchical clustering) is compared for the case considered here with the case in which no initial infrastructure is present. This is done to observe how much the worst-case response times deviate from the optimal scenario for different values of this threshold distance. The results obtained are shown in table 6.19. Note that the only considered initial infrastructure here are the EV charging stations. For both clusters, it is assumed that they can be sub-partitioned in at most one-third of the total data points that are present in the corresponding cluster. Rounding results in at most 50 sub-clusters for cluster 1 and 15 sub-clusters for cluster 2. Also notice that a worst-case response time for cluster 2 can be obtained that is below 3 minutes, but then more than 15 sub-clusters need to be present, which is out of the reported range in table 6.19.

Threshold distance (in m)	Cluster 1 worst-case response time hybrid (in min)	Cluster 1 worst-case response time (in min)	Cluster 2 worst-case response time hybrid (in min)	Cluster 2 worst-case response time (in min)
100	2.09	2.09	3.48	3.48
250	1.95	1.95	3.52	3.52
500	1.97	2.05	2.25	2.41
750	2.09	2.07	3.48	3.48
1 000	2.09	2.04	3.48	3.48
1 250	2.28	1.97	3.32	3.32
1 500	2.36	1.98	3.51	3.51
1 750	2.83	1.95	3.48	3.48
2 000	2.83	2.00	3.80	3.48
2 500	3.35	1.93	3.80	3.41
5 000	5.47	1.93	5.46	3.48
10 000	5.47	1.94	5.46	3.41

Table 6.19: Performance hybrid approach for cluster 1 and 2 compared with the case where no initial infrastructure is present. Here, the observed ranges are from 2 to 50 sub-clusters for cluster 1 and from 2 to 15 sub-clusters for cluster 2

When the threshold distance is low, the difference between the results obtained using the hybrid method and the case where no initial infrastructure is present is negligible can be explained by the fact that in those cases, almost all infrastructure points are new. On the contrary, when the difference between the obtained results using the two methods is quite large, then almost all infrastructure points are initial infrastructure points. This is in line with what would be expected intuitively. In between these two solutions, a lot of other solutions can be found, combining both initial and new infrastructure. These solutions typically use a clever combination of already present infrastructure with new infrastructure. The trick is to find the perfect balance between these two.
It is still the purpose to obtain solutions in which the worst-case response time is as low as possible. In table 6.19, it is seen

for cluster 1, that the worst-case response time in case the threshold distance is 100 meter and in case the threshold distance is 1 000 meters are the same. However, it could be the case that the number of new infrastructure points has decreased, and therefore, the case for 1 000 meters would be a better option, as it would require less new infrastructure to be constructed. For this reason, the ratio of new infrastructure to initial infrastructure will also be important to consider here. For the same threshold distance values as those reported in table 6.19, the ratios of new to initial infrastructure will be reported for both clusters. For cluster 1, there are in total 49 clusters, while for cluster 2, there are 15. These ratios are shown in table 6.20.

Threshold distance (in m)	Ratio new infrastructure to initial infrastructure cluster 1 (-/-)	Ratio new infrastructure to initial infrastructure cluster 2 (-/-)
100	44/5	15/0
250	32/17	14/1
500	16/33	9/6
750	13/36	7/8
1 000	9/40	6/9
1 250	6/43	3/12
1 500	4/45	3/12
1 750	4/45	3/12
2 000	2/47	2/13
2 500	1/48	3/12
5 000	0/49	0/15
10 000	0/49	0/15

Table 6.20: Ratio of new infrastructure to initial infrastructure for sub-partitioning of cluster 1 and cluster 2. Here, the observed ranges are from 2 to 50 sub-clusters for cluster 1 and from 2 to 15 sub-clusters for cluster 2

As can be seen from table 6.20, the ratio of new infrastructure to initial infrastructure decreases as the threshold distance increases. This is what could be expected as well. It is also observed that the most drastic change in the composition of the infrastructure happens when the threshold distance is small.

Combining the findings from table 6.19 and table 6.20, it follows that for cluster 1, the best threshold distance to work with would be 1 000 meters and the best one for cluster 2 would be 1 750 meters. These cases combine the characteristic that their obtained worst-case response time is as low as in the case where no initial infrastructure was present with the usage of quite some initial infrastructure in the obtained solution. This solution, therefore, combines an acceptable worst-case response time with efficient usage of the already present infrastructure.
Notice that for different data sets, different threshold distances would have to be used, as, for cluster 1 and cluster 2, different optimal threshold distances are used as well. Executing this method will therefore require quite some time and patience. Also, in performing this clustering method, enough attention should be paid such that eventually, good results are obtained.

For the optimal threshold distances, the characteristics of the solution obtained for cluster 1 and cluster 2 are shown in table 6.21. In this case, a total of 36 infrastructure locations are used, of which 25 were initially present. The majority of the infrastructure locations that are used are initial infrastructure locations, so this solution makes quite good use of the initial infrastructure that is present.

Cluster	Threshold distance (in m)	Worst-case response time (in min)	Infrastructure (new/initial)
Cluster 1	1 000	2.83	18 (5/13)
Cluster 2	1 750	2.32	18 (6/12)

Table 6.21: Solution characteristics distance-based hybrid clustering method. This solution is used by using a worst-case response time threshold value of 3 minutes

A final observation that is made here is that the optimal threshold distance for cluster 2 is larger than the one for cluster 1. This can be explained by the fact that less initial infrastructure is present in cluster 2 and by the fact that the data points in cluster 2 are spread out more.

To conclude this section, a final remark is given. To efficiently make the trade-off between the infrastructure cost and response time, it would be a good idea to perform a cost optimization analysis. In this cost optimization analysis, the response time will be quantified and the cost of introducing new infrastructure/adapting old infrastructure will be included as well. Minimizing the total cost there results in the optimal solution from a cost-based perspective. In the final part of this research, a brief cost optimization analysis will be performed to observe if the results obtained there are feasible or not.

6.8.2 Results initial infrastructure-based hybrid clustering approach

In this part, the approach proposed in section 5.8.2 will be put into practice.
In section 5.8.2, it is mentioned that the data set should first be pre-processed in two regions: one that will completely be served by already present infrastructure and one that will be served by new infrastructure only. For the city of Ghent, a reasonable partitioning is given in figure 6.26, where the EV charging stations are colored in red. Data points colored in blue will be served by initial infrastructure, while data points in yellow are served by new infrastructure points. As was already observed in a previous part, the more remote areas won't be served by initial infrastructure as there, the infrastructure network is not yet enhanced enough to be able to offer an acceptable service level.

In figure 6.26, it is clear that the area that is served by the new infrastructure consists of two parts. In the clustering procedure, these two areas will be served separately. In the following, the two clusters will be referred to as the south cluster and the north cluster. The cluster that is served by initial infrastructure is referred to as the center cluster.
In applying the clustering methods to these three separate clusters, the agglomerative hierarchical clustering step is skipped, as it seems to be that there is already a good sub-partitioning performed. However, in case no satisfying results are obtained, this can be reconsidered.
Then, applying the FCM algorithm to these three clusters, calculating the number of sub-clusters necessary to obtain a worst-case service time below certain threshold values, gives the results shown in table 6.22.

From table 6.22, it is clear that good results can be obtained using this approach. Only for the north cluster, the result seems not to be too great. For a total of 12 data points in that cluster, 9 sub-clusters are needed to obtain a worst-case response time below 3 minutes. The clustering approach seems to have some difficulties with this dispersed cluster containing just a few data points.

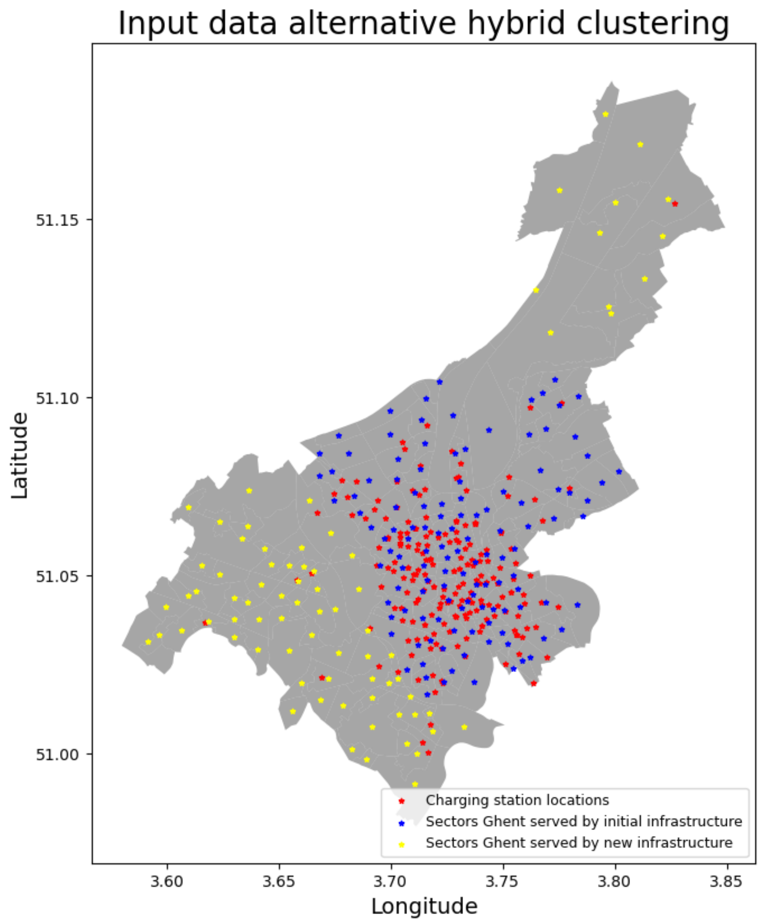


Figure 6.26: Sub-partitioning of data points in an area that is served by initial infrastructure (blue) and an areas that is served by new infrastructure (yellow)

Cluster	# sub-clusters for response time under 6 minutes	# sub-clusters for response time under 5 minutes	# sub-clusters for response time under 4 minutes	#sub-clusters for response time under 3 minutes
South cluster	4	4	5	12
North cluster	2	4	9	9
Center cluster	4	7	8	19

Table 6.22: Worst-case response time per amount of sub-clusters in case either new infrastructure is used (south and north cluster) or initial infrastructure is used (center cluster)

In total, 19 initial infrastructure points and 21 new infrastructure points are used to obtain a worst-case response time below 3 minutes, therefore resulting in 40 locations in total, of which 19 were initially present.

Visualizing the obtained result where the worst-case response time is below 3 minutes is shown in figure 6.27.

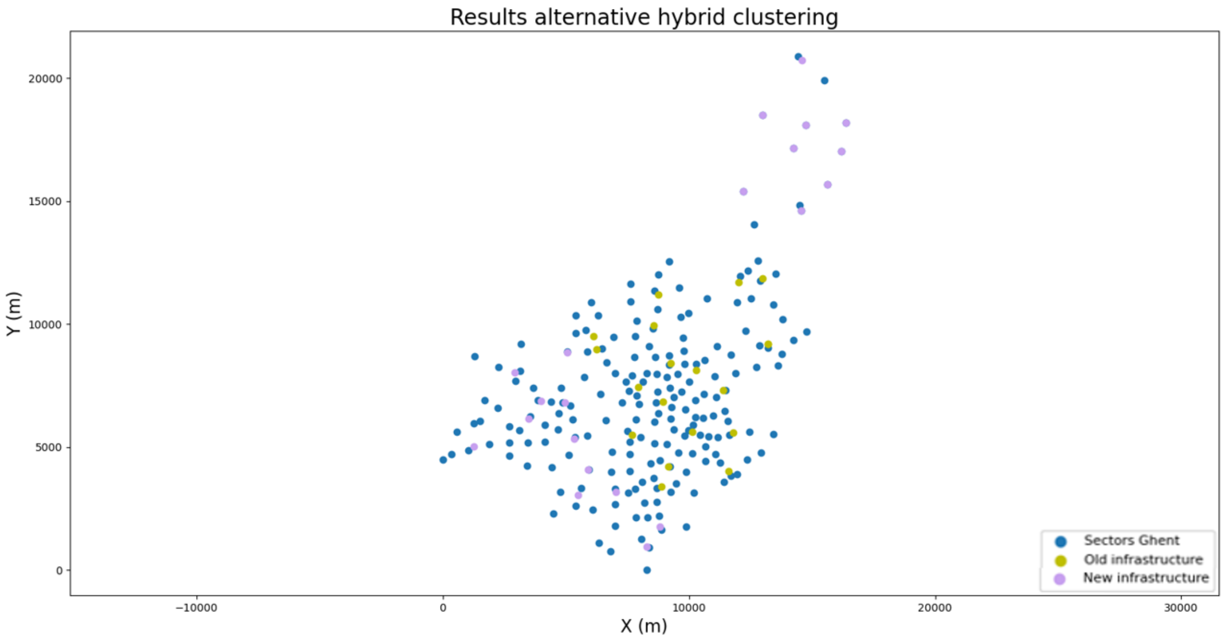


Figure 6.27: Eventual placement of initial and new infrastructure points obtained using initial infrastructure-based hybrid clustering approach

Comparing the results obtained here with the ones obtained using the distance-based hybrid clustering approach, it follows that the distance-based hybrid clustering approach is slightly better than this one. In that case, 36 instead of 40 locations were obtained in total, of which 25 were initially present compared to 19 here.
Therefore, for the case of the city of Ghent considered here, the distance-based hybrid clustering approach will be preferred above the initial infrastructure-based approach.

6.9 Clustering result when three UAV types are combined

Combining the three UAV types, a multi-use solution is obtained. In this eventual solution, the system includes a network in which three UAV types are used to serve multiple objectives, such as AED delivery and ambulance services.

To further improve this solution, it is chosen to group infrastructure locations in case they are located close to each other. This will enhance efficiency, as adding more UAV base stations comes at a cost as well. Therefore, the locations that are close to each other are relocated to the largest type of infrastructure. This means that for example, in case the initial solution suggested a new multicopter base station next to a helipad, the new multicopter base station is relocated to the helipad, as this was already present and has multiple uses.

Combining all of this, the number of each type of UAV base station used in the solution before and after this improvement, are reported in table 6.23.

Type of UAV base station	Number of stations before improvement	Number of stations after improvement
New multicopter base stations	11	10
Used EV charging stations	25	20
Used parking lots	6	6
Used helipads	3	3

Table 6.23: Summary of used infrastructure when all three UAV types are considered

From table 6.23, it follows that after improvement, 39 UAV base station of three different types are used. Visualising the locations of these UAV base stations results in figure 6.28.

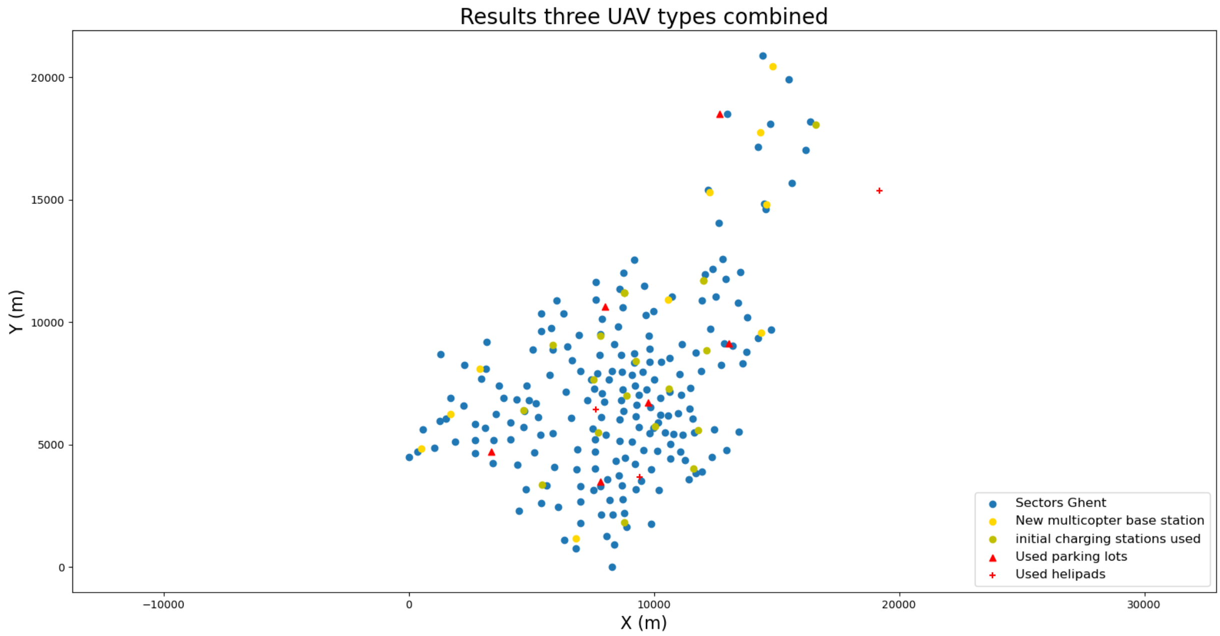


Figure 6.28: visualization of infrastructure used in case all three UAV types are considered

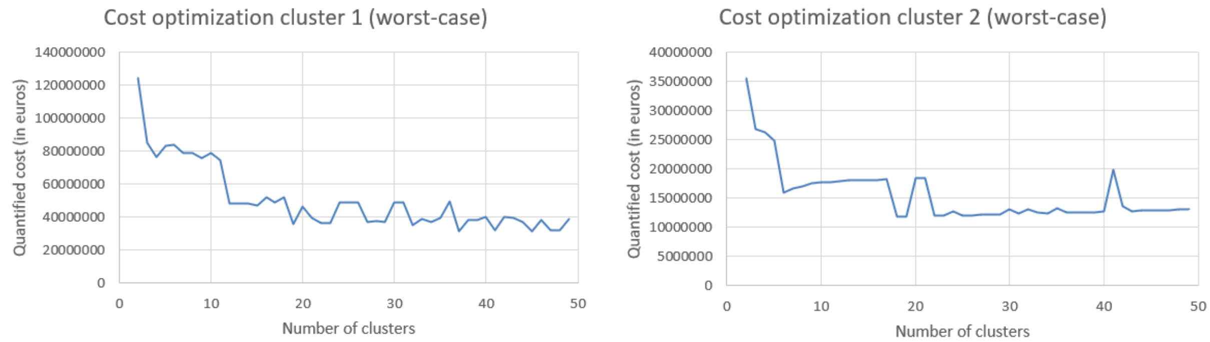
Finally, the worst-case response times achieved by the UAVs departing from the different types of UAV base stations of 6.28 are given in table 6.24.

Type of UAV base station	Worst-case response time (in min)
New multicopter base stations	2.32
Used EV charging stations	2.81
Used parking lots	2.70
Used helipads	3.15

Table 6.24: Worst-case response times achieved for each type of UAV base station

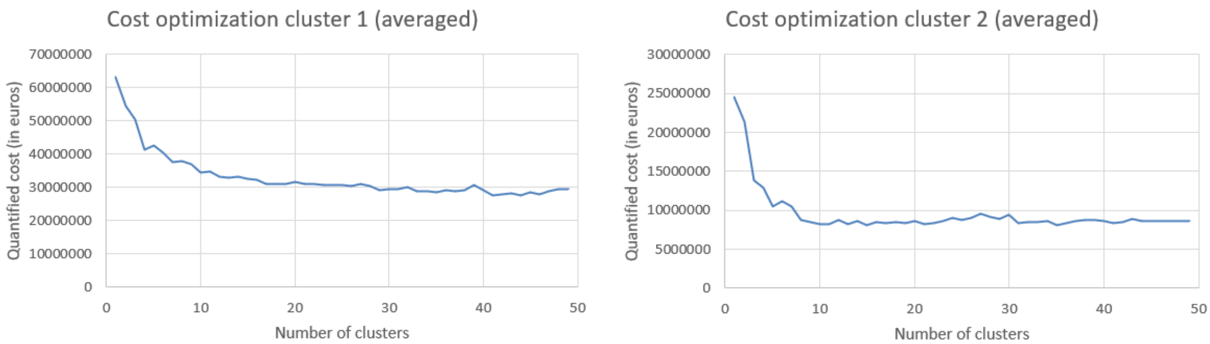
6.10 Results cost optimization analysis

The two cost optimization approaches presented in section 5.10 of chapter 5 are applied to the data set of Ghent. Again, it is assumed that the first partitioning by the agglomerative hierarchical clustering has already been performed. Then, the quantified cost as a function of the number of clusters in case the worst-case response time is used is shown in figure 6.29. For the case where the averaged response time is used, the results are shown in figure 6.30. For both approaches, the results are shown for cluster 1 and cluster 2. In this clustering method, again both initial and new infrastructure is considered. The distance-based hybrid clustering approach, which was designed in section 6.8 is used as in that case, it yielded good results. Also, to eventually compare the results obtained in both sections, using this method is most illustrative.



(a) worst-case response time-based cost optimization cluster 1 **(b)** worst-case response time-based cost optimization cluster 2

Figure 6.29: Worst-case response-based cost optimization for cluster 1 and cluster 2



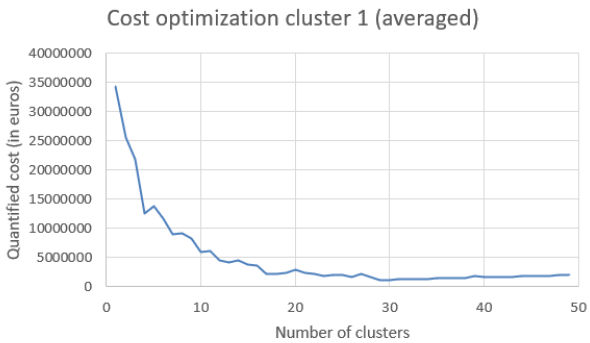
(a) Averaged response time-based cost optimization cluster 1 **(b)** Averaged response time-based cost optimization cluster 2

Figure 6.30: Averaged response time-based cost optimization for cluster 1 and cluster 2

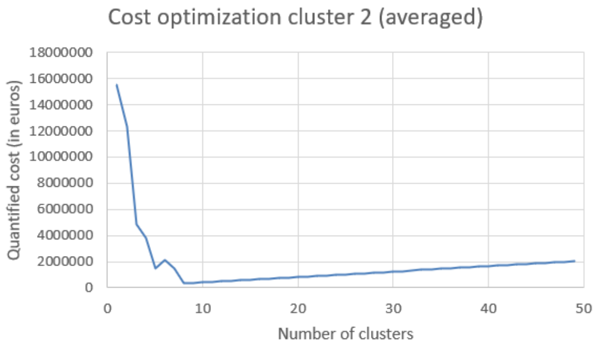
The course of the cost function in figure 6.30 is smoother than the course of this cost function in figure 6.29. This is because the averaged response time is much more resilient to fluctuations in the eventually selected response time. In the previous parts, the worst-case response time has frequently been used as a decision criterion. Therefore, in the further cost optimization analysis, the averaged response time is used as a decision criterion. This choice is made because it can be clarified to eventually compare the results obtained using the averaged response time here with the results that are obtained in the previous sections using the worst-case response time as a decision criterion.

In figure 6.30, it is assumed that if the averaged response time keeps decreasing, this results in the same cost decrease as was presented before. In reality, this won't be the case. When the response time gets sufficiently low, the gain that still can be made by lowering the response time becomes marginally small.

In the adjusted case, the value of life saved per minute of lower response time is considered to be stable until a response time of 2 minutes. For response times lower than 2 minutes, no cost decrease is achieved anymore, as the response time is already really low and further improvement won't result in a significantly higher chance of survival. The quantified cost as a function of the number of clusters in case the adjusted averaged response time is used is shown in figure 6.31.



(a) Adjusted averaged response time-based cost optimization cluster 1



(b) Adjusted averaged response time-based cost optimization cluster 2

Figure 6.31: Adjusted averaged response time-based cost optimization for cluster 1 and cluster 2

For both clusters, a rather clear minimum quantified cost is achieved in figure 6.31. From the course of the functions in figure 6.31 it is easier to observe a clear minimum value than in figure 6.30. However, in both cases, the main course of the functions is the same. For the number of clusters at which the minimum cost values are obtained in figure 6.31, it is observed that in figure 6.30, a plateau is reached for the values of the cost. However there, it is more difficult to select an optimal number of clusters that results in a minimum cost.

In case the adjusted averaged response time-based cost optimization is used, the resulting averaged response time, together with the number of infrastructure locations that are used in the solution is shown in table 6.25.

Cluster	Averaged response time (in min)	Infrastructure (new/initial)
Cluster 1	1.97	29 (6/23)
Cluster 2	1.86	8 (2/6)

Table 6.25: Optimal solution adjusted averaged response time-based cost optimization analysis

In total, there are 37 infrastructure locations used, of which 29 were initially present.

In section 6.8.1, using the distance-based hybrid clustering method with the worst-case response time as the decision criterion, 36 locations are selected, of which 25 were already present initially.

Comparing both results, it follows that almost the same amount of infrastructure locations are used. Also, in both cases, the majority of the infrastructure locations that are used are the ones that are initially present.

It can thus be concluded that both methods result in comparable solutions. The performed analysis, therefore, seems to be consistent.

7

Future Work

Some additional improvements or validations could be suggested to further fine-tune the designed approach. In this research, the designed approach is extensively applied to the case of Ghent. It could from that sense be interesting to investigate other cases for both larger and smaller cities to be able to extract or correct the results that are obtained in this research. For example, it could be interesting to investigate if there is a connection between the population distribution and the number of UAV base stations needed to serve all demand sufficiently.
Further on, advanced heuristics could be designed to let the clustering approach perform more efficiently or correct itself in case unacceptable solutions are obtained.

During the research, some assumptions were made to make the problem easier to solve. Some of these relaxations could in reality make the problem infeasible and therefore, the effect of leaving behind some of the relaxations could be interesting. Some of the considered relaxations that could be left behind are the following ones:

- The current model does not take into account further expansions in the urban environment under consideration. Shifts in population distribution could influence the optimal location of UAV base stations. Therefore, the model could be designed for the foreseen population distribution in the future, and weights could be assigned to both cases to make the solutions future-resistant. The same holds for including other aspects such as the distribution of the elderly around the city. Regions where more old people live, will probably require more emergency interventions.
- What if drones are not assumed to be sufficiently charged after a first intervention to respond to a new intervention? In this case, a hands-on charging strategy (such as battery swaps) or stand-by stations should be thought of.
- It is assumed that new UAV base stations can be located everywhere. In reality, this is not possible as some regions (such as parks and large buildings) are not suitable for UAV base stations. Therefore, introducing forbidden regions could complicate the solution.

In the clustering method, it is observed that in the case of small and dispersed clusters, the clustering method performs not too great. This is something that could be looked into in the future. It might be possible to design a slightly different model for these areas and then use this other model based on the number of data points per cluster or based on the rate of dispersion.

Finally, it could be interesting to further examine the enrolment of eUAM for other applications. In this research, the focus was directed on different emergency services, ranging from small to large UAVs. In future research, this research could be expanded to other applications such as package delivery or passenger transportation (not as ambulance services). In those cases, the focus will be directed more towards a cost perspective than towards achieving a low response time. Therefore, in investigating the feasibility of using UAVs in those other application areas, economic factors should certainly be studied in more detail. This is also why the cost optimization analysis was briefly touched on in this research. Expanding it for more UAV types and applications and studying it in more detail will result in a better judgment about the profitability of UAV usage in commercial applications.

8
Conclusion

The subject of the research conducted in this master thesis was to formulate a solution to the location-allocation problem for UAV base stations in an urban environment for emergency services. The goal was to analyze the demand in a whole urban environment and then allocate all the demand to UAV base stations, from where this demand is covered. In this master thesis, the focus was on designing a solution method that is applicable for the case of emergency services. Unlike other applications, for emergency services, covering the whole urban environment in a sufficiently low time is necessary as the first minutes are crucial for helping people who are in need.
More specifically, the urban environment that was considered is this of the city of Ghent. Lots of data are publicly available about this city and there is also a lot of initial infrastructure present that can be used as a starting point for setting up a network of UAV base stations

In solving this location-allocation problem, clustering is used to partition the demand data in clusters and allocate these demands to the corresponding cluster centers. In doing this, clustering methods are combined and used in a way such that a better-performing clustering method is achieved. This clustering method was fine-tuned for the basic case of Ghent, in which no initial infrastructure was present.
Afterward, more complicating aspects are investigated and added to the model. In doing this, the clustering method is adjusted to make sure it achieves to incorporate the additional effects adequately. In adjusting these clustering methods for more complicated cases, several options were considered and compared with each other to make sure the best possible clustering method is eventually selected. Finally, the results are combined for 3 UAV types, which differ in size and therefore have different applications within general emergency services.
Using a clever combination of initial and new infrastructure, which is solved by the best-proposed clustering approach, it is possible to achieve a network of UAV base stations from which all demand is served in a worst-case response time of about 3 minutes. Additionally, from a cost-based analysis, similar results are obtained offering an averaged response time of about 2 minutes. Notice that striving for a worst-case response time below 3 minutes is not optimal, as in that case, too many UAV base stations have to be added to achieve a quite small worst-case response time reduction.
Compared with traditional emergency services, eUAM offers a big improvement concerning achieved response times.

The relevance of this work lies in the fact that the obtained results indicate that it is possible to cover an urban environment using a reasonable amount of UAV base stations in a sufficiently low response time for emergency services. The proposed clustering method is applied to a real-life case and can be further verified in other real-life cases. It can also be used as a starting point to compare other methods and then use the results obtained in this work as a benchmark for future studies. Beyond the range of emergency services, the clustering method can also be used as a starting point to investigate the economic feasibility for other applications such as package delivery. However, the purpose will differ there which will require some adjustments in the clustering method.

As the location-allocation problem for UAV base stations in emergency service applications is certainly an important factor for the eventual deployment of eUAM on a large scale in urban environments, this research offers a step in the right direction. Even though there remain quite some questions to be answered in the area of eUAM, it is not unthinkable that soon, eUAM will already be deployed in the first urban environments. Hopefully, this will be the case for the city of Ghent as well.

Bibliography

[1] A. K. Jain, M. N. Murty, and P. J. Flynn, "Data clustering: A review," *ACM Comput. Surv.*, vol. 31, p. 264–323, sep 1999.

[2] Aurora consortium, *Technical Specifications (D 2.2)*, 2021. Version 1.0.

[3] N. McCarthy, "Traffic congestion costs u.s. cities billions of dollars every year [infographic]," Mar 2020.

[4] A. Milić, A. Randjelovic, and M. Radovanović, "Use of drones in operations in the urban environment," 10 2019.

[5] S. Watkins, J. Burry, A. Mohamed, M. Marino, S. Prudden, A. Fisher, N. Kloet, T. Jakobi, and R. Clothier, "Ten questions concerning the use of drones in urban environments," *Building and Environment*, vol. 167, p. 106458, 2020.

[6] S. Jafri, "4 reasons aeds aren't everywhere," Sep 2021.

[7] L. Cooper, "Location-allocation problems," *Operations Research*, vol. 11, no. 3, p. 331–343, 1963.

[8] A. Scott, "Location-allocation systems: A review," *Geographical Analysis*, vol. 2, pp. 95 – 119, 09 2010.

[9] A. M. Mestre, M. D. Oliveira, and A. P. Barbosa-Póvoa, "Location–allocation approaches for hospital network planning under uncertainty," *European Journal of Operational Research*, vol. 240, no. 3, pp. 791–806, 2015.

[10] H. D. Sherali and F. L. Nordai, "Np-hard, capacitated, balancedp-median problems on a chain graph with a continuum of link demands," *Mathematics of Operations Research*, vol. 13, no. 1, p. 32–49, 1988.

[11] L. Cooper, "Heuristic methods for location-allocation problems," *SIAM Review*, vol. 6, no. 1, pp. 37–53, 1964.

[12] D. Serra and V. Marianov, "The p-median problem in a changing network: the case of barcelona," *Location Science*, vol. 6, no. 1, pp. 383–394, 1998.

[13] M. Dzator and J. Dzator, "An effective heuristic for the p-median problem with application to ambulance location," *OPSEARCH*, vol. 50, no. 1, p. 60–74, 2012.

[14] F. Ndiaye, B. Ndiaye, and L. Idrissa, "Application of the p-median problem in school allocation," *American Journal of Operations Research*, vol. 02, pp. 253–259, 01 2012.

[15] N. Ramadhanti, A. Ridwan, and H. Pambudi, "Feasibility study of determination a new distribution warehouse location using p-median and analytical network process methods in one of the cement industries," *IOP Conference Series: Materials Science and Engineering*, vol. 982, p. 012057, 12 2020.

[16] J. Bendík, "Solving the p-median location problem with the Erlenkotter approach in public service system design," in *4th Student Conference on Operational Research* (P. C. D. Granado, M. Joyce-Moniz, and S. Ravizza, eds.), vol. 37 of *OpenAccess Series in Informatics (OASIcs)*, (Dagstuhl, Germany), pp. 25–33, Schloss Dagstuhl–Leibniz-Zentrum fuer Informatik, 2014.

[17] C. S. ReVelle and R. W. Swain, "Central facilities location," *Geographical Analysis*, vol. 2, no. 1, pp. 30–42, 1970.

[18] O. Kariv and S. L. Hakimi, "An algorithmic approach to network location problems. ii: The p-medians," *SIAM Journal on Applied Mathematics*, vol. 37, no. 3, pp. 539–560, 1979.

[19] S. C. Narula, U. I. Ogbu, and H. M. Samuelsson, "An algorithm for the p-median problem," *Operations Research*, vol. 25, no. 4, pp. 709–713, 1977.

[20] P. Järvinen, J. Rajala, and H. Sinervo, "A branch-and-bound algorithm for seeking the p-median," *Operations Research*, vol. 20, no. 1, pp. 173–178, 1972.

[21] N. Mladenovic, J. Brimberg, P. Hansen, and J. Moreno-Pérez, "The p-median problem: A survey of metaheuristic approaches," *European Journal of Operational Research*, vol. 179, pp. 927–939, 02 2007.

[22] O. Alp, E. Erkut, and Z. Drezner, "An efficient genetic algorithm for the p-median problem," *Annals of Operations Research*, vol. 122, pp. 21–42, 09 2003.

[23] S. Rahman and D. Smith, "Use of location-allocation models in health service development planning in developing nations," *European Journal of Operational Research*, vol. 123, pp. 437–452, 06 2000.

[24] C. Toregas, R. Swain, C. ReVelle, and L. Bergman, "The location of emergency service facilities," *Operations Research*, vol. 19, no. 6, pp. 1363–1373, 1971.

[25] R. Church and C. ReVelle, "The maximal covering location problem," *Papers of the Regional Science Association*, vol. 32, no. 1, p. 101–118, 1974.

[26] C. ReVelle, C. Toregas, and L. Falkson, "Applications of location set-covering problem," *Geographical Analysis*, vol. 8, pp. 65 – 76, 09 2010.

[27] J. M. Gleason, "A set covering approach to bus stop location," *Omega*, vol. 3, pp. 605–608, October 1975.

[28] M. Eben-Chaime and J. S. Pliskin, "Incorporating patient travel times in decisions about size and location of dialysis facilities," *Medical Decision Making*, vol. 12, no. 1, p. 44–51, 1992.

[29] S. Snyder and R. Haight, "Application of the maximal covering location problem to habitat reserve site selection: A review," *International Regional Science Review*, vol. 39, 09 2014.

[30] P. Yin and L. Mu, "Modular capacitated maximal covering location problem for the optimal siting of emergency vehicles," *Applied Geography*, vol. 34, pp. 247–254, 2012.

[31] B. Saeidian, M. S. Mesgari, B. Pradhan, and M. Ghodousi, "Optimized location-allocation of earthquake relief centers using pso and aco, complemented by gis, clustering, and topsis," *ISPRS International Journal of Geo-Information*, vol. 7, no. 8, 2018.

[32] G. Righini, "A double annealing algorithm for discrete location/allocation problems," *European Journal of Operational Research*, vol. 86, no. 3, pp. 452–468, 1995.

[33] A. T. Murray and R. L. Church, "Applying simulated annealing to location-planning models," *Journal of Heuristics*, vol. 2, no. 1, pp. 31–53, 1996.

[34] Y. Lin, H. Jia, Y. Yang, G. Tian, F. Tao, and L. Ling, "An improved artificial bee colony for facility location allocation problem of end-of-life vehicles recovery network," *Journal of Cleaner Production*, vol. 205, pp. 134–144, 2018.

[35] S. Salhi and M. Gamal *Annals of Operations Research*, vol. 123, no. 1/4, pp. 203–222, 2003.

[36] M. Ohlemüller, "Tabu search for large location–allocation problems," *Journal of the Operational Research Society*, vol. 48, pp. 745–750, July 1997.

[37] J. Brimberg, P. Hansen, N. Mladenović, and E. D. Taillard, "Improvements and comparison of heuristics for solving the uncapacitated multisource weber problem," *Operations Research*, vol. 48, no. 3, pp. 444–460, 2000.

[38] A. Ghodratnama, "Comparing three proposed meta-heuristics to solve a new p-hub location-allocation problem," *International Journal of Engineering*, vol. 26, Sept. 2013.

[39] V. Nasteski, "An overview of the supervised machine learning methods," *HORIZONS.B*, vol. 4, pp. 51–62, 12 2017.

[40] L. McInnes, "Topological methods for unsupervised learning," in *Geometric Science of Information* (F. Nielsen and F. Barbaresco, eds.), (Cham), pp. 343–350, Springer International Publishing, 2019.

[41] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement learning: A survey," *Journal of Artificial Intelligence Research*, vol. 4, p. 237–285, 1996.

[42] X. Zhu and A. B. Goldberg, "Introduction to semi-supervised learning," *Synthesis Lectures on Artificial Intelligence and Machine Learning*, vol. 3, pp. 1–130, Jan. 2009.

[43] S. K. Popat, "Review and comparative study of clustering techniques," 2014.

[44] F. Murtagh, "A Survey of Recent Advances in Hierarchical Clustering Algorithms," *The Computer Journal*, vol. 26, pp. 354–359, 11 1983.

[45] U. Kutbay *et al.*, "Partitional clustering," *Recent Applications in Data Clustering*, 2018.

[46] D. Bora and D. Gupta, "A comparative study between fuzzy clustering algorithm and hard clustering algorithm," *International Journal of Computer Trends and Technology*, vol. 10, pp. 108–113, 04 2014.

[47] S. Askari, "Fuzzy c-means clustering algorithm for data with unequal cluster sizes and contaminated with noise and outliers: Review and development," *Expert Systems with Applications*, vol. 165, p. 113856, 2021.

[48] Ş. Esnaf, T. Küçükdeniz, and N. Tunçbilek, *Fuzzy C-Means Algorithm with Fixed Cluster Centers for Uncapacitated Facility Location Problems: Turkish Case Study*, pp. 489–516. Berlin, Heidelberg: Springer Berlin Heidelberg, 2014.

[49] M. Bashiri, "A clustering based location-allocation problem considering transportation costs and statistical properties," *International Journal of Engineering Transactions B: Applications*, vol. 6, no. 26, 2013.

[50] R. Kumar, R. K. Chandrawat, B. P. Garg, and V. Joshi, "Comparison of optimized algorithms in facility location allocation problems with different distance measures," in *AIP Conference Proceedings*, Author(s), 2017.

[51] J. MacQueen *et al.*, "Some methods for classification and analysis of multivariate observations," in *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, vol. 1, pp. 281–297, Oakland, CA, USA, 1967.

[52] F. Yuan, Z.-H. Meng, H.-X. Zhang, and C.-R. Dong, "A new algorithm to get the initial centroids," in *Proceedings of 2004 International Conference on Machine Learning and Cybernetics (IEEE Cat. No.04EX826)*, vol. 2, pp. 1191–1193 vol.2, 2004.

[53] P. Drineas, A. Frieze, R. Kannan, S. Vempala, and V. Vinay, "Clustering large graphs via the singular value decomposition," *Machine Learning*, vol. 56, no. 1-3, p. 9–33, 2004.

[54] S. Na, L. Xumin, and G. Yong, "Research on k-means clustering algorithm: An improved k-means clustering algorithm," in *2010 Third International Symposium on Intelligent Information Technology and Security Informatics*, pp. 63–67, 2010.

[55] A. K. Jain and R. C. Dubes, *Algorithms for clustering data*. Prentice-Hall, Inc., 1988.

[56] K. Arvai, "K-means clustering in python: A practical guide," Jan 2021.

[57] J. C. Bezdek, *Pattern recognition with fuzzy objective function algorithms*. Springer Science & Business Media, 2013.

[58] J. C. Dunn, "A fuzzy relative of the isodata process and its use in detecting compact well-separated clusters," 1973.

[59] J. Bezdek, "Cluster validity with fuzzy sets," *Journal of Cybernetics*, vol. 3, 07 1973.

[60] X. Xie and G. Beni, "A validity measure for fuzzy clustering," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, no. 8, p. 841–847, 1991.

[61] M. Mohibullah, M. Hossain, and M. Hasan, "Comparison of euclidean distance function and manhattan distance function using k-mediods," *International Journal of Computer Science and Information Security*, vol. 13, pp. 61–71, 10 2015.

[62] T. Munandar and A. Musdholifah, "Comparative study between primitive operation complexity against running time application on clustering algorithm," *International Journal of Advanced Research in Computer Science*, vol. 5, pp. 164 – 169, 06 2014.

[63] V. Torra, "On the selection of m for fuzzy c-means.," in *IFSA-EUSFLAT*, 2015.

[64] F. Klawonn and F. Höppner, "An alternative approach to the fuzzifier in fuzzy clustering to obtain better clustering.," pp. 730–734, 01 2003.

[65] J. C. Bezdek, R. J. Hathaway, M. J. Sabin, and W. T. Tucker, "Convergence theory for fuzzy c-means: Counterexamples and repairs," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 17, no. 5, pp. 873–877, 1987.

[66] N. Pal and J. Bezdek, "On cluster validity for the fuzzy c-means model," *IEEE Transactions on Fuzzy Systems*, vol. 3, no. 3, pp. 370–379, 1995.

[67] M. Huang, Z. Xia, H. Wang, Q. Zeng, and Q. Wang, "The range of the value for the fuzzifier of the fuzzy c-means algorithm," *Pattern Recognition Letters*, vol. 33, no. 16, pp. 2280–2284, 2012.

[68] V. Schwämmle and O. N. Jensen, "A simple and fast method to determine the parameters for fuzzy c–means cluster analysis," *Bioinformatics*, vol. 26, pp. 2841–2848, 09 2010.

[69] T. S. Madhulatha, "An overview on clustering methods," *arXiv preprint arXiv:1205.1117*, 2012.

[70] F. Liu and Y. Deng, "Determine the number of unknown targets in open world based on elbow method," *IEEE Transactions on Fuzzy Systems*, vol. 29, no. 5, pp. 986–995, 2021.

[71] D. Marutho, S. Hendra Handaka, E. Wijaya, and Muljono, "The determination of cluster number at k-mean using elbow method and purity evaluation on headline news," in *2018 International Seminar on Application for Technology of Information and Communication*, pp. 533–538, 2018.

[72] T. Kodinariya and P. Makwana, "Review on determining of cluster in k-means clustering," *International Journal of Advance Research in Computer Science and Management Studies*, vol. 1, pp. 90–95, 01 2013.

[73] D.-W. Kim, K. H. Lee, and D. Lee, "On cluster validity index for estimation of the optimal number of fuzzy clusters," *Pattern Recognition*, vol. 37, no. 10, pp. 2009–2025, 2004.

[74] C. Shi, B. Wei, S. Wei, W. Wang, H. Liu, and J. Liu, "A quantitative discriminant method of elbow point for the optimal number of clusters in clustering algorithm," 08 2020.

[75] H. Sun, S. Wang, and Q. Jiang, "Fcm-based model selection algorithms for determining the number of clusters," *Pattern Recognition*, vol. 37, no. 10, pp. 2027–2037, 2004.

[76] A. S. Fotheringham, P. J. Densham, and A. Curtis, "The zone definition problem in location-allocation modeling," *Geographical Analysis*, vol. 27, no. 1, pp. 60–77, 1995.

[77] E. L. Hillsman and R. Rhoda, "Errors in measuring distances from populations to service centers," *The Annals of Regional Science*, vol. 12, no. 3, p. 74–88, 1978.

[78] M. F. Goodchild, "The aggregation problem in location-allocation," *Geographical Analysis*, vol. 11, no. 3, pp. 240–255, 1979.

[79] M. S. Daskin, A. E. Haghani, M. Khanal, and C. Malandraki, "Aggregation effects in maximum covering models," *Annals of Operations Research*, vol. 18, no. 1, p. 113–139, 1989.

[80] "Safe urban air mobility for european citizens," 2020. Consulted on 22 April 2022 via https://research.ugent.be/web/result/project/76d39427-a892-463f-91ce-04c1ae0af568/details/nl.

[81] Quan, *Introduction to Multicopter Design and Control*. Singapore: Springer, 1 ed., July 2017.

[82] I. Heyndrickx, "Meer gentenaars, minder overlijdens en minder scheidingen," 2022. Consulted on 22 April 2022 via https://stad.gent/nl/over-gent-stadsbestuur/nieuws-evenementen/meer-gentenaars-minder-overlijdens-en-minder-scheidingen.

[83] Stad Gent, "Statistische sectoren gent," 2022. Consulted on 24 March 2022 via https://data.stad.gent/explore/dataset/statistische-sectoren-gent/table/.

[84] Stad Gent, "Bevolkingsaantal per wijk per jaar gent," 2022. Consulted on 24 March 2022 via https://data.stad.gent/explore/dataset/bevolkingsaantal-per-wijk-per-jaar-gent/table/?sort=-period.

[85] Geopunt Vlaanderen, "Lambert 2008," 2019. Consulted on 29 April 2022 via https://www.geopunt.be/voor-experts/lambert-2008.

[86] "Aed's in gent," 2019. Consulted on 23 April 2022 via https://www.google.com/maps/d/u/0/viewer?ie=UTF8&view=map&oe=UTF8&msa=0&mid=1KjRx0Bes60GaiFQ86swmXxSxtGE&ll=51.04462616152806%2C3.711491630117947&z=12.

[87] Stad Gent, "Laadpalen wagens-gent," 2022. Consulted on 23 April 2022 via https://data.stad.gent/explore/dataset/laadpalen/information/?location=12,51.05585,3.75904&basemap=jawg.streets.

[88] L. Verledens, "Dit zijn de duurste en goedkoopste gemeenten voor huizen," Apr 2020. Consulted on 15 May 2022 via https://trends.knack.be/economie/immo/dit-zijn-de-duurste-en-goedkoopste-gemeenten-voor-huizen/article-normal-1777437.html.

[89] U.S. Department of Energy, "Charging infrastructure procurement and installation." Consulted on 24 May 2022 via https://afdc.energy.gov/fuels/electricity_infrastructure_development.html.

[90] U.S. Department of Energy, "Charging infrastructure operation and maintenance." Consulted on 24 May 2022 via https://afdc.energy.gov/fuels/electricity_infrastructure_maintenance_and_operation.html.

[91] AED Brands, "Aed buyer's guide: Defibrillator prices amp; comparison," May 2022. Consulted on 15 May 2022 via https://www.aedbrands.com/aed-buyers-guide/#:~:text=How%20Much%20Does%20an%20AED,or%20pads%20the%20device%20uses.

[92] E. Maria, E. Budiman, Haviluddin, and M. Taruk, "Measure distance locating nearest public facilities using haversine and euclidean methods," *J. Phys. Conf. Ser.*, vol. 1450, p. 012080, Feb. 2020.

[93] P. Sharma, "Distance metrics: Different distance metrics in machine learning," Apr 2020.

[94] J. Bezdek, "Mathematical models for systematics and taxonomy," 01 1975.

[95] F. Murtagh and P. Contreras, "Algorithms for hierarchical clustering: an overview," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 2, pp. 86–97, Jan. 2012.

[96] Scikit-learn developers, "Comparing different hierarchical linkage methods on toy datasets," 2007-2022. Consulted on 29 March 2022 via https://scikit-learn.org/stable/auto_examples/cluster/plot_linkage_comparison.html.

[97] J. P. Pell, "Effect of reducing ambulance response times on deaths from out of hospital cardiac arrest: cohort study," *BMJ*, vol. 322, pp. 1385–1388, June 2001.

[98] T. J. Kniesner and W. K. Viscusi, "The value of a statistical life," July 2019.

[99] T. R. Miller, "Variations between countries in values of statistical life," *Journal of Transport Economics and Policy*, vol. 34, no. 2, pp. 169–188, 2000.

[100] Belgische Cardiologische Liga, "Hartinfarct," Apr 2020. Consulted on 15 May 2022 via https://liguecardioliga.be/hartinfarct/.

[101] Statbel, "Structuur van de bevolking," 2021. Consulted on 24 April 2022 via https://statbel.fgov.be/nl/themas/bevolking/structuur-van-de-bevolking.

[102] Medical News Bulletin, "What is the average emergency response time?," Mar 2021. Consulted on 9 May 2022 via https://medicalnewsbulletin.com/response-time-emergency-medical-services/#:~:text=The%20average%20emergency%20response%20time%20for%20the%20arrival%20of%20EMS,million%20911%20calls%20every%20year.

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