Optimizing the Deployment of Automated External Defibrillators by a Data-Driven Algorithmic Approach

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Preface

I am proud to present my master's thesis, which has the unique honor of exhilarating me at this point practically as much as at the very beginning almost a year ago. The project has also the more questionable honor of deviously installing an AED detector in my body, as I suddenly see AEDs everywhere. And of course, I'm sure they are not where they should be!

Naturally, these wonders would never exist without the many people that were involved to some extent. I'd like to start with thanking the people from the AMC who collaborated with me and provided the necessary data. I greatly respect the work they do and I am honored of doing my part and (hopefully) contributing to society.

Then, although often taken for granted, I came to appreciate the power of current technology. I still remember how I would cut nice pictures from magazines and glue them in my reports many years ago... Now, I have programmed almost 5000 lines of code that could potentially help hundreds of people survive a cardiac arrest, while a few years ago, I wouldn't understand any of these lines. Without the computer and the Internet at my fingertips, I'm sure that this report and its results wouldn't be anything like they are in the current forms.

Moving on the really important parts — first and foremost, I'd like to thank my supervisor Derya who introduced me to the topic at the time when I almost gave up on finding a "really inspiring and challenging" graduation project. Although I tend to do "everything" (and eventually not the right thing) when I'm enthusiastic, she helped me staying on the right path during the entire journey.

I wouldn't be half as proud of this work if not for my second supervisor Johann, who effortlessly found some logic in the chaos that I wrote in the mathematical chapter. Although reading dozens of articles improved my ability to decipher the mathematical hieroglyphs, he helped me to actually write in logical, beautiful definitions. Nevertheless, Johann advised once to not *"write philosophically, but mathematically"*. I will oppose him for once, and remember Confucius: *"To put the world right in order, we must first put the nation in order; to put the nation in order, we must first put the family in order; to put the family in order, we must first cultivate our personal life; we must first set our hearts right."*

What I want to say is that everything would be so much harder, if not impossible, when your family and loved ones are not around. Therefore, I'd like to thank those people, who are the most important things in life, for their unconditional love, support and for just being with me.

— *Arthur Nazarian*

Summary

Treating out-of-hospital cardiac arrests (OHCAs) is extremely challenging due to their unpredictability and urgency of intervention. Despite exhaustive efforts and resources put into programs for responding to OHCAs, outcomes remain disappointing. However, the usage of public automated external defibrillators (AEDs) enables bystanders to treat OHCAs prior to the arrival of emergency medical responders and consequently improves survival outcomes. Nevertheless, the parallel observation that AEDs are used less frequently than desired seems to be due to insufficient public awareness, lack of bystander willingness and the absence of data-driven methods in choosing AED locations. Although the first two aspects are recently improved by incorporating systems where registered and willing civilian responders are guided to aid during an OHCA, the lack of data-driven methods in choosing effective AED locations has not been sufficiently tackled yet. Only recently, studies emerged suggesting methods for deploying AEDs with mathematical optimization techniques based on historic incidences of OHCAs.

With this research, we contribute to existing literature by proposing a comprehensive and efficient prescriptive optimization method that guides the deployment of AEDs. In addition to using a binary coverage function where an AED is considered to be either fully covered or not covered at all, we incorporate a decaying coverage function that realistically follows survival distributions in our algorithm. We do so by applying the generalized maximum coverage location problem (GMCLP) to the AED deployment problem. Our methodology accounts for the uncertainty of future cardiac arrest locations and incorporates the creation of candidate locations for AED placement. The latter enables controlling the granularity of possible AED locations and consequently affects the solution quality. The proposed heuristic optimization methods comprise an efficient and effective Greedy heuristic and a more complex hybrid algorithm that is based on a combination of the Greedy Randomized Adaptive Search Procedure (GRASP) and Simulated Annealing (SA). We extended GRASP with with "parameterized regret-based random sampling" to be able to control the placement of AEDs at more promising locations. SA is extended with "reannealing", which enables exploring neighborhood solutions in the proximity of the configuration that is found by the regular SA algorithm to possibly further improve the solution. Finally, we show that given the same computational resources, the combination of a high-density candidate locations with the Greedy algorithm outperforms more effective but complex methods with lower density candidate locations.

We employ the proposed methodology to the North Holland and Twente regions in the Netherlands using real data from an established cardiac arrest registry. By relocating existing AEDs in 43 municipalities in the study area, we show that the average proportion of instances where an AED can be retrieved within the first critical 6 minutes can be improved from 47.2 % to 68.5 %. Using the more realistic decaying coverage function, the coverage of future cardiac arrests improves by 73.5 %. In addition, we compute an approximation of the set covering location problem (SCLP) that shows how many AEDs are needed to cover all cardiac arrests within 6 min. We find median numbers of AEDs of 135 (interquartile range (IQR): 78–208) and 227 (IQR: 180–309) per municipality in North Holland and Twente respectively, while on average 19.0 % and 23.5 % of these numbers of AEDs are currently present.

This study is the first to utilize data-driven heuristic optimization techniques for allocating AED locations in the Netherlands. With the proposed methodology, we suggest that AEDs can be retrieved and applied to cardiac arrest victims within shorter time frames more often. Consequently, the implications are that more beneficial survival outcomes can be expected.

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List of Abbreviations

Notation	Description	Page List
ACLS	advanced cardiovascular life support	4
AED	automated external defibrillator	2–15, 17–20, 29, 31–37, 39–42, 44–55, 57–60, 63–76, 78
AMC	Academic Medical Center	31
ARREST	AmsteRdam REsuscitation STudies	31–33, 36
BLS	basic life support	5, 10
CI	confidence interval	35, 45
CL	candidate list	23, 24
CoSTR	International Consensus on Cardiopulmonary Resuscitation and Emergency Cardiovascular Care Science With Treatment Recommendations	5
CPR	cardiopulmonary resuscitation	1, 3–5, 8, 11, 12, 33, 34, 47, 73
CRS	civilian response system	4, 5, 8, 11, 12, 15, 32–37, 46, 48–50, 78
CVD	cardiovascular disease	1, 34
DHA	Dutch Heart Association	34, 35, 37, 45–47, 49, 74
EMS	emergency medical services	3, 4, 7, 11, 32, 47, 49, 74, 78
ERC	European Resuscitation Council	1, 5, 12, 13, 33, 42, 58, 73
FR	first responder	4, 32, 46, 47, 49, 78

Notation	Description	Page List
GA	Genetic Algorithm	11, 13, 22
GGD	Gemeentelijke Gezondheidsdienst	49
GIS	geographical information system	9, 10, 42
GMCLP	generalized maximum coverage location problem	18, 20–22, 29, 30, 73
GPS	Global Positioning System	5
GRASP	Greedy Randomized Adaptive Search Procedure	6, 22–26, 30, 58–63, 73, 76
ILCOR	International Liaison Committee on Resuscitation	5
ILP	integer linear program	10, 19, 58
IQR	interquartile range	32, 44, 46–48, 58, 65, 66, 72, 74
KDE	Kernel Density Estimation	9, 39, 41–45, 55, 58, 66, 68, 69, 75, 77
LB	lower bound	22, 57, 58
LP	linear program	19, 20, 58
LR	Lagrangian Relaxation	22
MCLP	maximum coverage location problem	8, 10, 11, 17–22, 29, 65, 70
mDFB	manual defibrillator	4, 48
NP	non-deterministic polynomial-time	14, 20, 29
OHCA	out-of-hospital cardiac arrest	1–3, 5–15, 17, 18, 31, 32, 34, 36, 39–42, 44–47, 49, 50, 52, 55, 58, 59, 63, 65–67, 71, 73–75, 78, 79
PAD	public access defibrillation	3, 35
RAF	regional ambulance facility	31, 32, 47, 74
RCL	restricted candidate list	23, 24, 26, 60

Notation	Description	Page List
SA	Simulated Annealing	6, 22, 23, 26–30, 59–61, 73, 76
SCLP	set covering location problem	8, 70–72, 74
SMS	short message service	5
TS	Tabu Search	22
UAV	unmanned arial vehicle	78
UB	upper bound	19, 57, 58
UTM	Universal Transverse Mercator	44
VF	ventricular fibrillation	2
VT	ventricular tachycardia	2
WGS84	World Geodetic System 1984	43, 44

List of Nomenclature

Notation	Description	Page List
$C(s)$	Objective value of solution s	23
$F(s)$	Set of locations with a placed facility in solution s	24
J_i^*	Variable denoting the facility placed at location j that is assigned to cover demand i	21, 22
$N(s)$	Neighborhood solution with respect to solution s	24, 27
R	Radius — distance from the center of a circle to any point on its circumference or the distance from the centroid of a polygon to a vertex.	53–55, 58, 62–66, 70, 71
W_{ij}	Variable denoting the amount of coverage that demand node i receives from a facility at location j at some nonzero level	19
Y_j	Variable denoting whether a facility is placed at location j	19
α	Parameter denoting the factor with which the RCL is determined	23, 24, 58–60
β	Parameter denoting the factor that determines the extent of the bias in choosing certain elements from a set	25, 58–60
χ	Parameter denoting the quantity of facilities that have to be deployed	19–21, 23, 24, 26
δ_c	Parameter denoting "cooling" factor with which the temperature is decreased after k number of iterations in the Simulated Annealing algorithm	27, 59
δ_h	Parameter denoting "heating" factor with which the temperature is increased when the reannealing process starts in the Simulated Annealing algorithm	29, 59

Notation	Description	Page List
η	Parameter denoting the factor with which the decaying rate of an exponentially decreasing function is determined	50
κ	Parameter denoting the number of Markov chains that are executed per temperature in the Simulated Annealing algorithm	27–29, 59
λ	Parameter denoting the number of iterations where no new neighborhood solutions are accepted	28, 59
$\mathcal{I}$	Set of demand nodes i that need to be covered by a facility	18, 19, 21, 23, 24, 28, 39, 41, 45, 51, 54, 55
$\mathcal{I}^t$	Set of simulated demand nodes ($i \in \mathcal{I}$) to train the model	39, 45, 55, 58, 62–65
$\mathcal{I}^v$	Set of simulated demand nodes ($i \in \mathcal{I}$) to validate (test) the model	39, 45, 55, 63
$\mathcal{I}_j$	Set denoting demand nodes ($i \in \mathcal{I}$) that can be covered by a facility at location j	21, 55
$\mathcal{I}_j^*$	Set denoting demand ($i \in \mathcal{I}_j$) that is assigned to be covered by a placed facility at location j	20–22
$\mathcal{J}$	Set of facility locations j	19, 21, 23, 24, 28, 39
$\mathcal{J}^c$	Set of potential locations ($j \in \mathcal{J}$) for placing a facility	18, 19, 23, 25, 40, 51, 54, 55, 58, 63
$\mathcal{J}^e$	Set of of existing facilities locations ($j \in \mathcal{J}$)	18
$\mathcal{J}_i$	Set of candidate locations ($j \in \mathcal{J}^c$) for facilities that are able to cover demand in $\mathcal{I}$	20, 55
$\mathcal{S}$	Set of solutions s in an algorithm	23
$NF(s)$	Set of locations with no placed facility in solution s	24
T	Parameter denoting the current temperature in the Simulated Annealing algorithm	27, 28
T_0	Parameter denoting the starting temperature in the Simulated Annealing algorithm	27, 28, 59–61
p_{accept}	Variable denoting the probability of accepting a neighborhood solution	27, 28
p_j	Variable denoting the probability of selecting element j	25

Notation	Description	Page List
r	Parameter denoting the number of reannealing processes that are performed in the Simulated Annealing algorithm	28
ψ_j	Variable denoting the priority of element j	25
θ	Parameter denoting the total number of solutions that an algorithm creates	23
φ_i	Variable denoting the coverage that demand node i receives in the current solution	21, 22, 58
φ_j^0	Variable denoting the total potential coverage that a facility can add tot the current solution if it would be placed at location j	21–26
φ_j^1	Variable denoting the actual total coverage that a facility that is placed at location j provides in the current solution	21, 22
c_{ij}	Parameter denoting the extent of coverage demand node i receives by a facility at location j	19, 21, 40, 50, 51, 55, 62
d_{ij}	Parameter denoting the shortest distance from location j to demand node i	18, 66
n^*	Parameter denoting the number of simulation iterations of the validation phase of optimization	45, 63, 64
r_1	Parameter denoting the length of the inner coverage radius of a facility	18, 50, 66
r_2	Parameter denoting the length of the outer coverage radius of a facility	18, 50, 66, 70
s'	Variable denoting the objective value of the current solution at a certain phase in an algorithm	24, 27
s^*	Variable denoting the best solution found so far at a certain phase in an algorithm	23, 24

Chapter 1

Introduction

1.1 Out-of-hospital cardiac arrests

Cardiovascular diseases (CVDs) are the leading cause for global mortality, being responsible for more than 17 million deaths annually (World Organization. World Heart Federation. World Stroke Organization, 2011). The number of patients who experience an out-of-hospital cardiac arrest (OHCA) has been reported to be 350 000–700 000 in Europe per year (Perkins, Handley, et al., 2015). A successful resuscitation is uncommon; a recent large scale study which included 27 nations found that only 5–30 % of persons are discharged alive from the hospital in Europe (Gräsner et al., 2016), while globally this number is as low as 1 % (Mehra, 2007). Hence, OHCAs are lethal in most cases (Weisfeldt et al., 2010).

Unfortunately, these statistics are not expected to improve substantially due to increasing rates of heart failure, the ageing of population in industrialized nations, and the growing prevalence of CVDs in developing countries (Keller & Halperin, 2015; World Organization. World Heart Federation. World Stroke Organization, 2011). Accordingly, it is concluded that OHCA is still a major health problem (Berdowski, Berg, Tijssen, & Koster, 2010; Gräsner et al., 2016).

Cardiac arrest is defined as "cessation of cardiac mechanical activity as confirmed by the absence of signs of circulation" (Jacobs et al., 2004, p.3387). In other words, it occurs when the heart stops pumping blood consistently due to abnormal heart rhythms. However, successful resuscitation (i.e. survival to hospital discharge) is possible and depends on several aspects as highlighted by the "chain of survival" of the European Resuscitation Council (ERC), as illustrated in Figure 1.1 (Perkins, Handley, et al., 2015):

1. early emergency activation,
2. early cardiopulmonary resuscitation (CPR),
3. early defibrillation,
4. timely and appropriate advanced care.

Approximately half of the people experiencing an OHCA have a shockable heart rhythm,

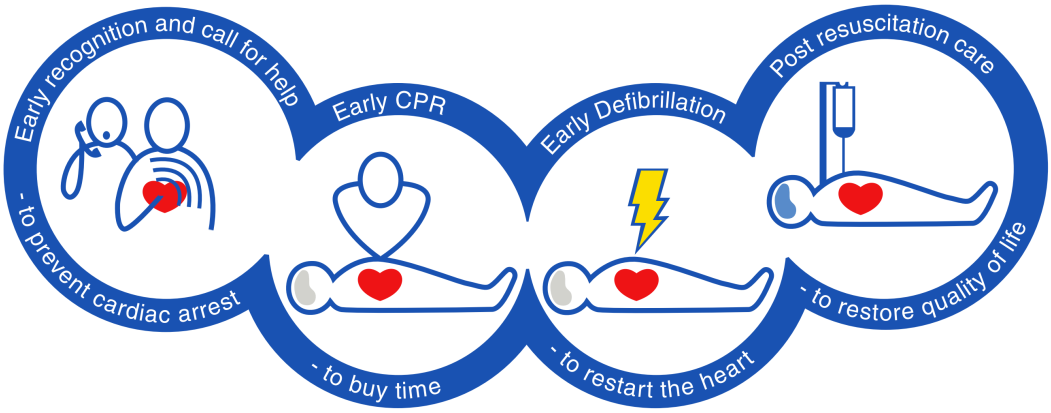


Figure 1.1: The chain of survival of OHCA. ©2015 from Perkins, Handley, et al.

i.e. ventricular fibrillation (VF) or ventricular tachycardia (VT) (Blom et al., 2016). For them, defibrillation — giving a shock — is of utter importance for survival as it has a chance to "reset" the heart to a regular rhythm. Defibrillation within 3–5 min after collapse can result in survival rates as high as 50–70 % (Berdowski et al., 2011; Blom, Beesems, et al., 2014; Ringh, Rosenqvist, et al., 2015; Valenzuela et al., 2000). The quality of life of OHCA survivors in general is good (Smith, Andrew, Lijovic, Nehme, & Bernard, 2014; van Alem, Waalewijn, Koster, & de Vos, 2004), while bystander defibrillation decreases the risk on brain damage and nursing home admission even further (Kragholm et al., 2017).

However, each minute of delay of defibrillation reduces the probability of survival to discharge by 10 % (Valenzuela, Roe, Cretin, Spaite, & Larsen, 1997). The larger the distance to a defibrillator, the longer it takes to retrieve the device and the more time passes before defibrillation can be applied to the OHCA patient. This implies that survival and therefore the "coverage" of an OHCA by a defibrillation device decreases as a function of distance (De Maio, Stiell, Wells, & Spaite, 2003; Larsen, Eisenberg, Cummins, & Hallstrom, 1993; Valenzuela et al., 1997; Waalewijn, De Vos, Tijssen, & Koster, 2001).

1.2 The Automated External Defibrillator

Since the development of the automated external defibrillator (AED) (Figure 1.2) by Diack, Welborn, Rullman, Walter, and Wayne (1979), the mobile device has seen considerable and successful usage specifically in recent years. An AED automatically assesses the cardiac rhythm and delivers an appropriate, potentially lifesaving defibrillation. The success of the usage of the device lies in the fact that it is safe and effective when used by lay responders with minimal or no training (Yeung, Okamoto, Soar, & Perkins, 2011). Even usage by children older than 8 years is considered to be appropriate (Akahane et al., 2013; Johnson et al., 2014; Mitani et al., 2013).

It has been widely reported that improved survival and neurological status at discharge are associated with the use of public access (or "on-site") AEDs for OHCA victims (Bækgaard et al., 2017; Hallstrom, 2004; C. M. Hansen, Kragholm, Pearson, et al., 2015; C. M. Hansen et al., 2017; Kitamura et al., 2010; Kragholm et al., 2017; Nakahara et al., 2015; Nielsen, Folke, Lippert, & Rasmussen, 2013; Ringh, Rosenqvist, et al., 2015). One of the largest studies has been performed by Kitamura et al. (2016) in Japan, where almost 44 000 OHCA instances with survival data were analyzed from 2005–2013. The research showed a 15-fold increase of AED usage, and at the same time an increase from 6 to 201 survivors whose survival with a favorable neurologic outcome was attributed to public access defibrillation (PAD). In the Netherlands it has also been statistically proven that the increase of survival can be explained for a considerable part by the growing usage of the AED (Berdowski et al., 2011; Blom, Beesems, et al., 2014). Zijlstra, Radstok, et al. (2016) widened the research by comparing six Dutch regions, and confirmed that a lower usage of AEDs translates to lower survivability in the region.

Interestingly, while research on the independent contributions of bystander CPR has shown a positive association with long-term survival — e.g. as recommended in the "chain of survival" (Figure 1.1) — Capucci et al. (2016) proved the effectiveness of *exclusively* on-site AEDs by avoiding bystander CPR usage during a 13-year long PAD program.

Such indisputable efficacy of AEDs can be explained by the *quick access* to an AED and hence a decrease of the time to defibrilliation. In contrast, the arrival of emergency medical services (EMS) is often lethally late for most OHCA patients (Rea et al., 2010). Therefore, lay responders should perform CPR and apply defibrillation within the crucial first minutes after collapse (Bradley & Rea, 2011; C. M. Hansen, Kragholm, Granger, et al., 2015). For example, with typical ambulance arrival times of 10–12 min, the probability for survival would be very low, whereas a typical AED shock can be delivered by a lay responder at a time when

Figure 1.2: Automated External Defibrillator device

the probability of survival is 40–70 % (Caffrey, Willoughby, Pepe, & Becker, 2002; Page et al., 2000; Valenzuela et al., 2000).

Moreover, as the cells in the heart use a great quantity of energy during a cardiac arrest, the heart rhythm changes to asystole (non-shockable rhythm with no electrical activity) due to the depleting energy sources (Salcido, Menegazzi, Suffoletto, Logue, & Sherman, 2009). Empirical results show that more than 60 % of patients have a shockable rhythm when a defibrillator is connected within 6 min, whereas this proportion decreases to 40 % at 12 min (Hulleman et al., 2016). Therefore, not only can an AED that is retrieved by lay responders deliver a shock earlier than the EMS can and thus improve survival rates, it can do so at the time when there is a higher chance of being able to deliver a shock at all — improving survival rates even further.

It must also be noted that effective AED deployment is not solely of major benefit for the survivability of patients — the total costs per patient are also lower, mostly due to shorter in-hospital stay (Alem, 2003; Berdowski, Kuiper, Dijkgraaf, Tijssen, & Koster, 2010).

1.3 Civilian response system

Traditionally, bystanders have been limited to a line-of-sight area when retrieving AEDs or to an arbitrary and ineffective search for such device. Until recently, there have been no practical methods to either recruit willing and competent bystanders to a cardiac arrest victim or to more efficiently retrieve an AED.

In this study, we use real data from a registry in the Netherlands that is discussed in Section 3.1. In the Netherlands, a civilian response system (CRS) is currently implemented in practically every region. The particular CRS in the study area with available AED data is called "HartslagNu" (https://www.hartslagnu.nl). A CRS contains registered civilian responders (volunteers who can provide CPR and AED defibrillation for a cardiac arrest victim) and a registry for AEDs. The CRS is activated as part of the general EMS dispatching efforts in the Netherlands. In case of a medical emergency, people call the national emergency number and reach the dispatch center. When the dispatcher suspects a cardiac arrest,

1. two ambulances of a single tier, with each vehicle being equipped with a manual defibrillator (mDFB) and able to perform advanced cardiovascular life support (ACLS)[1] and manned by a paramedic and a driver who can perform CPR, are sent;
2. "first responders (FRs)", i.e. police and fire fighters[2], equipped with an AED, are sent

[1]Besides performing CPR and defibrillation, ACLS involves the use of adjunctive equipment and drugs to further stabilize and manage a victim of cardiac arrest ("Chapter 32 - Preparation for Emergencies", 2018).

[2]According the CARES registry, FRs are defined as personnel "who respond to the medical emergency in an official capacity as part of an organized medical response team but are not the designated transporter of the patient to the hospital" (McNally et al., 2013, p.17). FRs are dispatched nationally in the Netherlands since 2010 (Beesems, Zijlstra, Stieglis, & Koster, 2012).

if they are located in the proximity of the OHCA;

3. the CRS is activated. In case of a suspected cardiac arrest, the CRS alerts registered volunteers by a short message service (SMS) or mobile application alert according to regional dispatch guidelines (Zijlstra, Pijls, et al., 2016). The CRS responders can be guided directly to the site of cardiac arrest, or can be first directed to collect the closest AED.

Figure 1.3 illustrates the workings of the particular CRS during the study period. When system is activated, all available AEDs and lay responders within a circle of 1000 m from the OHCA victim are identified [3]. Around each AED within this area, an additional circle with a radius of 500 m is generated within which alerted lay responders may be directed to retrieve the AED first ("responder (AED)" in Figure 1.3) and then head to the victim if this route is less than 5 % longer than a direct route to the victim. Otherwise, the lay responder is guided directly towards the victim to perform CPR ("responder (CPR)" in Figure 1.3). In total, a maximum of 30 registered lay responders are alerted via a text message or mobile application, from whom around two thirds is directed to an AED and the rest directly to the victim. If no AEDs are found, all lay responders are directed to the victim to perform CPR (*Hoe werkt een alarmering*, 2017).

There are a few reasons why CRS responders might not be dispatched. For instance, "no complete address known at moment of dispatch, an evidently non-cardiac cause, patient aged below eight years, ambulance or first responder nearby, or if an AED is already present" (Zijlstra et al., 2014, p. 1445).

The Dutch law allows anyone to apply an AED; however, to be part of the CRS, one must be at least 18 years old and must have finished a standard basic life support (BLS)/AED course according to the guidelines of the ERC[4], which should be renewed every two years (Berdowski et al., 2011). Registration of CRS responders is done via an online database and includes information such as contact details, specifications of BLS certificate, address and time when the responder is available (Zijlstra et al., 2014). Location information by Global Positioning System (GPS) can be enabled in the mobile application as well. Civilian responders are not obliged to act on an alert.

1.4 Research objective

Given the major potential impact that reducing defibrillation times can have on thousands of OHCA victims per year, we pursue contributing in this regard. The focus of this thesis

[3] During 2016, a newer version of the CRS incorporated a dynamic distance that uses the road network. In that case, lay responders are identified who can travel to the victim's address with a speed of 15 km/h within 6 min (i.e. 1500 m).

[4] The ERC guidelines are based on the most recent International Liaison Committee on Resuscitation (ILCOR) 2015 Consensus on International Consensus on Cardiopulmonary Resuscitation and Emergency Cardiovascular Care Science With Treatment Recommendations (CoSTR) (Hazinski et al., 2015).

is on providing a prescriptive method that can aid in optimizing the placement of AEDs and consequently could positively affect survival rates. More specifically, we seek to provide a data-driven algorithmic technique to efficiently solve the "AED deployment problem" — where to place AEDs such that the defibrillation times to future cardiac arrests are minimized.

We develop heuristic optimization methods that can effectively and efficiently solve complicated problems instances. We start by creating a relatively simple Greedy algorithm for the problem, and then devise more complex algorithms that are based on the hybridization of Greedy Randomized Adaptive Search Procedure (GRASP) and Simulated Annealing (SA) with some extensions. As part of the data-driven method to prepare the necessary data for optimization, we create a spatial probability density function of the cardiac arrest risk that is used to simulate new OHCA instances that serve as the demand input for our algorithm. Concerning the supply side of the problem, we propose a scalable method to efficiently create candidate locations for AED placement by means of subdividing the area with hexagons. We show that precise AED placement (with a granular set of candidate locations) in combination with simpler heuristics is more effective than a coarser density of locations in combination with more complex solution techniques.

Ultimately, we apply to our methods to two vast areas in the Netherlands with real data from an established OHCA registry and show that the proposed methods are very effective in solving the AED deployment problem and thus minimizing the time to defibrillation.

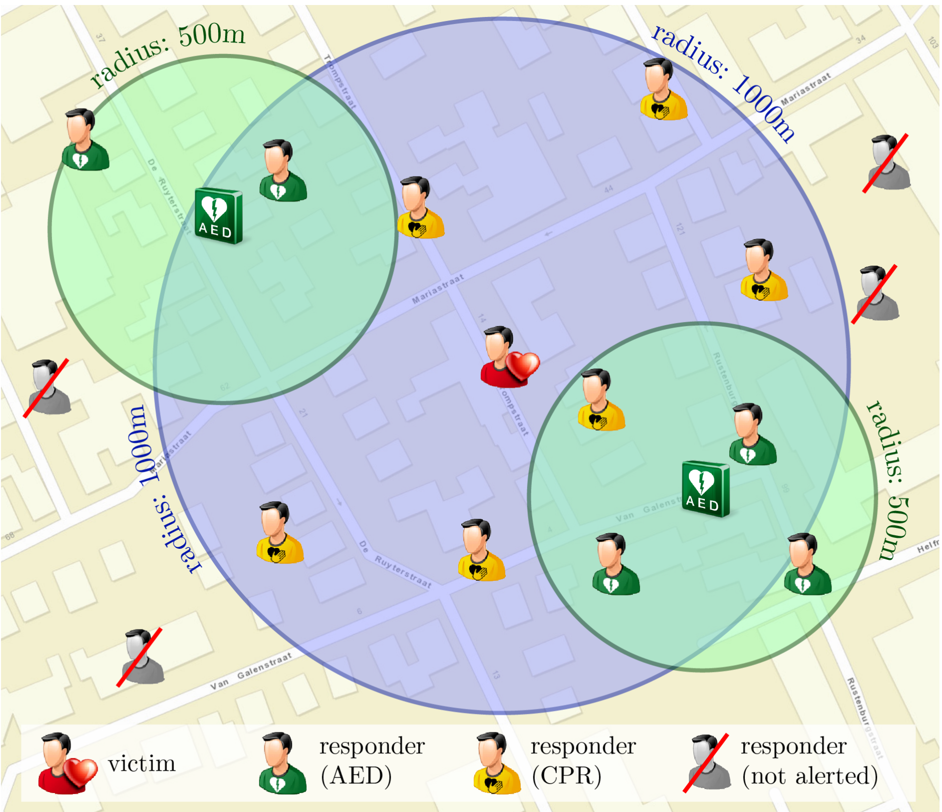


Figure 1.3: Specifics of the alert procedure of the civilian response system

1.5 Literature review

In this section we first describe how the AED location problem is formulated from a scientific perspective and then discuss previous work on the problem. Although there is substantial research on identifying areas that typically exhibit a higher probability of OHCA incidences, prescriptive methods that help in the actual and precise placement of AEDs is a relatively novel branch in academic literature. In Subsection 1.5.1 we introduce locations problems in general and then discuss specific AED research in Subsection 1.5.2. Lastly, Subsection 1.5.3 describes previous research on civilian response systems.

1.5.1 Location problems

Introduction to relevant location problems

The AED location problem belongs to the family of location problems, namely "facility location" or "location analysis", which have been numerously investigated by operations researchers. The key objective in those problems is to determine the locations of "facilities" with respect to "demand" and a distance function. Classical applications include locating EMS bases, fire and police stations, airline hubs, waste disposal sites, warehouses and many more. An extensive list of applications can be found in Hale and Moberg (2003).

Location problems can be categorized according to their location space: discrete, network or continuous (Eiselt & Marianov, 2011). In discrete models, the locations of facilities are restricted to to a pre-specified set of potential locations. These locations are "nodes" in network models, which are interconnected by arcs. Continuous models are more flexible as they seek to determine the locations anywhere on the plane; thus, there is an infinite number of potential locations for the facilities.

Another way to categorize location problems is according to the type of objective function: minisum (or "median problems"), minimax (or "center problems") and covering (Laporte, Nickel, & da Gama, 2015). In the minisum problem, new facilities are placed such that the weighted sum of the distances from demand locations to the nearest facility is minimized. The minimax problem minimizes the maximal weighted distance, which is often used for worst case analyses. Covering problems require demand locations to be within a specific given distance or time from facilities in order to be considered as "covered" by the facilities' service.

Regarding our AED problem and the location space, it can be considered as any of the three models. The difference between the continuous and discrete model is that the former can give better results due to not having the restriction of specific candidate locations. However, it is inherently harder to solve. The network model can be considered as a specific discrete model where candidate locations for AED placement and cardiac arrest locations are represented by nodes and the possible routes between these nodes are represented by arcs. However, realistically determining these routes can be extensive and challenging. Therefore, we model our AED problem as a discrete space model. Chapter 4 provides more insight into this choice.

In relation to the objective function, there is more clarity. In the AED location problem, there is a critical time and thus distance within which the demand (i.e. cardiac arrest) needs to be served if it is to be considered as covered by a facility (i.e. AED). Therefore, rather than using the distances between demand and facilities as variables that the minisum and minimax models utilize, the provided *coverage* to demand is of the essence. Hence, the problem falls into the covering models. This class can be further divided in three basic types: p-center problems, set covering problems, and maximal covering problems (Daskin, 2008).

The p-center problem seeks to place at most p facilities to minimize the maximum distance between all demand nodes and their assigned facility (Hakimi, 1964, 1965). In the set covering location problem (SCLP), the objective is to minimize the number of opened facilities subject to covering all demand (Toregas, Swain, ReVelle, & Bergman, 1971). The form of the maximum coverage location problem (MCLP) can be considered to be the inverse: maximizing the demand covered subject to a limited number of facilities that may be opened (Church & ReVelle, 1974). These models can all be used for the AED problem. However, the MCLP is more applicable to the real world as resources are often limited (hence, the number of facilities is pre-determined) and coverage is restricted to a certain time within which an OHCA victim should be defibrillated (hence, the coverage distance is pre-determined).

1.5.2 Relevant literature on AED deployment

Applying the facility location models to AEDs

Significant research in AED location problems only started in the last decade. Ahmadi-Javid, Seyedi, and Syam (2017) conducted an extensive survey of operations research studies in light of healthcare facility location that are published since 2004, and from the approximately 150 considered articles, only 5 % comprised "public access devices", while primary care facilities and ambulance stations were covered in 55 % of the articles. This may be due to the fact that translating classic facility location approaches to the AED deployment problem is not straightforward, as the location of an AED is not necessarily known by lay responders. Consequently, demand is not satisfied by the closest "facility" at all times, as is usually considered in conventional location problems. Traditionally, there is not necessarily a single lay responder who (omits giving CPR and) travels directly to an AED, nor does the responder travel to the closest AED by definition. This implies that the AED location problem presents a multiple-responder model that maximizes coverage in which more than one AED can contribute to the coverage of a cardiac arrest as, for example, proposed in Chan, Demirtas, and Kwon (2016). However, with the increasing usage of novel technologies that guide lay responders to a nearby AED such as the CRS (see Sections 1.3 and 1.5.3), some of these uncertainties can be alleviated as lay responder behavior can be predicted or even controlled to some extent.

Identifying high risk cardiac arrest locations

Prior to applying facility location problems to AEDs, one of the earliest streams in directing AED placement was by analyzing locations with high cardiac arrest risk (e.g. Becker, Eisenberg, Fahrenbruch, & Cobb, 1998; Brooks, Hsu, Tang, Jeyakumar, & Chan, 2013; Engdahl & Herlitz, 2005; Folke et al., 2009; Gratton, Lindholm, & Campbell, 1999; Fedoruk, Currie, & Gobet, 2002; Iwami et al., 2006; Murakami et al., 2014; Muraoka et al., 2006; Sun, Brooks, Morrison, & Chan, 2017). These studies typically identified specific building types that showed a higher cardiac arrest risk, for example airports, railway stations, nursing homes, playgrounds, golf courses and workplaces.

There are straightforward implications for AED deployment with this practice, as stakeholders can identify the pre-determined high-risk buildings easily in their particular region and develop partnerships with the building owners to place AEDs. However, a significant number of cardiac arrests occur outdoors (Fredman et al., 2016; Koster, 2013; Rea et al., 2010) and cannot be categorized under any building type, which diminishes the quality and realism of such method. Moreover, high-risk buildings are profoundly reliant on heterogeneous demographics and specific spatial characteristics and thus cannot be generalized accurately.

A more generalizable approach is to analyze the spatial distribution of historical OHCAs and then identify high risk areas. Many studies utilized geographical information system (GIS) methods to identify OHCA clusters (Chrisinger et al., 2016; Dahan et al., 2016; Lerner, Fairbanks, & Shah, 2005; Lin et al., 2016; Malcom, Thompson, & Coule, 2004; Moon et al., 2015; Ong et al., 2008; Raun, Jefferson, Persse, & Ensor, 2013; Sasson et al., 2012; Semple et al., 2013; Soo, Huff, Gray, & Hampton, 2001; Warden, Daya, & LeGrady, 2007). For instance, Moon et al. (2015) used Kernel Density Estimation (KDE) on OHCA and AED locations and found that their respective locations not necessarily coincide. Dahan et al. (2016) compared three strategies, namely placing AEDs at locations where an OHCA occurred every 5 years, a grid-based strategy and a strategy to place AEDs at a specific landmark. Somewhat differently, without using historical OHCA locations, C.-C. Chen and Chen (2017) used computer vision to detect human movement indoors to aid AED placement decisions.

These spatial methods are definitely an improvement on the building-only restriction to broadly identify focus for AED placement and to more effectively target interventions outdoors. However, in general, resources are limited and it is financially infeasible to install AEDs at each "high-risk" region. Alternatively, if resources do allow deploying AEDs in all high-risk regions, the challenge remains identify specific locations for AED placement within those regions. Also, outside those high-risk regions, there is no guidance to place AEDs at sites that are considered to possess a lower cardiac arrest risk. Therefore, it is of essence to determine a relevant subset of locations for AED placement that have the maximum impact on OHCA coverage. A prescriptive method for explicit and accurate AED deployment would be most useful.

Methods for guiding AED deployment

Mathematical models are able to improve upon the previously mentioned problem of not having a prescriptive framework for placing AEDs. One of the first mathematical approaches was by Mandell and Becker (1996), who proposed a multi-objective integer linear program (ILP) model by using overall survival and equity of survival rates to help selecting BLS units on which an AED should be placed. Rauner and Bajmoczy (2003) combined a decision model with an ILP model to eventually conclude that equipping all ambulances with AEDs is cost-effective.

Starting from 2009, research appeared on actual on-site AED placement — Myers and Mohite (2009) applied a MCLP model to optimize AED placement in a university community. By relocating two AEDs, they increased the coverage from 78 % to nearly 95 % while also reducing the additional number of AEDs from 5 to 2 to achieve a 100 % coverage. There are also studies incorporating "vertical" AED placement. Dao, Zhou, Thill, and Delmelle (2012) combined GIS and ILP to optimize AEDs in a multi-story academic building and Chan (2016) compared placing AEDs in elevators and lobbies to minimize the distance travelled to a cardiac arrest in a high-rise building. On a "regular" plane, Chan et al. (2013) established a data-driven MCLP approach where geographic clusters of cardiac arrests in Toronto (Canada) are identified and prioritized with the MCLP, which outperformed an intuitive population-based method. Siddiq, Brooks, and Chan (2013) used the same registry and approach but examined the effect of different AED coverage ranges and number of AEDs to be deployed. Sun, Demirtas, Brooks, Morrison, and Chan (2016) optimized AED placement in Toronto by taking into account both location and hours of operation of the buildings that AEDs were located in. The study predicted a 25 % improvement in actual coverage, with the greatest possible gain during nighttime, which corresponds with the time period where survival rates were worst. Chan et al. (2016) extended the research in Toronto by introducing realistic multi-responder models with a probabilistic extension of the MCLP with gradual coverage, and consequently improved coverage with as much as 40 %. Chan, Shen, and Siddiq (2017) used a row-and-column generation algorithm for deploying AEDs in public areas by using a conditional value-at-risk objective function to mitigate the risk of unacceptably long distances between cardiac arrest locations and their nearest AEDs. Finally, Kwon, Kim, Lee, Yu, and Huh (2017) used a GIS approach to improve AED deployment by including a pedestrian network dataset and network barriers in two urban districts in Seoul (South Korea).

In contrary to the previously mentioned studies, only few authors have used a heuristic approach. Tsai, Ko, Huang, and Wen (2012) used two spatially and temporally weighted models to consider the spatial and temporal characteristics of convenience stores and cardiac arrests in Taipei City (Taiwan) and used a Genetic Algorithm (GA) to solve the AED location problem. Bonnet, Gama Dessavre, Kraus, and Ramirez-Marquez (2015) applied the MCLP in an urban environment by using a multi-objective GA and incorporated both availability of AEDs and the number of AEDs as an objective function.

1.5.3 Prior literature on civilian response systems

All previously mentioned studies did not incorporate civilian response systems (CRSs), as described in Section 1.3. Knowing the location of AEDs greatly improves the time of retrieving the device (Riyapan & Lubin, 2016). The CRS facilitates a multitude of trained civilian responders to react to an OHCA by guiding them to the victim and also by helping them in retrieving an AED first. This enables a higher rate of CPR efforts by trained responders and a higher utilization of nearby AEDs. For example, without the usage of a CRS, Agerskov et al. (2015) found that in Copenhagen (Denmark) only 3.8 % of all OHCAs had an AED applied prior to ambulance arrival, although in 15.1 % instances an AED was present within 100 m of the cardiac arrest. Similar unfavorable results were found in Sweden even when using guidance by the dispatcher via phone to a nearby available AED (Fredman et al., 2016). However, quicker and clearer guidance with the use of mobile phone technology of a CRS could improve these results.

Prior studies utilizing mobile phone technology to improve bystander CPR and defibrillation efforts during an OHCA date back to 2011 and were performed in Sweden (Ringh, Fredman, Nordberg, Stark, & Hollenberg, 2011; Ringh, Rosenqvist, et al., 2015), Japan (Sakai et al., 2011; Yonekawa et al., 2014), Denmark (S. M. Hansen et al., 2015) the United States (Brooks, Simmons, Worthington, Bobrow, & Morrison, 2016) and Switzerland (Caputo et al., 2017). Most of the researches found improved CPR and defibrillation times, although some (mostly older) studies report opportunities for improvement concerning the implementation of the CRS. For instance, Sakai et al. (2011) found a significant improvement in travel distance when using the CRS, but this did not translate to a reduced time to retrieve an AED due to the additional time for operating the system.

The Netherlands was and is also active on the front of CRS development and research. Scholten, van Manen, van der Worp, IJzerman, and Doggen (2011) was one of the first to collect relevant information about using a CRS and used the same registry as our study in the first three months in 2010 in the region of Twente in the Netherlands. Per OHCA victim, of whom 84.6 % had the incident at home, an average of 62 civilian responders were alerted and 11 came into action. A few years later, Zijlstra et al. (2014) analyzed the functioning of the same CRS with the focus on response times and early defibrillation and expanded the study region to North Holland. They also found the CRS being very effective for residential OHCAs. In general, the time to connection was 2:54 shorter than the connection times by EMS. Most recently, the prospective registry study of Pijls, Nelemans, Rahel, and Gorgels (2016) assessed whether the usage of a CRS improves survival after OHCA in the province of Limburg in the Netherlands. The CRS' responders were the first to initiate CPR and defibrillation 25 % of the time, and the respective cardiac arrest victims had increased survival to hospital discharge when compared with those without civilian responders.

1.6 Motivation and contributions

In this section we describe the gaps in literature and practice that motivated this research with regards to AED deployment. Consequently, we end this chapter with stating the contributions that this research proposes and give an overview of the remainder of this work.

1.6.1 Potential for improving current AED locations

Despite the fact that the benefits for survival of using AEDs are unequivocal, the actual proportion of OHCAs with bystander applied AEDs is at times not significant. For instance, only 2.1 % of 13 769 OHCAs had an AED applied in North America (Weisfeldt et al., 2010), in Japan an AED shock was delivered in only 3.7 % cases (Kitamura et al., 2010), a study in Hampshire (England) reported 4.25 % successfully retrieved AEDs during 1035 confirmed cardiac arrests (Deakin, Shewry, & Gray, 2014) and a study in Toronto (Canada) found 8 % of cardiac arrests where a bystander AED was applied (Sun et al., 2016). Apparently, even with significant statewide interventions, increasing defibrillation rates by public AEDs proves to be challenging (C. M. Hansen, Kragholm, Pearson, et al., 2015).

The AED usage rates depend mostly on the amount of public awareness, the degree of bystander willingness and adequate placement of AEDs. Thus, improving these factors should yield more frequent usage and survival. Regarding the AED lcoations, the official guideline by the European Resuscitation Council (ERC) is that the placement of AEDs are considered to be cost-effective in areas where one cardiac arrest per 5 years can be expected (Monsieurs et al., 2015). However, this is often in contrast with actual practice. For example, Yoon, Jeong, Kwon, and Lee (2016) showed that while 99.5 % of AEDs in Busan Metropolitan City (South Korea) were well-maintained and in operable condition, the actual usage of an AED is once per 26.3 years in average due to placement in low-priority locations. Danish studies found that 94.6 % of all AEDs were placed in areas with low risk or no cardiac arrests at all in Copenhagen (C. M. Hansen et al., 2014) and an AED was located within 100 m only in 15.1 % of all cardiac arrest incidences (Agerskov et al., 2015). In Toronto 21.5 % of AEDs was inaccessible when needed (Sun et al., 2016). These studies all indicate the existing potential of improving AED network strategies.

A first step would be deploying more AEDs. However, plainly increasing the number of AEDs is not viable, as the placement of a large amount may be very costly if not managed properly and preceded by public awareness (Folke et al., 2009; Zorzi et al., 2014). Also, although Ringh, Jonsson, et al. (2015) reported a tremendous increase of public AEDs in Stockholm (Sweden), the proportion of public defibrillations increased only marginally in comparison. The authors regard aspects as "logistics" and "information" to be "more efficient than the spread of unregulated AEDs in terms of AEDs used" (p.6).

Thus, currently there is insufficient coordination of AED deployment efforts (Merchant & Asch, 2012). We mentioned the sole official guideline by the ERC of placing AEDs where cardiac arrest per 5 years can be expected. Unfortunately, such limited and equivocal guideline is hard to implement without quantifiable guidance. The ERC guidelines appropriately acknowledge that there is indeed a "knowledge gap" (Travers et al., 2015, p. S71) in regards to optimized AED deployment strategies.

1.6.2 Knowledge gaps

In addition to the practical opportunities for further improvement, we address the knowledge gaps in literature as follows:

Need for tractable solution approaches. Previously, Section 1.5.2 mentioned that most research on the AED deployment problem used exact methods. However, exact methods may be very costly regarding the required computational resources. For example, Chan et al. (2016) used a computer cluster for solving the exact mathematical models — something that stakeholders most likely will not possess. On the other hand, we found only two heuristic approaches to the AED problem by Tsai et al. (2012) and Bonnet et al. (2015), indicating that heuristics are not substantially exploited in this regard. For example, both authors used established Genetic Algorithm (GA) metaheuristics[5], while there are many other heuristics and methodologies.

Need for analyzing a broader set of candidate locations. To the best of our knowledge, all previous research on AED deployment used a predefined (subset of) buildings or landmarks as candidate locations for AED placement. Other methodologies and applications are not yet studied, even though it is currently customary and appropriate to place AEDs outdoors without limiting the locations to buildings only.

Need to expand research to a larger set of OHCAs. Besides the potential exploring other methodologies, most research (e.g. the studies in Toronto) used only public OHCAs. As these are a small subset (typically 20–40 %) of all cardiac arrests, the impact of such research is rather small when viewed in the context of the overall OHCA burden. Also, all mentioned studies optimized in a confined urban environment, while in practice, stakeholders could consider a larger or more heterogeneous area.

[5] Blum, Puchinger, Raidl, and Roli (2011) define metaheuristics as "approximate algorithms for optimization that are not specifically expressed for a particular problem" (p.4135).

1.6.3 Contributions

With the motivation in the previous subsection stating the aspects where new research can contribute to, we summarize the contributions of this study below:

Novel algorithm to effectively optimize the AED deployment problem. Aside from having no central decision maker that oversees (national) AED deployment or taking into account the usual time delay of translating the research phases into practice (Morris, Wooding, & Grant, 2011), we believe a part of the barriers to implement evidence-based methods lie in the optimization methods. Moreover, also in the research field the effort of converting an existing technique to a new study area can be significant. One of the reasons is that the AED deployment problem is NP-hard, meaning that in the worst case, exact methods are expected to require exponentially more computational resources as the problem size grows. In contrast, our proposed algorithm calculates and presents a solution of most instances *within limited time without extensive computational resources*. Additionally, such performance enables the proposed algorithm to be implemented for large instances (e.g. large areas such as entire regions or even countries) and/or with great precision (e.g. many potential AED locations).

Methodology for dynamically creating high quality problem instances. Besides using a powerful optimization technique that gives good solutions in a short time, we introduce a dynamic methodology that creates candidate locations for AED placement. This technique depends on historical cardiac arrest data only, thus removing the requirement of obtaining data of e.g. the coordinates of buildings that can be used as candidate locations. More specifically, we implement a scalable hexagonal tessellation for the creation of candidate locations. To the best of our knowledge, generating problem instances in a similar fashion is not previously studied in AED deployment literature. Moreover, this method enables having control over the potential solution quality of the AED deployment model. We show with real data that the combination of a granular tessellation with the developed efficient algorithm outperforms an exact method with a manageable, but therefore coarser, granularity of candidate locations. Thus, not only is less data required, the solution quality can be improved as well.

First data-driven AED deployment method in the Netherlands. To the best of our knowledge, this research is the *first* to apply data-driven AED deployment methods in the Netherlands. The study features *real data* from two regions and uses this data for the analysis of the current situation and the application of the proposed methodology. In addition, what relatively distinguishes this study from previous literature, is that we consider both *urban and rural* areas as well as cardiac arrests that occurred at both *public and residential* areas. Consequently, this research affects most out-of-hospital cardiac arrests in a vast and heterogeneous area. With the proposed definition of when and to what extent a cardiac arrest is considered "covered", we eventually improve the current average coverage of 43 municipalities in the Netherlands by 73.5 % when relocating existing AEDs. Therefore, using the positive trend in the Netherlands — a growing number of applied AEDs (Blom et al., 2016) and promising results with the usage of the CRS (Zijlstra et al., 2014) — as a catalyst, our data-driven method is another step forward in improving the survival of OHCAs.

Introduction to remainder of this work

The remainder of this research is organized as follows. Chapter 2 formally defines the AED deployment problem and presents the methodology for solving the problem. A straightforward but efficient "Greedy" algorithm is proposed as well as more complex but effective methods. In Chapter 3, the context of cardiac arrests in the Netherlands is described along with the characteristics of the obtained data. Next, in Chapter 4, the data that is necessary for our optimization method is created by transforming available raw data. More specifically, the spatial distribution of cardiac arrest risk is analyzed, after which future cardiac arrests are simulated. Then the function that determines to what extent a cardiac arrest is considered to be "covered" is defined. The chapter concludes devising the method to create candidate locations for AED placement. Finally, Chapter 5 shows the results of solving the AED deployment problem with the proposed methodology and real cardiac arrest data, after which Chapter 6 completes this work with a conclusion and discussion.

Chapter 2

Methodology

We have previously discussed that a structured AED placement program with a focus on coordination is more effective than the spread of unregulated AEDs (Siddiq et al., 2013; Ringh, Jonsson, et al., 2015). The previous chapter presented examples of how existing studies show promising results by prioritizing AED placement depending on historical OHCA episodes. In this chapter, we contribute to existing literature and present a prescriptive framework to help decision-makers in the placement of AEDs. In Section 2.1 we discuss the mathematical formulation of the AED deployment problem. Section 2.2 discusses a straightforward Greedy heuristic to solve the optimization model and more complex algorithms that may further improve the solution quality.

2.1 Mathematical optimization model

We have discussed in the previous chapter that the MCLP is a viable model to solve the AED deployment problem. However, the classical MCLP utilizes a binary coverage function, meaning that the amount of coverage that an AED provides to any cardiac arrest within its coverage radius is the same, irrespective of the actual distance to the arrest. Figure 2.1 illustrates two important characteristics that imply that such binary coverage function can be unrealistic.

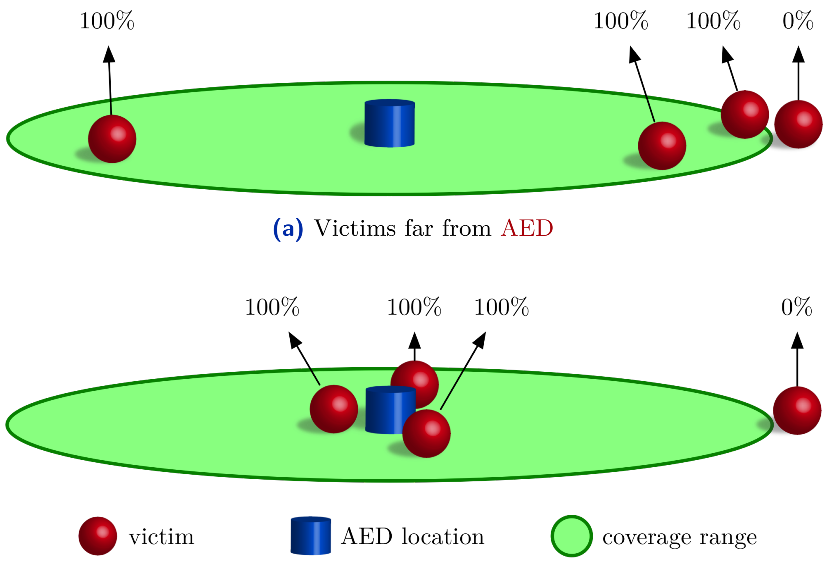
The three cardiac arrest victims within the circle in Figures 2.1a and 2.1b are considered to be fully covered, even though the victims in (2.1b) are much closer to the AED than in (2.1a). Note that one victim on the far right is not covered at all (0 % coverage) in both cases. However, a victim close to the non-covered victim in (2.1a) is considered to be 100 % covered. Realistically, the coverage between these two nearby victims should not be that different.

Note that in total, in both scenarios the AED provides full coverage to 3 cardiac arrests. Realistically, a nearby AED would be quickly found and retrieved, while an AED at a larger distance would be harder to find and would need more traveling time for bringing the device to the victim. Thus, a more appropriate coverage definition should account for the provision of better/quicker service as this directly relates to the survival of an OHCA.

Based on the above, we incorporate an extension of the MCLP that utilizes a "gradual coverage decay model". Such model was first introduced by Berman and Krass (2002) and is also used by Chan et al. (2016) to overcome the mentioned problem regarding realistic AED coverage. This generalized maximum coverage location problem (GMCLP) generalizes and improves upon the abrupt termination of coverage of the traditional MCLP. We use a similar approach since gradual coverage is more realistic for the AED problem.

We now define the mathematical model that utilizes the GMCLP to some extent. In the remainder of this chapter we use a general terminology with "facilities" (i.e. AEDs) that provide coverage to a certain "demand" (i.e. OHCAs).

Let $\mathcal{I}$ denote the set of demand nodes, $\mathcal{J}^e$ denote the locations of existing facilities (i.e. facilities that are already opened) and $\mathcal{J}^c$ denote the candidate locations for new facilities. Furthermore, let $\mathcal{J} = \mathcal{J}^e \cup \mathcal{J}^c$ and assume $\mathcal{J}^e \cap \mathcal{J}^c = \emptyset$. Each facility has two coverage radii r_1 and r_2 with $r_1 \leq r_2$. Furthermore, let d_{ij} be the distance between a demand node at location i and a facility at location j. If $d_{ij} < r_1$, then the demand node i is considered to be "fully covered" by facility node j. If the distance between demand node i and facility node j falls in between the two radii of the closest facility, i.e. $r_1 < d_{ij} \leq r_2$, demand node i is considered to be partially covered. The level of partial coverage (proportion of the available service provided) is given by a monotonic non-decreasing "coverage decay function" $f(d_{ij})$ (Berman, Krass, & Drezner, 2003). Finally, if demand node i is located farther than the outer radius ($r_2 < d_{ij}$) from facility node j, the demand is considered to be not covered by facility node j. We assume without loss of generality that $\mathcal{J}^c$ contains only locations j for



(a) Victims far from AED

(b) Victims close to AED

Figure 2.1: Two illustrations that show unrealistic characteristics of the traditional MCLP with a binary coverage function

which at least one demand node i with $d_{ij} \leq r_2$ exists. The coverage level c_{ij} of facility j for demand node i is formally defined in Equation (2.1). Note that with $r_1 = r_2$, coverage is identical to the conventional binary MCLP.

$$c_{ij} = \begin{cases} 1 & \text{if } (d_{ij} \leq r_1); \\ f(d_{ij}) & \text{if } (r_1 < d_{ij} \leq r_2), \quad \forall i \in I, \forall j \in J; \\ 0 & \text{otherwise.} \end{cases} \tag{2.1}$$

We can now formulate the mathematical model that employs this coverage level. The number of facilities to be deployed is denoted by χ. We define decision variable Y_j to be 1 if a facility is placed at location j, and 0 otherwise. Furthermore, we define binary variables W_{ij} to be 1 if if demand node i is covered by a facility at location j at some nonzero level (either partially or fully covered) and 0 otherwise. Using these variables we now formulate the given problem by the following mathematical model:

$$\begin{aligned}
\text{maximize} \quad & \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} c_{ij} W_{ij} && \text{(2.2a)}\\
\text{subject to} \quad & \sum_{j \in \mathcal{J}^c} Y_j \leq \chi, && \text{(2.2b)}\\
& Y_j = 1, \quad \forall j \in \mathcal{J}^e && \text{(2.2c)}\\
& W_{ij} \leq Y_j, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}^c && \text{(2.2d)}\\
& \sum_{j \in \mathcal{J}^c} W_{ij} \leq 1, \quad \forall i \in \mathcal{I} && \text{(2.2e)}\\
& W_{ij} \in \{0,1\}, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}^c && \text{(2.2f)}\\
& Y_j \in \{0,1\}, \quad \forall j \in \mathcal{J} && \text{(2.2g)}
\end{aligned}$$

The objective function (2.2a) maximizes the coverage level that facilities from $\mathcal{J}$ provide to demand nodes in $\mathcal{I}$. Constraint (2.2b) limits the number of locations in which new facilities are placed to χ. Constraint (2.2c) defines existing facilities as already having a placed facility at location j and these facilities are not moved. Constraint (2.2d) ensures that demand can only be covered by a placed facility. Constraint (2.2e) allows each demand i to be covered by at most one facility from $\mathcal{J}^c$. Finally, note that Constraint (2.2c) is a facultative constraint, as it depends on the decision-maker whether existing facilities can be relocated. In Section 5.4 we assess the potential of relaxing Constraint (2.2c) and redeploying existing AEDs.

Berman and Krass (2002) found that the solution of the linear program (LP)-relaxation of model (2.2) is often all-integer, thus providing an optimal solution to ILP (2.2). The authors noted that "the reasons for this unusual behavior are poorly understood" (p.570). In all our instances in Chapter 5, solving the LP-relaxation indeed results in feasible integer solutions. However, it is possible to construct instances where this is not the case and the relaxation then provides an upper bound (UB) to the ILP problem. In those cases, integrality can be restored by branching on the non-integer variables.

2.2 Algorithmic models

The mathematical model in the previous section is an extension of the MCLP and we noted that the LP-relaxation can be equivalent to the integer problem. Nevertheless, the MCLP has been proven to be non-deterministic polynomial-time (NP)-hard (Megiddo, Zemel, & Hakimi, 1983). This means that it is not expected that the problem can be solved in polynomial time, i.e. the computational time grows exponentially in most cases. Practically, this translates to the fact that exact optimization techniques, as most recently used by Chan et al. (2016), can exhibit problems in solving the problem. They cannot solve large problem sizes within foreseeable time, or in some cases they cannot give *any* feasible solution *at all*.

A heuristic approach, in contrast to exact methods, does not guarantee an optimal result. However, in most cases the results are very close to the optima and the benefit is that the computation time is much shorter and memory requirements are much more favorable. In other words, such algorithm should be able to solve problems with a large solutions space.

In the remainder of this section we devise an effective algorithm to solve the AED deployment model from the previous section. We start with a straightforward Greedy heuristic and gradually improve upon this algorithm so that better solutions can be reached.

2.2.1 The Greedy algorithm

The Greedy algorithm is a prime example of an approach that "considers specific information of the problem". Church and ReVelle (1974) first proposed Greedy Adding (in short: "Greedy") for the MCLP. The translation to the GMCLP is straightforward.

Greedy is an efficient polynomial-time heuristic. At each iteration, it chooses the current "best" location, with respect to the objective function, to be added to the solution. Its "greediness" is given by the fact that it is not looking ahead to account for how the current decision will impact later decisions and alternatives. Greedy can be considered a multi-stage method that optimally selects one location ($\chi = 1$) at each stage. Naturally, the overall solution that is constructed during multiple stages is not optimal per se.

Before discussing our Greedy algorithm for the GMCLP in further detail, we first define some extra sets and variables that are used in the forthcoming algorithms. Note that an overview of the used notation is available at page xxi.

Let $\mathcal{I}_j \subseteq \mathcal{I}$ denote the set of demand nodes i that can be covered by a facility at location j, and similarly, let $\mathcal{J}_i \subseteq \mathcal{J}^c$ denote the set of locations j that can cover demand i, i.e. $\mathcal{I}_j := \{i \in \mathcal{I} \mid c_{ij} > 0\}$ and $\mathcal{J}_i := \{j \in \mathcal{J}^c \mid c_{ij} > 0\}$. From the deployed AEDs in $\mathcal{J}_i$, the one with the best coverage in regards to cardiac arrest i is assigned to that cardiac arrest, which is denoted by the variable $J_i^* := \mathrm{argmax}_{(j \in \mathcal{J}_i | Y_j = 1)}(c_{ij})$, for all $i \in \mathcal{I}$. If no facility can cover cardiac arrest i (i.e. $\mathcal{J}_i = \emptyset$), then $J_i^* = \mathrm{nil}$. Related is $\mathcal{I}_j^*$, which is the set of all demand i to which the facility at location j is assigned to. Thus, $\mathcal{I}_j^* := \{i \in \mathcal{I}_j \mid J_i^* \neq \mathrm{nil}\}$, for all $j \in \mathcal{J}^c$. Note that $J_i^* \in \mathcal{J}_i \subseteq \mathcal{J}^c \subseteq \mathcal{J}$ and $\mathcal{I}_j^* \subseteq \mathcal{I}_j \subseteq \mathcal{I}$.

Algorithm 2.1 Greedy algorithm for the GMCLP

```
procedure GREEDY(𝓘,𝓙,c_ij,χ)
    Facilities_deployed ← 0
    Determine φ_j^0, ∀j ∈ 𝓙
    while Facilities_deployed < χ do
        BestLocation ← argmax_j φ_j^0
        PLACEFACILITY(BestLocation)                    ▷ See procedure in Algorithm 2.2
        Facilities_deployed ← Facilities_deployed + 1
    end while
end procedure
```

Let φ_i denote the best coverage that demand i receives in the current solution, $\varphi_i := \{c_{iJ_i^*} \mid J_i^* \neq \text{nil}\}$. In case that no facility is assigned to demand i (i.e. $J_i^* = \text{nil}$), we define $\varphi_i := 0$. Furthermore, let the variable φ_j^0 denote the total potential coverage that a facility at location j can add to the current solution, assuming that currently no facility is placed at location j, thus $\varphi_j^0 := \sum_{i \in \mathcal{I}_j} \max\left(\left(c_{ij} - \varphi_i\right), 0\right)$. In case a facility *is* placed at location j, let φ_j^1 denote the actual total coverage that the facility provides, thus $\varphi_j^1 := \sum_{i \in \mathcal{I}_j^*}(c_{ij})$. Note that with these formulations, the objective function of maximizing the total provided coverage can be formulated as $\sum_{i \in \mathcal{I}}(\varphi_i)$, $\sum_{j \in \mathcal{J}}(\varphi_j^1)$, $\sum_{i \in \mathcal{I}}\left(c_{ij} \mid j = J_i^*\right)$ or $\sum_{j \in \mathcal{J}}\left(\sum_{i \in \mathcal{I}_j^*}(c_{ij})\right)$.

Using the introduced notations, we now define the Greedy algorithm for the GMCLP. Procedure GREEDY is shown in Algorithm 2.1 and has sets $\mathcal{I}$ and $\mathcal{J}$, the coverage matrix c_{ij} and the number χ of facilities to be deployed as an input. Greedy is a constructive algorithm, meaning that it is "constructing" the solution by placing one facility at a time — as such, there are χ iterations. After all φ_j^0 are determined, the algorithm selects per iteration simply (greedily) the location with the highest φ_j^0.

The needed update of all necessary values after a choice is made is depicted in procedure PLACEFACILITY (see Algorithm 2.2). The goal is to check all demand that can be covered by the new facility (in set $\mathcal{I}_j$) and assign them to this new facility if their coverage is improved. As opposed to the MCLP, with the GMCLP, already assigned demand can be reassigned to a newly added facility since this might provide better coverage. Namely, if facility m is assigned to demand node i with a low coverage and another facility n is placed in the neighborhood that can cover i with a higher value (i.e. $c_{im} < c_{in}$), the demand node is reassigned to facility n and thus $\mathcal{I}_j^*$ and J_i^* are changed. In the binary MCLP, there is no distinction in coverage, and demand nodes will not be reassigned.

Berman and Krass (2002) noted that Greedy performs well for this problem, with the theoretical worst case bound of the relative error being 37 %. In the computational experiments they found that Greedy typically provided optimal solutions or solutions within 1 % of optimality. We empirically confirm this in Section 5.1 as we found an optimality gap between Greedy and the optimum of 0.087 % for mid-sized instances of the GMCLP. In these experiments, Greedy gave the optimal solution in 27.9 % cases.

Algorithm 2.2 Procedure for placing a facility at location j

procedure PLACEFACILITY(j)
  $\varphi_j^0 \leftarrow 0$ ▷ Initialization
  for $i \in \mathcal{I}_j$ **do** ▷ Loop over all i that j can cover
    if $J_i^* = \emptyset$ **then** ▷ If no j is assigned to i yet...
      Update J_i^*, $\mathcal{I}_j^*$, φ_i, φ_j^0, φ_j^1 ▷ ...assign i to j
    else ▷ If a facility is assigned to i already...
      if $\varphi_i < c_{ij}$ **then** ▷ ...but the coverage from i is better...
        Update J_i^*, $\mathcal{I}_j^*$, φ_i, φ_j^0, φ_j^1 ▷ ...assign i to j
      end if
    end if
  end for
end procedure

2.2.2 Improving upon Greedy: GRASP

Motivation for developing a hybrid algorithm

A Greedy algorithm, such as given in the previous section, is an efficient algorithm that can be easily implemented to solve problems. For this reason, it is often used as the lower bound (LB) for a subsequent, more effective, method — either a more intelligent heuristic, or an exact approach (where the LB may be used to discard certain "branches" at an early stage).

Farahani, Asgari, Heidari, Hosseininia, and Goh (2012); Li, Zhao, Zhu, and Wyatt (2011); Murray (2016) listed papers that solve the MCLP and other covering problems. Many popular metaheuristics have already been used, e.g. GA, Lagrangian Relaxation (LR), Tabu Search (TS) and SA. We use another another metaheuristic to design a better heuristic for the GMCLP, namely the GRASP (Feo & Resende, 1995) in combination with SA (Kirkpatrick, Gelatt Jr., & Vecchi, 1983). The GRASP metaheuristic computes multiple solutions, whereby each solution is constructed in two phases — a construction phase, where a feasible solution is constructed based on a stochastic variant of Greedy, which starts at the constructed solution and applies iterative improvement until a locally optimal solution is found. The SA is an effective local search metaheuristic that can escape from local optima and can therefore serve as good replacement of GRASP's second phase.

Before going into more detail about the specifics of these heuristics, we justify the choice of using GRASP and SA as follows: as shown in the previous subsection, the Greedy heuristic is expected to perform well, and we expect the GRASP, which is based on Greedy for a significant part, to perform even better. Also, GRASP is a multi-start heuristic that can produce multiple solutions, similar to many other popular population-based heuristics such as GA. To the best of our knowledge, GRASP has only been employed by Resende (1998) to solve covering problems, while GA has shown mixed results (e.g. Jaramillo, Bhadury, & Batta, 2002; Li et al., 2009). Therefore, it is interesting to add to the literature how GRASP performs on the GMCLP. In addition, population-based metaheuristics are usually very effective in finding good solutions in extremely large solution spaces (i.e. “exploring” the solution space), but tend to be inferior to local search metaheuristics such as SA for “exploiting” a particular solution. For this reason, researchers often develop hybrid algorithms that employ both type of heuristics. Therefore, considering the first phase phase of GRASP as the exploratory phase and SA as the phase for exploitation, we expect the hybridization of these heuristics to produce good results.

The GRASP metaheuristic for the gradual MCLP

Having chosen the GRASP metaheuristic as a basis to develop an algorithm that is more effective than Greedy, we continue with an overview of GRASP. Let $\mathcal{S}$ denote the set of solutions found in the algorithm, where initially, $\mathcal{S} = \emptyset$ and in total, θ number of solutions are constructed. Furthermore, let s^* denote the best solution among all solutions and $C(s)$ denote the objective value of a solution s. The generic GRASP is given in Algorithm 2.3. Repeated applications (θ times) of the construction procedure yields diverse starting solutions for the local search and the overall best solution (s^*) is kept as the result.

The construction phase RandomizedGreedy is very similar to “Semi-Greedy”, independently proposed by Hart and Shogan (1987). At each iteration within RandomizedGreedy, the next element to be added is now *randomly* selected from a restricted candidate list (RCL), as opposed to the deterministic selection as in Greedy. The RCL is a subset of an overall candidate list (CL) that consists of all candidate elements where no facility is placed yet, thus CL $:= \{k \in \mathcal{J}^c \mid Y_k = 0\}$. We determine the RCL by choosing the elements with the best φ_j^0 values. This probabilistic component of GRASP of randomly choosing from a set of good locations allows for different solutions to be obtained at each iteration. Note that by setting $|\text{RCL}| := 1$, we get back to Greedy.

Algorithm 2.4 shows the construction phase. For selecting the elements for the RCL, we do not use a simple cardinality-based procedure, but a different, more dynamic, value-based mechanism. This procedure Construct(CL, α) depends on parameter $\alpha \in [0, 1]$ and defines

Algorithm 2.3 General procedure of GRASP

procedure GRASP($\mathcal{I}$,$\mathcal{J}$,φ_j^0,χ,θ,α)
  $s^* \leftarrow 0$
  for *iteration* $= 1$ **to** θ **do**
    $s \leftarrow$ RandomizedGreedy($\mathcal{I}$,$\mathcal{J}$,φ_j^0,χ,α) ▷ See function in Algorithm 2.4
    IterativeImprovement($\mathcal{J}^c$,s) ▷ See procedure in Algorithm 2.5
    if $C(s) > C(s^*)$ **then** ▷ Update best solution if current solution is better
      $s^* \leftarrow s$
    end if
  end for
end procedure

the RCL by:

$$\text{RCL} := \left\{ j \in \mathcal{J}^c \middle| \varphi_j^0 \geq \left(\min_j \varphi_j^0 + \alpha \left(\max_j \varphi_j^0 - \min_j \varphi_j^0 \right) \right) \right\}. \tag{2.3}$$

This means that being a member of the RCL depends on the relative quality of the elements with respect to their potential added value denoted by parameter φ_j^0. Consequently, the length of the RCL may be different during each iteration of placing a facility.

Naturally, the solutions computed during the construction phase are in general not of high quality. Hence, a second phase is added to GRASP, the local search phase. The simplest form of local search is "iterative improvement", where neighborhoods are continuously explored to find better solutions. Let $N(s)$ denote the neighborhood of solution s and s' be a such neighborhood solution. We define a s' as any solution where only one location of a placed facility differs from the current solution. Furthermore, let $F(s)$ be the set of locations with a placed facility in s, i.e. $F(s) := \{k \in \mathcal{J}^c \mid Y_k = 1\}$, and let $NF(s)$ be the set of locations with no placed facility in s, i.e $NF(s) := \{k \in \mathcal{J}^c \mid Y_k = 0\}$. Note that $NF(s) = \mathcal{J}^c \setminus F(s) =$ CL. Using these definitions, we implement iterative improvement for the second phase of GRASP as defined in the procedure in Algorithm 2.5.

In the procedure, the initial solution is the solution found with RandomizedGreedy. This solution is stored as the best solution (s^*) and the procedure seeks to improve this best solution. We take each facility from that solution and relocate it iteratively to candidate locations where no facility was placed yet. In other words, facilities are "exchanged" with an empty location and as such, a neighborhood solution is created. If the objective function of the neighborhood solution improves upon the previously best solution, we replace the best solution with this neighborhood solution. After all possible exchanges of each placed facilities are performed and a new solution has been accepted, a new iteration of the procedure starts to explore the neighborhood of that new solution. Otherwise, a local optimum with regards to its direct neighbors is found and the procedure terminates.

Algorithm 2.4 Function of GRASP's construction phase

function RandomizedGreedy($\mathcal{I}$,$\mathcal{J}$,φ_j^0,χ,α):s
    $\mathit{Facilities}_{deployed} \leftarrow 0$
    while $\mathit{Facilities}_{deployed} < \chi$ **do**
        CL $\leftarrow \{j \in \mathcal{J}^c \mid Y_j = 0\}$
        RCL $\leftarrow$ Construct(CL, α)
        Choose *ChosenLocation* randomly from RCL
        PlaceFacility(*ChosenLocation*) ▷ See procedure in Algorithm 2.2
        $\mathit{Facilities}_{deployed} \leftarrow \mathit{Facilities}_{deployed} + 1$
    end while
    Result $\leftarrow s$
end function

Algorithm 2.5 Procedure of GRASP's local search phase

```
procedure ITERATIVEIMPROVEMENT(𝒥^c, s)
    s* ← s                                          ▷ Current solution is stored as best solution.
    SolutionIsImproved ← TRUE
    while SolutionIsImproved = TRUE do              ▷ Iterate until local optimum is reached.
        SolutionIsImproved ← FALSE                  ▷ First assume that we do not improve the solution.
        for m ∈ F(s) do                             ▷ Loop through all facilities that are placed.
            REMOVEFACILITY(m)                       ▷ Similar to PLACEFACILITY.
            for n ∈ NF(s) do                        ▷ Place facility from m to all empty candidate locations.
                PLACEFACILITY(n)                    ▷ See Algorithm 2.2
                if C(s) > C(s*) then                ▷ If solution is improved...
                    s* ← s                          ▷ ...save the solution as the best solution.
                    SolutionIsImproved ← TRUE       ▷ A new solution is accepted, so another while-loop...
                end if                              ▷ ...will be performed to explore the neighborhood of the new solution.
                REMOVEFACILITY(n)
            end for
            PLACEFACILITY(m)
        end for
        s ← s*                                      ▷ The best solution found so far becomes the incumbent solution for next iteration.
    end while
end procedure
```

Incorporating a bias in the construction phase

Although the previously defined general GRASP algorithm is known to perform well, quicker and/or better results can be achieved when incorporating specialized knowledge about the specific problem. This way, it is possible to consequently "guide" the algorithm towards potentially better solutions.

This "guidance" can be realized for the RANDOMIZEDGREEDY algorithm by differentiating between elements in regards to their potential quality. Bresina (1996) introduced "heuristic-biased stochastic sampling" for Greedy-based algorithms where the selection of the next element is determined by a certain pre-defined probability function (e.g. linear, logarithmic, polynomial). Similarly, we incorporate "parameterized regret-based random sampling" (Kolisch & Drexl, 1996) that was originally used for scheduling problems. By using φ_j^0 as a proxy for quality, we first define priority ψ_j of selecting element j and based on this priority we define the probability p_j of selecting element j. The priority ψ_j is determined as follows:

$$\psi_j := \varphi_j^0 - \min_k \varphi_k^0, \quad \forall j \in \text{RCL} \tag{2.4}$$

Then the relative probability p_j can be determined by:

$$p_j := \frac{(\psi_j + 1)^\beta}{\sum_{j \in \text{RCL}} (\psi_j + 1)^\beta}, \quad \forall j \in \text{RCL}, \tag{2.5}$$

where $\beta \in [0, \infty)$ is a parameter which characterizes the bias within the method. As can be seen in Figure 2.2, an increasing value of β increases the probability of selecting the better

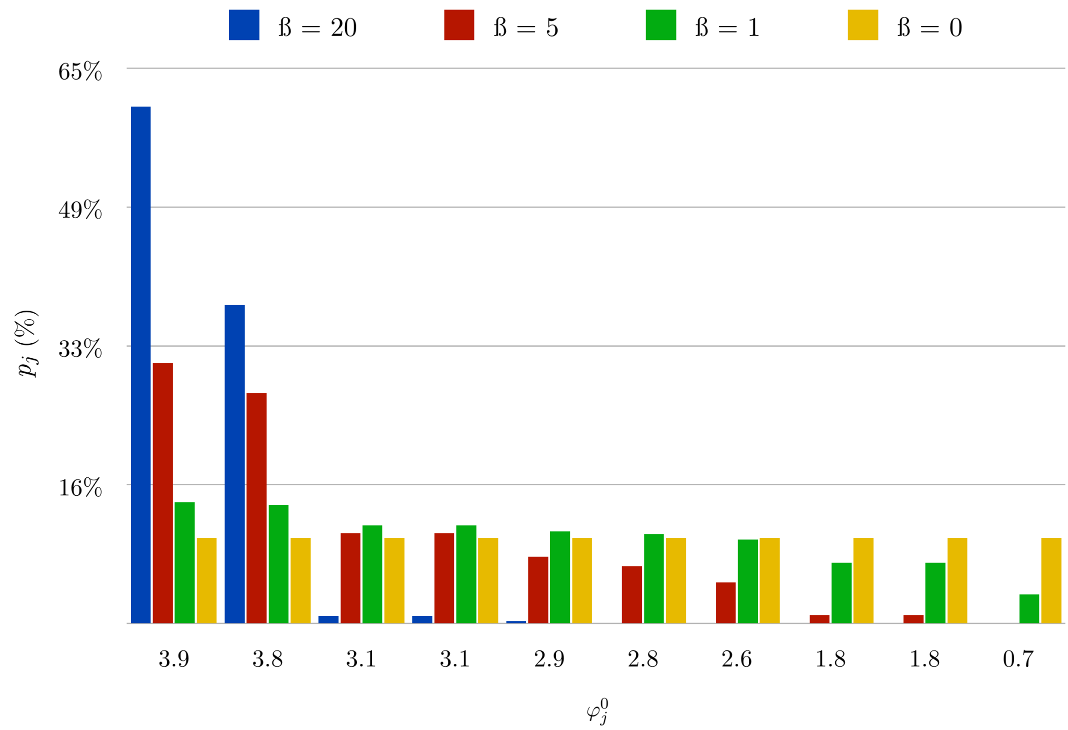


Figure 2.2: Effect of different bias factors on the probability density function of selecting an element from a set of 10 elements. Note that the distribution is determined by the value of φ_j^0 on the horizontal axis.

solutions with respect to φ_j^0. $\beta := 0$ gives random selection (the default method in GRASP) and $\beta \to \infty$ gives deterministic selection (equal to regular Greedy).

The priorities and probabilities are determined for each element in the RCL during each iteration of RandomizedGreedy, thus χ times per construction of a solution. The difference of this technique with the one from Bresina (1996) is that it does not assume a certain pre-defined probability function, but determines the probability function dynamically by accounting for the quality of candidate elements. Incorporating the bias component facilitates good solutions within fewer iterations as we show in the computational results in Section 5.2.

2.2.3 Hybridization with Simulated Annealing

Introducing Simulated Annealing

In the previous section we discussed the two phases of GRASP — the construction and local search phase. The GRASP metaheuristic is widely and successfully implemented as discussed by Festa and Resende (2011). We have extended the first phase with an optional bias to control the probability of choosing certain elements. In this section we focus on the second phase of GRASP and substitute the used local search based on iterative improvement by a more sophisticated heuristic, namely Simualated Annealing (SA).

The major downside of iterative improvement is that it easily gets "trapped" at a (poor) local optimum. To overcome this and allow the local search to leave the local optimum, neighborhood solutions that yield a deterioration of the objective function to some extent can be considered.

Simulated Annealing (Kirkpatrick et al., 1983) uses this principle. It is inspired by the physical annealing process of solids, where the solid is heated until it melts. In this state, particles move frantically in a random fashion. Then the temperature is carefully lowered, and the particles slowly arrange themselves in a highly structured lattice, for which the corresponding energy is minimal.

SA adopts this principle of randomly moving to neighboring structures, even with deteriorations of the objective function. In the early phases (exploring phase), almost all randomly selected neighborhood solutions are accepted. However, depending on the progress, the probability of moving to deteriorating solutions gets smaller. Eventually SA enters a phase (exploiting phase) where almost only neighborhood solutions are accepted that improve the incumbent solution. In other words, SA starts with a high temperature and with a "random search" to escape local minima; then the temperature gradually cools down and the algorithm converges to iterative improvement[1].

The Simulated Annealing algorithm

SA is tuned by determining a temperature scheme and rules on computing and accepting neighborhood solutions. Generally, a starting temperature T_0 is chosen and after each iteration, the temperature is lowered by a determined rule. The metaheuristic is often viewed as a process in which a sequence of Markov chains (Isaacson & Madsen, 1976) is generated, one for each value of temperature T. Each chain consists of a sequence of κ trials, where neighborhood structures ($N(s)$) are computed and possibly accepted as the new incumbent solution (Aarts, Korst, & Michiels, 2005). The algorithm stops after a certain termination criterion is met. Such general SA algorithm is shown in Algorithm 2.6.

Based on extensive experiments in the field of applied mathematics, van Laarhoven and Aarts (1987) mention several options for determining an effective tuning. T_0 is often chosen such that almost all neighborhood solutions, irrespective of their quality, are accepted. The number of iterations κ per temperature T can be set empirically and the cooling of the temperature can be realized by a "cooling factor" $\delta_c \in (0, 1)$ and $T_{k+1} := \delta_c * T_k$. Most SA schemes utilize the Metropolis criterion (Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953) to accept a deteriorating neighborhood configuration. Combining this with always accepting a neighborhood that improves the current solution, we compute the probability $p_{\text{accept}}(s,s',T)$ to accept a neighborhood solution by:

$$p_{\text{accept}}(s, s', T) = \min\left(1, \exp\left(\frac{C(s) - C(s')}{T}\right)\right) \tag{2.6}$$

[1]It is proven that under some assumptions, SA guarantees asymptotic convergence to the global optimum with an infinite number of transitions (Aarts & Korst, 1989).

Algorithm 2.6 General Simulated Annealing procedure

procedure Simulated Annealing($\mathcal{I}$,$\mathcal{J}$,T_0,κ, termination criterion, s)
  $s^* \leftarrow s$ ▷ Current solution is set as best solution.
  $T \leftarrow T_0$ ▷ Initial temperature is set as current temperature.
  while termination criterion not met **do**
    for $l = 1$ **to** κ **do**
      $s' \in N(s)$ ▷ Generate neighborhood solution.
      if $p_{\text{accept}}(s, s', T) > \text{random}[0, 1)$ **then** ▷ If neighborhood solution is accepted...
        $s \leftarrow s'$ ▷ ...save neighborhood solution as as current solution.
        if $C(s) > C(s^*)$ **then** ▷ If current solution is better than best solution...
          $s^* \leftarrow s$ ▷ ...save current solution as best solution.
        end if
      end if
    end for
    Update T
  end while
end procedure

Note that with a large T and a deteriorating neighborhood solution, p_{accept} is indeed rather high, while with a lower temperature, the probability is low. Also, setting $T := 0$ corresponds to a version of iterative improvement[2]. Finally, the termination criterion is often set as a threshold value of the temperature or a threshold value of the number of iterations where no neighborhood solution is accepted. We employ the latter with λ denoting the number of iterations where no new neighborhood solutions are accepted.

Simulated Annealing with reannealing

There are plethora of extensions for SA in literature (e.g. Tsallis & Stariolo, 1996; Szu & Hartley, 1987). Inspired by Ingber (1989), we devise a "reannealing" method. Once the termination criterion is reached, meaning that in the last λ iterations no new solution has been accepted, we "reheat" the temperature to start a reannealing process. By doing so, we increase the probability to accept worse solutions again so that other solutions than the found (local) optimum can be explored.

Reheating the temperature to T_0 again would introduce too much randomness and deterioration of neighborhood solutions. Consequently, practically a completely new solution would be reached before the exploitation phase starts. This would essentially be the same as running the regular algorithm multiple times with a different start solution. The goal of the reannealing, however, is to *slightly* explore neighborhood solutions that are not substantially different from the found local optimum to then hopefully find a neighboring local optimum that is better. This process is visualized in Figure 2.3.

Let r denote the number of the reannealing iteration in the algorithm. To enable the "light

[2] In iterative improvement however, the neighborhood solutions are not necessarily examined randomly.

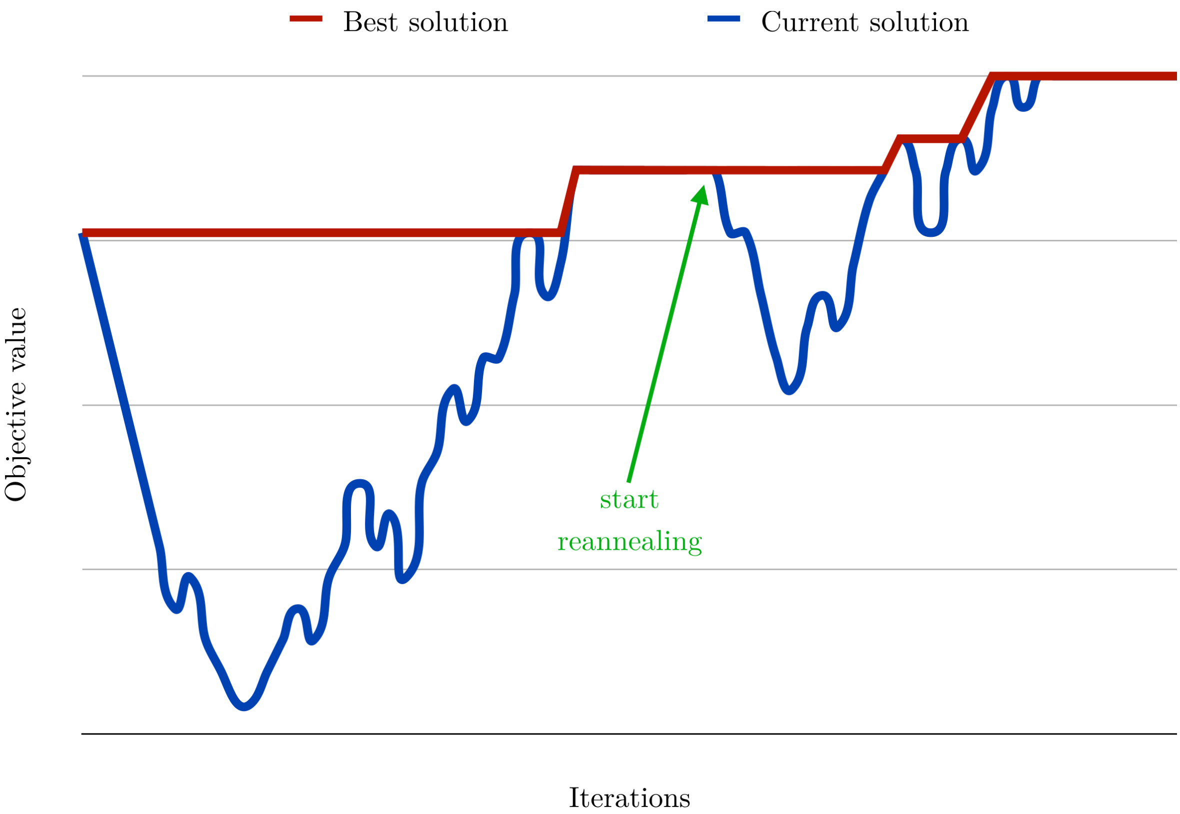


Figure 2.3: Illustration of the objective value in a maximization problem solved with a Simulated Annealing algorithm with a single reannealing process. Note that before reannealing starts, the algorithm converged to a local optimum. By slightly moving away from this local optimum in the reannealing phase, a better optimum is eventually found.

exploration" when reannealing starts, we employ a similar approach as with the cooling of the temperature after each sequence of Markov chains (κ) by using a "heating factor" $\delta_h \in (0, 1)$. More precisely, we set $T := T_0 * (\delta_h)^r$. This means that the more often reannealing is applied, the less deterioration is accepted from the found solutions so that the already good solutions are not completely lost. In Chapter 5 the effectiveness of extending SA with our proposed reannealing method is investigated.

2.3 Conclusion on methodology

In this section, we have first formulated the mathematical model for the AED deployment problem. The model is based on the GMCLP, which is an extension of the classical MCLP that incorporates a more general coverage function. This coverage function defines to what extent demand is considered to be covered by a facility and thus, as opposed to the MCLP, enables partial coverage. This is important for the AED deployment problem, since a victim of a cardiac arrest will benefit of quicker defibrillation times.

Since the MCLP has been proven to be NP-hard, it is likely that the problem cannot be easily solved with exact methods. Therefore, we developed a Greedy algorithm for the

GMCLP that gives good results with little computational resources. To reach even better results, we developed a more complex algorithm utilizing the GRASP heuristic that consists of a constructive phase and a local search phase. We extended the construction phase with parameterized regret-based random sampling to be able to control the placement of facilities at more promising locations. Subsequently, we devised a SA algorithm that is effective at escaping from local optima to find a better optimum and extended this with reannealing. Reannealing enables exploring neighborhood solutions in the proximity of the configuration that is found by the regular SA algorithm without falling back to inferior solutions.

Although both algorithms —GRASP with biased sampling and SA with reannealing — can be used on their own, we expect better results when combining the algorithms. Such hybridization may be realized by substituting the regular local search phase in GRASP with SA. In Chapter 5 we test the algorithms with real data and present the results.

Chapter 3

Case study

In this chapter, prior to applying our heuristic optimization method to real data, we provide the context of the obtained data. Section 3.1 introduces the used data for the rest of this study. In Section 3.2 we investigate efforts of improving cardiac arrest survival in the Netherlands, the availability of AEDs and the currently used methodology of deploying AEDs.

3.1 Study design

This section describes the origins of the obtained data and consequently the scope of our study regions. We also discuss what data we consider for the optimization model and give descriptive characteristics of the included data set.

3.1.1 Cardiac arrest and AED data origins

The historical OHCA data that is used in our analysis origins from a large-scale community-based registry – AmsteRdam REsuscitation STudies (ARREST) – and is obtained in cooperation with the Academic Medical Center (AMC) in Amsterdam. The registry has started in June 2005 to identify genetic, clinical, pharmacological and environmental determinants of OHCAs (Blom, van Hoeijen, et al., 2014). ARREST is an ongoing, prospective observational registry of all OHCAs in the province North Holland (excluding the region of "Gooi- and Vechtstreek"), the region of Twente and the municipality of Breda in the Netherlands (Zijlstra, Radstok, et al., 2016). There were 25 regional ambulance facilities (RAFs) (or Regionale Ambulancevoorziening (RAV) in Dutch) and 21 ambulance dispatch centers in the Netherlands, but the latter is reduced to 10 centers since 2017.

In cooperation with the AMC, AED data is obtained from the HartslagNu foundation and consists of spatial coordinates of all AED locations within our study area that are recorded in the registry. The medical ethics review board of AMC approved this study protocol. All studies with the ARREST registry are conducted according to the principles expressed in the Declaration of Helsinki (World Medical Association, 2013).

3.1.2 Study regions

This study is comprised of two regions in the Netherlands — the majority of the province of North Holland and the region of Twente. Although not the entire province North Holland is included, we refer to the considered region as "North Holland". There are three RAFs in North Holland and one in Twente (*Overzicht RAV's en meldkamers in Nederland*, 2017).

Interesting to note is that to the best of our knowledge, this is one of the first studies to optimize the deployment of AEDs in such a vast and diverse area, including both rural and urban settings. On municipality level, the population density ranges from 84–3530 km^{-2} in the municipalities of Texel and Hoorn respectively (Centraal Bureau voor de Statistiek, 2015).

3.1.3 Data inclusion

The original data was collected from 1 January 2006 to 31 December 2016 in North Holland and 1 February 2010 to 31 December 2016 in Twente[1] and consists of all persons with an OHCA, irrespectively of cause. Note that the CRS is gradually implemented in Twente since 2008 and in North Holland since 2009 (Beesems et al., 2012).

AED and cardiac arrest data are obtained of the entire region of Twente while some municipalities in North Holland do not have AED data. The included study areas and their respective available data are illustrated in Figure 3.1. A detailed overview of the included areas is given in Appendix A.1. In total, we include 43 municipalities in our optimization analysis.

The included data consists of a total of 12 455 OHCAs with 10 667 and 1788 OHCAs in North Holland and Twente respectively and is derived from a total of 26 178 patients with suspected OHCAs. We refer the reader to the respective methodology for obtaining the OHCA and AED data sets to Appendix A.2. Table A.1 depicts the main medical characteristics of the included cardiac arrest data set.

3.1.4 Data characteristics

Examining the data, most notably, we find the interval from emergency call to the connection of an AED being 06:10 (interquartile range (IQR): 03:54–08:12) in public areas and 07:43 (IQR: 06:21–09:28) in residential areas[2]. This can be explained by the number of deployed AEDs in residential areas often not being on par with public areas[3] (e.g. Fredman et al.,

[1] Data prior to 1 February 2010 from the region of Twente is considered unreliable and is omitted in our and all prior researches using the ARREST registry.

[2] OHCAs witnessed by EMS, FR and general pracitioners are not considered.

[3] For instance, a recent Danish study found that even with extensive nationwide initiatives to facilitate public-access defibrillation, the situation at residential locations remained unchanged during almost 12 years (S. M. Hansen et al., 2017). At the same time, bystander defibrillation increased from 1.2 % to 15.3 % at public locations.

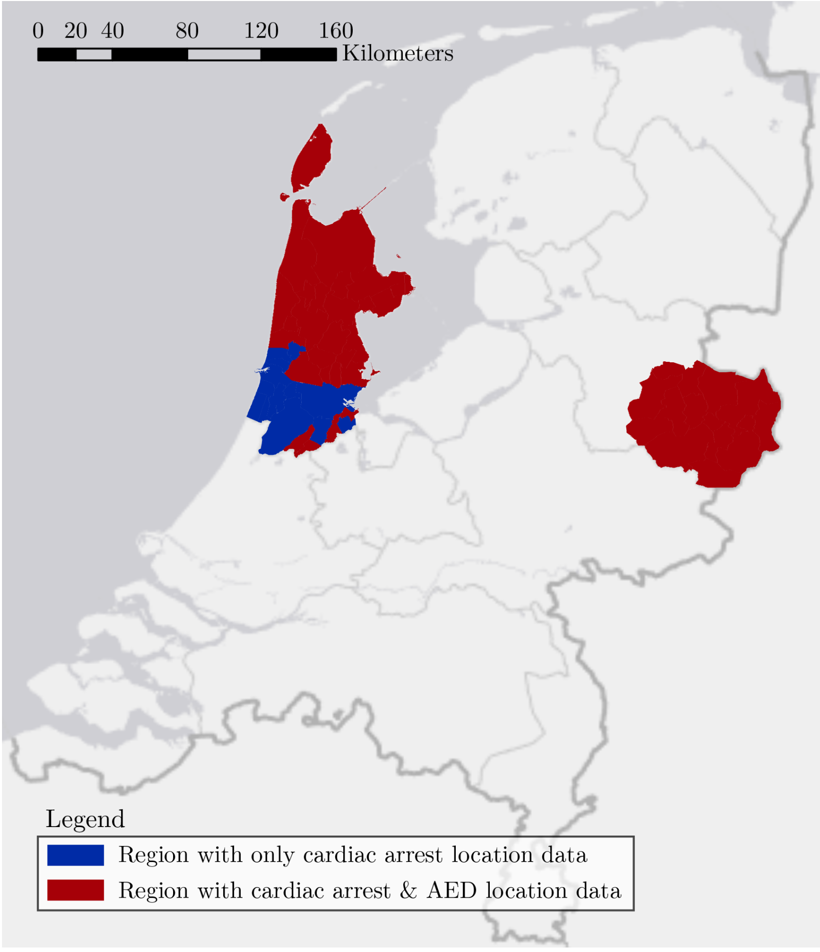


Figure 3.1: Map of the Netherlands with the considered study regions

2017). Moreover, as stated by the ERC guidelines: "the full potential of AEDs has not yet been achieved, because they are mostly used in public settings, yet 60–80 % of cardiac arrests occur at home" (Perkins, Handley, et al., 2015, p.91). Therefore, contrary to many previous studies, we are pleased to suggest a method to improve the deployment of AEDs for the *complete* population of the regions – in both public and residential areas.

Fortunately, a CRS can influence the outcomes at residential locations, as it is designed in such way, that trained lay responders will *voluntarily come with the goal to perform CPR and apply an AED*. The literature that includes CRSs, does indeed report improvements on bystander-delivered defibrillation rates in both public *and residential* areas. For example, although Berdowski et al. (2011), using the ARREST registry, have shown that on-site AEDs were less effective in residential locations, a later study has shown that the majority of CRS AEDs were used on victims at home in comparison to on-site AEDs (Zijlstra et al., 2014).

We concur the findings that CRS AEDs are mostly used at residential locations with our data. Namely, only 8.0 % of connections in residential areas were by on-site AEDs while this number is 32.9 % for the CRS AEDs. However, the opposite is true in the case of public connections: on-site AEDs were connected the most often relatively to their total number

(52.9 %) and the CRS AEDs perform the worst (12.0 %).

Therefore, on-site AEDs are very useful for public OHCAs, while AEDs that are deployed by the CRS are often used in residential areas, meaning that the two scenarios of retrieving an AED complement each other. Note that most CRS AEDs can be considered as "on-site" when not retrieved with the aid of the system. Thus, although we utilize only registered AEDs in our optimization methods, the results may also affect events where lay responders retrieve an AED without the CRS. Nevertheless, optimizing for *all* available AEDs would be most effective. Thus, with time, as more AED are registered, our optimization methods may yield even better results.

3.2 Efforts in improving cardiac arrest survival

We continue with a discussion of the actual deployment efforts in our study area. We show that the Netherlands is actively engaged in improving resuscitation and defibrillation efforts and that recruiting civilian responders for the CRS is successful. Naturally, this is of great interest to our optimization model since our AED data is obtained from the CRS.

3.2.1 Dutch Heart Association

In the Netherlands, the foundation Dutch Heart Association (DHA) ("Nederlandse Hartstichting" in Dutch) is the largest organization in the country that strives to improve the survival and quality of life of CVDs. The foundation states that if CPR and defibrillation is started within 6 min, survival increases to 25 %[4]. The DHA wishes that the Netherlands becomes a single 6 min zone (Dutch Heart Association, 2016). In other words, it should be possible to defibrillate each OHCA incident in the entire country within 6 min after an emergency call. For the 300 OHCAs that occur in the Netherlands per week, such zones would save 2500 additional lives per year (Dutch Heart Association, 2016).

The foundation attempts to achieve this by building a network of civilian responders and AEDs with the CRS. The goal of obtaining 1 % civilian responders compared to the of the country's population has been recently reached (*Mijlpaal bereikt: 170.000 burgerhulpverleners in Nederland*, 2017), possibly due to successful media campaigns[5]. See also the current average proportion of civilian responders per province in Figure 3.2.

However, obtaining more AEDs in the system appears to be difficult and will take significantly more time (Dutch Heart Association, 2016). Currently there are at least 11 603 AEDs registered while the official goal is 30 000 devices.

[4]A recent study came to a similar conclusion and reported a response time threshold of 6.5 min for favorable neurological outcomes after OHCAs (Ono et al., 2016).

[5]Enami, Takei, Goto, Ohta, and Inaba (2010) showed that due to the increased number of reports on successful resuscitations by citizens, more people learn how to use an AED and are more willing to use it. This may partly explain why DHA's efforts are successful in regards to recruiting civilian responders.

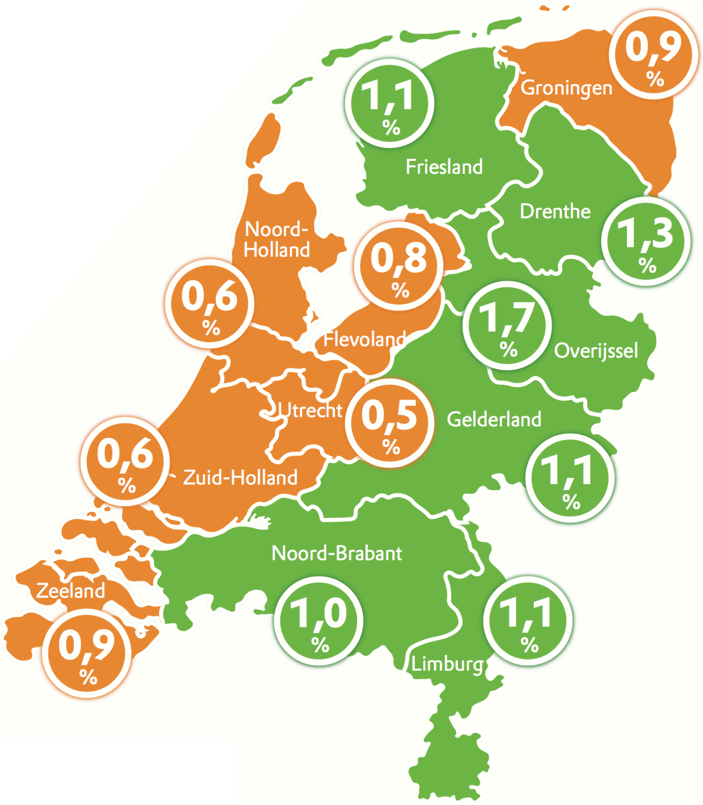


Figure 3.2: Proportion of the population of civilian responders per province in the Netherlands as of December 2016. 1 % is the goal and is considered as "100 % coverage". ©2016 Hartstichting, from Dutch Heart Association.

3.2.2 Availability of AEDs

The temporal availability of AEDs is important for this study as it directly influences the efficacy of deployed AEDs. In this regard, C. M. Hansen et al. (2013) found that AED coverage decreased by 53.4 % at the time when 61.8 % of all cardiac arrests in public locations occurred in Copenhagen (Denmark). Similarly, Sun et al. (2016) found a decrease of 21.5 % of actual coverage when accounting for the hours of operation of the buildings where AEDs were placed in Toronto (Canada). Thus, not only strategic placement but also uninterrupted AED accessibility is critical to affirm effective PAD programmes.

With our data, we found the average availability to be 84.6 % (95 % confidence interval (CI): 83.4–85.9) over all years, which is more favorable than in the previously mentioned studies. Moreover, modern policies in the Netherlands aim to place AEDs outdoors for continuous availability. For example, the DHA states that all new AEDs that are registered in the CRS should be available 24 h a day and refer to buying an outdoor AED cabinet (*AED-buitenkast kopen*, 2017).

Also, the DHA collected funds in 2016 to place as much as 1000 new AEDs outdoors in dedicated cabinets (Dutch Heart Association, 2016, p.15,43). The municipality of Breda even relocated almost half of its AEDs to outdoor locations for the use by the community

(*Breda AED proof - Eindrapportage aanpak AED-netwerk Breda*, 2012). Therefore, with these measures, it is very likely that the overall availability of AEDs will improve over time. Consequently, we assume uninterrupted AED availability in our optimization methods.

3.2.3 Placement of AEDs

AEDs are stimulated to be placed in public areas such as schools, sport facilities, retirement homes, work spaces. However, the deployment is not centrally controlled or directed (Berdowski et al., 2011) as only about 40 % of all AEDs are managed by the municipality and are placed in "strategically situated places" (Zijlstra et al., 2014).

Interesting to note is that data-driven methods to determine specific AED locations seem absent. In Twente, the foundation Twente Hart Safe[6] advised that within a radius of 500 m, there should be one AED, without a derivation to this number (Matthijssen & Suijkerbuijk, 2009). In 2009 the entire province of Limburg started a project of improving AED locations and applied a slightly less homogeneous deployment strategy. The advice was that at densely populated areas, at every 500 m one AED should be placed, whereas for sparsely populated areas the distance should be 2000 m (Matthijssen & Suijkerbuijk, 2009). As discussed in previous literature (see Section 1.5.2), cardiac arrest risk is not directly and solely dependent on population, nor is it homogeneously dispersed over the entire area. This means that equally distributing AEDs over the plane or placing new AEDs at "white spots" (i.e. areas without AED coverage) would not be very effective method for reducing defibrillation times.

Yet, some cities or municipalities claim to have "full AED coverage"[7]. However, the emphasis is on the number of civilian responders in the region, less on the number of AEDs. At the same time, information about prescriptive *deployment strategies* of AEDs seem completely non-existing.

3.3 Conclusion on case study

This chapter we discussed that we have obtained historical cardiac arrest data from the AmsteRdam REsuscitation STudies (ARREST) registry and AED location data from the civilian response system (CRS) "HartslagNu". The study area consists of two vast regions in the Netherlands — the region of North Holland and Twente. After examining the data, we found that the AEDs that are within the CRS registry were relatively very effective in defibrillating OHCA victims at residential locations, while historically, most research was mostly aimed at public OHCAs. Since 60–80 % of all OHCAs occur at residential locations,

[6] http://www.twentehartsafe.nl/

[7] For example, the foundation "Breda AED Proof" states that when an AED can be retrieved within 6 min in the entire region, this region can call itself "AED Proof" (www.breda-aed-proof.nl). The municipality of Breda is allegedly the first such region.

using AEDs from the CRS allows us to suggest a method that possibly has significant impact on improving defibrillation efforts for the complete study population.

The potential impact of our proposed AED deployment optimization method is augmented by the environment in the Netherlands. Namely, to the best of our knowledge, there has been no research or practical efforts for deploying AEDs with a data-driven technique. On the other hand, the Dutch Heart Association (DHA) actively pursues increasing the registry with civilian responders and AED locations and has reported significant success in this regard. Moreover, increasingly more AEDs are placed or even relocated to outdoor locations. This enables us to assume that the deployed AEDs by our optimization methods will have uninterrupted availability for the community.

Chapter 4

Data preparation

Our optimization method enables deploying AEDs at locations such that the AEDs can be retrieved as quickly as possible and deliver a shock to an OHCA victim. However, the method requires certain data and definitions, and some of those are not necessary known at this point. For this purpose, this chapter analyzes and transforms the known data into data that *can* be used by the optimization method.

To make certain steps in the methodology clear, we first present an overview of the plan of approach in Section 4.1. Hereafter, all data, parameters and definitions are determined in the subsequent sections. In the next chapter we incorporate these aspects in the proposed optimization method and present the results.

4.1 Methodology overview

To guide the reader through the steps of our methodology, we present a flowchart of the required data and processes in Figure 4.1. As can be seen on the left side of the figure, we need demand data (consisting of cardiac arrests at locations $i \in \mathcal{I}$) that should be covered by AEDs), supply data (consisting of candidate locations $j \in \mathcal{J}$ where AEDs can be placed) and a definition of of the coverage function (that quantifies to what extent a cardiac arrest at location i is covered by an AEDs at location j).

Concerning the demand data, in Section 4.2, we transform the raw data with historical OHCAs and existing (registered) AEDs into location data that can be used by our optimization methods. Hereafter, Kernel Density Estimation (KDE) analyses are performed that determine the distribution of the OHCA risk. Knowing the cardiac arrest risk, we simulate new locations that serve as forecasted OHCAs locations. With these locations, we define $\mathcal{I}^t$ and $\mathcal{I}^v$ for respectively training and then validating our optimization models.

In Section 4.3 we analyze different events that typically occur during a cardiac arrest with respect to the time they take. Hereafter, we can more realistically assess how and to what extent AEDs provide coverage to OHCAs in our study. Accordingly, we set the parameters

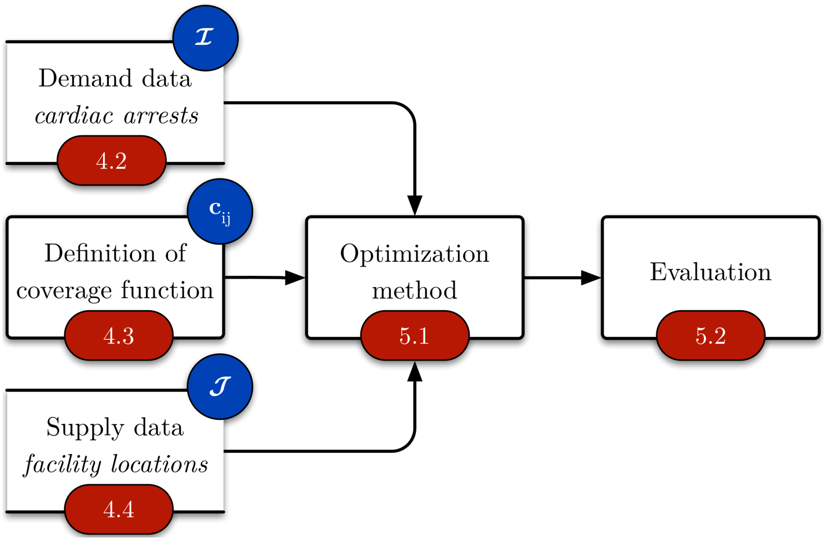


Figure 4.1: Flowchart of the methodology of AED optimization. The red ellipses indicate in which section the respective process is described; the blue circles indicate what data is defined by that process.

for the coverage function c_{ij} that we have introduced in Equation (2.1).

Lastly, in Section 4.4, we discuss the characteristics of efficient and effective locations and devise a method to create our own set of candidate locations ($\mathcal{J}^c$).

At this point, all data, parameters and definitions are defined and can be used as an input for our optimization methods that were previously defined in Chapter 2. As discussed in that chapter, we can solve the AED deployment problem with an exact method (with the mathematical model in Section 2.1) and with a heuristic approach (discussed in Section 2.2). The exact method guarantees an optimal solution, but for very large problem sizes, it will not be able to give a solution due to excessive computer memory requirements. Our proposed heuristic optimization methods are suggested to give a solution within a foreseeable time, but the challenge is in acquiring as good as possible results.

Chapter 5 consists of the computational results of the previously defined methods. First we compare the algorithms to an optimal solution in Section 5.1 and tune the parameters so that the best possible results can be obtained with our heuristic algorithms. Next we apply the tuned algorithms to our problem and present the results in Section 5.4.

4.2 Cardiac arrest locations

We continue with more detailed spatial analyses and transformations of historical cardiac arrests to create the demand data. Our ultimate goal is to deploy AEDs such that they can improve the probabilities on survival for future OHCA victims. Therefore, we need to estimate the distribution of the cardiac arrest risk. To do so, we first transform the raw data into location data in Section 4.2.1 and discuss the validity of using these locations of historical cardiac arrests for determining the cardiac arrest risk distribution in Section 4.2.2. In Section 4.2.3 we determine the risk distribution with a KDE method. Lastly, in Section 4.2.4, the cardiac arrest risk distribution is discretized into point data which can be used as an input for set $\mathcal{I}$ in our algorithms.

4.2.1 Acquiring spatial data

First, the data is processed in such way that it can be used by the optimization models. Since the potentially life-saving potential of AEDs can only be achieved if an AED can deliver a shock in time, there is an inherently temporal dimension to the AED location problem. This temporal dimension can be converted to a spatial dimension as a proxy, since, prompt delivery can only be realized by proximate locations of the devices in relation to an OHCA. Hence, acquiring data of spatial coordinates of the OHCAs and AEDs is a crucial aspect.

The included OHCA data, as opposed to the AED data, does not contain spatial coordinates but addresses in a string. Therefore, the raw data cannot be used directly to determine the coverage that AEDs provide to OHCAs and therefore should be transformed. An appropriate and straightforward methodology is *geocoding*. Goldberg, Wilson, and Knoblock (2007, p. 33) describes geocoding as the "act of turning descriptive locational data such as a postal address or a named place into an absolute geographic reference".

We discuss the our methods of geocoding in Appendix A.3 in detail. After excluding inappropriate locations, the final data set that is used for the AED optimization consists of 5781 cardiac arrests and 2185 AEDs.

4.2.2 Spatiotemporal stability

Due to the stationary nature of AED locations, deployment strategies can only be effective if it is possible to predict future cardiac arrest risk. However, accurate prediction is very challenging as OHCA incidence rates depend on a plethora of factors, for instance health characteristics of patients with no cardiac history (Deo et al., 2016), population movement (Marijon et al., 2015) and socio-economic factors (Dahan et al., 2017). Not only is developing an accurate prediction model troublesome, obtaining the necessary data is often difficult too.

However, previously it has been shown that cardiac arrest risk is spatiotemporally stable (Chan et al., 2016; Demirtas, Brooks, Morrison, & Chan, 2015; Onozuka & Hagihara, 2017; Sasson et al., 2010). In other words, historical OHCAs locations tend to remain stable over time and current risk areas are likely to be representative for the future. On a large scale, this is implicitly acknowledged in the Netherlands as the annual incidence of OHCAs remains stable over 6 regions (Zijlstra, Radstok, et al., 2016). In addition, we have illustrated the incidence rates of the region of Amsterdam as hotspots in Figure 4.2 to visually confirm the tendency of stability.

Consequently, the spatiotemporal stability helps to justify using historical cardiac arrests for AED deployment optimization strategies and ensuring that stationary AED placement will provide long-term benefits.

4.2.3 Kernel Density Estimation of cardiac arrests

Although we have discussed the validity of using historical OHCA locations for AED deployment, the takeaway is that cardiac arrest *areas* remain stable over time. In other words, we cannot optimize bluntly for exact locations of past incidences but need to determine the spatial distribution of the OHCA risk. Thus, the point measures (historical OHCAs) need to be converted to a spatial probability distribution.

A widely used GIS method is Kernel Density Estimation (KDE) (Sheather & Jones, 1991), which has the advantage of utilizing clusters that do not follow administrative or geopolitical boundaries. Prior studies used KDE to identify OHCA risk areas (Chrisinger et al., 2016; Lerner et al., 2005; Moon et al., 2015; Ong et al., 2008; Semple et al., 2013) and for optimization purposes such as in this research (Bonnet et al., 2015; Chan et al., 2016, 2017).

The KDE method applies a continuous density function at each observed data point with a "bandwidth", which is proportional to the standard deviation of the density function. The aggregated density function is the result of the KDE, with the bandwidth acting as a smoothing factor. Thus, the higher the bandwidth, the more uncertainty of the OHCA risk.

We use the bivariate KDE model by Botev, Grotowski, and Kroese (2010) to determine

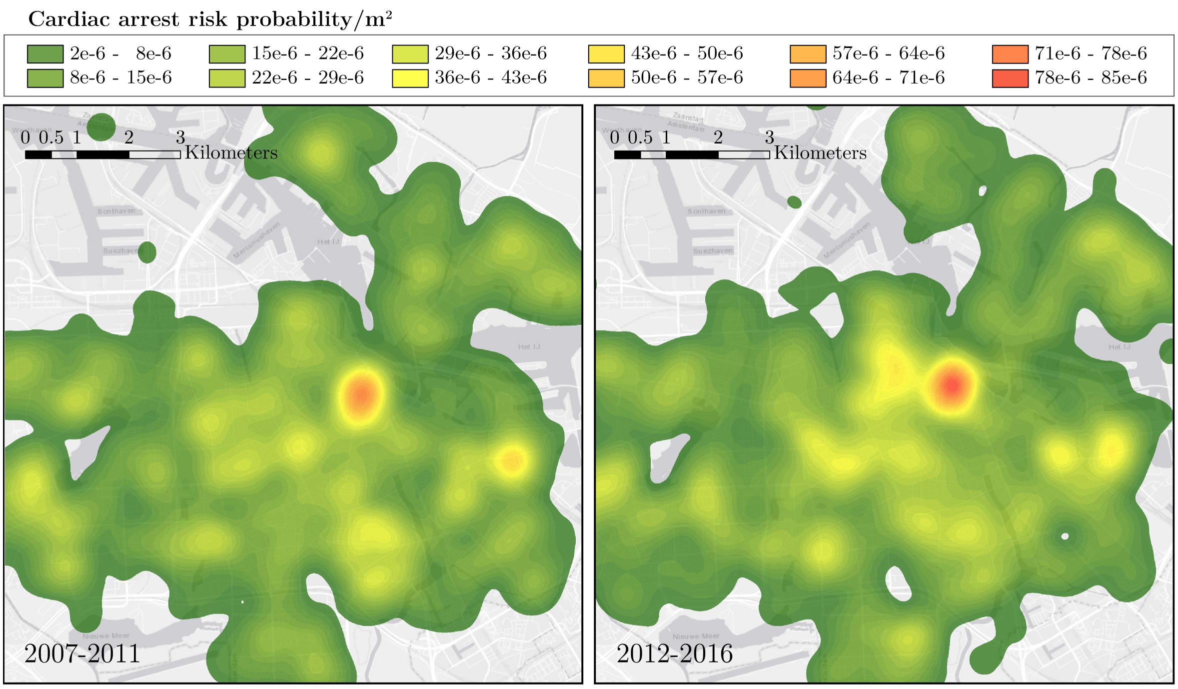
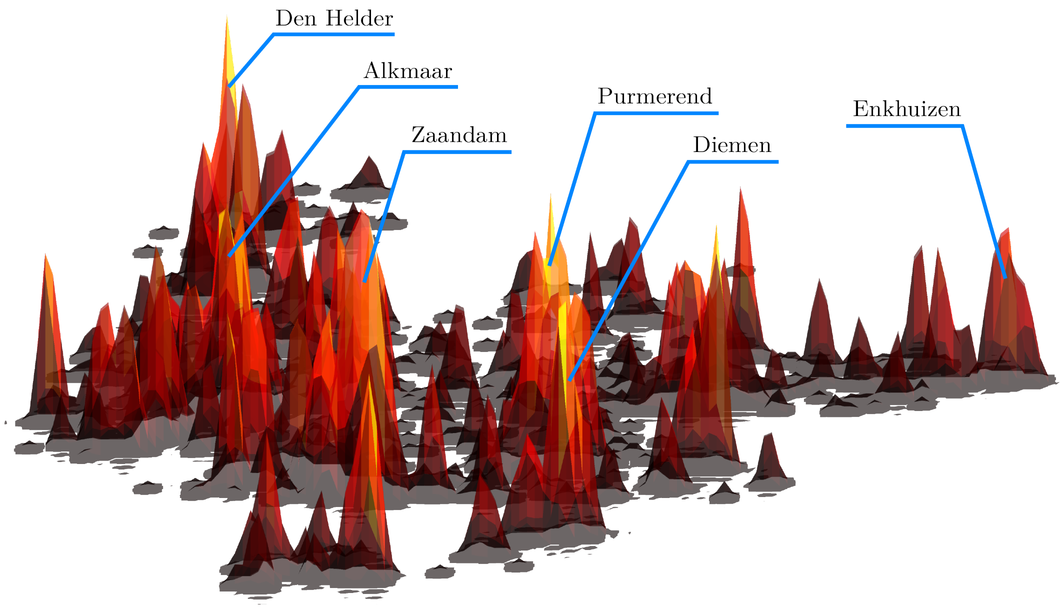
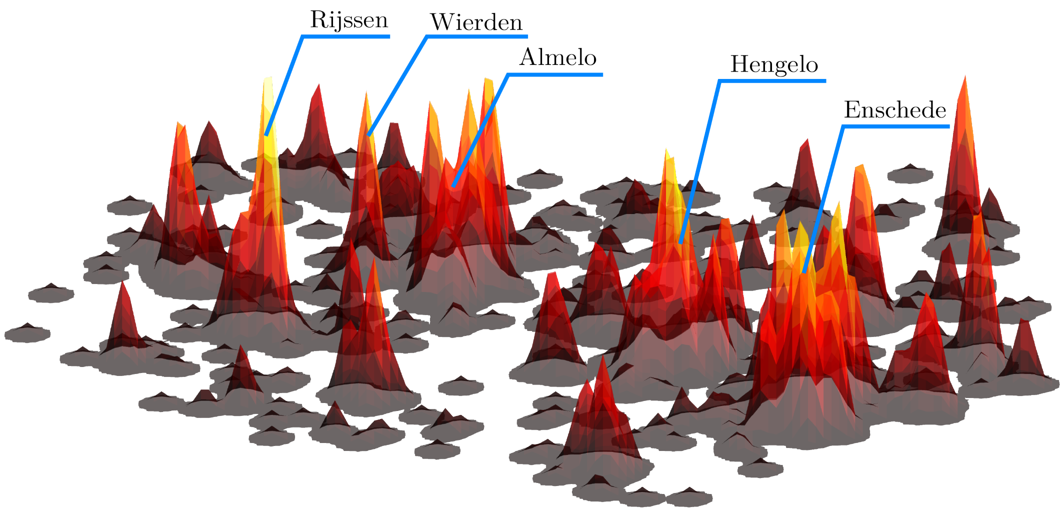


Figure 4.2: The region of Amsterdam (North Holland) with four cardiac arrest risk analyses with the KDE method (see Section 4.2.3), aggregated per 5 years. Note that the ERC recommends placing AEDs where OHCAs occur once every 5 years and that the hotspots in the illustrations above seem stable over the years.



(a) KDE of North Holland



(b) KDE of Twente

Figure 4.3: Three-dimensional probability densities by the bivariate KDE. Higher peaks indicate a higher cardiac arrest risk at the location on the plane.

the appropriate bandwidth. The particular method improves upon the classical model — for instance, it is immune to accuracy failures in the estimation of multimodal densities with widely separated modes. The two bandwidth parameters are chosen optimally without the assumption of a parametric model for the data or any "rules of thumb".

However, the original data consists of the conventional World Geodetic System 1984 (WGS84) coordinate system, i.e. latitude and longitude, and cannot directly be utilized in the KDE. Namely, distance metrics depend on their location on the spherical Earth, for which our KDE method cannot account for[1]. Therefore, we convert the coordinates from

[1]Consider the (extreme) example of two points with a difference of 10° longitude located on the equator

WGS84 to the European Datum 1950 Universal Transverse Mercator (UTM) coordinate system (zone 31N). This is a practical 2-dimensional Cartesian coordinate system that instead of utilizing a single map projection, employs 60 zones to identify locations on the Earth. The practical benefit is that the UTM system facilitates the usage of the metrical system for easy calculations of Euclidean distances. For example, a typical latitude-longitude format as 52°20′33.0″N 6°40′1.5″E is transformed to 5 805 674.5N 749 872.3E with meters as units.

We note that an Euclidean distance is an overestimation for the actual distance, since such calculation takes a straight-line "shortcut" through the spherical Earth instead of following the curvature. Logically, the error increases with the distance. We have empirically tested different distances when an AED can be retrieved at different locations in our study area and found no significant differences for our purposes (error did not exceed 1 m) between the Euclidean distance (with UTM) and the great circle distance (with WGS84).

With the UTM coordinates and using the KDE method, we establish the uncertainty of the clustering of a certain region by calculating the bandwidth. Consequently, the aggregated probability density function of cardiac arrest risk is determined. We found the two-dimensional bandwidth (east–west; north–south) to be (253.0 m; 416.1 m) for North Holland and (347.3 m; 313.7 m) for Twente. Figure 4.3 shows the resulted bivariate KDE distributions of our two study regions.

As the most applicable single decision makers for AED deployment are usually municipalities (see Section 3.2.3), we focus on analyzing municipalities individually. This will accurately cluster AED deployment efforts and will give the most practical insights. Therefore, we have also determined the bandwidth for all 43 municipalities, with the median of the horizontal bandwidth being 247.1 m (IQR: 201.7–344.4) and the median of the vertical bandwidth 282.3 m (IQR: 231.5–367.1).

4.2.4 Simulating cardiac arrests

With the distribution of the OHCA risk known, we can simulate cardiac arrest incidences that follow the density function. However, when using a simulated cardiac arrest set for optimization, "overfitting" can occur where the model parameters are optimized for the given data but may perform poorly with independent data (Simon, Radmacher, Dobbin, & McShane, 2003). In other words, we can optimize with excellent results for a given problem instance, but this does not automatically translate to a robust deployment for the future. Consequently, it is essential to obtain an unbiased solution with the optimization model. Methods for obtaining unbiased results include cross-validation or using independent data sets for "validating" the model.

(i.e. 0° latitude). The distance between these two points is 1112 km. The same difference in longitude at 70° latitude (e.g. at the hight of Norway) results in a distance of 380 km. Consequently, KDE's bandwidth in degrees would be meaningless.

We choose the latter approach — for each optimization run, we compute a set of simulated cardiac arrests that is used as an input for the optimization method. In other words, this set ($\mathcal{I}^t$) "trains" the model. Hereafter, we evaluate the output of our model using separately generated "validation" sets ($\mathcal{I}^v$). Note that we interchange $\mathcal{I}$ by $\mathcal{I}^t$ or $\mathcal{I}^v$ in the optimization models.

We follow the guidelines for discrete event simulation proposed by Karnon et al. (2012) where possible. For example, we use identical random number seeds for the testing phase to ensure that all models can be compared correctly, and use randomized random number seeds for generating the validation sets. Also, given the probabilistic characteristic of a simulation model, the output has a random aspect as well. Thus, the more instances in the training set, the better the discrete values will follow the KDE's probability distribution. Also, the more iterations in the simulation model during the validation phase, the more accurate the performance metrics are estimated. We adapt the technique of Law (2014) to our method for determining an appropriate number of $\mathcal{I}^v$ sets, denoted as n^*, to ensure that our output metrics are sufficiently accurate.

A confidence interval (CI) can give an indication of accuracy; a CI is defined as $\overline{X} \pm t_{n-1,1-\alpha/2}\sqrt{s^2/n}$, with t denoting the Student's t-distribution, α the significance level, $\overline{X}$ the sample mean and s denoting sample variance. We can perform as much iterations until the width of the CI, relative to the average, is sufficiently small. The relative error can be estimated by $\gamma = |\overline{X} - \mu|/\mu$. However, by using γ directly as an estimate, the actual relative error would be at most $\gamma/\left(1-\gamma\right)$. This can be improved by using the corrected target value $\gamma' = \gamma/\left(1+\gamma\right)$. Finally, combining this with the CI, the minimum number of simulation runs n^* for which the estimated relative error is $\leq \gamma'$ is found by:

$$n^* = \min\left\{n : \frac{t_{n-1,1-\alpha/2}\sqrt{s^2/n}}{\overline{X}} \leq \frac{\gamma}{1+\gamma}\right\} \tag{4.1}$$

We apply Equation 4.1 to our data and find an appropriate number for n^* in Section 5.3.

4.3 Determining coverage

To maximize the efficacy of any AED deployment strategy, the used method should incorporate the real-life scenario(s) as much as possible. Therefore, to determine the aspects and key factors that influence OHCA outcomes, we consider typical events during a cardiac arrest. Hereafter we can determine the parameters within the previously formalized coverage function that defines when an OHCA is considered to be "covered" by an AED in our model.

4.3.1 Collapse-to-call

The first interval, also being the first link in the Chain of Survival (Figure 1.1), considers the time between collapse and call to the dispatch center. Although it is not part of DHA's

6 min guideline, the collapse-to-call interval causes a significant delay of defibrillation that strongly influences positive outcomes of OHCAs (Swor, Compton, Domeier, Harmon, & Chu, 2008; Takei et al., 2015). Creating more awareness in the society and increasing the community of medically trained lay responders, something the DHA is successfully pursuing (see Section 3.2.1), may improve this time interval. Likely for this same reason, Strömsöe et al. (2015) found that the collapse-to-call interval has improved from 5 to 2 min in Sweden over 19 years. Therefore, although we do not have information on collapse and thus are not able to assess this aspect in our study area, even a minute of improvement in this stage may have significantly positive consequences on OHCA survival.

4.3.2 Events considered in the 6 minute zone

Next, we consider the events starting with the call to the dispatch center. We remind that the DHA guidelines state that the call-to-shock time should be at most 6 min. Our data shows that the call-to-connection times of CRS AEDs is well beyond 6 min in our study area, with a median of 7:42 (IQR: 6:29–9:12), while the on-site AEDs had a median of 4:12 (IQR: 2:23–6:39) when considering only instances when the respective AEDs were connected first[2]. Naturally, our methods aim to improve these numbers. Therefore, we need to establish the time that can be allocated to the travel time of bringing an AED to the victim to implement this in our model correctly. Since the data shows that AEDs that are retrieved with the aid of the CRS generally have worse defibrillation times than on-site AEDs and the former case consists of more (complex) actions, we first focus on the procedures of retrieving CRS AEDs.

We analyze all key events during the allocated time frame of 6 min and find the time that we can use for the AED optimization. Figure 4.4 illustrates the events up to the defibrillation by an AED after a typical OHCA in the Netherlands with an implemented CRS. The blue segments (number 1 and 7) are derived from the data. However, the red segments are not directly known. Note that realistically, the duration of retrieving an AED is also determined by AED placement. However, since the locations of alerted civilian responders are unknown to us, we cannot determine this interval correctly and need to make assumptions.

The green segment (number 5) is the actual time the responder travels with an AED. This time frame directly influences within what distance an AED should be located to be able to deliver a shock in time. Our goal is to determine this time frame and then implement it in our model. Obviously, all other variables should be improved (e.g. minimizing the call-to-alert interval, minimizing the set-up time of AEDs, etc.) whenever possible, but this is outside the scope of this research.

[2] Berdowski et al. (2011) previously reported an expected survival rate of 49.6 % for OHCAs that were defibrillated by on-site AEDs with a historical call-to-shock interval of 4.1 min (median), survival of 17.2 % for AEDs from FRs with a 8.5 min interval and survival of 14.3 % with no defibrillation at all.

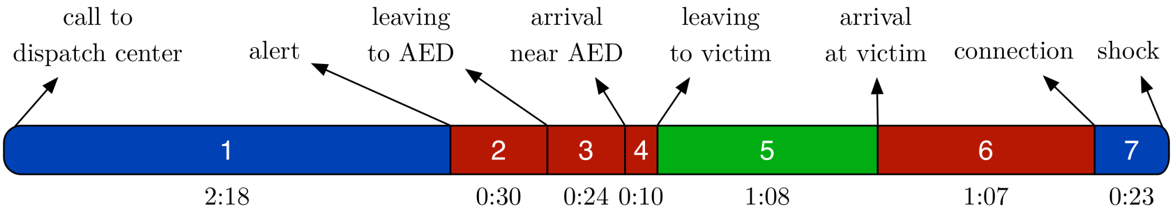


Figure 4.4: Time intervals between the call to dispatch center and AED shock. Blue segments denote intervals that are determined with historical data; red segments denote intervals that are not directly known and are determined by assumptions or from literature; the green segment denotes the interval that is determined after all other events are considered. The allocated times are discussed in Sections 4.3.3–4.3.5. As recommended by the DHA, the maximum allocated time for all events is 6 min.

4.3.3 Call-to-alert

The first interval in Figure 4.4 is call-to-alert. Early identification of a cardiac arrest during emergency calls increases the provision of bystander CPR and defibrillation and consequently survival of OHCAs (Viereck et al., 2017). However, such recognition remains a challenge to dispatchers. Previously, 29 % of included cardiac arrests were not recognized as such in the RAF of Amsterdam in 2004 (Berdowski, Beekhuis, Zwinderman, Tijssen, & Koster, 2009).

Existing literature reported results of a median interval the call-to-alert of 2–4 min (Herlitz et al., 2003; Swor, Jackson, Walters, Rivera, & Chu, 2000; Takei et al., 2010) with a high accuracy of recognition of OHCAs by medical dispatchers (Møller et al., 2016). The median of the interval from our data is 2:18 (IQR: 1:34–3:29)[3]. Ideally, bystanders would call prior to the cardiac arrest. However, in such cases the victim has more often a non-shockable rhythm (Eisenberg, Cummins, Litwin, & Hallstrom, 1986).

Although not within the scope of this research, the length of this interval is significant and greatly limits the time that is left to start defibrillation by AEDs. A quick visual glance at Figure 4.4 shows that this even takes most of the time within the allocated 6 min compared to other events. It is worth noting that a recent study found a mean of 0:35 for this same interval (Caputo et al., 2017). For the study's region with a population density of 1251/km^2 and challenging terrain as mountains, valleys, and lakes, this is an impressive result (in comparison, the mean of our complete dataset is 2:50). Moreover, a recent Danish study touched upon using machine learning for recognizing cardiac arrests, and reported much improved results compared to human recognition (Blomberg, Folke, Møller, & Lippert, 2017). This indicates that improvement in this area is possible and should be pursued to have a significant effect on defibrillation times.

[3]Excluding instances with EMS, FRs and general practitioners as a witness and including only the common time periods of the data of the two regions — i.e. 1 February 2010 to 31 December 2016

4.3.4 Alert-to-AED-retrieval

The alert-to-AED-retrieval considers the segments 2–4 in Figure 4.4. Realistically, this interval does not fully consist of only traveling time. In the first of these events, time passes before a civilian responder actually receives and reads the alert. Also, the responder needs to end his/her current doings and possibly perform other actions before leaving the original location. We allocate 0:30 for this timeframe (segment 2).

Then the route towards the AED starts (segment 3). Currently, the CRS uses a 500 m radius around each AED within which a civilian responder can be assigned to for retrieving the device (also see Figure 1.3). Although the CRS strives to assign responders to AEDs such that the route would be less than 5 % longer than a direct route to the victim, this scenario cannot be guaranteed. This means that in the worst case, assuming a 15 km/h traveling speed (as used by the CRS), segment 3 will take 2:00 for a distance of 500 m. On the contrary, in the best case scenario, in which the AED is located exactly on the route towards the victim, segment 3 would not take any additional time. We make a conservative assumption that on average, the responder will travel 100 m, which translates to 0:24.

Segment 4 denotes the time of visually finding the AED once arrived at the location and possibly retrieving it from its cabinet. Cabinets are often secured with a lock. We allocate 0:10 for this event.

4.3.5 Arrival-to-shock

We determine the travel time between the locations of the AED and the victim after having determined all other intervals. Thus, we continue with the next event — the arrival-to-connection in segment 6. When a lay responder has arrived to the victim, the AED should be turned on, the clothing of the chest of the victim should be removed and the AED pads should be applied. Only then a connection can be made.

Hereafter, during the connection-to-shock in segment 7, the AED automatically analyzes the hearth rhythm and shocks the victim if it deems necessary[4]. This is not always successful on the first trial.

Our data has no information of the time of arrival of lay responders, but the connection and shock times are recorded. The median interval of AED connection-to-shock (segment 7) for our complete study region is 0:22 (IQR: 0:19–0:28) when only an AED was connected, and 0:23 (IQR: 0:20–0:35) when first an AED was connected and then an mDFB. This is in agreement with Hosmans et al. (2008), who reported an interval between the application of electrodes to the delivery to shock of 0:23, with no significant difference between whether an automatic or semi-automatic AED was used. We allocate 0:23 for this interval.

Gundry, Comess, DeRook, Jorgenson, and Bardy (1999) found an average arrival-to-shock

[4]This is in the case of a fully automatic AED. With a semi-automatic AED, the devise prompts the user to press a button for a shock.

time of 1:30 for six-graders and 1:07 for paramedics. We assume 1:30 for this interval and subtract the time of connection-to-shock to find 1:07 for the arrival-to-connection interval.

4.3.6 Conclusion on time to retrieve and connect an AED

Subtracting the discussed segments from DHA's 6 min guideline, we can determine how much time there is left to bring an AED to the victim (i.e. segment 5 in Figure 4.4). This results in 1:08 or 283 m with a speed of 15 km/h. When considering a quick walking speed of 8 km/h for the distance of traveling to the AED and to the victim, segment 3 takes 0:45 which leaves 0:47 for the travel time to a victim. This is equivalent to a distance of 104 m.

If we consider the scenario when an on-site AED is used, segments 1–3 (call-to-arrival at AED) of Figure 4.4 differ from the situation with the CRS. This leaves 4:20 for retrieving an AED. However, in this scenario a nearby lay responder should make a return route and is often unguided in the search for an AED. Nevertheless, if we assume that the search starts immediately after the call to dispatch center and the responder travels with a perfect route to an AED, the responder can retrieve the AED at 289 m when considering a speed of 8 km h^{-1}.

Given the relative conservative assumptions and the previous discussion, in the current situation, we choose 300 m as the borderline of the distance within which it is possible to retrieve an AED successfully with or without a CRS. We can additionally justify this by comparing the results of previous research (see Section 1.5.3). There, incorporating a CRS, different distances are used that consider AEDs "covering" a particular OHCA. The distances range from 100–500 m, with a notable example of Ringh et al. (2011), who showed that in their study, only 2.5 % of responders who were at a distance of 400–500 m from the cardiac arrest arrived prior to the ambulance.

The distance of our CRS of up to 1500 m is controversially longer. With that distance, the responder would need an average travelling speed of 79 km h^{-1} when considering the time that we have allocated to travel from the AED to the victim. Possibly for this reason, some municipalities did not implement the CRS[5]. Perhaps the CRS of our study region envisions that civilian responders could drive a car or ride a bicycle and therefore accommodate an extra distance for its alerts. Or, given the fact that up to 30 responders may be alerted, the idea is to better have too many alerted responders than too few[6].

Nevertheless, we find the used 1500 m distance a significant overestimation of the current

[5] In 2012, the municipality of Leiderdorp has rejected the implementation of the same CRS as in our study region because the Gemeentelijke Gezondheidsdienst (GGD) (the national public health institute in the Netherlands) concluded in their research that the system does not in fact improve survival since lay responders often cannot reach the victim within 6 min (Schouten & Driessen-Jansen, 2012). We have also shown that the median call-to-connection time of the historical OHCAs is 7:42 when only considering the instances where the CRS-AED was connected first. The results are worse when including all instances.

[6] Brooks et al. (2016) found that when a "long" distance is used (400 m in the study), EMS or FRs often arrive prior to the civilian responders. In this case, effective lay responder efforts can be hampered by their feelings of "frustration of responding and then not being able to participate" (p.24).

situation and thus implement a maximum distance of 300 m in our optimization model as a more realistic approach.

4.3.7 The coverage function

In the previous subsection we have determined that a distance between an AED and OHCA of 300 m can be considered acceptable in regards to the efficacy on survival. Thus, as such we have implicitly set the outer radius r_2 of Equation (2.1) to 300 m.

For the rest of the parameters in Equation (2.1), we examine previous literature on the rate of survival with respect to time to defibrillation. Chan et al. (2016) chose 20 m for r_1 as lay responders can immediately spot an AED within this distance. We concur with the argumentation that it is very likely that an AED within 20 m will be visually spotted and immediately retrieved. Moreover, we have previously discussed that the median delay for activating the CRS is 2:18, which is significant. If an AED could be retrieved because it was within the "line of sight", prior to the CRS alert, such situation would be vastly superior. In short, since an AED located within 20 m is as good as it gets, we consider such scenario as "fully covered" and set $r_1 = 20$ m.

Regarding the scenario that the cardiac arrest is located between the two radii and only partial coverage exists, there is consensus in prior literature of a decreasing survival probability with the time of collapse to defibrillation as the independent variable. However, the studies do not necessarily report the same numerical values. Most likely, indisputable numbers cannot be ensured as too many factors exist that may affect results. However, most studies do acknowledge an *exponentially* declining rate of survival after an OHCA as the time to defibrillation increases (e.g. Callans, 2004; De Maio et al., 2003; Nordberg et al., 2015; Valenzuela et al., 1997; Waalewijn et al., 2001; Yasunaga et al., 2011). An exponentially decreasing survival rate implies that at some point, the delay to defibrillation does not affect survival significantly any more. This is also confirmed by van Alem et al. (2004), who found that extreme delays to defibrillation are not significantly different from moderate delays in regards to quality of life. Therefore, regarding the scenario that the cardiac arrests is located between the two radii and only partial coverage exists, we use the specific distance as a proxy for survival and adapt $f\left(d_{ij}\right)$ in Equation (2.1) with an exponential function.

Consequently, adapting the coverage function to our situation, c_{ij} is defined as follows:

$$c_{ij} = \begin{cases} 1 & \text{if } (d_{ij} \leq 20); \\ e^{-\eta(d_{ij}-20)} & \text{if } (20 < d_{ij} \leq 300); \; \forall i \in I, \forall j \in J; \\ 0 & \text{otherwise.} \end{cases} \tag{4.2}$$

To have a similar function to the survival rates, we set $\eta = 0.015$ in the exponential component. This results in a function as illustrated in Figure 4.5.

Note that we use Euclidean distances for determining coverage. The Euclidean distance is shown to be highly correlated with road distance and with travel time (Boscoe, Henry, & Zdeb,

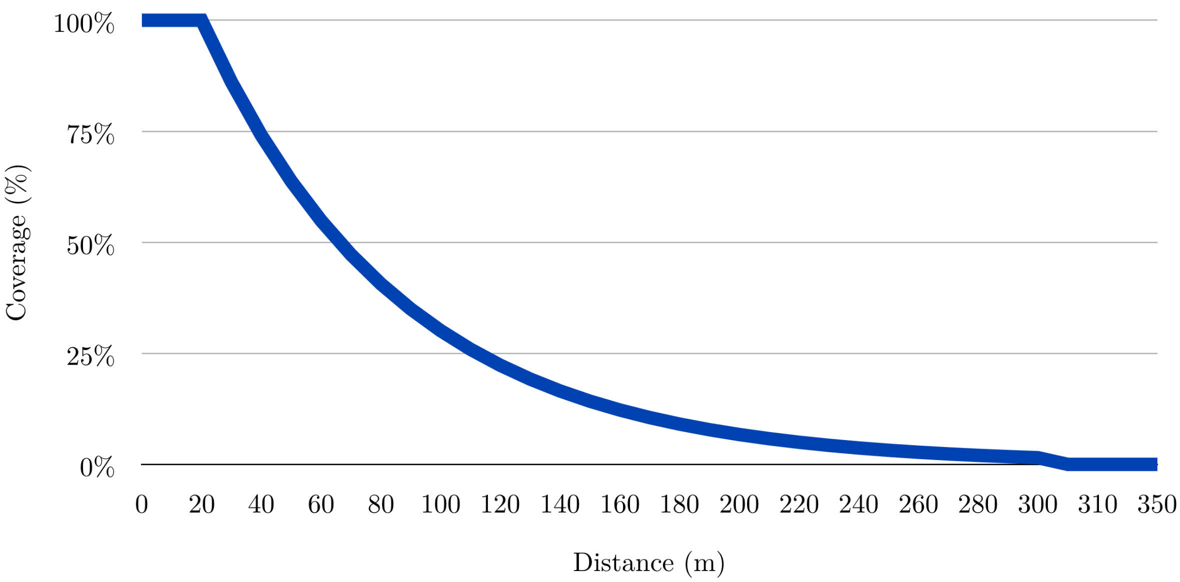


Figure 4.5: Exponential coverage decay function for optimization model. Used parameters: $r_1 = 300\,\mathrm{m}$, $r_2 = 20\,\mathrm{m}$ and $\alpha = 0.015$. See Equation (4.2) for the corresponding function.

2012; Jones, Ashby, Momin, & Naidoo, 2010; Phibbs & Luft, 1995). Only physical barriers (e.g. multiple floors, walls, waterways) may negatively affect the precision of the Euclidean distance. On the other hand, straight-line distances are especially adequate when considering the routes that can be taken by lay responders, as the responders can take shortcuts that are not on a road network.

4.4 Effective candidate locations

We remind that any facility location optimization strategy as discussed in the literature in Section 1.5 requires (1) a set of demand nodes (i.e. cardiac arrest locations in our study, in set $\mathcal{I}$), (2) a coverage function (c_{ij}) that determines to what extent demand is covered by a facility and (3) a set of potential facility locations (i.e. AED locations, in set $\mathcal{J}^c$) for optimization. In this section we finalize the methods for determining the data for set by discussing how potential AED locations are determined. In the next chapter we present the optimization results.

4.4.1 Motivating the characteristics of adequate candidate locations

We have previously discussed that most prior research used (a subset of) existing buildings as candidate locations for AED placement (e.g. Bonnet et al., 2015; Chan et al., 2016; Tsai et al., 2012). Others have used landmarks such as postal collection boxes (Srinivasan, Salerno, Hajari, Weiss, & Salcido, 2017) and bike sharing stations (Dahan et al., 2016). However, we note that the quality of solutions not solely depends on effective algorithms, but arguably even more so on input data. More specifically, candidate locations should facilitate high quality problem instances to assure the potential of good coverage results. Even though using buildings or landmarks seems sensible from a practical point of view, we argue that using a pre-defined set of locations is is not the very practical nor effective.

For example, data of building locations or landmarks is not always available, which makes the entire AED deployment optimization impossible at times. In addition, building locations consist of address locations, indicating that, in most cases, AEDs are bound to the entrance of buildings. This means that the possibility of AEDs on the street are omitted, despite positive outcomes of such deployment strategies (e.g. Capucci et al., 2016). Moreover, we discussed in Section 3.2.2 that in our study area, an increasing number of AEDs are placed outside and even relocated from indoors to outdoors. Arguably most importantly, the dependency on address locations or a subset of the study area (as in the case when choosing a certain landmark) means that some OHCA incidences could be not covered *at all*, while other OHCAs could have abundant AED placement options in the proximity with ample overlap.

A hypothetical example of this phenomenon is visualized in Figure 4.6. The illustration shows that when using addresses (mostly front entrance) of building locations as candidate locations for AED placement, optimization can be inefficient and yield ineffective results. Namely, in the front of the image, there are 5 cardiac arrest victims, but due to the relatively large buildings and thus sparse possible locations, there are only few options for placing AEDs. A completely different situation is in the rear of the illustration, where there are densely built smaller buildings, which results in an abundance of candidate AED locations for just one cardiac arrest. Consequently, this single cardiac arrest enjoys substantial computational efforts while most of the cardiac arrests in the front cannot even be covered.

In our opinion, these arguments give enough reason to investigate other methods for computing candidate locations for facilities and improving the potential of the quality of solutions. Hence, instead of using pre-defined locations, we seek to generate potential facility locations that can cover any area on the plane, such that it is possible to control the density of the locations. This way, the user can determine how many locations are analyzed, with possibly better solutions when using more locations.

Assuming all AEDs are equal and thus have a homogeneous spatial coverage, the most representative theoretical shape of "coverage" would be a circle. Since it is not possible to distribute the plane with circles such that every area is covered without any overlap, we seek to find a scalable method that distributes circles with as little overlap as possible. Less overlap translates to fewer locations and thus a more efficient set of candidate locations.

Since circles are symmetrical, the "pattern" of the candidate AED locations should be symmetrical too. Therefore, we divide the plane in equal shapes, or, in other words — "regular" polygons, which have equal sides and angles. The three possibilities are triangles, squares and hexagons (Carr, Olsen, & White, 1992). The technical name for creating such subdivisions of a plane is "tessellating".

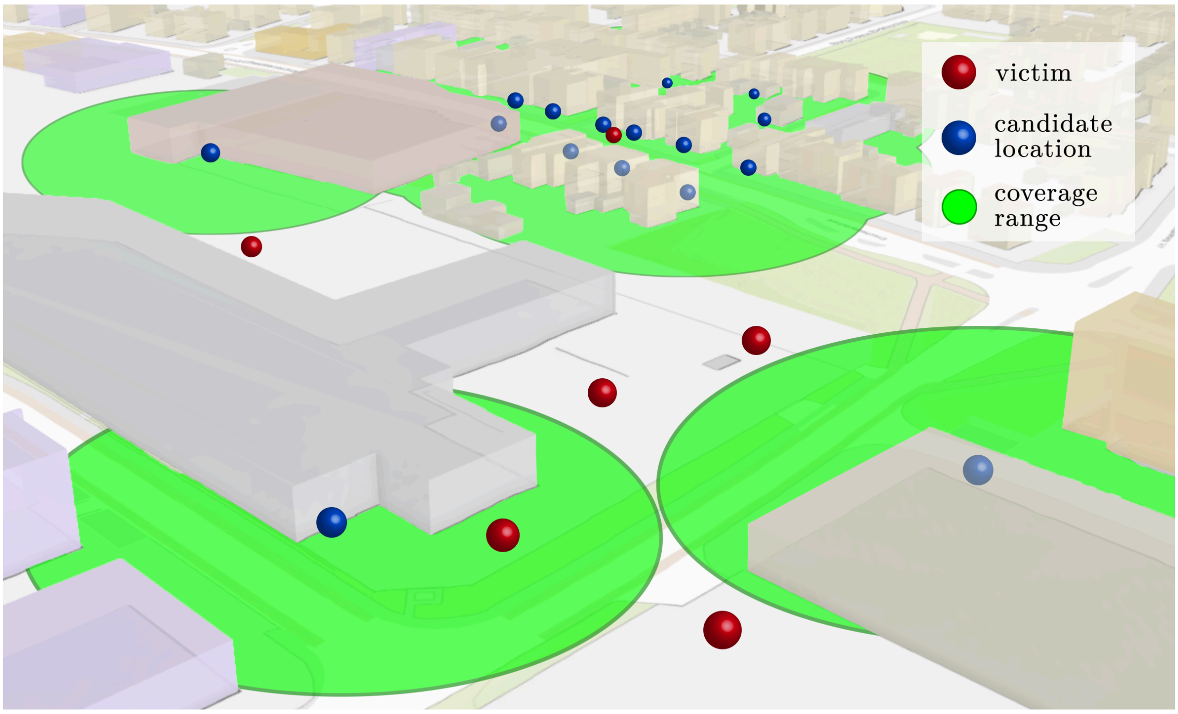


Figure 4.6: A hypothetical scenario with a 3D-view from a real city in the Netherlands. At the front of the illustration, 1 out of 5 cardiac arrests can be covered by one potential AED location; at the rear of the image, a single cardiac arrest can be covered by many potential AED locations.

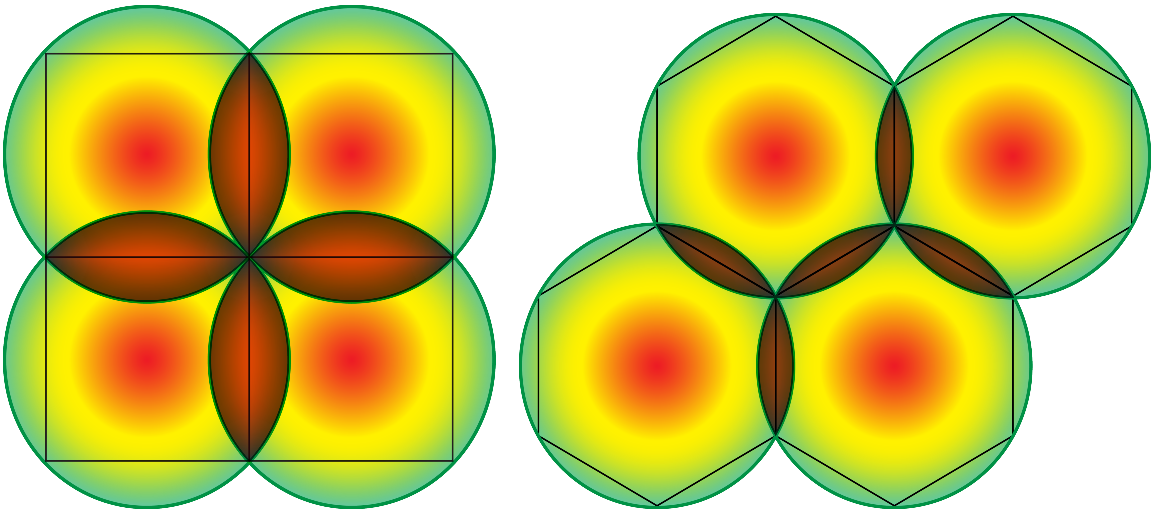
4.4.2 The hexagonal tessellation

The first tessellation we have mentioned, the triangular tessellation, requires the triangles to have two different orientations (one vertex pointing upwards or downwards), which is for most applications undesirable. The hexagonal tessellation is less popular than the rectangular tessellation[7], likely due to more difficult implementation characteristics since cells in the hexagonal tessellation are aligned along three axes as opposed to two axes (a horizontal and vertical axis) in the square tessellation. This makes the coordinate system less straightforward (see e.g. Snyder, 1999).

However, Kershner (1939) mathematically proved that if the Euclidean plane is covered with circles, the density of the covering would be at least $\frac{2\pi}{3\sqrt{3}}$, and proved that if circles would be positioned in the centroid of hexagons, such hexagonal tessellation has a density equal to the minimum density, thus being optimal. This is also immediately evident when visually comparing the overlap of the two tessellations in Figure 4.7.

Moreover, it can be determined that the following is true in regards to tessellations by squares and hexagons with a circle at the respective centroids: $area_{\text{square}} = 2R^2$ and $area_{\text{hexagon}} = \frac{3}{2}\sqrt{3}R^2$ with R being the circumradius of the polygon (or in other words: the radius of the circumscribed circle as in Figure 4.7). This means that squares have an area

[7] Birch, Oom, and Beecham (2007) found that in the journal "Ecological Modelling", 64 papers used a rectangular and only 2 the hexagonal tessellation



(a) Tessellation by squares

(b) Tessellation by hexagons

Figure 4.7: Overlap of equal circles when placed at the centroids of the respective polygons of the square and hexagonal tessellation.

that is $\frac{2}{\frac{3}{2}\sqrt{3}} \approx 77\%$ of the area of hexagons. Or in other words, there are 23 % fewer locations needed when using the hexagonal tessellation instead of the square tessellation.

We have confirmed this empirically by tessellating the entire region of our data sets and removing locations that have no coverage potential. We found that there are on average 23 % fewer locations needed to cover all demand in comparison to the square tessellation. This is entirely in line with the theoretical proportion we mentioned earlier.

Consequently, using the centroids of hexagons in the tessellation as candidate AED locations enables covering any demand on the entire Euclidean plane with minimal density. As such, we choose the hexagonal tessellation for creating candidate AED locations. Depending on demand data $\mathcal{I}$ and the set radius for a hexagon R, we create candidate locations $\mathcal{J}^c$ with the hexagonal tessellation as shown in Algorithm 4.1.

By altering parameter R, the granularity of candidate locations can be controlled. This allows us to create solutions spaces anywhere between having only few possibilities to place facilities, and having endless possibilities to place facilities. With the latter, the optimal solution approaches the quality of the optimum of continuous optimization[8] and in most cases represents the reality better.

Previously we mentioned that exact methods will always give the optimal solution but they cannot solve large problem instances. On the other hand, heuristic methods do not guarantee optimal solutions but are able to solve large problem instances. Projecting this on the power of controlling the granularity of candidate locations, this means that with a predefined quantity of computational resources, exact methods can give an optimal solution to

[8]When optimizing with continuous variables, facilities can be placed anywhere on the plane and are not limited by pre-determined candidate locations. However, such methods are computationally very intensive and most often not tractable.

Algorithm 4.1 Procedure of creating candidate facility locations with a hexagonal tessellation

1: **procedure** HexagonalTessellation($\mathcal{I}$,R)
2: Find maximum and minimum coordinates of $\mathcal{I}$ in x and y direction
3: Tessellate the rectangular area within this range with hexagons with R as hexagon radius
4: $\mathcal{J}^c \leftarrow$ Find and delete locations without coverage potential, i.e. $c_{ij} = 0$
5: Compute $\mathcal{I}_j$ and $\mathcal{J}_i$ for utilization in algorithm
6: **end procedure**

a problem that is far from the continuous problem. On the other hand, an effective algorithm can give a *close-to*-optimal solution to a problem that is near the continuous problem.

In short, we state that "given an effective heuristic, finding a heuristic solution to an exact problem *may be* superior to finding an exact solution to an approximate problem." We evaluate this statement by assessing the power of controlling the granularity of candidate locations in Section 5.2 by solving with the exact and algorithmic methods.

4.5 Conclusion on data preparation

In this chapter we have determined the necessary data, which was not defined yet, for our optimization methods from Chapter 2. Firstly, we converted point data of the locations of historical cardiac arrests into a spatial probability density function with the Kernel Density Estimation (KDE) method. We showed that the historical distribution stays stable over time and thus is an appropriate representation of cardiac arrest risk. This ensures that adequate AED placement will stay effective on the long-term. With this distribution, we simulated new cardiac arrest locations that can serve as data for the sets $\mathcal{I}^t$ and $\mathcal{I}^v$. The former so called "training" set is used as a direct input for an optimization model, and the independent "validation" set $\mathcal{I}^v$ is used to test the output of the model on its performance with respect to the total provided coverage.

Then we examined the different events that occur during a typical OHCA and established the necessary parameters for the coverage function c_{ij} that determines to what extent an AED at location j covers a cardiac arrest at location i. We determined that when an AED is located within 20 m from a cardiac arrest, the AED provides full coverage, and that up to 300 m a cardiac arrest can be covered within 6 min (as recommended by the medical guidelines). Cardiac arrests that are located farther than 300 m are considered as not covered, while cardiac arrests in between 20 and 300 m are partially covered. This partial coverage is determined by a exponentially decreasing function that follows typical survival functions with respect to the time to defibrillation.

Lastly, the set $\mathcal{J}^c$ was determined, consisting of potential locations for AED placement. We found that the by subdividing the plane with regular hexagons and using their centroids as candidate locations is an appropriate method. This way, the user is not limited to pre-defined locations and can scale the density of the locations by altering the size of the hexagons.

Chapter 5

Results

Having defined the necessary sets, parameters, definitions and methodology to solve the AED deployment problem in the preceding chapters, we apply our techniques to the actual data. In Section 5.1 we fine-tune our optimization setup with respect to the data so that the best possible results can be obtained. Then, in Section 5.4, the tuned algorithm is applied to all 43 municipalities that included in this research and consequently we discuss the results.

5.1 Determining the algorithm tunings

In this section we evaluate different heuristic approaches to find the most suitable method with which we can obtain the best possible results when solving several realistic AED deployment problems in the next section. First, we find upper and lower bounds in Subsection 5.1.1 to get a sense of the solution quality of the developed algorithms. In Subsection 5.1.2 we determine the most appropriate parameter settings for the algorithms and determine the most relevant approach to solve the problems. Then, in Subsection 5.2, we examine different densities of the candidate locations in regards to their solution quality and further narrow down to an effective combination of an algorithm and granularity of the tessellation. Finally, in Subsection 5.3, we define the final setup for solving the AED deployment problem.

Before detailing the results, we have defined the used software and hardware for this research in Appendix A.4, including a short discussion on the choice of using a "compiler" for optimization.

5.1.1 Bounds and metrics

As discussed in Chapter 2, the solution obtained from the Greedy heuristic can serve as a lower bound (LB) and the exact solution as an upper bound (UB). With these bounds, we can tune the algorithms and subsequently evaluate the quality of the resulted solutions.

We apply our methods to all 43 municipalities in this subsection at all times. This results in very diverse problem instances. Each municipality has a different cardiac arrest risk distribution over different geographical areas and thus heterogeneously clustered demand nodes. Also, the number of existing AEDs is diverse — from 1 up to 127 per municipality. Tuning the algorithms with diverse problem instances yields more robust algorithms. Therefore, the tuning is performed for a scenario where existing AEDs are relocated.

We have discussed in Section 2.1 that we can often substitute the ILP formulation with the LP-relaxation when being cautious about whether we obtain all-integer solutions. The complexity of the problem is determined by the number of simulated cardiac arrests in training set $\mathcal{I}^t$ and the number of candidate locations in set $\mathcal{J}^c$. The latter is controlled with the radius of hexagons — denoted by parameter R.

We first define the size of $\mathcal{I}^t$. We remind that the ERC guidelines state that it is cost-effective to place AEDs at locations where at least one OHCA occurs in 5 years. Considering all municipalities, the highest average historical OHCA incidence rate per years is 56. Consequently, to simulate 5 years, we create 300 cardiac arrests and thus set $|\mathcal{I}^t| = 300$ in each of the 43 municipalities using the municipalities' bandwidth that was previously computed with the KDE method in Section 4.2.3.

The number of candidate locations can then be determined such that the problem can be solved by the exact method. This is empirically realized by setting $R = 50\,\text{m}$ which results in a median of 3267 (IQR: 2583–4392) candidate locations in set $\mathcal{J}^c$.

We report the results as the total average coverage received by all OHCAs in a municipality (i.e. $\sum_{i \in \mathcal{I}}(\varphi_i)$ divided by the number of cardiac arrests), averaged over all municipalities. Note that the results consider the gradual coverage as defined by Equation (4.2). Consequently, a value of 50 % does not mean that half of the OHCAs are covered, but that in average, the OHCAs received 50 % coverage.

The average coverage per OHCA per municipality as found by Greedy is found to result in 30.09 %, and the optimum is 30.18 %. Hence, the average optimality gap is 0.087 %. In 12 of 43 municipalities (i.e. 27.9 %), Greedy has found the optimal coverage value. Table 5.1 shows the found results of the Greedy and optima, as well as other algorithms after tuning their parameters. We discuss the tuning of the algorithms and their results next.

5.1.2 Tuning GRASP and Simulated Annealing

Although the Greedy solutions are excellent with respect to the optima, we try to further improve the quality of the results. First, GRASP with local search (defined in Section 2.2.2) is tuned by determining the parameters α and β such that a good performance is found. Figure 5.1 shows the relative scores of different values for α and β. We define "relative scores" as relative performance in regard to the Greedy solution as the LB and the optimal solutions as UB. In other words, with s^* denoting the best found objective value of an optimization method, relative score $= 100 * \left(C\left(s^*_{\text{algorithm}}\right) - C\left(s^*_{\text{Greedy}}\right)\right) \big/ \left(C\left(s^*_{\text{optimum}}\right) - C\left(s^*_{\text{Greedy}}\right)\right)$.

Table 5.1: Algorithm results on medium sized problem instances

Method	Average[a]	Optimal[b]	Score[c]	Time[d]
	%	%	%	s
Greedy	30.09	27.9	0.0	0.03
Randomized Greedy[e]	30.15	44.2	63.8	118.7
GRASP[f]	30.17	67.4	84.6	16.3
biased GRASP, no.1[g]	30.17	69.8	84.7	15.8
biased GRASP, no.2[h]	30.17	72.1	85.3	103.2
SA (random start)[i]	29.47	4.7	−7.1	101.4
SA (Greedy start)[i]	30.16	55.8	73.4	100.9
SA (Randomized Greedy[j] start)[i]	30.16	55.8	73.6	118.2
SA (Randomized Greedy[j] start) + reannealing[k]	30.17	62.8	84.9	128.7
Exact method (optimal)	30.18	100.0	100.0	107.2[l]

Note: GRASP = Greedy Randomized Adaptive Search Procedure, SA = Simulated Annealing.

[a] Average coverage provided to 300 simulated OHCAs over all 43 municipalities in study area when relocating existing AEDs.

[b] Proportion of instances (with respect to the 43 municipalities) when the optimal solution is found.

[c] The score is defined as the relative difference between the Greedy and optimal solution. Note that more precise results are used for the calculations than the numbers shown in the "Average" column.

[d] Average running time per municipality in seconds.

[e] $\alpha = 0.98$, 2000 iterations.

[f] $\alpha = 0.98$, 5 iterations.

[g] $\alpha = 0.98$, 5 iterations, $\beta = 11$.

[h] $\alpha = 0.98$, 50 iterations, $\beta = 8$.

[i] $T_0 = 0.02$, $\delta_c = 0.999$, $\kappa = 100$, $\lambda = 40000$.

[j] $\alpha = 0.98$, 100 iterations, $\beta = 11$.

[k] $T_0 = 0.03$, $\delta_c = 0.999$, $\kappa = 80$, $\lambda = 40000$, $\delta_h = 0.750$, number of reannealings = 5.

[l] Note that although the exact solution is relatively fast, memory requirements are the bottleneck.

Tuning GRASP with biased sampling

Figure 5.1 shows the results of different α of GRASP stratified by β. The figure suggests that incorporating biased sampling can improve the regular GRASP heuristic. For the used problem instances, β in the range of 8–11 result in better objective values for all α. Regarding α, values in the range of 0.97–0.98 yield the best results. Note that with a carefully chosen α, the algorithm is less sensitive to the value of β.

We remind that the higher the α and β, the more "greedy" the algorithm performs. Also note that these parameters are tuned to these problem instances; larger problems will likely benefit from less "greedy" tunings so that more exotic/complex structures can be explored.

With the right tuning, as can be seen in Table 5.1, GRASP yields a relative score of 84.6 % with only 5 iterations, while incorporating the biased sampling marginally improves the score to 84.7 %. When increasing the number of iterations to 50, the score jumps to 85.3 % or, alternatively stating — the optimality gap is 0.043 %. We have also tested only the first part of GRASP, the Randomized Greedy construction phase without local search. Randomized Greedy is not competitive with GRASP as it yields an inferior score of 63.8 % even with significantly more computational resources.

Tuning Simulated Annealing

Applying SA (defined in Section 2.2.3) to the same problems gives mixed results. Firstly, using the classical temperature scheme where most neighborhood structures are accepted (i.e. with a high value of T_0) in the first phase never performed better than Greedy. In the exploratory phase, the objective value deteriorates significantly and becomes approximately 5 times worse than the global optimum. The problem is that getting back to favorable solutions in the exploiting phase appears to be challenging.

The reason may be that in our AED deployment problem, there is a relatively high number of candidate locations and most of them have a relatively low coverage potential. Thus, most of the solutions are not very competitive. This means that if the incumbent solution is mediocre, there are relatively few possible transitions that will change the solution

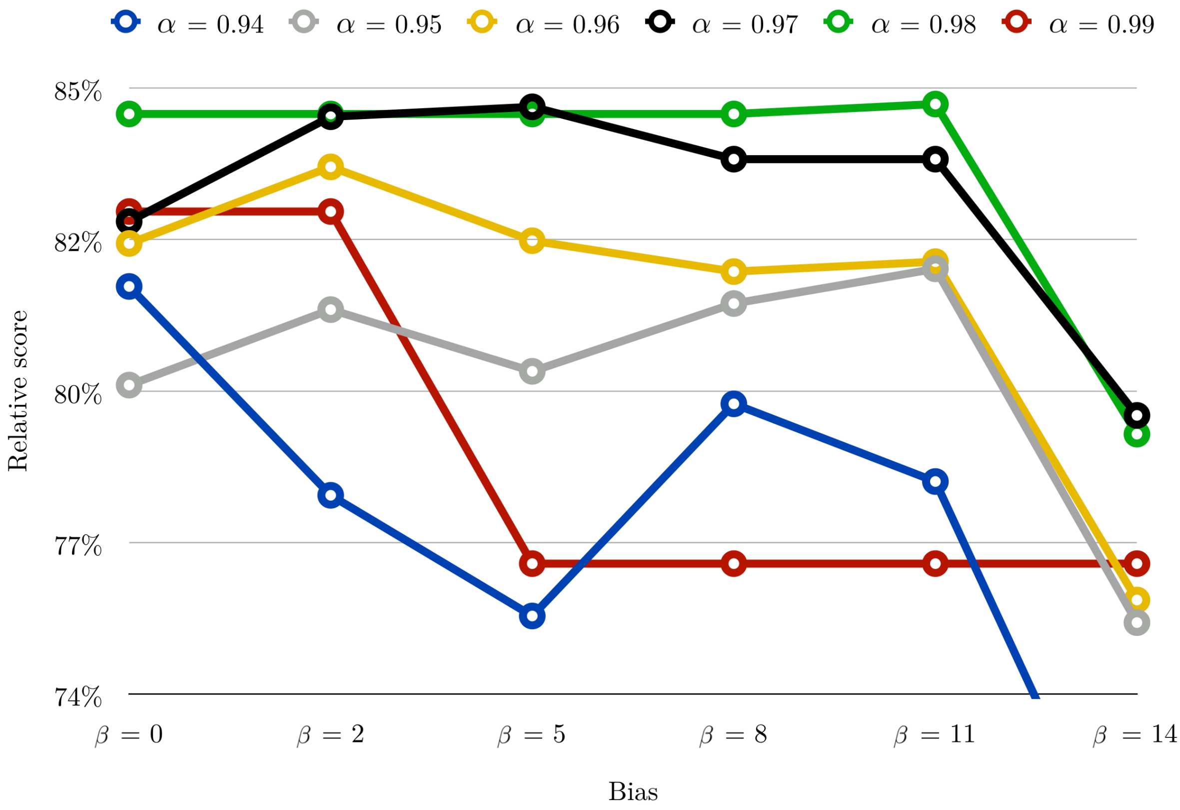


Figure 5.1: Results of the average scores of all 43 municipalities calculated by the GRASP algorithm with biased sampling. "Relative score" depicts the difference between the Greedy solution (0 %) and the optimal solution (100 %). Different α factors dynamically determine the elements for the restricted candidate list (RCL) and are stratified by the bias factor β. Note that $\beta = 0$ is equal to the regular GRASP with no bias.

to a favorable objective value. Due to the random nature with which SA generates its neighborhood structures, selecting these particular neighborhood solutions is unlikely, and the objective values doe not improve as much as one would desire. Consequently, once a good solution is found, only relatively *minor deteriorations* should be allowed.

This explains why with a random starting configuration (and thus often mediocre starting solutions), SA is not able to get good results and the average solutions are even worse than Greedy. Table 5.1 shows that this approach yields a relative score of −7.1 %.

However, when starting with a good initial configuration, i.e. from Greedy or the first phase of GRASP (Randomized Greedy), and only allowing relatively minor deteriorations by setting T_0 accordingly, SA eventually *does* improve the initial solution. After empirically testing a few dozen temperature schemes, the best scheme resulted in a relative score of 73.4 % and 73.6 %.

Still, the quality of results are worse than GRASP's results, even compared to the GRASP algorithm with only 5 iterations. This can be explained by the sensitivity to the temperature scheme per problem instance. Namely, when using a lower T_0 to limit the deteriorations, the algorithm may converge immediately on its initial solution on some problem instances. On the other hand, when using a higher T_0, the solutions may deteriorate too much on some problem instances and thus the algorithm gets "trapped" in mediocre solutions. Consequently, defining a single tuning for SA for all municipalities is not without compromises, and this explains why GRASP fares better when applied to many heterogeneous problem instances.

When factoring in the extension of reannealing, SA's performance is favorably affects, resulting in a relative performance of 84.9 % with approximately the same computational resources. As we have mentioned in Section 2.2, reannealing enables the algorithm to find not-too-distant but better neighbors. Nevertheless, biased GRASP performs slightly better than SA with reannealing, scoring 85.3 % versus 84.9 %. However, we empirically found that when SA with reannealing is properly tuned per problem instance, it can be superior to biased GRASP. Moreover, the iterative improvement phase of GRASP becomes extremely time-consuming for large problem instances, while SA can maintain competitive results within a reasonable amount of time.

Conclusion on algorithm tuning

In this subsection, we have evaluated the performance of different algorithms for medium-sized problems with known optima that were calculated with an exact method. Greedy performed very well with little computational resources, while GRASP was able to give improved results. Extending GRASP with biased sampling further improved the results. SA, especially with reannealing, is capable of giving competitive results but is sensitive to its tuning depending on the problem instance. Consequently, GRASP performs more consistently when a single is tuning is used on multiple heterogeneous problem instances.

5.2 Optimization compared to candidate locations

We have discussed in Section 4.4 that by controlling the radius R of the tessellation, theoretically, the solution quality of continuous optimization can be approached. We test this by solving the relocation problem for all municipalities with different R.

We were able to compute hexagonal tessellations on all municipalities with R being as small as 15 m. More granular settings required more computer memory than in our possession. A tessellation with $R > 1500$ m would be infeasible for some municipalities as a hexagon of that size could not be placed within the geographical bounds. Therefore, we solve the relocation problem with $|\mathcal{I}^t| = 300$ and $R = [15, 1500]$. Results of solving the problems with different optimization methods can be found in Figure 5.2.

Regarding the optimal solutions, as discussed in the previous subsection, the maximum granularity with which the problem instances could be solved was with $R = 50$ m with on average 3556 locations per municipality. Larger problem sizes could not be solved due to rapidly increasing memory requirements[1].

We previously showed that GRASP can give near-optimal solutions consistently over different problem instances, with an average optimality gap of 0.043 %. However, Greedy performs also well (optimality gap = 0.087 %) and does so with minimal computational efforts. We found that GRASP could solve problem instances with $R = 30$ m (on average 9836 locations per municipality) and $R = 20$ m (22 083 locations) in respectively 1.1 min and 14.4 min on average per municipality. We did not attempt to solve for $R = 15$ m (39 221 locations) with GRASP since a single municipality could not be solved within an hour. However, Greedy solved all 43 municipalities with $R = 15$ m in 1.2 s per municipality on average.

Figure 5.2 makes it evident that the impact of solution methods is substantially smaller than the impact of more granular hexagons. With the computational resources at hand, with the exact methods we can obtain an average objective value of 31.18 % with $R = 50$ m; with GRASP — 32.57 % with $R = 20$ m in 14.4 min; with Greedy — 32.76 % with $R = 15$ m in 1.2 s. Also note that near $R = 15$ m, the objective value in Figure 5.2 starts to converge, meaning that more granular tessellations would yield only marginally better results.

Thus, Greedy can ultimately yield superior results in much less time. Therefore, referring to and updating our statement in Section 4.4, "Given a high-quality heuristic, finding a heuristic solution to an exact problem instance *is* superior to finding an exact solution to an approximate problem instance" for our study purposes. With this in mind, we further narrow down our optimization method to Greedy with an as granular as possible hexagonal

[1]For example, an instance with 3×10^6 variables and constraints required ~6GB RAM. Solving with $R = 40$, 30 and 20 m and 300 demand nodes and taking the largest problem instance per given R, the exact method would have more than 5, 9 and 20×10^6 variables and constraints respectively and an exponentially increasing size of the c_{ij} matrix.

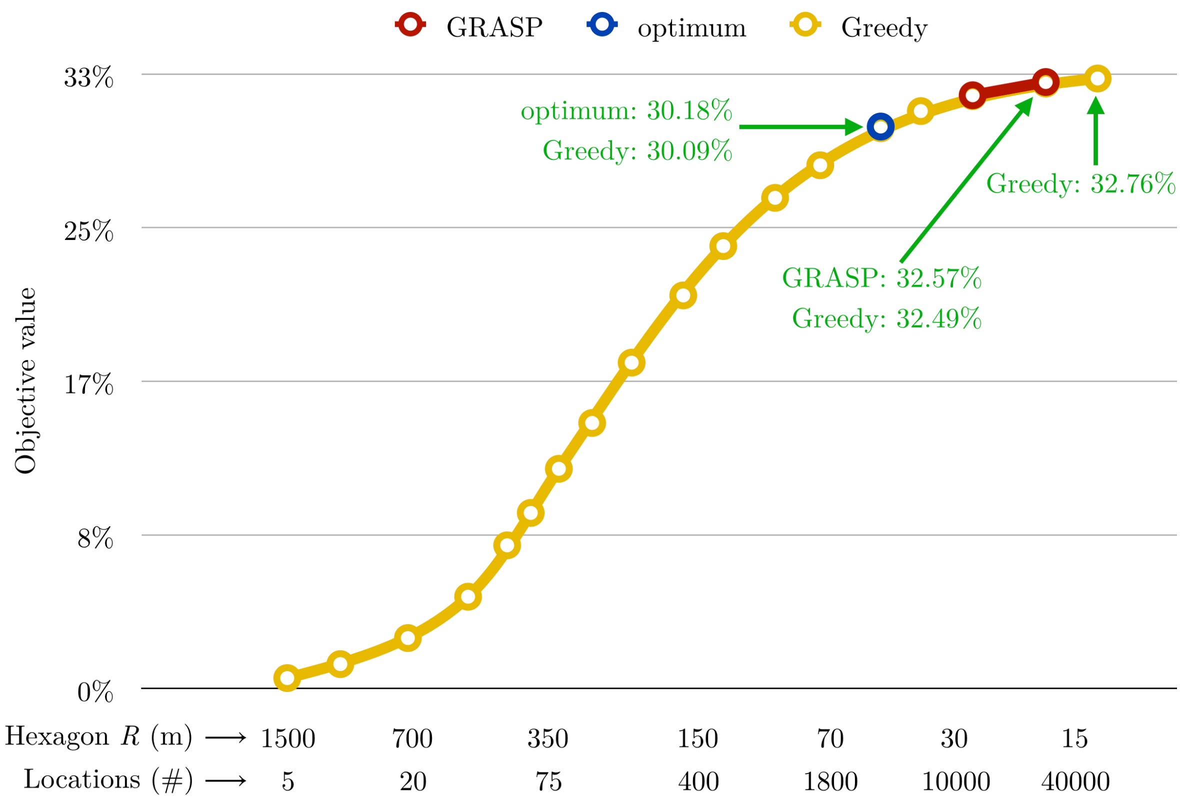


Figure 5.2: Performance of the Greedy algorithm relative to the granularity of the hexagonal tessellation as input $\mathcal{J}^c$. The resulting objective values are the average results when relocating existing AEDs of all 43 munipalities with 300 simulated OHCAs. Since the number of locations exponentially increases with R, a logarithmic horizontal scale is used. For comparison, the best solutions found by the exact method (with $R = 50\,\mathrm{m}$) and GRASP (with $R = 20$–$30\,\mathrm{m}$) are also included.

tessellation for creating the candidate locations.

5.3 Simulation setup

Up until now we have optimized a given demand set without accounting for the probability of deviations of demand locations. Following the methodology in Section 4.2.4, we solve the AED deployment problem with a large training set ($\mathcal{I}^t$) and then create a sufficient number (n^*) of independent validation sets ($\mathcal{I}^v$) to test the deployment on its performance and robustness.

However, increasing the size of $\mathcal{I}^t$ also increases the problem size — most evidently because the cardiac arrest set is increased, but also because due to the higher quantity of simulations, cardiac arrests are often spatially more dispersed and thus more candidate locations are needed to be able to cover all demand.

In the previous subsection, we used $R = 15\,\mathrm{m}$ with $|\mathcal{I}^t| = 300$. With fixed computational resources, improving the robustness of our solutions by increasing the number of simulated demand in $\mathcal{I}^t$ is only possible at the expense of a larger R. However, a larger R decreases the solution quality as we have seen in the previous subsection. Therefore, we test different values of R with different $\mathcal{I}^t$ to find adequate parameters for the best possible coverage solutions. Starting with the lowest possible $R = 15\,\text{m}$, $|\mathcal{I}^t|$ is increased until computer memory was insufficient with $|\mathcal{I}^v| = 60$ (maximum average number of cardiac arrests in a year) and $n^* = 500$ (discussed in Section 4.2.4). The size of n^* is expected to be sufficient — we evaluate this later in this section. The best results of this approach are displayed in Figure 5.3.

The figure illustrates that the previously used optimization setups are not robust in regards to independent validating sets, even though we have shown that more granular candidate locations can result in better solutions for the training set. In general, it is better to increase the size of $\mathcal{I}^t$ to some extent, at the expense of R. The best trade-off is found at $R = 140$ and $|\mathcal{I}^t| = 50\,000$ with an objective value of approximately 14.2 %. Possibly, with more efficiently implemented data structures, memory would be less of an issue and more granular tessellations could be used with larger training sets

We can now evaluate the appropriate amount of simulation runs of the validation set with Equation (4.1). This results in an average n^* of 59 per municipality. However, one outlier has $n^* = 474$. This can be explained by the fact that the municipality has only three AEDs registered — the performance of a few AEDs is not sufficiently pooled with other devices and thus more random behavior can be expected. Nevertheless, we set $n^* = 500$ for subsequent optimization runs to confidently obtain meaningful metrics.

Consequently, the final configuration of our methodology to solve the AED deployment problem is the Greedy algorithm, $R = 140\,\text{m}$, $|\mathcal{I}^t| = 50\,000$, $|\mathcal{I}^v| = 60, n^* = 500$.

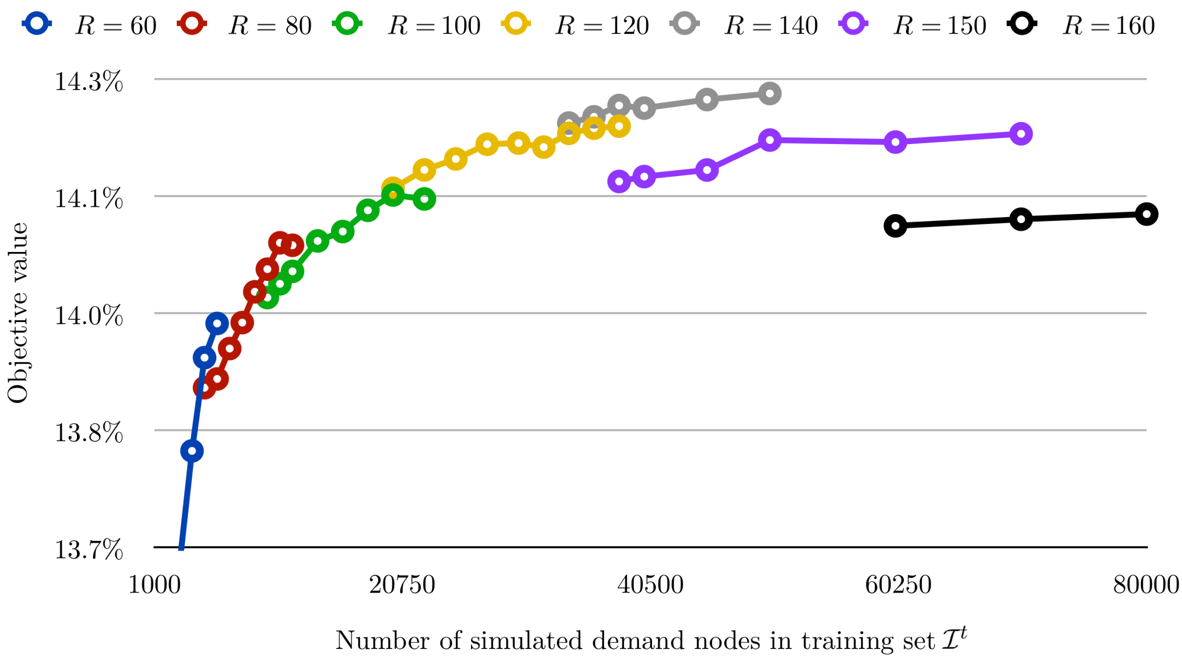


Figure 5.3: Average performance of R stratified by number of simulations, tested by validation sets. Tested by relocating existing AEDs of all 43 municipalities with Greedy algorithm, by gradually increasing the training set $\mathcal{I}^t$. $|\mathcal{I}^v| = 60, n^* = 500$.

5.4 Potential of optimizing AED deployment in the Netherlands

In the previous section we have determined the most appropriate optimization setup to solve the AED deployment problem. In this section we analyze the current situation regarding AED coverage in the study areas in the Netherlands and assess the potential of implementing our optimization methods.

5.4.1 Results of complete study area

The results of solving the AED deployment problem for all municipalities with different scenarios are presented in Table 5.2. The very first line reports the existing coverage of currently registered AEDs, which gives a total coverage of 8.20 % in average over all municipalities. Note that the binary coverage results are the solutions of the MCLP and indicate the proportion of OHCAs that could be covered within 6 min.

The median number of existing AEDs is 44 (IQR: 23–83). By deploying an additional 25 in each municipality and using the more realistic gradual coverage with our algorithmic approach, the results are more than doubled. Relocating the existing AEDs is also very effective — coverage is improved up to 14.23 %, which has more impact than placing an additional 10 AEDs to the currently deployed AEDs (coverage of 13.04 %).

In the last three columns, the average percentage of OHCAs that are “fully”, “partially” and “not” covered over all 500 simulation runs is reported. Separately, we have also solved the problems with the classical binary coverage, with much more optimistic results as expected.

Also note that theoretically, a better overall solution can be obtained by solving for the entire region of Twente and North Holland. Namely, AEDs can be moved from municipalities that have a relative large number of devices to municipalities that have worse coverage results. However, as we have discussed in Subsection 5.3, a high number of cardiac arrests should be simulated for the $\mathcal{I}^t$ set so that the deployment is significantly robust to uncertain future cardiac arrest locations. With the aid of Figures 5.2 and 5.3 we discussed that with a given computer memory, there is a trade-off between the R (and thus the potential solution quality) and the number of simulated nodes in $\mathcal{I}^t$ (and thus the robustness with regards to uncertain future cardiac arrest locations). Aggregating municipalities requires even more simulations or coarser granularity of candidate locations. Consequently, due to these reasons we could not obtain more favorable results when optimizing for a whole region than optimizing each municipality individually.

5.4.2 Municipality-specific results

In addition to the general results in the previous subsection, we present a few interesting cases of optimizing on municipality level.

Effect of determined cardiac arrest risk

We observe that the precision of the determined cardiac arrest risk (with KDE) affects the quality of results. For instance, although the average coverage when relocating existing AEDs was 14.23 %, one municipality fared much worse (3.60 %), even though there are relatively many AEDs (99). In comparison, a neighboring municipality with 72 AEDs had a coverage of 22.57 %.

This can be explained by quite random behavior of historical OHCA incidences and having relatively few data points (49) that resulted in a bandwidth of [1875.9 m, 1970.0 m] (horizontal, vertical). This is much higher than the typical bandwidth as reported in Section 4.2.3. Consequently, simulated cardiac arrests are very evenly spread and hotspots cannot be accurately determined. Therefore, we can state that in some instances, future cardiac arrest locations cannot be determined adequately by using the KDE. However, since the bandwidth of most other municipalities is fairly consistent, an assumption can be made with possibly an optimistic and pessimistic scenario.

Table 5.2: Different scenarios of existing AED coverage and deployment optimization

AED setup		**Coverage (%)**[b]		**IQR**[c]	**Covered OHCAs (%)**[c]		
existing AEDs[a]	new AEDs (n)	binary	gradual	%	fully[d]	partially[d]	not[d]
existing fixed	0	47.16	8.20	6.64–10.19	0.35	46.87	52.78
	10	67.98	13.04	11.14–14.88	0.63	60.72	38.65
	25	79.54	17.54	15.27–19.73	0.93	67.40	31.68
	50	87.95	22.82	19.55 –25.91	1.33	73.87	24.78
	100	91.63	29.47	25.41–33.57	1.88	80.85	17.27
relocated	0	68.49	14.23	11.50–17.87	0.75	53.73	45.52
	10	78.96	17.25	14.61–19.33	0.93	61.57	37.50
	25	85.86	20.77	18.36–24.54	1.18	67.05	31.77
	50	91.18	25.11	22.42–28.71	1.50	73.73	24.78
	100	93.08	30.77	27.26–34.19	1.88	81.50	16.63

Note: Solved with Greedy algorithm, $R = 140\,\mathrm{m}$, $|\mathcal{I}^t| = 50\,000$, $|\mathcal{I}^v| = 60, n^* = 500$. Average difference between coverage solution of training set and validation sets is 2.21 %. AED = automated external defibrillator, IQR = interquartile range, OHCA = out-of-hospital cardiac arrest.

[a] Median number of existing AEDs of municiplities in study area is 44 (IQR: 23–83).

[b] Gradual coverage defined as in Section 4.3.7; binary coverage is computed by setting $r_1 = r_2$.

[c] With respect to gradual coverage.

[d] "Fully covered" applies when $d_{ij} \leq 20\,\mathrm{m}$, "partially covered" when $20 < d_{ij} \leq 300\,\mathrm{m}$ and "not covered" when $d_{ij} > 300\,\mathrm{m}$ in accordance with Equation (4.2). Percentages are the average of all 500 simulation runs.

Improving the coverage of municipalities

Another interesting observation is that the average improvement of relocating currently deployed AEDs is 73.5 %. For the following municipalities, we could improve the coverage by only 41–48 %: Borne, Oldenzaal, Purmerend, Twenterand, Bergen (NH.) and Hoorn. On the other end of the spectrum, Uithoorn, Zaanstad, Aalsmeer and Wormerland could be improved by 206–252 %. Most notably, Zaanstad appears to have 44 AEDs located at ineffective locations, while the other 3 municipalities only have less than 8 AEDs overall.

Figure 5.4 shows the situation in Zaanstad. Currently, the existing 44 AEDs provide 2.8 % coverage but relocating these AEDs with our optimization method results in 9.1 % coverage (225.0 % improvement). Note that in the current case it can be easily observed that the hotspots of predicted cardiac arrest risk and the locations of existing AEDs do not adequately coincide.

Similarly, Figure 5.5 shows the currently placed AEDs (providing 8.2 % coverage) in the municipality of Borne and the relocation of existing AEDs improves the coverage to only 11.5 % (40.2 % improvement). Note that in this case the currently placed AED are more in line with the predicted cardiac arrest risk. However, not that in practice, it is not uncommon to place AEDs after a (first) OHCA incident. Therefore, it is possible that in some cases, the deployment strategy is performed retrospectively while we seek to optimize the placement of AEDs prior to OHCAs by predicting the incidence risk.

The results of Borne illustrate another phenomenon. Due to the characteristics of our objective function in the optimization model, AEDs are placed at locations that maximize overall survival. Thus, with a limited amount of AEDs, there will be no AEDs deployed at locations with lower cardiac arrest risk such as rural areas. In Borne we see only AEDs in the neighborhood of the city center. Although this is what should be expected from an optimization standpoint, such approach is conflicting with the “equity” of provided service (see also the study of Mandell and Becker (1996) who used a trade-off between equity and effectiveness).

In addition to relocating the existing 23 AEDs in Borne, we increase the total number of AEDs that should be deployed by our optimization method until AEDs are placed outside the city center. After approximately 70 total AEDs, the devises are placed outside the city center, as can be seen in Figure 5.6. Note that due to the decaying coverage function (Equation 4.2), our method prioritizes placing AEDs at the high risk areas in the city center *with overlap*, rather than placing AEDs at low risk locations but *covering a larger area*. Or in other words, the optimization method takes into account that quicker defibrillation at high risk areas might be more beneficial than plainly covering a larger but low risk area where a cardiac arrest can be defibrillated within 6 min.

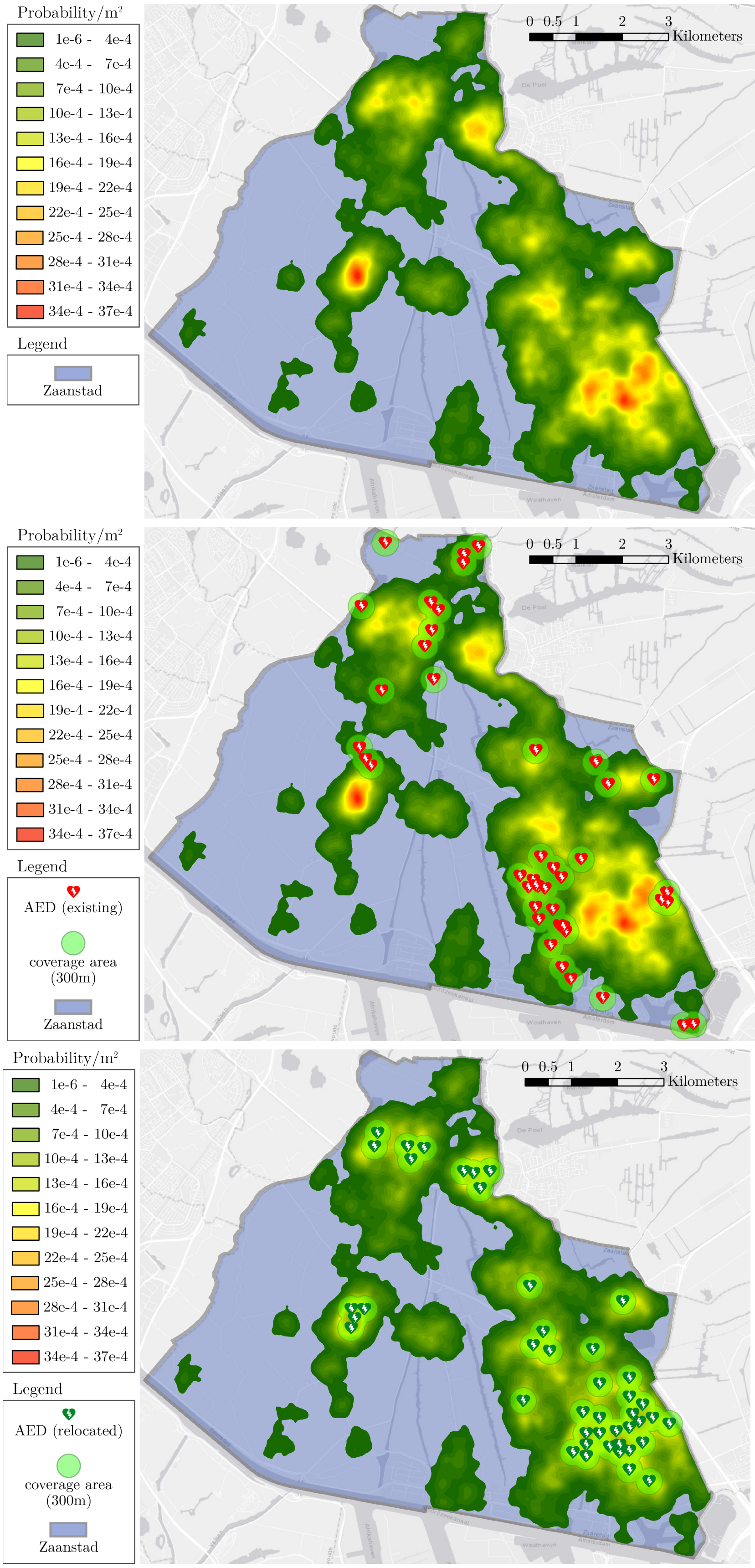


Figure 5.4: Locations of 44 AEDs in the municipality of Zaanstad. *Top image:* cardiac risk probability distribution (KDE method); *center image:* current deployment of existing AEDs (2.8 % coverage); *bottom image:* optimized deployment by relocating existing AEDs (9.1 % coverage).

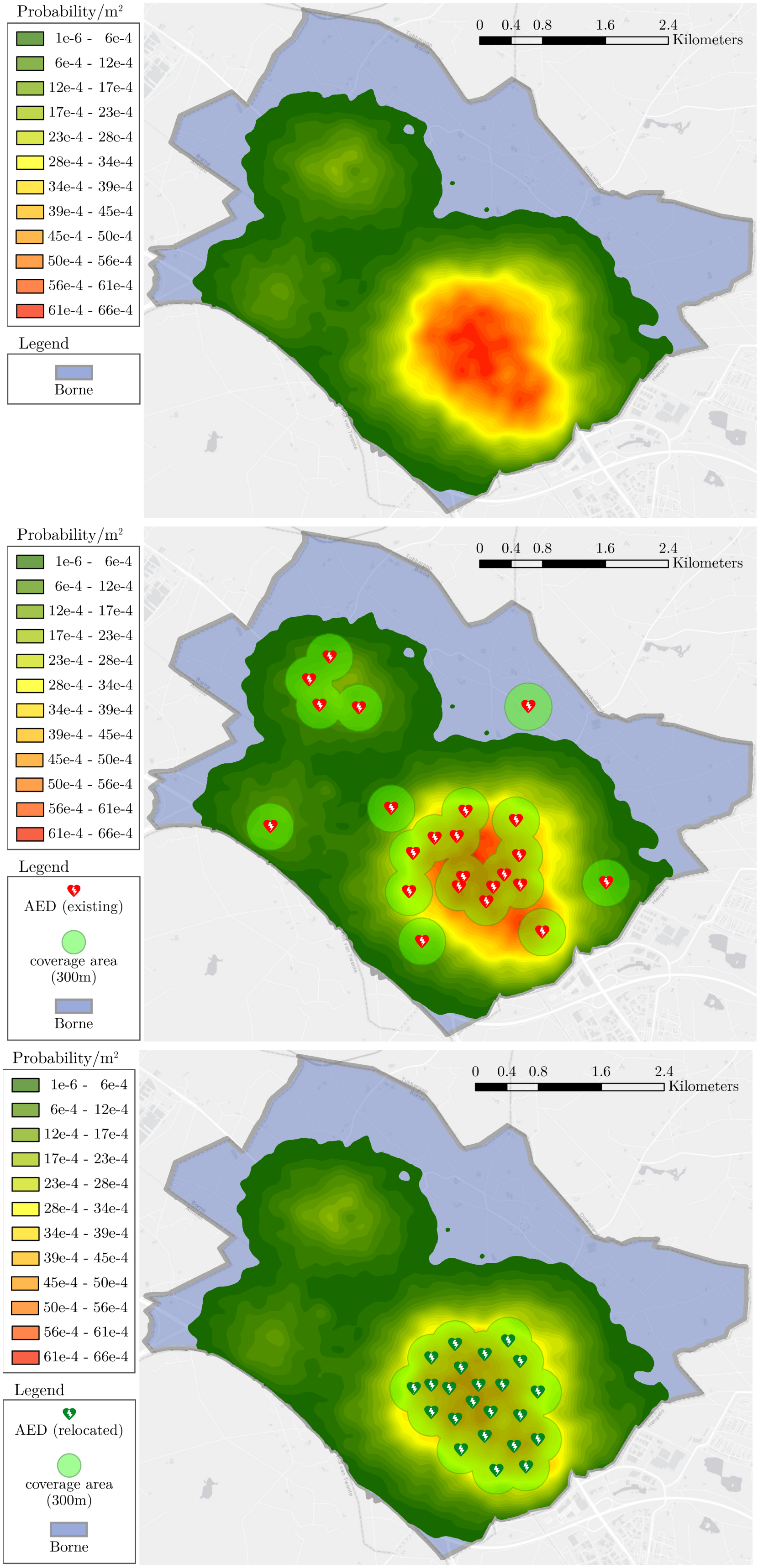


Figure 5.5: Locations of 23 AEDs in the municipality of Borne. *Top image:* cardiac risk probability distribution (KDE method); *center image:* current deployment of existing AEDs (8.2 % coverage); *bottom image:* optimized deployment by relocating existing AEDs (11.5 % coverage).

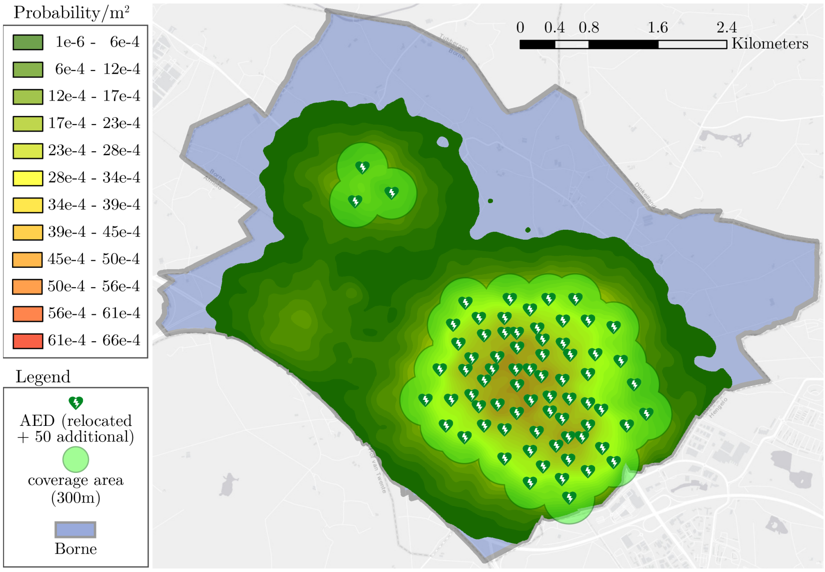


Figure 5.6: Results of relocating 23 existing AEDs in the municipality of Borne and deploying 50 additional AEDs (73 AEDs in total). Total coverage = 24.7 %. Note that only after having more than 70 AEDs, the devices are placed outside the city center.

Value of additional AEDs

Figure 5.7 shows the results of the current deployment, and when relocating existing AEDs with 0, 10, 25, 50, 100, 250 and 500 additional "new" AEDs in some municipalities of Twente. As expected, relocating the current AEDs improves the coverage significantly. Also, adding extra AEDs in a situation where there are already a substantial number of AEDs improves the solution relatively slightly. For example, the objective value of the municipality of Almelo improves evidently more when adding 10–50 AEDs than when adding 500 AEDs. Note that this effect is less evident for situations with lower coverage, e.g. the municipalities of Tubbergen or Enschede. Consequently, the general takeaway is that even when adding a large number of AEDs, the improvement in coverage might be considered worthwhile.

5.4.3 Number of AEDs needed for "full coverage"

The method of using the hexagonal tessellation enables us to get an indication of the SCLP solution as well. In other words, we can determine the least number of facilities are needed to enable "full coverage"[2] and where these facilities should be placed. Namely, by setting $R = r_2$ in our model, all candidate locations that cannot cover the simulated cardiac arrests within 300 m are deleted (see also Algorithm 4.1). Then, placing AEDs at all candidate locations automatically covers all demand.

Note that this is an upper bound for the optimal solution — if a demand node falls within the overlapping region (see Figure 4.7b), one of the hexagons could be deleted if there is no

[2] according to the MCLP, meaning that a demand at a distance of 300 m from a facility is considered to be sufficiently covered

other demand in the non-overlapping regions. Also note that this heuristic solves the SCLP instance with $R = 300$ and better solutions can be expected when solving the SCLP with regular optimization techniques and more granular radius.

Nevertheless, solving the SCLP with this approach gives a (possibly overestimated) indication of how many AEDs are needed in a region to cover all cardiac arrests within 300 m. The results are shown in Table 5.3. Notable good performers are the municipalities of Hoorn, Oldenzaal and Edam-Volendam, respectively possessing 65.6 %, 51.4 % and 46.7 % AEDs of the total number that is needed to cover all future cardiac arrests that we have modelled. On the other hand, there are 8 municipalities in North Holland that have fewer than 10 AEDs and consequently possess less than 7 % of the total desired number of AEDs. Municipalities that would need municipalities are Beemster, Hollands Kroon and Haaksbergen, having 11–12 % of the desired number of AED. Overall, the average proportion of AEDs that is currently present in the entire study area is 18.8 %.

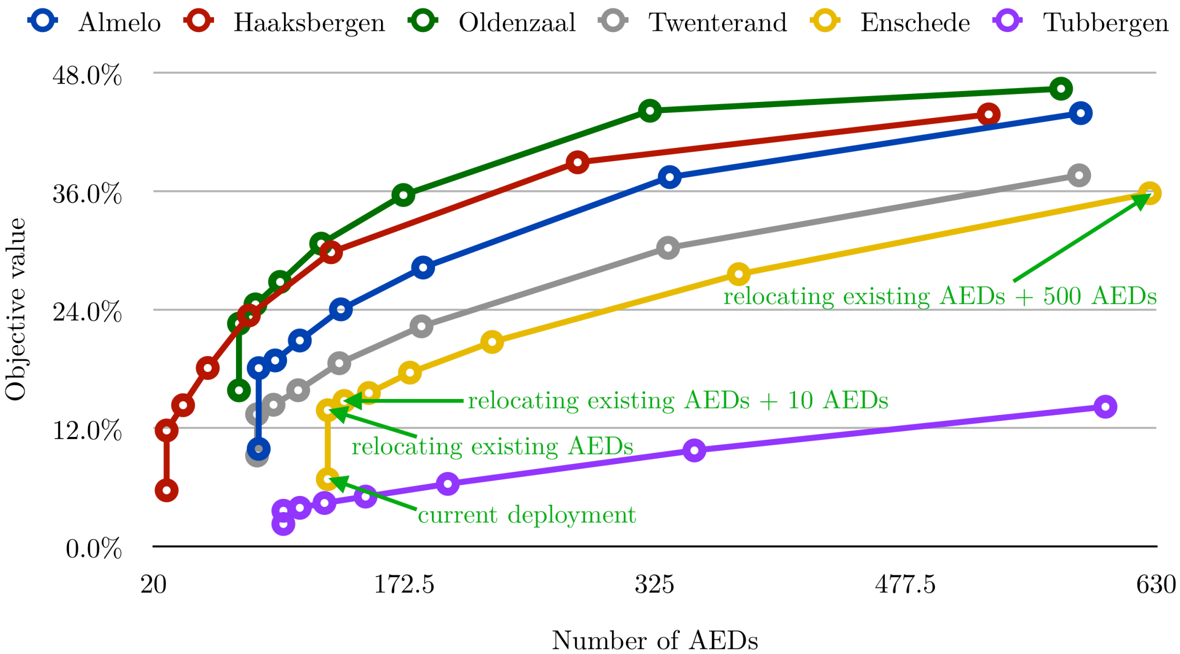


Figure 5.7: Average objective value of provided coverage to all OHCAs in the validation sets stratified by the number of AEDs per municipality. Per municipality, the first up to the eighth node consider respectively (1) the currently deployed AEDs, (2) relocating the existing AEDs with the proposed optimization method, (3) relocating the existing AEDs and adding 10 AEDs, (4) relocating and adding 25 AEDs, (5) relocating and adding 50 AEDs, (6) relocating and adding 100 AEDs, (7) relocating and adding 250 AEDs, (8) relocating and adding 500 AEDs. Solved with Greedy algorithm, $R = 140$ m, $|\mathcal{I}^t| = 50\,000$, $|\mathcal{I}^v| = 60, n^* = 500$.

Table 5.3: Median number of AEDs in the regions compared to SCLP solution

	North Holland		Twente	
	n	IQR	n	IQR
current AEDs	35.0	11.5 – 60.5	77.5	39.0 – 105.5
SCLP solution[a]	174.0	113.0 – 246.5	278.0	242.0 – 410.5
	%	IQR	%	IQR
AEDs currently present[b]	20.1	10.2 – 24.5	27.9	16.1 – 25.7

Note: SCLP = set covering location problem; IQR = interquartile range; AED = automated external defibrillator.

[a] These numbers indicate how much AEDs are needed to cover all cardiac arrests. Solved with $|\mathcal{I}^t| = 10\,000$.

[b] When comparing the current number of AEDs to the total number of AEDs required per municipality by the SCLP solution. Overall average proportion of AEDs present of the entire study area is 18.8 %.

Chapter 6

Conclusions

In this work, our ultimate goal was to aid decision-makers in improving the survival rates of out-of-hospital cardiac arrest (OHCA) victims, which currently are worse than one would desire. Although quick defibrillation by automated external defibrillators (AEDs) has a high potential in improving these rates, this has often not been realized yet in practice. The European Resuscitation Council (ERC) states appropriately that "any technology that improves the delivery of swift bystander cardiopulmonary resuscitation (CPR) with rapid access to an AED is to be encouraged" (Monsieurs et al., 2015, p.5). Our research contributed with such a prescriptive tool that guides in deploying AEDs at effective locations that enable quick defibrillation. Moreover, contrary to many existing retrospective approaches, we account for the uncertainty in future cardiac arrest locations and thus provide more robust results.

We presented different heuristic optimization techniques to tackle the mathematical AED deployment problem — where to place AEDs such that the total provided coverage to cardiac arrests is maximized. For the "coverage", we implemented a realistic gradual coverage function, which follows typical survival functions that depend on the time to defibrillation, as defined by the generalized maximum coverage location problem (GMCLP). Naturally, our proposed methods can easily be translated to other facility covering location problems with decaying service distances or times.

First we developed a Greedy algorithm that yields excellent results (optimality gap: 0.087 %) with little computational efforts. We proposed a second, more complex heuristic based on Greedy Randomized Adaptive Search Procedure (GRASP) and extended it with "parameterized regret-based random sampling" and showed that it can further improve the results. This GRASP algorithm is robust to heterogeneous problem instances and consequently decreased Greedy's optimality gap by 85.5 %. For large problems where high-quality solutions are desired, we developed a Simualated Annealing (SA) algorithm with "reannealing" that works in conjunction with Greedy or GRASP. Given an appropriate tuning, SA with reannealing can yield superior results within a foreseeable and limited time.

In addition to the solution techniques, we incorporated a hexagonal tessellation method to dynamically create candidate locations. With this scalable method, we can control the size of problem instances and inherently the potential solution quality. Moreover, incorporating this approach eliminates the requirement of obtaining coordinates of candidate locations (e.g. buildings) for decision-makers. The power of this addition is shown in the computational results where we compared different optimization techniques with different candidate locations set. Here we showed that a granular density of candidate locations in combination with a fast algorithm as Greedy outperforms more complex (and computation-intensive) algorithms with less granular candidate locations set. With this dynamic method, solutions can be reached that are close to the continuous problem where AEDs can be placed on the plane without any restrictions.

Eventually we applied our methods on historical cardiac arrest data from two vast regions with 43 municipalities in the Netherlands. The municipalities have heterogeneous spatial characteristics and we included both public and residential cardiac arrests. We showed that by relocating existing AEDs (median number of AEDs per municipality is 44 (interquartile range (IQR): 23–83)), an average improvement of 73.5 % can be achieved. Approximately, this is more effective as buying and deploying 10 additional AEDs. As part of the methods, we could simply derive an approximate solution to the set covering location problem (SCLP) solution — minimizing the number required AEDs that can cover all demand. We found that currently, the average number of AEDs per municipality is 18.8 % with respect to the total number needed to cover all OHCAs within the critical time.

Limitations

Naturally, our research has its limitations. One is that we used a subset of the actual available AEDs in the discussed study area — only registered AEDs. However, it is not very likely that a bystander would search for an unregistered AED and find it, especially since the emergency medical services (EMS) guided systems are increasingly entrenching into society. Moreover, there are increasingly more AEDs are registered. For example, at the moment of writing, the Dutch Heart Association (DHA) is placing 1400 additional AEDs at “well spread locations” throughout the Netherlands (*Hartstichting reikt 1400 AED-buitenkasten uit*, 2017). Also, although AED owners might be willing to register their AED to a public system, the costs per usage of approx. €150 might restrain them of making their AED public. A new motion in the Netherlands might improve the AED registration rates, as residents may be compensated for the usage of their AED directly through the regional ambulance facility (RAF) starting from 1 January 2018 (Schippers, 2017).

Also, we did not account for the temporal availability of AEDs in our optimization methods. This is mostly relevant for existing AEDs, as we assumed and gave justification from reports that newly placed AEDs will mostly be placed outdoors and therefore will be always available. However, even then it is possible that an AED is not available, for instance due to being elsewhere or due to operational issues.

Also, due to the symmetrical aspect of the hexagonal tessellation that we used for the creation of candidate AED locations, it might be possible that our models will allocate AEDs to infeasible locations. However, we mentioned that in practice the actual location of AEDs will deviate from a model anyway, since aspects like architectural design and building function need to be considered on-site. Therefore, the locations of deployed AEDs should be considered as a guideline. Mathematically speaking, an effective approach would be to run our model, physically place one AED with the model's solution as a guideline, and then update the coordinates of the newly placed AED in the model. Then, that AED should be set as "fixed" and the model can be run again. With the approach, the method will account for the deviations per actually placed AEDs and consequently adjust other locations when needed.

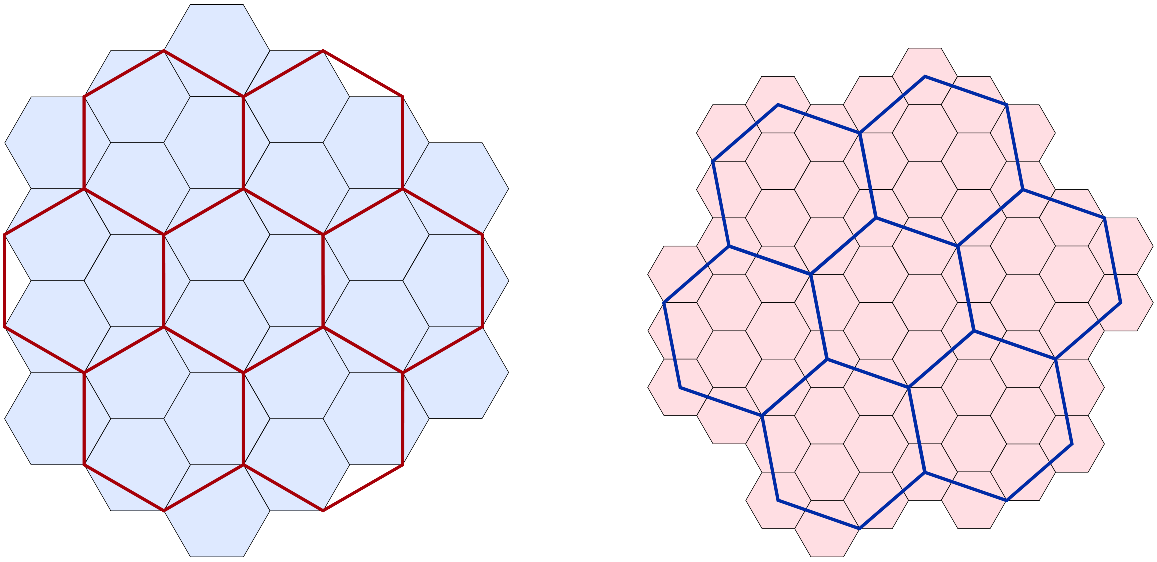
We have also assumed that the historical distribution of OHCAs is representative for future incidences. Although we justified this by referring to findings in previous research, aspects such as population movement are not considered. Also, we used a certain bandwidth to assess the extent of the OHCA risk per municipality. By doing so, we aggregated and generalized the spread of the risk over the entire municipality, while realistically there might be different clustering on smaller level (e.g. neighborhoods).

Unfortunately, with the given computational resources, the most effective approach was to optimize with relatively large hexagons since a large training set of simulated OHCAs was necessary to ensure robust solutions. Namely, AEDs should be deployed at locations that are representative for future cardiac arrests (as tested with independent validation set). However, we have shown that the best possible results can be achieved by a more granular tessellation. Consequently, we have not fully exploited the potential of the solution quality due to computational limitations. However, to the best of our knowledge, among AED deployment literature, we are (1) the first to determine an adequate size of the training set, (2) the first to determine an adequate number of validation sets, (3) the first to examine the effect and potential of the granularity of candidate locations. Consequently, we optimized with a compromise between the settings that yield the best overall results.

Future research

Arguably the greatest improvement can be gained by the usage of better tools to more accurately determine future cardiac arrests. Even though we have discussed that the Kernel Density Estimation (KDE), given spatio-temporal stability of OHCAs, is a viable and effective method, there is plenty of potential on improving the accuracy (e.g. Dahan et al., 2017; Deo et al., 2016). Thus, using and combining different data and techniques to better predict future cardiac arrest incidences is encouraged.

We mentioned that our models maximize the overall coverage and, therefore, with a



(a) Nesting with scaling factor = 3

(b) Nesting with scaling factor = 7

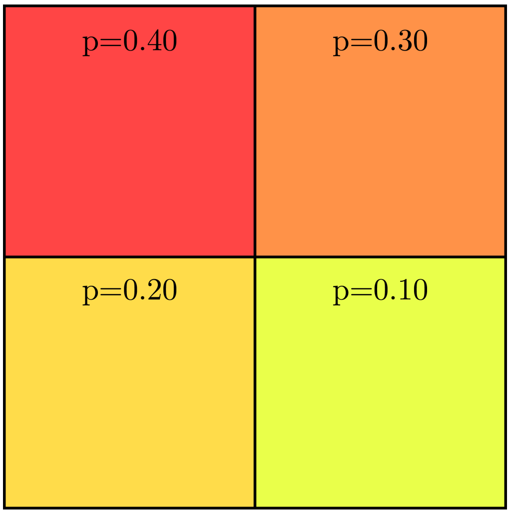
Figure 6.1: Nesting a bigger hexagonal tessellation onto an existing tessellation

limited number of AEDs, no AEDs would be placed at areas with lower incidence rates. We discussed that a trade-off between effectiveness and equity can be used, but, we think other aspects can be incorporated as well — namely, the decision-maker might place certain priorities for AED deployment on specific areas (e.g. Allahi, Mobin, Vafadarnikjoo, & Salmon, 2015). For instance, certain areas might have more allocated funds. Or, there might be a difference of effective AED usage between regions, e.g. due to expected differences in witnessed incidences, shockable rhythm and bystander behavior. Therefore, our models could be extended to incorporate weights that model such aspects of certain regions.

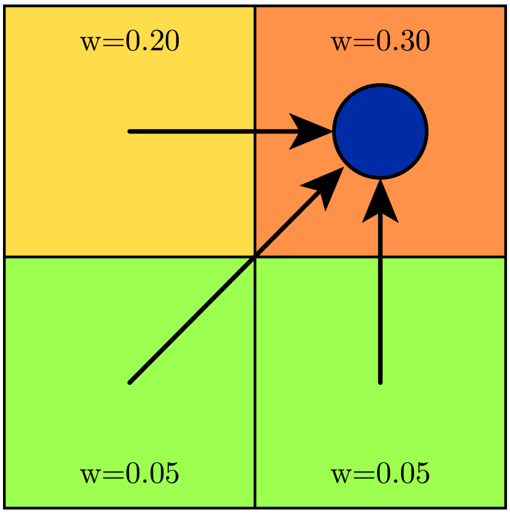
We have shown that the algorithms we have developed yield good results, but improving on this regard is possible. We mentioned the existence of many extensions for both GRASP and SA which could be explored for the AED deployment problem. Also, using more intelligent, case-specific neighborhood transitions would benefit the local search algorithms.

In addition, we note that the hexagonal tessellation can be scaled and nested onto an existing tessellation as in Figure 6.1. Such nesting can be applied to generate candidate locations even more efficiently and effectively. Namely, by identifying higher demand regions, nesting can allow the creation of candidate locations with higher densities at those regions. On the other hand, regions with lower demand will contribute less to the objective function than high density candidate locations. Thus, nesting enables dynamically distributing candidate locations with consequently better potential solution quality while attaining tractable solution spaces.

Other notable possibilities are methods to further improve the quality of the candidate location sets. For instance methods that account for the actual physical location such as pattern recognition (e.g. Zhang, Ai, Stoter, Kraak, & Molenaar, 2013). This way, it might



(a) KDE with probabilities per cell



(b) Candidate location with weight components

Figure 6.2: Figure 6.2a illustrates a typical KDE simplified to four cells. Figure 6.2b illustrates the weight components, which belong to a candidate location in the upper right corner, per KDE cell. The weight is determined by the coverage function and considers the probabilities of the KDE. In this example: weight = 100 % of probability if candidate location is in the considered cell, 50 % for a directly neighboring cell and 25 % for a cell at a neighboring diagonal.

be possible to detect infeasible locations, such as private buildings and water.

However, we have shown that a high solution quality does not guarantee good actual performance if data is used that is not representative. For this reason, we used a large set of simulated cardiac arrests to train our model at the expense of solution quality. Ultimately, this proved to be more effective. However, there are methods that can alleviate the loss of quality between the training and validation sets. In this research, we simulated demand for both training and validation sets from these KDE cells. Consequently, this introduces randomness and thus the mentioned disparity between sets occurs. However, these KDE cells can be used as demand areas directly with certain weights extracted from their probability values. See a basic illustration in Figure 6.2. Figure 6.2a shows a typical KDE with four cells. Normally, we would simulate demand with these spatial probabilities, and with sufficient simulations, there would be twice as much demand nodes in the upper left cell as in the lower left cell. Instead, the values of the probabilities can be used directly. Using a decaying coverage function as in this research, only now considering distances to a KDE cell instead of a simulated node, these probabilities can be converted to weights as in Figure 6.2b. The total weight attributed to the illustrated candidate location is the sum of the neighboring KDE cells: 0.50. Note that with this method, not only is the loss of quality due to using separate training and validating sets eliminated, but also the data for optimization is no longer a two-dimensional (distance) matrix but a one-dimensional array of weights. It would be interesting to compare this method with the method using simulations that we have used in this research.

We also note that in this research, we have incorporated only AEDs as devices that deliver defibrillation to OHCA victims. However, one obvious example is that in the close proximity of hospitals, no AEDs should be placed since hospitals already possess a defibrillator and can deliver it directly. Thus, a more realistic and efficient approach would incorporate a certain distance around hospitals were no AEDs should be placed. Also other defibrillators might be integrated. For instance, if first responders (FRs) are always present in a certain region, there is no need to place additional AEDs there. Note that such extension can easily be achieved with our proposed model: by placing an “existing” AED at e.g. the locations of hospitals and possibly giving them a different coverage function than the one we used for the AEDs, our optimization model will account for these locations correctly and will not place AEDs in the proximity.

Another similar future extension is integrating a defibrillator drone network to the existing AED network. Since recently, unmanned arial vehicles (UAVs) (or “drones”) are developed that bring a defibrillator to a victim (e.g. Boutilier et al., 2017; Claesson et al., 2017; Mark, Hansen, Starks, & Cummings, 2017; Pulver, Wei, & Mann, 2016). The obvious benefit of drones is that they are very fast and thus have a greater coverage range. Research shows that especially rural areas can benefit from such defibrillator drones. This is nicely in line with our AED optimization that prioritizes regions with high cardiac arrest risk, which are often in the more urban areas. Also note that we have modelled the AED placement as static locations. However, drones can be modelled with dynamic locations, meaning that the locations can account for daytime/nighttime incidence rates, seasonal changes, certain events, etc. Thus, extending our optimization methods and integrating AEDs, drones, hospitals and possibly other defibrillators can further improve coverage and decrease the time to defibrillation.

We have argued that it is much worthwhile to consider cardiac arrests occurring in residential locations, although these locations have typically fewer witnessed incidences. However, the still yearly increasing trend of wearable devices might eventually mitigate the dire consequences of unwitnessed cardiac arrests. A recent study enrolled 6158 users of an application on Apple Watch© to train a deep neural network. The algorithms could distinguish atrial fibrillation from a normal heart rhythm with 97 % accuracy (*Artificial Intelligence Automatically Detects Atrial Fibrillation Using Apple Watch’s Heart Rate Sensor*, 2017). Separately, Apple launched a joint study with Stanford Medicine to recognize irregular heart rhythms (*Apple Heart Study launches to identify irregular heart rhythms*, 2017). If an irregular heart rhythm is identified, users will receive a notification. The further implications are that in case of a cardiac arrest (or other cardiovascular problem), EMS could be automatically triggered by these wearable devices over the Internet in the future. This is similar to the “implantable arrest alarm device” discussed by Wellens et al. (2016), although wearable devices can arguably have more impact as their user base is far greater. Consequently, in combination with effective deployment of AEDs and a well-implemented civilian response system (CRS), even unwitnessed OHCAs might have a positive outcome. In addition, these devices enable a quick, automatic and reliable recognition of a cardiac arrest, in contrast to the “manual” recognition over the phone, and thus further improve the time to defibrillation and survival.

However, all mentioned measures only help improving survival *after* a cardiac arrest. More benefit to society can be achieved by not only improving better outcomes of OHCA victims, but also reducing the overall number of OHCA incidences. Modifiable behavioral factors, including aspects of hypertension, hypercholesterolemia, diabetes, obesity, and smoking have been shown to predict cardiac arrests (Kannel, Cupples, & D’Agostino, 1987; Wannamethee, Shaper, Macfarlane, & Walker, 1995). With pertinent prevention measures, it is estimated that 80 % of cardiovascular deaths can be avoided (Willet, 2002). Although not necessary an extension of this research, the similar goal of decreasing cardiac arrest deaths is evident. Therefore, prevention of cardiac arrests should be a fundamental strategy to pursue.

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