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Increasing cardiac arrest survival by improving the volunteer alerting algorithm

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Preface

I am proud to present you my master's thesis. The process that brought this together has been one with ups and downs that ultimately has taken more than a year. The application of simulation in a field as important as cardiac arrests has been a very interesting, informative and challenging experience. And it has been an honor for me to have been a part, however small, in improving care for cardiac arrest patients. I would like to thank a number of people that made this project possible.

First of all, I want to thank Tom Kooy and all others at Hartslagnu for making this project possible, for answering all my questions, commenting on the report and for welcoming me at their office.

I would like to thank my lead supervisor Derya Demirtas, first of all for bringing me in touch with Hartslagnu and this project, but also for her important feedback on numerous versions of this report. I thank my supervisor Martijn Mes for his valuable contributions and comments and for adding his expertise in the field of simulation to this thesis. I am thankful to both supervisors for taking time throughout the duration of this project for meetings and for keeping me on the right track.

Last but not least I would like to thank my family and friends for their support, most importantly my parents for letting me move back into their house and for supporting me, even when this project took longer than expected.

- Gunnar Slaa

Management summary

Hartslagnu is a system for alerting volunteers in cases of out-of-hospital cardiac arrest (OHCA). In response to a call to the emergency number, the system is automatically activated, once an emergency dispatcher has classified the situation as a case of OHCA. Volunteers are alerted via app or sms and are tasked either with going directly to the patient to perform cardiopulmonary resuscitation (CPR) or with first picking up an automated external defibrillator (AED) and then travelling to the patient. Volunteers often arrive before the ambulance and are thus able to perform lifesaving treatment.

The current alerting algorithm used in the Hartslagnu system has no analytical foundation. This research aims to test whether the current alerting algorithm can be improved upon in order to increase the survival chance of OHCA patients. We aim to answer the following research question:

What alternative strategy to the current alerting method improves patient survival chance?

Method

We first analyzed historical data from the Hartslagnu system to determine distributions for the number of available volunteers and AEDs per alert as well as the distance of volunteers to the alert and volunteer acceptance rate and reaction time. We tried to create prediction models to predict volunteer acceptance rate and reaction time based on historical data, but none of the tested models provided accurate predictions. We then developed a Monte Carlo simulation to test the effect of various alternative alerting strategies. The baseline outcomes of this simulation in terms of survival chance are very close to results from research into the Hartslagnu system by Pijls, Nelemans, Rahel and Gorgels (2016). We used this simulation to test a number of alternative strategies to determine which volunteers are alerted, which of these volunteers are sent to pick up an AED and when and how the alert is cancelled.

Outcomes

The current alerting strategy, as used by Hartslagnu, can be summarized as follows:

- **AED area:** AEDs are used in a radius of 500 meter around the incident
- **AED choice:** If volunteers are sent to an AED, they are sent to one closest to their current location
- **Alerting Volunteers:** All volunteers are alerted within 750 meter from the incident
- **Cancelling the alert:** Volunteers are cancelled when 5 volunteers have accepted the alert
- **AED allocation:** Volunteers pick up an AED if one is available within 250 meter of their location

The best alerting strategy found using our simulation is the following:

- **AED area:** Increase the radius for AED use to 250 meter above the volunteer alert radius
- **AED choice:** Send volunteers to the AED that minimizes their total distance to the incident, instead of the AED closest to the volunteer

- **Alerting Volunteers:** Alert up to 105 volunteers in a maximum radius of 1000 meters
- **Cancelling the alert:** Switch volunteers tasks after one volunteer has accepted for CPR or two volunteers have accepted for AED
- **AED allocation:** Let volunteers pick up an AED if this increases their distance to the patient by at most 700 meter

This strategy increases the mean simulated survival chance of patients from 13.7% to 15.5%, a relative increase of 13.1%, while only increasing the mean number of volunteers alerted from 24.1 to 29.3. For comparison, we also simulated a scenario with only ambulances and bystanders influencing survival, but without the Hartslagnu system. The simulated survival chance in this scenario is 11.5%. This means the proposed improvements can increase absolute increase in survival chance by the Hartslagnu system from 2.2% to 4.0%.

We found that multiple strategies for determining which volunteers are alerted and determining which volunteers are sent to an AED result in a similar increase in performance.

We also found that using different strategies per case based on the number of available volunteers and AEDs does not increase the predicted survival chance.

If, at the moment the alert is sent, it is known whether or not a bystander is available to perform CPR, the survival chance can further be increased to 16.3% if the alerting strategy is adapted to that information.

In addition, we have found that in a situation where all volunteers are alerted via app, a different alerting strategy performs better. In this case, fewer volunteers will need to be alerted, as acceptance rates among app-alerted volunteers are higher.

We have shown that the proposed alerting strategy still performs well, when we change assumptions related to the duration of parts of the timeline and volunteer movement speed.

Lastly, we found that the proposed strategy performs well under different functions to calculate patient survival chance as well as in other sets of randomly created cases.

Contents

Abbreviations

AED automated external defibrillator. ii–v, 1–8, 16–18, 20, 22, 23, 27–30, 32–35, 37, 38, 41–49, 52, 53

CPR cardiopulmonary resuscitation. ii, iii, 1–4, 6, 16, 17, 20, 22, 27, 33, 34, 41, 42, 45–48, 52–54

CRS community response system. iv, 3, 12, 19–21, 23, 24, 53

FAFS first alerted first sent. 3

OHCA out-of-hospital cardiac arrest. ii, iv, 1–8, 12, 19–24, 27–30, 33, 52–54

ROSC return of spontaneous circulation. 1

VF ventricular fibrillation. 1

VT ventricular tachycardia. 1

Chapter 1

Introduction

In this report, we propose alternative alerting solutions for Hartslagnu, a system to alert volunteers in cases of OHCA. In this chapter, we first explore the medical background of OHCA in which Hartslagnu operates. We then take a more in depth look at the ways in which Hartslagnu and its competitors operate. Finally we explain the knowledge gaps that currently exist in this field of study and the objective of this research.

1.1 Background

In this section, we address the medical background of OHCA and the use of volunteers in this environment. We first explore the basic medical facts of OHCA. We then talk about the main ways of treating this condition and finally we explain the importance of the use of lay person volunteers in the treatment.

Out-of-hospital Cardiac Arrest

OHCA is an important cause of death in developed countries, with around 275,000 occurrences annually in Europe (Atwood, Eisenberg, Herlitz & Rea, 2005). In the Netherlands, around 7,000-8,000 are treated for OHCA each year (Hartstichting, n.d.-b).

The chance to survive an OHCA is very low, but varies widely around the globe with rates as low as 2% in Asia compared to an average of 9% in Europe and 11% in Australia according to a systematic review by Berdowski, Berg, Tijssen and Koster (2010). Another systematic review by Sasson, Rogers, Dahl and Kellermann (2010) looking at a large number of developed countries finds that the survival rate has stayed constant over time. However other studies found increasing trends in survival rate over time (e.g., Daya et al., 2015). An important factor influencing survival rate is whether the OHCA is witnessed and resuscitation is attempted by a bystander. Lee et al. (2017) found that survival is much higher in enclosed pedestrian walkway systems where foot traffic and hence probability of bystander CPR and bystander AED use are higher.

The most important factor determining a patients survival chance is whether or not they have a shockable rhythm, i.e. ventricular fibrillation (VF) or pulseless ventricular tachycardia (VT)(Meaney et al., 2010). Over time however these rhythms deteriorate and the patient becomes no longer shockable (Waalewijn, Nijpels, Tijssen & Koster, 2002).

Cardiopulmonary resuscitation and defibrillation

Besides the initial rhythm of the patient, the most important factor determining the survival chance is the time it takes for the patient to get treatment. Without any treatment the chance to survive decreases by 8-10% each minute (Callans, 2004).

Two types of treatment are relevant for OHCA patients. The first is CPR, which has been used since the early 1960s (Paraskos, 1993). The chances for return of spontaneous circulation (ROSC) by means of CPR alone are extremely low (De Maio et al., 2001). CPR can however slow down the process of deterioration of a shockable rhythm (Waalewijn et al., 2002) and thus slow down the decrease in survival chance.

Defibrillation is seen as the only means to save a patient with sudden cardiac arrest. Defibrillation is the process of applying an electrical shock to the heart to stop a dysrhythmia, after which the heart can restart its natural rhythm, although the precise working of defibrillation is not well understood (Trayanova, 2006). An important step in the development of defibrillation treatment was the invention of the AED (Diack, Welborn, Rullmann, Walter & Wayne, 1979). This is a version of the defibrillator that can be used outside of the hospital due to its low weight and the fact that it uses a battery. An AED can detect whether the patient has a shockable rhythm and can shock if applicable. Because the decision to shock is made by the AED it requires little to no training to use (Gundry, Comess, DeRook, Jorgenson & Bardy, 1999). In the Netherlands, approximately half of the patients have a shockable rhythm at the time the AED is connected (Zijlstra, Radstok et al., 2016).

Because it is crucial to connect an AED quickly, effort is made to increase the number of AEDs available. One such effort in the Netherlands is an initiative where people can organize their neighbourhood to save up for an AED together (BuurtAED.nl). It is especially important to increase the number of AEDs in residential areas, because nearly 80% of OHCA incidents occur in residential areas.

However, even without placing new AEDs, better results can be achieved by simply improving the placement policy (Chan et al., 2013). Researchers have shown that in Toronto, coverage of AEDs can be increased by 40% by optimizing their locations (Chan, Demirtas & Kwon, 2016; Sun, Demirtas, Brooks, Morrison & Chan, 2016). Currently, no central policy is in place to optimize AED placement. The placement of AEDs is determined by someone, usually the owner of a building, deciding to buy and place an AED.

Use of lay responders in OHCA

The target for ambulance arrival in the Netherlands in case of emergency (Dutch ambulance code A1) is 15 minutes. In 2017 this target was met in 92.4% of the cases with an average response time of 9:41 minutes (Ambulancezorg Nederland, 2018). Because survival chances after this amount of time are low, efforts should be made to defibrillate a patient before the ambulance arrives. To achieve this, action has been taken to encourage lay people to respond in case of an OHCA.

These lay responders can be divided into two types. The first type are coincidental bystanders witnessing the cardiac arrest and responding by performing CPR or fetching and connecting a nearby AED. In this report, we refer to this first type as bystanders. The second type of lay responders are alerted by a system usually activated by emergency dispatchers in response to a phone call to an emergency number, we refer to this second type as citizen responders. Help by bystanders can increase survival rate by decreasing the time-to-shock, a systematic review by Bækgaard et al. (2017) finds a median survival rate of 53% in cases where bystanders have connected an AED. This survival rate is much higher than the overall survival rate for OHCA, but the chance for bystanders to pick up an AED is quite low. A study in Sweden equipped emergency dispatchers with an overview of all AED locations, but they only directed bystanders to an AED in 4.3 % of all cases with an accessible AED within 100 meter and where the caller was not alone on the scene (Fredman et al., 2016). Sakai et al. (2011) tried using a public app to display all AED locations, but this did not reduce the time it took for a bystander to fetch an AED. Because the chance of bystanders witnessing an OHCA is of course higher in public places, the chance of bystander AED use is about ten times higher than in residential areas (Hansen et al., 2017). The chance of a shockable rhythm at the moment an AED is attached is more than four times higher in public places, although research suggests this might have other reasons than the time until AED connection, like age and prior conditions of the patients (Weisfeldt et al., 2011).

A new type of volunteer has emerged to improve on the points where the care provided by bystanders shows disappointing results. These volunteers are enrolled in a system that alerts them in case of an OHCA in their vicinity, either by sms of by use of a mobile app. These volunteers are then directed either to the patient directly to perform CPR, or via a nearby AED.

Several apps have been launched in various countries to coordinate volunteers in case of OHCA. Because these apps are a relatively recent development, the research into their effectiveness is quite scarce and not yet conclusive, but the first research seems to suggest the use of these apps can result in increased chance of a patient receiving resuscitation (Ringh et al., 2015), earlier defibrillation and increased survival chances (Pijls et al., 2016).

Research also shows that alerting by app can reduce arrival time of the volunteers by as much as two minutes compared to alerting by sms (Caputo et al., 2017).

Future developments

New technologies will keep improving care for OHCA patients in the future. Earlier detection might be achieved by outfitting at-risk patients with a smartwatch or smartphone app (Leijdekkers & Gay, 2008) that is able to detect cardiac arrest.

The need for volunteers to pick up an AED on their way to the patient might be eliminated by drones that transport the AED to the location (Pulver, Wei & Mann, 2016).

These developments may increase survival rates for OHCA by decreasing the time-to-shock, but due to the fact that no data is available about these products they fall outside the scope of this report.

1.2 Hartslagnu

This report is focused on the Dutch CRS Hartslagnu, developed by STAN, which covers all of the Netherlands. In the current situation, Hartslagnu uses both sms messages and an app to alert volunteers. Volunteers can opt to be alerted either by app, sms or both. To receive sms alerts volunteers have to enter one or more addresses (e.g. their home and work address) and the usual parts of the week they will be available at these addresses. They will then receive alerts if an incident happens close to any of these addresses in the relevant timeframe.

App alerts improve on this system because the actual location of the volunteer can be tracked as long as the app is running in the background. These volunteers are then alerted if an incident occurs near their current location. For the rest of this report, available volunteers will refer both to volunteers using the app near an incident at the time it happens and to volunteers using the sms with their preset locations near the incident.

Volunteers see the location of the incident before accepting or declining the alert. While volunteers are encouraged to reply, it is possible that some volunteers skip this, either because they forget or because they consider it a waste of crucial time.

When the Hartslagnu system is triggered by the emergency dispatcher, all available volunteers within 750 meter from the cardiac arrest are alerted either by app, sms or both. When a positive response is received from 5 volunteers, all others will receive a second message informing them their help is no longer required. This happens rarely, due to the low acceptance rate combined with the fact that many sms-alerted volunteers take action without responding. The current system is called first alerted first sent (FAFS).

Any volunteer that is within 250 meter of an AED that is within 500 meter from the incident will be sent to pick up this AED. All other volunteers are sent directly to the patient to perform CPR. The decision of which volunteers to send directly to the patient to perform CPR and which volunteers to send to an AED first is made at the initial alert and not changed when volunteers accept or decline the alert.

The overall acceptance rate of all alerted volunteers is around 5%. It is possible that the actual acceptance rate is higher, because this does not include volunteers that respond to the alert, but do not send a reply.

The average reaction time for volunteers is just over 90 seconds. At first glance this seems quite long, given the fact that every second counts in cases of OHCA.

In the next chapter we look into the influence of variables like volunteer age, gender, distance to event and way of alert (app or sms) on the response chance and reaction time.

1.3 Other OHCA CRS systems

Other than Hartslagnu, several apps exist to alert volunteers to OHCAs, track the location and status of AEDs or both. Some of these apps are already widely used, like Pulsepoint in the USA and GoodSAM in the UK and some other countries. Other apps on the other hand are only being tested in small communities, like EVapp in Belgium. While these apps have a similar goal and work in roughly the same way, there are some differences that we discuss in this section.

Alerting radius

One aspect where large variance exists between the various apps is the radius around a cardiac arrest in which volunteers are alerted. EVapp for example alerts volunteers up to 2km from the patient (EVApp, 2016). It seems highly implausible that a volunteer at that distance can arrive in time to make a difference. While most apps use a static radius, some apps start with a small alerting radius and increase this radius until enough volunteers have accepted the alert (e.g. Smith et al., 2017). It would be interesting to investigate which effect the static and expanding alerting radius have on the time it takes to get help to a patient and the number of volunteers that is eventually alerted.

Type of volunteers

Hartslagnu and some of the other systems allow anyone to be a volunteer as long as they have a valid certificate in CPR and AED use. Some other systems however apply higher standards and only allow volunteer firefighters, medically trained personnel, off duty police officers and the like. This results in a significantly lower number of registered volunteers. This does not seem to be a problem because the response rate of these volunteers seems to be a lot higher than average, which results in needing to alert significantly fewer volunteers (Smith et al., 2017). Pulsepoint on the other hand does not require any qualification, since they argue CPR can be learned from videos and AED use requires no training at all. For AED this seems to be true (Gundry et al., 1999), but CPR is more effective if given by properly trained people (Geddes, Boland, Taleyarkhan & Vitter, 2007).

Connection to Emergency Dispatch Center

Most of the apps are connected to the EMS callcenter, so that volunteers can be alerted in case of a call to the emergency phone number (e.g. 112 or 911). iHelp seems to be the only exception to this. The app itself is used to signal the system. This means the system will only be alerted if someone near the patient knows about the system and has the app installed, because of this iHelp seems clearly inferior to the EMS-connected systems.

1.4 Knowledge gaps

Research on OHCA is quite extensive. The importance of early CPR and AED use is well documented and significant research has been done into factors that increase survival once the patient is in the hospital (e.g. Langhelle et al., 2003). The practice of EMS-activated civilian responder systems is relatively new, however first results show their effects on patient survivability. But there is almost no research in optimizing the alerting strategies of these systems. This report addresses the following gaps in current research:

No comparison between alerting strategies

With alerting strategies we mean the algorithms that determine which volunteers are alerted, when they are alerted and which volunteers are sent to an AED and which volunteers are sent directly to the patient. Descriptions of different alerting strategies do exist, but often very little explanation can be found for the implementation of a certain strategy. No quantitative or even qualitative comparisons of different alerting strategies has been found. Neither has any research been found in optimizing the parameters of a certain alerting strategy, like alerting radius or number of volunteers to alert.

Differences between volunteers not taken into account

No research has been done into the factors that influence acceptance rate and reaction time of individual volunteers. Using an alerting system that takes these factors into account might yield better results.

Mean and variance of reaction time underestimated

One result that emerged from initial research of the historical data from Hartslagnu is that the mean and variance of the time it takes a volunteer to reply to an alert is very high. This makes it impossible to use deterministic modelling to decide whether to send a certain volunteer directly to the patient or via an AED, because at the moment of this decision the response of other volunteers is yet unknown.

1.5 Research objective

The goal of this research is to provide a systematic and quantitative comparison of different strategies to alarm and direct volunteers in order to increase survival rate for OHCA patients. The question this report tries to answer is the following:

What alternative strategy to the current alerting method improves patient survival chance?

In order to answer this question, we build a simulation model to test various alternative alerting algorithms. The following subquestions need to be answered in order to build a simulation model that reflects the reality of the Hartslagnu system and determine which interventions and scenarios need to be tested in order to find the optimal alerting algorithm.

Subquestions

1) What influence do volunteer characteristics like age, gender, location, number of volunteers in the vicinity, and method of alerting (app/sms) have on volunteer reaction time and acceptance rate?

It is likely that there are significant differences in reaction time and rate between different types of volunteers. Volunteers in areas with few volunteers most likely have a higher response rate, while app users most likely have a faster reaction time, because they need to reply before seeing the location of the OHCA as opposed to sms volunteers. These more specific distributions of response rate and time are required to build a realistic simulation in order to answer further questions.

2) Does the experience in prior alerts influence the response rate and reaction time of volunteers (e.g., arrival when EMS is already at the scene)?

There seems to be reason to believe that some volunteer might get discouraged after being alerted several times and arriving after the ambulance. People do not understand why the system would alert them in such a situation and sometimes people already turn around halfway to the location if they hear the sound of the ambulance approaching.

3) How can the alerting algorithm be changed, in order to prioritize volunteers closer to the victim, such that they are less likely to have the alert cancelled before they respond?

Because the alert is cancelled after a certain amount of people have responded, it is possible that a volunteer very close to the patient is too late to respond even though he still could have been the first volunteer on the scene. Possible ways to prioritize closer volunteers are using an extending alerting radius or sending reminders to closer volunteers to increase the chance they will respond.

4) How can data on estimated ambulance arrival time and specific response rate distributions be used to decrease the number of volunteers alerted without significantly lowering the survival chances of the patient?

Some other apps use data on ambulance arrival times to reduce the number of volunteers alerted. Again this minimizes frustration by people being alerted unnecessarily as mentioned above. The improved distribution for response rate can be used to prioritize alerting volunteers with higher estimated response rates so less volunteers will have to be alerted overall while maintaining estimated survival chance.

5) How can the decision of which volunteers is sent to do CPR and which is sent to pick up an AED be changed to improve survival chances?

Another area where some optimization might be possible is in determining which volunteers should pick up an AED. As acceptations by volunteers arrive at different points in time this could be modeled stochastically using the specific distributions for response rate and time found in the earlier subquestion.

6) How can we combine the findings of all earlier subquestions in an alerting policy that increases survival chances of OHCA patients?

Ultimately the goal of the research is to come up with an alerting strategy that combines all findings into a useful strategy that improves survival for OHCA patients.

7) What performance increase can be expected from implementing this alternative alerting policy?

We estimate the expected increase in survival chance that proposed solutions will yield as well as the expected number of volunteers that will be alerted under the proposed systems.

Research approach

To answer the first subquestion, we analyze the historic data from Hartslagnu. In order to answer the other subquestions, we first explore what alternative solutions are already used by systems similar to the Hartslagnu system. We then build a simulation to test these alternatives together with a number of alternatives proposed by Hartslagnu and ourselves. The results of this simulation will then be used to choose the optimal alerting algorithm and estimate the expected increase in patient survival chance.

Chapter 2

Current situation

In this chapter, data related to the OHCA care pathway is gathered from a number of sources to be able to construct a realistic simulation in later chapters.

The primary source of our data is the Hartslagnu app, from which we analyze 5,646 instances in which the system was activated between November 2016 and December 2017. For these instances a total of 132,133 alerts were sent to 24,821 unique volunteers.

2.1 Number of volunteers and AEDs per alert

We need to determine a distribution for both the number of volunteers and the number of AEDs available for an alert to build a simulation. In 21.1 % of the cases in our data, no volunteers were alerted, as none are available in the 750 meter radius. Figure 2.1 shows the historical distribution of the number of volunteers alerted per alarm (i.e. the number of volunteers within 750 meters of the patient, alarms with zero volunteers are omitted) and a fitted truncated normal distribution ($\mu = 28.940, \sigma = 22.351, lowerlimit = 0$). A more in depth reasoning regarding the use of these distributions as well as other distributions used in the simulation can be found in Appendix A.

To determine the distribution for the number of AEDs available for an alert, we take the coordinates of all alerts and all AEDs in the database and count the number of AEDs within 1000 meters for each of the alerts. In the current system, AEDs are only alerted up to a radius of 500 meters, but analyzing AEDs up to 1000 meters from the incident gives us the ability to chance this radius in the simulation. Because all of the AEDs currently in the database are used, the possibility exists that we count an AED as available for a certain alert, even if that AED was not yet available at the time. However, because this report is meant to advise on the future of the system, it is reasonable to take all current AEDs into account. It is remarkable that in 47% of the cases noAED is available, stressing the need to encourage further increases in the number of available AEDs. We fit a truncated exponential distribution to all cases with one or more available AEDs. As shown in Figure 2.2, this distribution fits the data very closely.

2.2 Volunteer acceptance rates

Of all alerts in our database, about 9.4% are sent via the app, while the other 90.6% are sent via sms. Because Hartslagnu recently updated the system to deny responses more than five minutes after the alert was sent, we treat all responses after this time as a non-response for our analysis. Volunteers respond to 41.5% of the app alerts and 4.2% of the sms alerts. Of the response to app alerts, 26.8% are positive, whereas for the sms alerts volunteers can only send a positive response or no response at all. When we look at the positive responses as percentage of all alerts sent, we find that the acceptance rate for app alerts is significantly higher than for sms alerts (11.1% for the app versus 4.2% for sms). Note that it is technically possible for sms users to send a negative response if they answer with the word “Nee” (No), but it is extremely rare that volunteers do this. Any other response, even of just one character, is treated as a positive response.

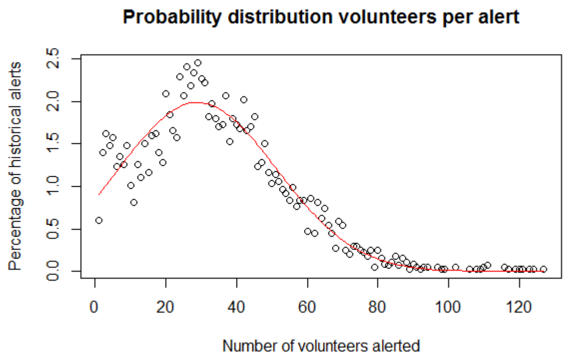

Figure 2.1: Historical distribution of alerted volunteers per alarm (one or more volunteers alerted) and fitted truncated normal (28.940, 22.351) distribution.

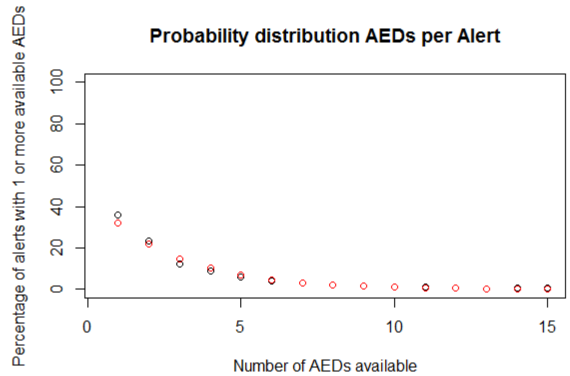

Figure 2.2: Historical probabilities (black) for AED count (one or more AEDs available) and predicted probabilities (red) based on truncated exponential (0.3841) distribution.

In addition to data from the Hartslagnu database we have information from questionnaires volunteers answered after an alert. This questionnaire has been filled out 39,802 times in total. Approximately a quarter of these volunteers have responded positively to the alert. This is significantly higher than in the total group of alerted volunteers. This means that volunteers that responded positively are more likely to fill out the questionnaire, which makes intuitive sense. It is not registered whether the volunteers that answered were alerted by app or sms.

Out of 29,980 answers to the question on why volunteers did not respond to the alert, a total of 14,659 volunteers answer that they are not close to the location of the alert. Because users are not alerted via the app if this is the case, we can assume that all these answers come from volunteers alerted by sms. Because we know from Hartslagnu data that app users constitute 8.7% of the non-responses, we can calculate that 12,705 (91.3% * 29,980 - 14,659) of the questionnaire respondents received an alert via sms and ignored it for a different reason than not being in the area. In other words, 53.6% of the times an sms alert is ignored, this happens because the volunteer is not in the area. Because we know from data that the response rate for sms alerts is 4.2% and that 90.6% of the alerts are sent via sms, we can compute that 51.3% (53.6% * 95.8%) of sms alerts or 46.4% (51.3% * 90.6%) of all alerts are sent to volunteers that are not in the area of the incident. This explains a large part of the difference in acceptance rate between app and sms alerts. Although if we take this into consideration, the app alerted volunteers still have a higher acceptance rate than sms alerted volunteers comparably close to the incident (11.1% for app alerts versus 8.7% for sms alerts to volunteers in the area).

Factors influencing volunteers acceptance rates

We look into several factors that might influence the chances a volunteer will respond.

Number of prior alerts received

Figure 2.3 shows that the number of alerts a volunteer has received before seems to have no influence on the acceptance rate of app volunteers, but a strong negative effect on the acceptance rate of sms volunteers. As discussed before, sms alerted volunteers know the address before accepting the alert. Their declining response rate might show that volunteers that have received prior events more often decide to skip the response in favor of travelling to the OHCA scene sooner.

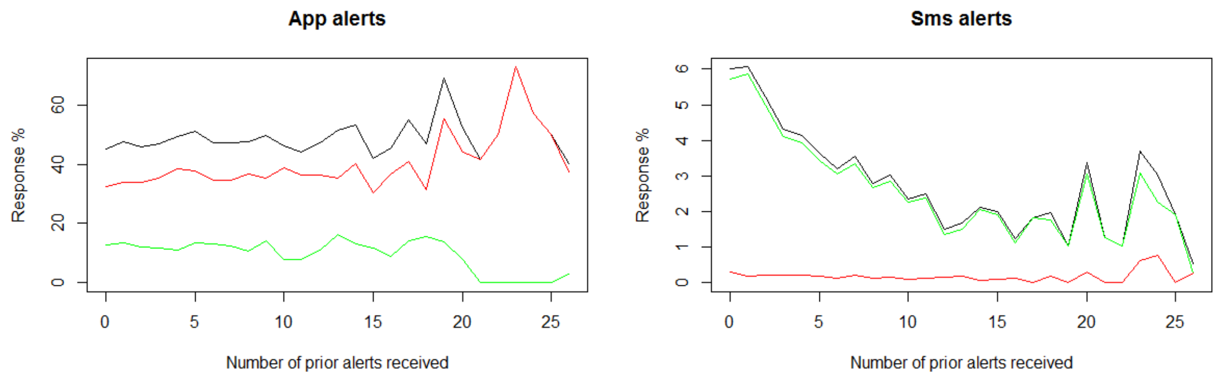

Figure 2.3: Total (black), positive (green) and negative (red) response rates (%) as factions of all alerts sent, based on the number of prior alerts a volunteer has received. The high variance in the data for high numbers of prior alerts is because there is not much data is available (few volunteers have received such a high number of alerts).

		Volunteer gender		
Response type		Unknown	Male	Female
App alerts	Total	48.38%	44.06%	32.52%
	Positive	13.33%	12.32%	7.59%
	Negative	35.05%	31.73%	24.93%
	No response	51.62%	55.94%	67.48%
Sms alerts	Total	2.65%	6.12%	5.40%
	Positive	2.58%	5.90%	5.27%
	Negative	0.07%	0.22%	0.13%
	No response	97.35%	93.88%	94.60%

Table 2.1: Total, positive and negative response rates (%) distinguished per volunteer gender.

Time of day and day of the week

As expected, the acceptance rate for both app and sms varies highly with the time of the day, as shown in Figure 2.4. Acceptance rates are significantly lower at night and peak during the evening. The acceptance rate is practically stable over the days of the week.

Volunteer age and gender

As shown in Figure 2.5, the acceptance rate for app alerts shows no clear trend related to age, but the chance for sms users to accept an alert rises significantly with age. A possible explanation for this trend is that younger people are more likely to use the app alongside sms alerts and prefer to use the app to send their response, as this is quicker than using an sms message.

People whose gender is not known in the Hartslagnu database are significantly more likely to respond to app alerts, but less likely to respond to sms alerts (Table 2.1). Furthermore the response rate for male volunteers is higher than for female volunteers for both app and sms alerts. No clear explanation can be found for the fact that the relationship between gender and acceptance rate differs so widely between app and sms alerts.

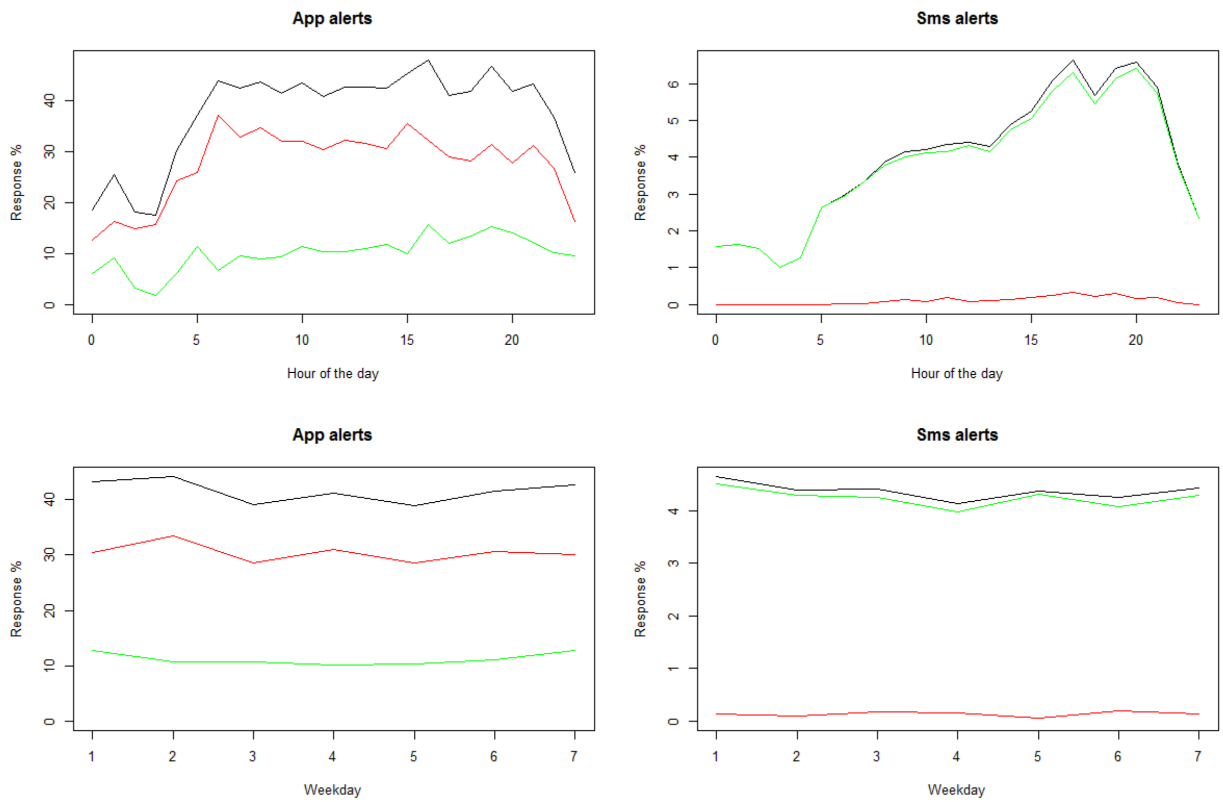

Figure 2.4: Total (black), positive (green) and negative (red) response rates (%) as function of the time of day and day of the week.

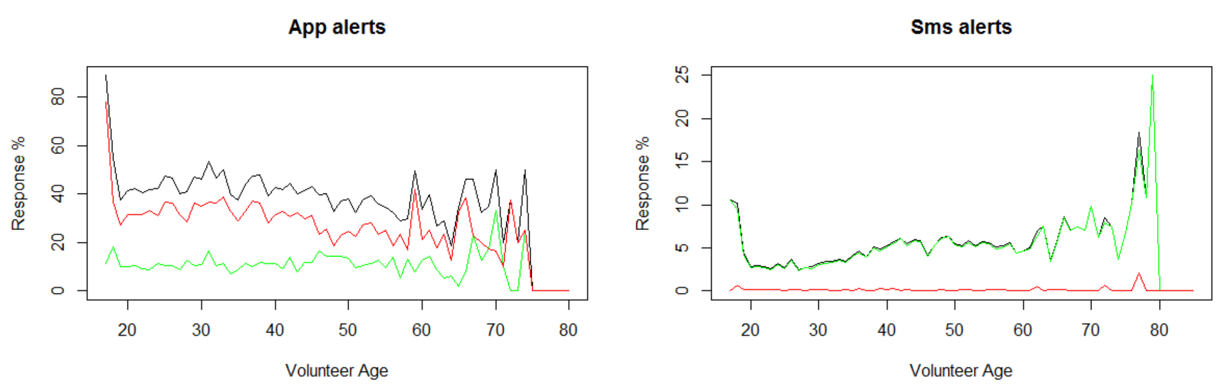

Figure 2.5: Total (black), positive (green) and negative (red) response rates (%) as function of volunteer age. High variance for very low and high age groups can be explained by low number of volunteers in these age groups.

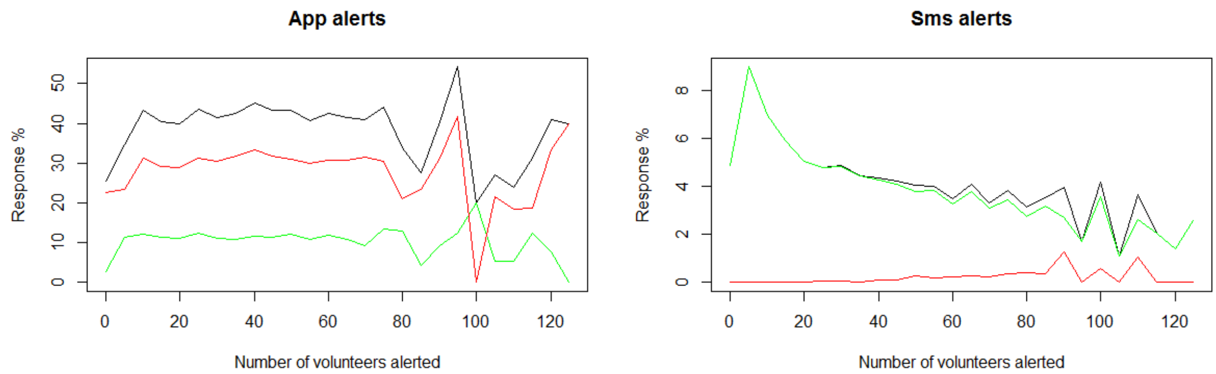

Figure 2.6: Total (black), positive (green) and negative (red) response rates (%) as function of the number of volunteers alerted for an incident. High variance for very high counts of alerted volunteers can be explained by low numbers of alerts with that many volunteers.

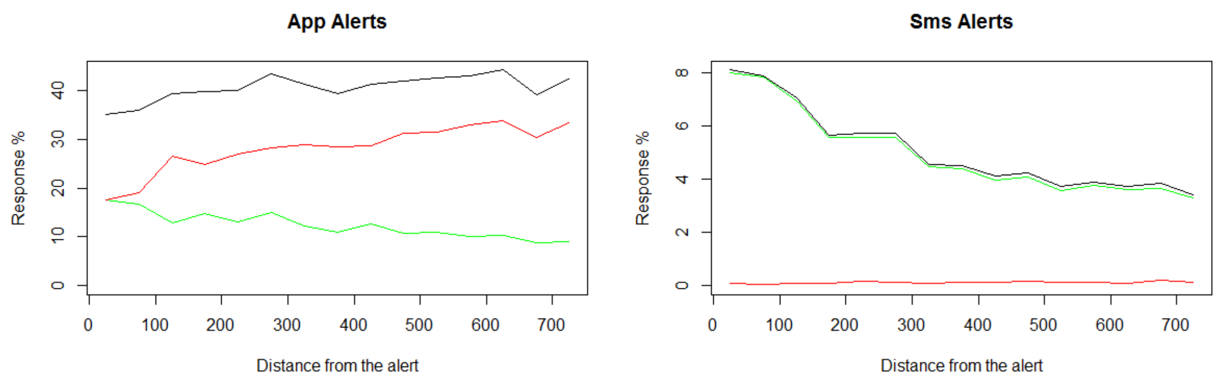

Figure 2.7: Total (black), positive (green) and negative (red) response rates (%) as function of the distance of volunteers to the incident.

Number of volunteers alerted

Although volunteers are not aware of the number of volunteers alerted for a certain incident, the number of volunteers alerted can be seen as an indication of the number of volunteers active in the region. If a volunteer is aware that very few or very many volunteers are active in the region, this might influence the acceptance rate (e.g. a volunteer might be more inclined to accept if they know there are very few volunteers nearby). Figure 2.6 shows that this seems to be true for sms alerts, but the acceptance rate for app alerts seems to be more or less independent of this factor.

Distance to the incident

Figure 2.7 shows the relation between volunteer acceptance rates and their distance to the incident. It is clear from the graph that volunteers are more likely to accept an alert the closer they are. This relation is similar for both app and sms alerts.

2.3 Timeline for emergency care in case of OHCA

In this section we will try to find distributions for all parts of the timeline in order to be able to build a realistic simulation. The first part of the OHCA timeline is the time between the cardiac arrest and the call to the emergency phone number. However the length of this interval is impossible to know, except in very specific cases, such as casinos with extensive security camera coverage (Valenzuela et al., 2000). For this reason the timeline we research starts at the moment of the call.

Emergency dispatch center

The time it takes for the emergency dispatch center to activate the ambulances and the volunteers can be divided into two parts. When the dispatcher concludes that the patient is unconscious, an ambulance is dispatched. Further questions are needed to figure out whether it concerns a cardiac arrest. When this is confirmed, the Hartslagnu system is activated. From experience Hartslagnu has from cooperating with emergency dispatch centers, the time between the call to the emergency number and the activation of the system is estimated to be around two minutes, which we assume to be deterministic and the same for each case. The time between the call and the activation of an ambulance is included in the ambulance response time.

Ambulance arrival

As seen in the previous chapter, some OHCA CRS systems use data on estimated ambulance arrival times to prevent alerting volunteers in cases where it is very unlikely they will arrive before the ambulance. It should be noted that a volunteer arriving after the ambulance is not entirely useless, they can for example help in dealing with bystanders, but for this research we assume that a volunteer arriving after the ambulance does not increase the survival chance of the patient.

For the simulation, we will need distributions for ambulance arrival times in the Netherlands. Kommer and Zwakhals (2010) report an average response time of 9 minutes and 45 seconds with a coefficient of variation of 0,39, which translates to a standard deviation of approximately 3 minutes and 48 seconds. Response time is the time from the moment the call is made to the emergency number until the arrival of the ambulance at the scene, so this interval includes the time it takes for the emergency dispatch center to activate the ambulance. Kommer and Zwakhals (2010) do not give an explicit distribution of the response time, but judging from Figure 2.8, response time distribution seems to be shaped approximately like a normal distribution albeit with a slightly fat right tail. According to Ambulancezorg Nederland (2018) average response time has remained relatively stable since 2009. So because no more recent information is available on other parameters of the distribution, we assume the distribution for 2009 is still relevant.

Ambulance arrival time is of course highly variable on the location, specifically on the distance to the closest ambulance station. As shown clearly by Verlaat, van der Meulen and Schoof (2017) some areas in the Netherlands can not realistically be reached within the 15 minute norm whereas in locations very close to an ambulance station the ambulance may already be at the scene when volunteers are alerted. This difference is not taken into account in the current alerting algorithm, but the chance for volunteers to contribute to a patients survival chances is strongly dependent on the time it takes for an ambulance to get to the scene.

Activation of Hartslagnu system

After the Hartslagnu system is activated by the emergency dispatcher, it takes approximately 15 seconds for the alerts to be sent to the volunteers. For this research we assume this 15 seconds to be deterministic and thus the same for each instance.

Volunteer reaction time

In our analysis of reaction time we distinguish between the three different kinds of response. For the app we distinguish between the positive and the negative response, while for sms a positive response is the only

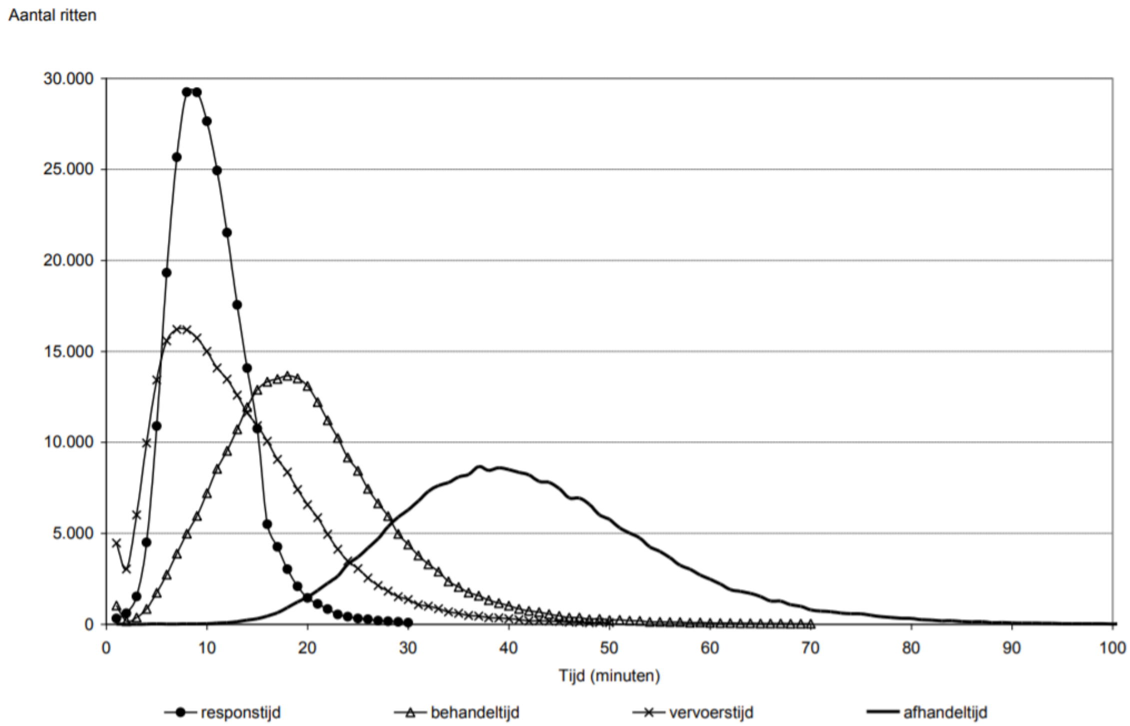

Figure 2.8: Histograms of response time, treatment time, transport time and total time (minutes) for emergency ambulance trips (A1) in the Netherlands in 2009 (Kommer & Zwakhals, 2010).

possibility. The historical distributions for the intervals for these three responses are shown in Figure 2.9. Although these distributions look relatively similar, there are notable differences in the median reaction times. The average interval for a positive response via the app is 76 seconds (IQR: 32-103), whereas a negative app response takes an average of 90 seconds (IQR 39-123). The comparison with a positive response via sms might be more important. The average interval for a positive sms response is 90 seconds (IQR: 47-121), confirming our earlier hypothesis that alerting via app is faster than via sms.

Factors influencing volunteers reaction time

We look into several factors that might influence the reaction times of volunteers.

Number of prior alerts received

Figure 2.10 shows that reaction time for app alerts slowly decreases as volunteers have received more prior alerts. This could be explained by volunteers getting more familiar with the app and recognizing the alerting sound more quickly. For the sms alerts no trend seems apparent.

Time of day and day of the week

We have seen that the acceptance rate is significantly lower during the night, as expected the reaction time is significantly higher during the night (Figure 2.11). The obvious explanation for this trend that people are asleep at this time and thus slower to respond to the alert. Just like the acceptance rate, variation of reaction time over the days of the week is very small.

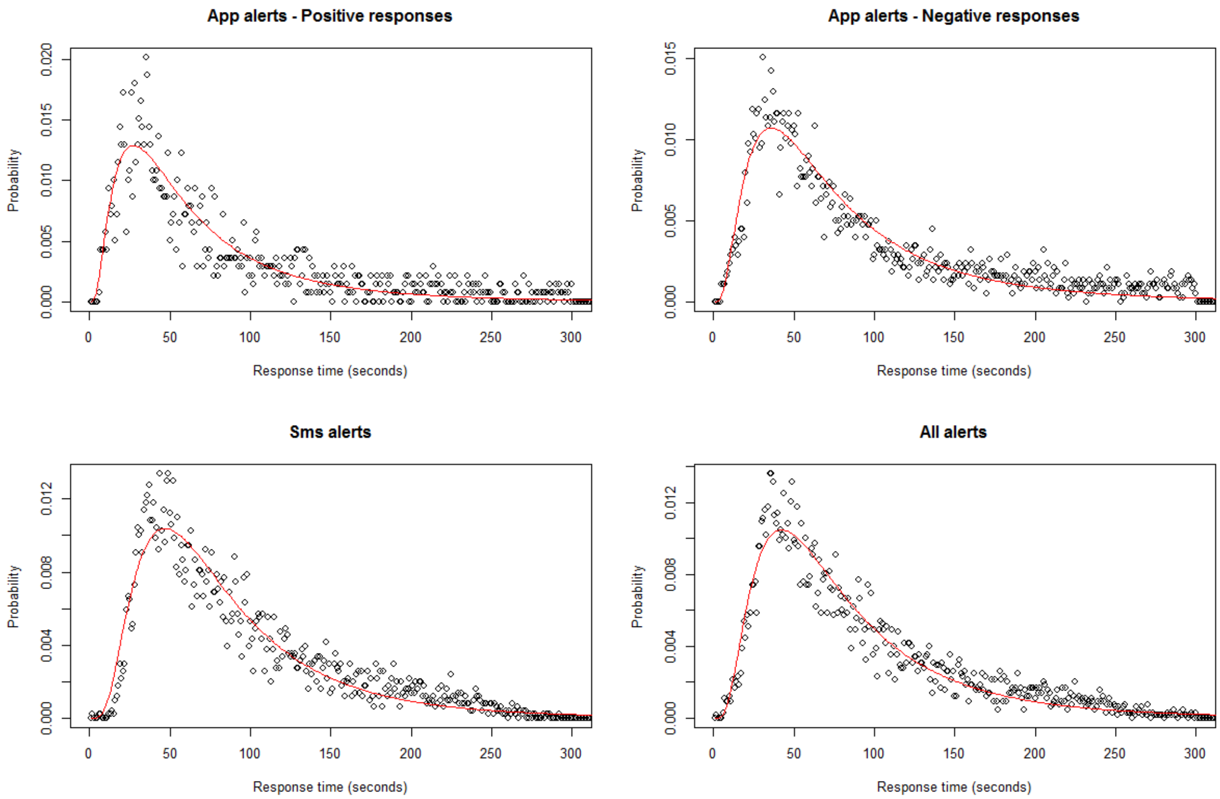

Figure 2.9: Historical distributions of reaction time for different responses with fitted lognormal distributions (red).

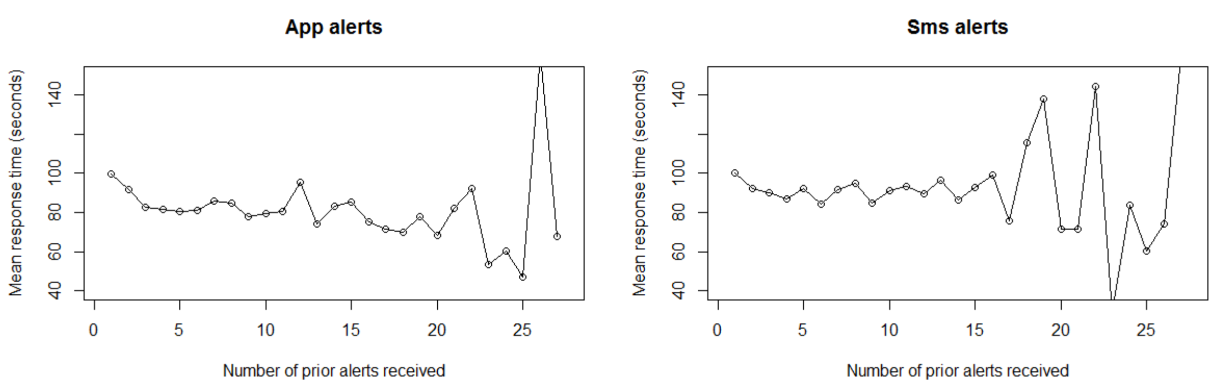

Figure 2.10: Mean reaction time as a function of the number of prior alerts a volunteer has received. The high variance in the data for high numbers of prior alerts is because not much data is available (few volunteers have received such a high number of alerts).

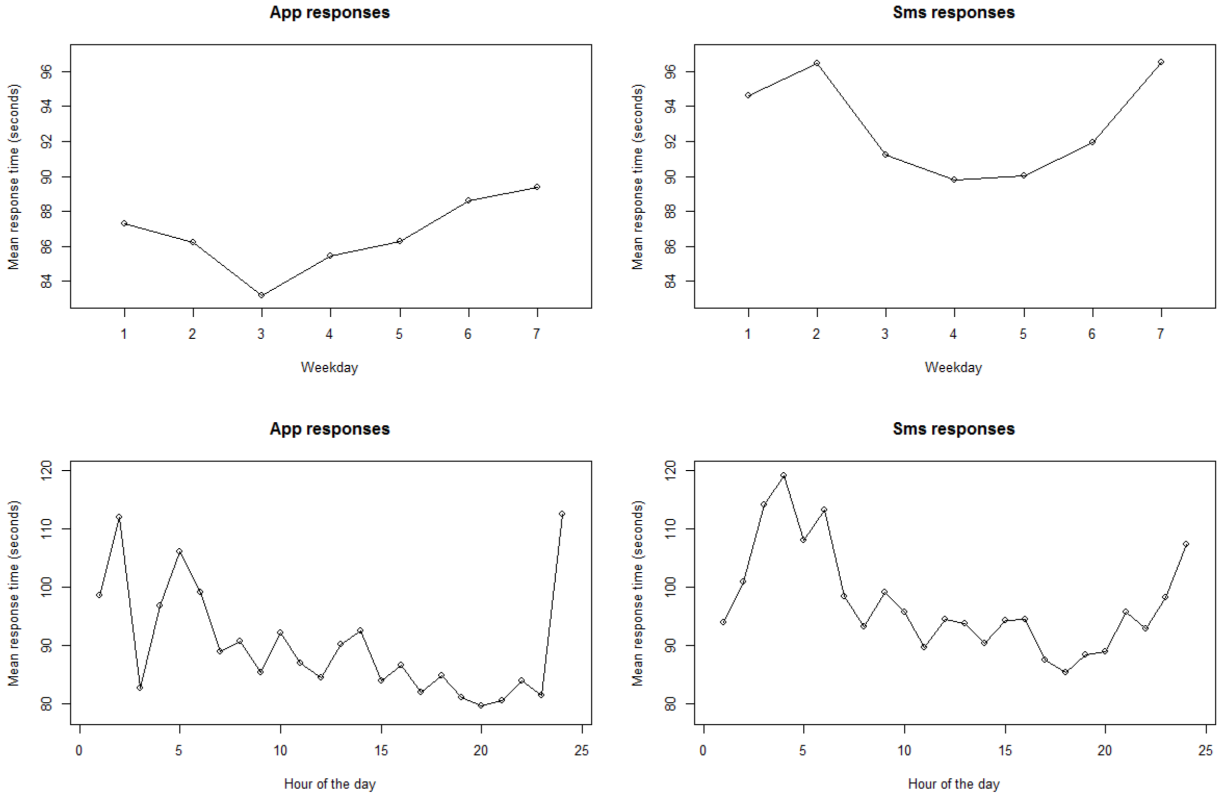

Figure 2.11: Mean reaction time as a function of the time of day and day of the week.

	Volunteer gender		
Response type	Unknown	Male	Female
App alerts	82	86	90
Sms alerts	94	93	90

Table 2.2: Mean reaction time distinguished per volunteer gender.

Volunteer age and gender

As shown in Figure 2.12 the reaction time for sms alerts shows a slight increase for older volunteers. This trend is not clearly visible for app alerts, but it might be obscured by the small sample sizes for older volunteers using the app.

Table 2.2 shows mean reaction times distinguished per volunteer gender. Although some slight trends seem to appear, the differences between the genders are not significant.

Distance to the incident

Figure 2.13 shows the relation between mean volunteer reaction times and their distance to the incident. This graph shows that there is no clear relationship between these variables.

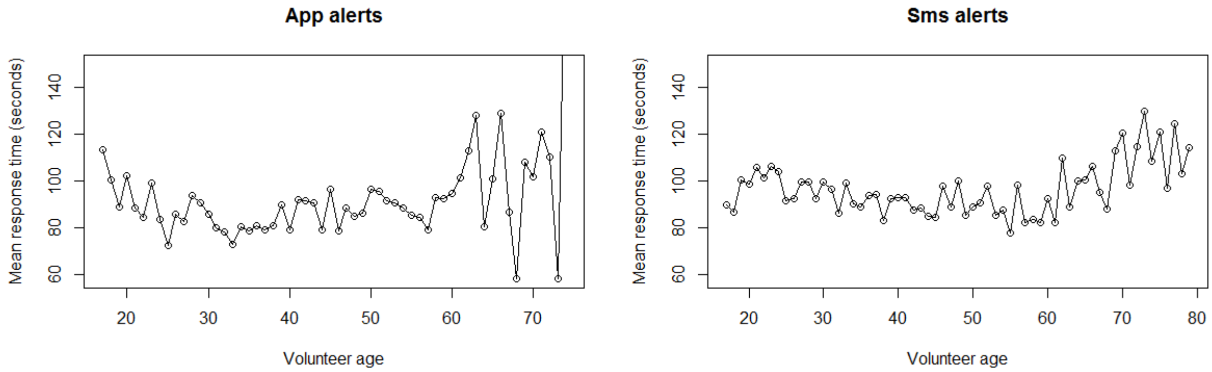

Figure 2.12: Mean reaction time as function of volunteer age.

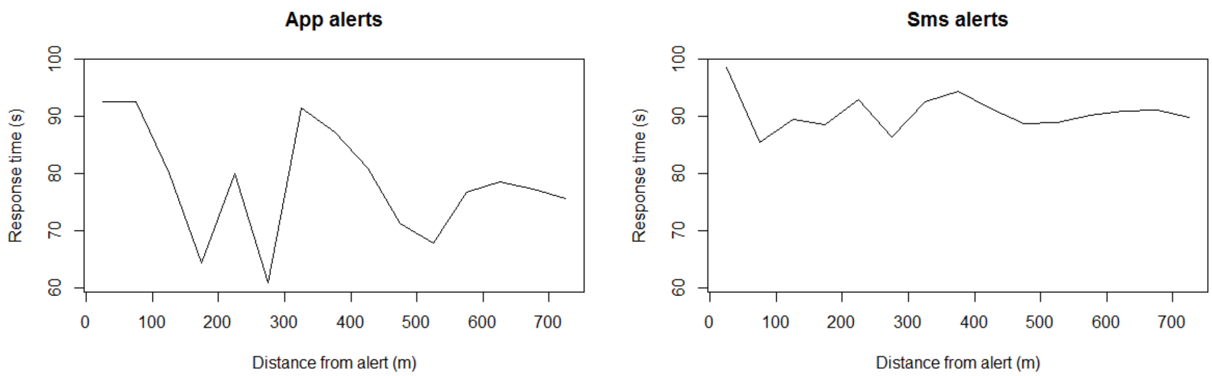

Figure 2.13: Mean reaction times (seconds) as function of the distance of volunteers to the incident.

Volunteer travel time

For this part we have to distinguish between the volunteers sent to fetch an AED and those sent directly to the patient to perform CPR. We know from the questionnaires that volunteers have filled out that 71.2% of volunteers travel to by bike, whereas most of the rest walk to the incident. For the simulation we assume a speed of 6 km/h for walking volunteers and a speed of 20 km/h for volunteers on bike.

AED connection

Gundry et al. (1999) find a mean time to defibrillation of 67 seconds with trained professionals. Because all of the Hartslagnu volunteers have been trained in the use of AEDs we assume this number is applicable in this situation. For this research, we assume this number to be deterministic and the same for each instance.

Timelines

The timelines for the different types of responders are shown in Figures 2.14, 2.15 and 2.16. The timelines consist of parts that are treated as deterministic, stochastic parts and parts that are dependent on distances that are based on stochastically determined locations.

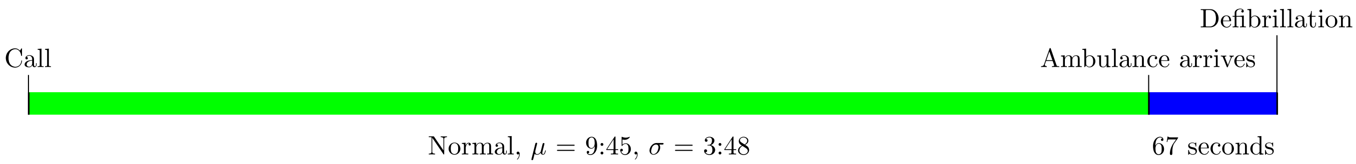

Figure 2.14: Timeline for ambulance response, to scale for mean ambulance arrival time. Blue parts are deterministic, green parts are stochastic.

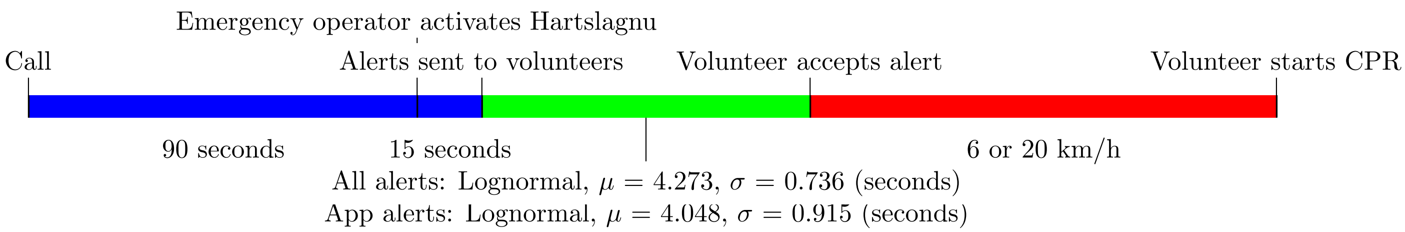

Figure 2.15: Timeline for CPR volunteer, bar sizes are to scale for a volunteer, traveling by bike, at 600 meter from the patient, with average (positive) response time for app alert. Blue parts are deterministic, green parts are stochastic and red parts are dependent on the distance and mode of transport, which are generated stochastically.

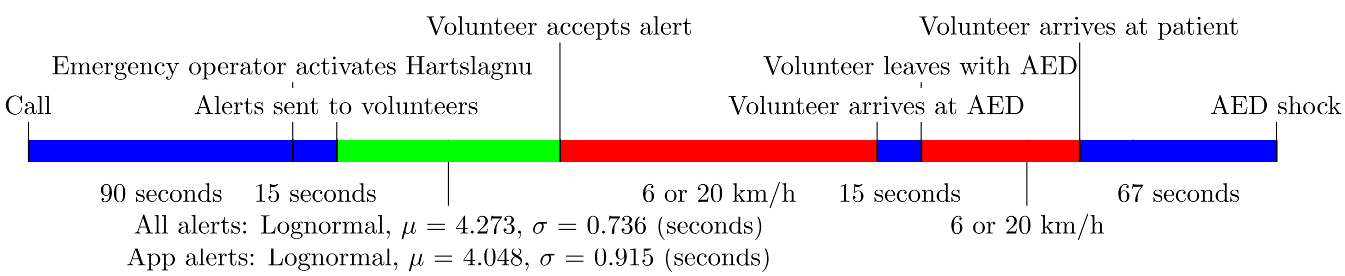

Figure 2.16: Timeline for AED volunteer, bar sizes are to scale for a volunteer, traveling by bike, at 600 meter from the AED and 300 meter between AED and patient, with average (positive) reaction time for app alert. Blue parts are deterministic, green parts are stochastic and red parts are dependent on the distance and mode of transport, which are generated stochastically.

2.4 Conclusion

In this chapter, we analyzed the current situation based on historical data from the Hartslagnu system. Distributions have been found for the numbers of available volunteers and AEDs per alert as well as the volunteer and ambulance reaction times. Some factors influencing volunteer acceptance rate and reaction time have been identified, however these relations are not always as clear and pronounced as we had initially expected.

Chapter 3

Literature review

In this chapter we look for existing solutions or partial solutions to optimize the alerting strategy of Hartslagnu.

First we review existing systems for alerting volunteers in cases of OHCA as well as other systems for alerting citizens. We review these systems to see whether they contain ideas that are worth testing in the simulation. We then analyze literature relating to a number of themes relevant for our simulation methodology, most importantly equations to estimate the patient survival chance.

3.1 Other OHCA CRS systems

The most obvious place to look for possible directions to improve the alerting strategy are other OHCA CRS systems. In Chapter 1 we briefly reviewed some things these other systems do differently from Hartslagnu. In this section we analyze some of these systems more in depth.

Pulsepoint

Pulsepoint is an OHCA CRS system active in most of the United States. Brooks, Simmons, Worthington, Bobrow and Morrison (2016) performed an in-depth research into the workings of Pulsepoint. This research found an average response rate of 23% for cases of OHCA in public places, which the researchers cite as one of the challenges of successful implementation of the app even though it is remarkably higher than the current response rate of Hartslagnu volunteers. Another problem the researchers mention is that only 32% of volunteers that arrived on the scene found a patient unconscious and not breathing normally. This indicates a high rate of false positives with the emergency dispatchers activating the system. This does not seem to be a problem in the Netherlands. The alerting strategy Pulsepoint uses is a simple radius with a default of 400 meter, although local operators can adjust this radius. Pulsepoint seems overall very comparable to Hartslagnu with the mayor difference being the smaller default radius.

GoodSAM

GoodSAM is an OHCA CRS app developed in London and currently being used in the UK, Australia, New Zealand, India, USA, Brazil, South Africa and in parts of Europe. GoodSAM has a remarkably low number of volunteers enrolled in the system with just over 8,000 volunteers across the United Kingdom (Smith et al., 2017). This low number is the result of stricter requirements for volunteers. To have a working system with this low number of volunteers, high response rates are required. Although it is not clear how 8,000 volunteers can cover the entire United Kingdom. GoodSAM only alerts the closest three volunteers within a 300 meter radius. More volunteers are only alerted if one or more of the alerted volunteers decline or do not respond within 20 seconds. We can conclude from looking at GoodSAM that the choice of which volunteers to enroll in the system is an important determining factor in the design of the system.

Momentum

Momentum is a Swiss OHCA CRS app that is active under different names in Switzerland, Czech Republic, and in some Italian regions. Momentum uses preset locations for the initial alert and only uses live locations if a volunteer accepts the alert. Momentum uses a patented alerting method in which the alert is reevaluated at the moment a volunteer accepts it. This is necessary because that is the first moment the actual location of the volunteer is known to the system. If the required number of volunteers has already accepted the alert, the new volunteer will only be sent to the alert if they are closer to the scene than the other volunteers. Hartslagnu does not include the possibility for someone to accept the alert when the limit has been reached even if that volunteer is closer than all volunteers that have accepted the alert already.

Conclusion

Other OHCA CRS apps use different alerting methods that are possible improvements on the current method used by Hartslagnu. In the next chapters we will use simulation to compare and optimize these methods.

3.2 Other alerting systems

When thinking about improvements for an alerting CRS system it might be worthwhile to look into other systems where people are alerted to aid in an emergency. When comparing, a number of important characteristic of the OHCA CRS system should be kept in mind:

Very high urgency The need to optimize the system arises partly from the very high urgency to recruit help in the case of OHCA. If other systems cover less acute situations, they could be designed with other benchmarks than speed in mind.

Targets specific people OHCA CRS systems do not alert everyone in a certain area, but only those that are trained in CPR and AED use and are enrolled in the system.

Alerts more people than need to react OHCA CRS systems target more people than are required to respond, because the acceptance rate is below 100%.

All three of these characteristics are important in designing and optimizing an alerting strategy. Other systems that do not present all of these characteristics might have alerting strategies that would not be optimal if used for OHCA CRS systems. Keeping this in mind we will look at a number of other emergency alerting systems.

NL Alert

NL Alert is a Dutch system used to alert civilians in case of natural disasters or other dangerous situations While this system matches our criterion on urgency, it does not meet the other criteria and because of this the strategy of blanket alerting of everyone in the surrounding area is fundamentally unfit for use in an OHCA CRS system.

Amber Alert

Amber Alert is a system used to alert large amounts of people in the case of a missing child deemed in immediate danger. A comparison between Amber Alert and and OHCA CRS system suffers from the same problems as mentioned for NL Alert in the sense that it uses a very wide strategy to alarm a very large number of people. This works because the system only alerts in very few cases with high urgency, only being activated as little as 1 or 2 times per year in the Netherlands. If the systems would be activated more often willingness to respond to the alert would most likely decrease severely. Due to the relatively high occurence of OHCA this type of alerting in which very many people are unnecessarily alerted is not desirable.

Ready2Help

Ready2Help is a system used by the Dutch Red Cross to alert volunteers to help with a variety of things raging from placing sand bags in preparation for heavy storms to visiting elderly people in periods of extreme heat (Het Nederlandse Rode Kruis, 2018). The system alerts volunteers based on their postal code and uses an expending radius until a certain number of volunteer has accepted the call (Het Nederlandse Rode Kruis, 2017). Ready2Help does not meet our criterion of very high urgency, which is why the system of an expanding radius might work so well in this case. There is enough time to expand the radius if not enough people have accepted the alert.

Burgernet

Burgernet is a system quite comparable to Hartslagnu with the major difference being that it is used in the case of missing persons or crimes, like burglaries or robberies, instead of medical emergencies. One notable similarity is the fact that the Burgernet system is activated by an emergency dispatcher in response to a phone call to the emergency number. According to recent figures by Burgernet, the system is activated 26.000 times yearly of which 8.000 situations are time critical (Burgernet, 2018). Burgernet uses a simple radius to alert people based only on their preset address, not on their current location. Because the object of the alert is often moving in the case of Burgernet, generally a larger radius is used than in the case of OHCA. This radius is highly dependent on the situation, ranging from a small radius for a missing elderly person to a large radius for robbers that left the scene on a scooter. These differences (the large radius, no use of current volunteer location and moving object of the alert) ultimately make Burgernet an unsuitable place to look for ideas to improve OHCA CRS systems.

Neighbourhood watch groups

In addition to Burgernet, several groups of civilians have organized themselves in groups to surveil their neighbourhood. Although some providers of the specialized apps report clear and quantified results like a 30% decrease in burglaries (Veiligebuurt.nl, n.d.), scientific research does not show this type of clear advantages (Lub, 2016). This system relies upon the participants to alert each other although they are encouraged to contact the police first in urgent situations.

For Hartslagnu, giving lay persons the ability to activate the system based on their own diagnosis might result in a lot of false positives, i.e. cases where the system is activated even though there is no cardiac arrest. It seems better to keep the responsibility of activating the system with the emergency dispatchers, who are trained to make this kind of decisions under severe time pressure.

Conclusions

Most of the mentioned systems work differently from OHCA CRS systems. But the way these systems work can not be translated to the OHCA case for different reasons. These systems work specifically because they operate in a different environment from critical medical situations. Of all the researched systems, only Burgernet is somewhat comparable to OHCA CRS systems in all of our criteria, but the absence of the time-critical aspect makes Burgernet an unsuitable comparison. As opposed to the described OHCA CRS systems, for the systems mentioned in this chapter very little is known on their specific alerting algorithms. Overall these alerting systems seem simpler and more rudimentary than those used in case of OHCA, making it more likely that ideas from OHCA CRS systems can be used to improve these systems than the other way around.

3.3 Methodology

In this section, we analyze literature relevant to simulating the survival chance of OHCA patients.

Survival functions

A number of different functions are used to estimate the survival chance for OHCA patients, notable an exponential one by Valenzuela et al. (2000) and a linear one by Larsen, Eisenberg, Cummins and Hallstrom (1993). The first function uses two variables: the time from collapse to CPR and the time from collapse to connection of an AED. The second function uses a third variable: the time from collapse to advanced life support. In this simulation we interpret the start of advanced life support as arrival of an ambulance, the start of AED as connection of AED either by a volunteer or ambulance personnel and the start of CPR by arrival of any help, be it the ambulance or a volunteer either with or without an AED.

$$\begin{aligned} SurvivalChance = 0.67 - 0.023 * MinutesToCPR - 0.011 * MinutesToDefibrillation \\ -0.021 * MinutesToAdvancedLifeSupport \end{aligned} \tag{3.1}$$

$$SurvivalChance = \frac{1}{1 + e^{-0.260 + 0.106 * MinutesToCPR + 0.139 * MinutesToAED}} \tag{3.2}$$

As these survival functions are both around two decades old, we also use the version of the function by Valenzuela that is updated by Matinrad, Granberg, Vogel and Angelakis (2019) to reflect the increases in survival chance over the last decades (Formula 3.3).

$$SurvivalChance = \frac{1}{1 + e^{-1.3614 + 0.3429 * MinutesToCPR + 0.18633 * MinutesToAED}} \tag{3.3}$$

Because these survival functions are all based on patients with a shockable rhythm, we also need a function to determine the probability of a patient having a shockable rhythm as a function of the time passed since the collapse. Renkiewicz et al. (2014) show that this relation is given by the following simple linear function:

$$P(ShockableRhythm) = 0.45 - 0.017 * MinutesSinceCollapse$$

Performance measures

The current performance measure used by the Dutch Heart Association (Hartstichting) is based on the so-called 6-minute zone (Hartstichting, n.d.-a), which means the goal is to have AEDs in places where one can be present at any incident within 6 minutes. There are two problems with this approach to measuring the performance of an emergency treatment system for OHCA.

First the way the Hartstichting interprets this 6-minute zone seems somewhat unrealistic. The Hartstichting translates this 6-minute zone into a radius of 1500m around each incident in which an AED should be found (Zijlstra, Pijls et al., 2016). This translates to a speed of 15 km/h if we ignore all other steps in the timeline. This is an improbable speed for someone on foot, so it should be regarded as very optimistic at best to call this a 6-minute zone.

The second problem is that this is a very binary approach to whether an incident is covered or not. This is a very simplistic representation of reality, in fact it does make a difference whether a volunteer arrives in 2 minutes compared to 5 minutes or 7 minutes compared to 12 minutes. In addition to the fact there does not seem an objective reason for placing the cut-off point.

Even though the simplicity of the concept of a 6-minute zone might make it a practical marketing tool to get communities to work on the goal of improving AED coverage, it is not a sufficient objective function for optimizing a simulation.

In the previous section we found a useful survival function to estimate survival chances based on time to CPR and time to AED shock. We could use this function to optimize our simulation for maximum survival chance, which seems a more objective way to look at the situation.

Simulation

The most viable alternatives to simulation for solving this problem are mathematical modeling and experimentation on the existing system.

Experimentation on the actual system is not a viable option for obvious reasons. Experimentation using actual OHCA cases might harm patients and is thus unethical. Experimentation by means of fake training alerts will most likely undermine the willingness of volunteers to cooperate in the system.

The complexity of the situation makes mathematical modeling a less viable option than simulation. Because there are many interacting stochastic processes (e.g. volunteer acceptance rate, reaction time and travel time) determining the outcome a mathematical model would be very hard to compute. Furthermore a simulation approach makes it easier to try a number of alternative approaches and parameter settings.

Prior use of simulation in OHCA care optimization

No research was found using discrete event simulation or any other form of computer simulation in the optimization or analysis of alerting citizen responders in case of OHCA.

We did however, find one case of real-life simulation from the very early days of OHCA CRS systems. Ringh, Fredman, Nordberg, Stark and Hollenberg (2011) performed a simulation in Stockholm using 25 volunteers acting as citizen responders. They alerted these volunteers for simulated OHCAs at historical locations of actual OHCAs using an alerting radius of 350 meter. They then compared the arrival time of the volunteers to the arrival time of the EMS at the actual incident. They found that in 72% of the cases, the volunteers arrived before EMS.

This experiment is problematic because the fact that a volunteer is cooperating in an event like this will most likely have a large influence on their reaction time and acceptance rates. The volunteers were randomly moving through Stockholm waiting to be alerted as opposed to going about their daily lives. The mean reaction time reported in the experiment was 22 seconds, which is significantly shorter than the mean reaction time of Hartslagnu volunteers and probably not realistic in any real-life situation.

Once the actual system was implemented, citizen responders arrived before EMS in 45% of the cases, confirming that the simulation outcomes were indeed somewhat optimistic. It should also be noted that this experiment was conducted in central Stockholm with a mean of 12 responders available in a radius of 500 meter from an incident. These results might not be translatable to more rural or less public settings.

Distances

In alerting, Hartslagnu uses a radius to alert volunteers, not taking into account their actual travel distances to the incident. This is done mainly because calculating travel distances would take too much time, delaying the sending of the alert.

We have no historical data on the actual time the volunteers arrived at the scene. For the simulation we therefore have to use an estimate based on the distance between the volunteer and the time of the incidence.

To make a proper estimation of the time it takes for a volunteer to travel to a patient or an AED we need to translate direct distance to actual travel distances. Since it is not viable to calculate actual travel distance for a large number of volunteers at run time, a viable compromise might be to use a simple factor with which to increase the direct distance. A realistic factor for people on foot or bike in the Netherlands is between 1.2 and 1.4 (Kennisinstituut voor Mobiliteitsbeleid, 2015). We will need to look into the Hartslagnu data to establish whether this is also a realistic factor on the short distances traveled to an OHCA incident or AED.

Future changes in available data

Hartslagnu will expand their data collection in the near future. They will start gathering data on the time volunteers and AEDs arrive at the scene as well as whether a certain AED was used to deliver a shock. This data can be used to eliminate a number of assumptions we made in the previous section, resulting in a more precise simulation. Although it is impossible to incorporate that data in this report, it is definitely recommendable to revisit the simulation when this data becomes available.

3.4 Conclusion

No research has been found that uses simulation as a means to analyze or optimize OHCA CRS systems. We found a number of alerting methods used by other OHCA CRS systems that are worth researching in our simulation. Other alerting systems do not provide relevant methods to our scenario, because several factors make them unsuited for comparison, most notably the time-critical aspect of OHCAs that is not found in these other environments. Some relevant literature has been found relating to inform our simulation methodology.

Chapter 4

Simulation methodology

Our simulation aims to estimate time until arrival of a volunteer as well as survival chance based on the alerting algorithm used. We can then use this simulation model to compare different algorithms in the next chapter.

4.1 Prediction models

Before we start simulating we attempt to create prediction models for both acceptance rate and reaction time based on volunteer-specific variables.

Acceptance rate

The data in Chapter 2 clearly shows relations between some of the tested variables and the volunteer response rate. Based on this we expect to find meaningful classification models to predict responses. We use four different models to predict the volunteer acceptance rate: random chance based on the historic probability for each response type, a decision tree, an artificial neural network and a linear model based only on the hour of day and the distance to the hour of the day and the distance from the volunteer to the incident. The models are evaluated using 10-fold cross-validation. We use these four models to predict the acceptance rates for app and sms alerts separately. For the decision tree, we use Weka 3.8 (Frank, Hall & Witten, 2016). For the artificial neural network we use the neuralnet library in R version 3.4.3.

We pick distance and hour of day for the linear model because these variables show a clear relation to the acceptance rate. We use factors for all 24 hours of the day and a linear relation between acceptance rate and the distance to the alert to calculate a specific probability for each of the three possible outcomes (No response, positive response or negative response) for each alerted volunteer. We then assign each volunteer a random response according to these probabilities. This model is shown in the following equations, with distance in km. Hour factors range between 0.235 and 1.509:

App positive:

$$P(Response) = (0.1645 - 0.1105 * Distance) * HourFactor$$

App negative:

$$P(Response) = (0.2233 + 0.2023 * Distance) * HourFactor$$

Sms positive:

$$P(Response) = (0.0755 - 0.0638 * Distance) * HourFactor$$

Sms negative:

$$P(Response) = (0.0002 + 0.0015 * Distance) * HourFactor$$

The kappa statistic for all four of the used prediction models is shown in Table 4.1. More detailed outcomes are shown in Appendix B. The kappa statistic is a measure of how much better a prediction model

	Kappa coefficient	
Prediction model	App	Sms
Random	0	0
Decision tree	0.094	0.045
ANN	0.124	0.023
Linear model	0.014	0.012

Table 4.1: Kappa statistic for different models to predict volunteer response.

	Root mean square error (seconds)	
Prediction model	App	Sms
Linear regression	68.21	56.15
ANN	99.73	64.54
Mean	68.63	58.74

Table 4.2: Mean square error for different models to predict volunteer reaction time.

performs compared to random chance. It is defined as follows (Cohen, 1960), with p_0 = the fraction of cases correctly predicted and p_e = the fraction that would be predicted correclty by pure chance:

$$\kappa \equiv \frac{p_0 - p_e}{1 - p_e}$$

Conclusion

The rate of correct predictions differs only slightly between the different prediction models, including the random chance model. We conclude that the models are not accurate enough to warrant the use of volunteer-specific characteristics in deciding which volunteers get alerted. We opt to use the simple model in the simulation. Even though it does not accurately predict individual responses, it will reflect the overall influence of the time of day and distance to the alert on acceptance probabilities.

Reaction time

We then tried to predict reaction time using the same variables as used for the acceptance rate as well as the response (positive, negative or none). For this we used a linear regression model and an artificial neural network. We compare these two models to simply guessing the mean reaction time for each case. The outcomes of these models are shown in Table 4.2. As already became clear from the graphs shown in Chapter 2, the relation between the tested variables and reaction time is notably less pronounced than it is for acceptance rate. The outcomes show that these models are not accurate predictors for volunteer reaction time, with the neural network performing worse, and the linear regression model only slightly better, than simply guessing the mean. We opt to use the same distribution for reaction time for each volunteer in the simulation, only differentiating between volunteers alerted by app or sms.

Conclusion

All of the methods we tested to provide useful and significant predictive models turned out to deliver disappointing results. Ultimately, we have to conclude that the acceptance rate and reaction time of volunteers depends heavily on data that is not available to us. We can easily imagine a number of factors outside of our knowledge that might heavily influence volunteer behaviour: the activity the volunteer is engaged in, the distance to their phone and the level of sound in their environment at the time of the alert are just some factors. Because of this outcome, volunteer-specific data like age, gender and response history does not factor into our simulation. We do, however, use the time of day and distance to the alert to more accurately simulate the responses from volunteers.

4.2 Assumptions

To create a working simulation, we have to make a number of assumptions about data that is not available. In this section we explain these assumptions, whether we believe they correspond to reality and what possibilities might exist to test these assumptions when new data becomes available.

Volunteer movement speed

In the current system, Hartslagnu gathers no data about what happens after a volunteer accepts an alert, other than through questionnaires. This means we have to make an assumptions for the speed with which volunteers move to the scene of the incident. We know most volunteers travel either by foot or by bike, so we can assume this speed to be somewhere between 6 and 20 km/h. We will test the influence of this variable on the survival chance as well as whether this speed has an effect on which of the simulated strategies is the best.

We assume that all volunteers have an equal ratio of actual traveling distance to euclidean distance to both the patient and to AEDs. We assume this ratio to be between 1.2 and 1.4 based on literature. In combination with the range of travel speed mentioned above, this means we will test for adjusted travel speed between 6/1.4 and and 20/1.2 km/h.

Data concerning volunteer movement speed will become available when Hartslagnu will start tracking volunteers after they have accepted an alert.

Number and location of volunteers

We will simulate cases where the radius, either static or increasing, is larger than the current radius of 750 meters, up to 1000 meters. Our data shows that for areas up to 750 meters, the number of volunteers present is linearly dependent on the area in which volunteers are alerted. We assume that this trend holds for areas with a radius up to 1000 meters.

We also assume the locations of the volunteers for each case are randomly distributed over the circle in which the alert is sent.

Bystanders

According to research into the Hartslagnu system by Pijls et al. (2016) CPR is started by witnesses or bystanders in about 63% of the cases. It is difficult to make an assumption on the time it takes for these bystanders to start CPR as this will be dependent on whether the case is immediately recognized as an OHCA and whether the bystanders have experience with CPR or need to be instructed by the emergency operator over the phone. We will assume a thirty seconds delay and test for sensitivity in the survival chance to changes in this assumption.

As shown in Chapter 1, AED use by bystanders is very unlikely, even when one is available very close to the incident. For the sake of simplicity we will assume that no AEDs are fetched and connected by bystanders. All AEDs in the simulated scenario's are connected by Hartslagnu responders or ambulance personnel.

Independence of variables

To build a simulation we have to assume independence between a number of certain variables, even if we have no data to test this assumption. Because we have no data on volunteer travel speed, we assume this to be independent from all other variables and the same for each volunteer. This assumption might be wrong, as people that have to travel further might be more likely to choose for faster modes of transportation (e.g. take the bike instead of walking). New data that Hartslagnu will gather on volunteers will make it possible to test this assumption.

Because we only have an overall distribution for ambulance response time (by Kommer and Zwakhals (2010), as reported in Chapter 2), we assume this response time is independent of all other variables. In reality it is likely that ambulance response time is negatively correlated with the number of volunteers. It is known that the ambulance has a lower rate of meeting target response times in less populated areas (RTL Nieuws, 2016).

4.3 Simulation design

We designed a Monte Carlo simulation, where we simulate a number of cardiac arrests with certain parameters, calculating the survival chance for each patient based on the simulated arrival of the first volunteer, first AED and first ambulance. The overall algorithm for the simulation is shown in Algorithm 1. Different scenario's that will be simulated will result in different ways of executing mainly step 6 and 7. These scenario's will be further explained in the next two chapters.

Algorithm 1 Overall algorithm for the simulation

```
1. Instantiate cardiac arrest
2. Pick time of day from distribution
3. Pick number of volunteers from distribution
4. Pick ambulance arrival time from distribution
5. Instantiate volunteers
for all Volunteers do
  Generate position
end for
6. Instantiate AEDs
for all AEDs do
  Generate position
end for
7. Decide which volunteers are alerted
for all Volunteers do
  Generate response (positive, negative, none) and reaction time
end for
8. Allocate AEDs to volunteers according to an algorithm
9. Cancel the alarm for certain volunteers if applicable
10. Calculate arrival time for each volunteer
11. Calculate survival chance of patient
```

4.4 Validation of simulation for the current setup of the Hartslagnu alerting system

Because Hartslagnu gathers no data on the outcome of the OHCAs we cannot use internal data to validate the simulation. Instead we use data from the research Pijls et al. (2016) did into the Hartslagnu system. The researchers looked at 1546 cases of OHCA over two years from April 2012 to April 2014 in the Dutch province of Limburg out of which the Hartslagnu system was activated in 422 cases. We compare the simulation to this article on three metrics: the probability of at least one positive response, the probability of a volunteer arriving first to the scene and survival rate of the patients.

Setting up the simulation for comparison

Some things mentioned in the article by Pijls et al. (2016) about the system are not the same as the way the system is currently set up. We change these factors in our simulation to enable a better comparison. For example, the article mentions a volunteer alerting radius of 1000 meters instead of the current 750 meters. Although it is not mentioned in the article, we assume the radius for AEDs to be used is also 1000 meters around the incident. Other than that, the article mentions that two thirds of the volunteers are sent to pick up an AED, this suggest a different system from the current one based on the distance to an AED. We assume the two thirds of volunteers closest to an AED are selected to pick one up.

Probabilities of positive response and volunteer first arrival

The data by Pijls et al. (2016) consists of 131 cases where no volunteer responded and 291 cases where one or more volunteers responded, which means the probability of getting at least one response is 69.0%, compared to 51.2% for historical Hartslagnu data and 57.2% if we adjust the alerting radius in our simulation 1000 meters to fit Pijls et al. (2016) (54.4% with a 750 meter alerting radius). The article reports that volunteers are the first to start basic life support in 24.7% of the cases versus 13.9% of the cases for ambulance and first responders. In the simulation we find that volunteers are the first to arrive on the scene in 31.8% of the cases and the ambulance in only 8% of the cases. So, even though the probability of finding at least one volunteer is slightly lower in the simulation, the probability of a volunteer arriving first at the scene is larger. This can be explained by increased familiarity of volunteers with the system and the addition of app users, which we know respond faster than sms users. Together, these numbers do not offer a clear image on which we can accept or reject the simulation as a realistic model for the operation of the Hartslagnu system, so we have to look into the survival chance outcomes to determine the validity of the simulation.

Survival chance

The article then reports a survival rate of 16.0% for cases where no volunteer showed up (which is essentially the situation without Hartslagnu existing) to the scene versus 27.1% for cases where one or more volunteer showed up. We have to make a few assumptions and calculations before we can compare these survival rates to the results of our simulation.

First of all, in accordance with the Utstein OHCA template (Jacobs et al., 2004), the report excludes 461 cases, because these patients were already dead at the moment EMS arrived. Excluding this group obviously results in a significantly higher survival rate. There are two possible solutions to account for this. Firstly we could adapt the simulation to determine whether the patient is still alive at the moment EMS arrives. However, the survival rate formulas that we use are related to the survival to hospital discharge, not the immediate survival rate at the scene. In addition to that we would need a formula for the conditional survival rate, i.e. the survival rate given the fact that the patient was still alive at a certain time t. Because neither of these functions are available, we cannot realistically adapt the simulation in this way. We therefore opt to recalculate the survival rate reported in the article to include this group in order to make it comparable to the outcomes of the simulation.

The research also excludes a group of 171 patients whose cardiac arrest is from a non-cardiac origin, but this fits with the survival chance functions we use, because those assume cardiac origin. In addition a small numbers of 38 patients is excluded because these OHCAs happened in the ambulance. This exclusion is also not a problem for our research, since the Hartslagnu system would not be activated in such a situation. In addition, 5 patients are excluded, because there is no follow-up data of their survival, as they moved to a hospital outside the Netherlands. Because this last group is so small, and because the survival rate of this group can be assumed to be similar to the group of which the survival rates are reported, the exclusion of this group will not have significantly impacted the reported survival rates.

Lastly, in 411 cases that otherwise fit the inclusion criteria for the research, the Hartslagnu system was not activated for a variety of reasons. The included cases are then divided in a group where no volunteers showed up and a group where one or more volunteers showed up.

	Simulation Probability of shockable rhythm				Pijls et al.(2016)	
	Static probability		Linearly decreasing probability			
Survival function	No volunteers	One or more volunteers	No volunteers	One or more volunteers	No volunteers	One or more volunteers
Valenzuela	8.7%	13.7%	10.5%	15.9%		
Larsen	11.0%	16.4%	13.6%	18.2%	**11.0%**	**18.6%**
Matinrad	9.4%	15.3%	**11.5%**	**18.3%**		

Table 4.3: Survival chance outcomes (%) for two simulated scenarios as well as Pijls, Nelemans, Rahel and Gorgels (2016) for different settings for calculating the probability of a shockable rhythm and different formulas to calculate survival chance.

If we assume the 461 cases excluded because the patients already died are proportionally distributed among the four others groups (i.e. non-cardiac origin, system not activated, no volunteer showed up and at least one volunteer showed up) we can recalculate the survival chance for both groups included in the research as 11.0% for the cases without volunteers attending and 18.6% for the cases where one or more volunteers attended.

In addition to recalculating these survival rates, we need to adapt our simulation to match the circumstances of the article. Earlier we found a linear function to calculate the probability of a patient having a shockable rhythm, decreasing as the time from collapse increases. This function decreases from a 45% probability at the moment of collapse. Pijls et al. (2016) however, report that 46.5% of the patients in the scenario without volunteers are found having a shockable rhythm at the moment the AED is attached, compared to 59.9% for cases with volunteers. This shows that the probability is indeed decreasing with time, but overall significantly higher than indicated by the function mentioned. The left two columns of Table 4.3 show the outcome of using these probabilities as a static probability for the relative scenarios.

But we know that a static approach is not realistic, so we opt to adjust the linear function to approximate the probabilities found by Pijls et al. (2016). If we try to find a suitable linear approximation on the reasonable assumption that this probability can never be higher than one we find the following function:

$$P(ShockableRhythm) = 1 - 0.045 * MinutesSinceCollapse$$

Using this linear function results in a mean probability of a shockable rhythm of 49.5% for the scenario without volunteers and 60.8 % for the scenario with at least one positive volunteer response. These values are of the same order of magnitude as the values found by Pijls et al. (2016), but the difference between the two is smaller. These results show that it is likely that the decline of the probability of a shockable rhythm over time is not accurately described by a linear function, but no better data on this relation is currently available. The simulated results when using this linear function are shown in the middle two columns of Table 4.3.

Conclusion

The probability of at least one positive response and the probability of a volunteer being the first to arrive at the scene are close to what would be expected on the base of the research by Pijls et al. (2016), when accounting for the fact that volunteers become more familiar with the system and the addition of app alerts.

The survival rate outcomes of the simulation are very similar to the outcomes reported by Pijls et al. (2016) when using the survival function by Matinrad and the linearly decreasing function for the probability of a shockable rhythm. It is expected that the Matinrad function results in the closest fit, because this function is the most recent and thus more likely to fit the current (or 2016) standing of OHCA care. The close fit in survival chance between the simulation and the research gives us confidence that the simulation outcomes will be a good prediction of the effect of different interventions on the outcome of the Hartslagnu system. We use the Matinrad function to report on results in the next chapters.

Chapter 5

Simulated scenarios and interventions

In this chapter we explain the interventions on the current alerting algorithm we test in the simulation as well as the various simulation experiments we perform using these interventions. The interventions considered are shown in Table 5.1. We divide the interventions into four groups. Group 0 consists of two changes that will always increase survival chance, regardless of which interventions are used in other groups. Group 1 consists of the different methods to decide which volunteers get alerted, group 2 concerns the different methods to cancel the alert and group 3 concerns the decision of which volunteers are sent to an AED. Only one intervention per group can be used at a time.

5.1 Intervention group 0: Two changes that will increase survival chance in every combination.

We make two changes to the algorithm before we test any other interventions. First, we increase the radius around the incident in which AEDs are selected to be picked up. In the current situation this radius is 500 meter. We increase this radius to the volunteer alert radius plus 250 meters. Increasing the number of AEDs that can be used in an alert increases the survival chance with little downside.

Secondly, we change the method of deciding which AED a volunteer is sent to when more than one AED is available. In the current system volunteers are sent to the closest AED. We alter this to send the volunteer to the AED that minimizes the total distance a volunteer needs to travel via the AED to the patient.

We

5.2 Intervention group 1: Alternative methods of deciding which volunteers to alert

The first of the three things that can be changed about the current alerting algorithm is the way in which it is determined which volunteers will be alerted. We test two different interventions in this step of the alerting process.

Intervention 1a: Adjusting the volunteer radius

The first intervention is simply changing the predetermined radius to other values than 750 meter. We test different values on a range between 300 and 1250 meter.

Intervention 1b: Alerting a predetermined number of volunteers

The other intervention in this step still uses a simple circular radius, but this radius is not of a predetermined size. The radius is specific to each alert in such a way that a predetermined number of volunteers are alerted.

This might result in a smaller or larger radius than the 750 meters currently in use. We test the outcome of alerting between 10 and 150 volunteers with a maximum radius of between 750 and 1250 meter.

5.3 Intervention group 2: Changing when and how the alert is cancelled

In the current system the alert is cancelled after five volunteers have accepted the alert. The alert is cancelled at the same moment for all volunteers that have not yet responded. We propose four interventions in this step of the alerting process.

Intervention 2a: Changing the maximum number of acceptances

The first intervention into this step of the alerting process is simply to change the number of acceptances after which an alert is cancelled. We test for a maximum of between 1 and 10 acceptances.

Intervention 2b: Volunteers close to the patient can still accept even if max volunteers has been reached

In addition to changing the maximum number of acceptances, we can add a small radius around the alert in which volunteers are never cancelled. These volunteers are more likely to still be able to arrive on the scene before other volunteers and not cancelling them can thus improve patient survival chance. We test the outcomes of a maximum number of acceptances between 1 and 5, with a radius between 50 and 500 meter within which volunteers are never cancelled.

Intervention 2c: Cancel alerts for volunteers when volunteers closer than them accept

The third method for cancelling the alert is cancelling for each volunteer once a certain number of volunteers closer than that volunteer have accepted the alert. In this intervention, the alert is not cancelled at the same time for everyone. The moment the alert is cancelled is not based on the reactions of all volunteers, but only on the volunteers closer than the volunteer concerned. We simulate cancelling the alert after between 1 and 5 closer volunteers have accepted.

Intervention 2d: Switch volunteer tasks after a number of acceptances

Instead of cancelling volunteers after a certain number of acceptances, we can change them to the task that still needs volunteers. This means that we switch all volunteers to CPR after a number of volunteer has accepted for AED or vice versa. Volunteers will still be cancelled if the maximum number for both tasks has been reached or if the maximum number of CPR volunteers has been reached, but no AED is available near the incident. In contrast to the other cancelling methods, this method has the potential to increase the survival chance for patients, compared to not cancelling at all, as the number of volunteers for either CPR or AED is increased. We test switching tasks after between 1 and 5 volunteers have accepted for CPR and after between 1 and 5 volunteers have accepted for AED.

5.4 Intervention group 3: Optimize decision on which volunteers to send to AED

The last step in the alerting process we look at is the decision which volunteers are sent to an AED. In the current system, if an AED is available within 250 meters from the volunteer, the volunteer is always sent to pick it up. It can occur that every volunteer alerted to a certain OHCA is sent to pick up an AED in some areas with a particularly high number of AEDs. In these cases the patients survival chance might increase if some of these volunteers are sent directly to the patient to perform CPR. In other cases no volunteers may be sent to pick up an AED, even though one is available, because none of the volunteers are close enough to that AED.

Intervention 3a: Changing the maximum distance of a volunteer to an AED

For the first intervention we again chance the settings in the method currently used. Simply changing the maximum distance a volunteer has to travel to an AED can change the number of AEDs picked up and thus the survival chance of the patient. We test a maximum distance a volunteer travels to an AED of between 50 and 750 meter.

Intervention 3b: Changing the maximum distance increase of a volunteer via an AED

Instead of taking the distance a volunteer has to travel to an AED, in this intervention we look at the distance increase as a result of picking up an AED as compared to the direct distance from the volunteer to the patient. This could result in more logical decisions as it becomes more likely that volunteers are sent to make a small detour to an AED and less likely that they are sent to move away from the incident first to pick up an AED. We simulate a maximum distance increase for picking up an AED between 50 and 750 meter.

Intervention 3c: Sending a predetermined percentage of volunteers to an AED

In this intervention a predetermined percentage of volunteers are sent to an AED, prioritizing those volunteers with the shortest distance via an AED to the patient. This method ensures that the volunteers that can get an AED to the patient the quickest are sent to do so, while also making sure that some volunteers are sent directly to the patient to perform CPR. We test for a percentage of volunteers to be sent to an AED between 0 and 100%.

Interventions 3d and 3e: Greedy algorithm for AED allocation

Lastly, we propose a greedy algorithm to optimize AED allocation. In this algorithm we start with every volunteer going to the patient directly and with each step we assign an AED to one volunteer, where we pick the volunteer to maximize the increase in survival chance. We do this until no more improvement in survival chance is possible. We always send the volunteer to the AED that minimizes their total travel distance via the AED to the patient. Algorithm 2 shows this algorithm. We also make this algorithm dynamic by recalculating the optimal solution every time a volunteer responds either positively or negatively to an alert. Because of the nature of greedy algorithms, the decision of sending a certain volunteer to an AED is not reevaluated once it is made. This means that, while a reasonable approximation might be found, the algorithm is not guaranteed to result in an optimal outcome. We still opt to use this algorithm, because trying all possible combinations would be computationally infeasible for even relatively large numbers of volunteers.

Algorithm 2 Greedy algorithm for optimizing AED allocation

```
Old survival chance = 0
All volunteers set to CPR
New survival chance = Survival chance based on all volunteers CPR
while New survival chance is higher than Old survival chance and one or more volunteers are set to CPR
do
  for all Volunteers set to CPR do
    Set this volunteer to AED
    Calculate survival chance and add to List
    Set this volunteer to CPR
  end for
  New survival chance = max(List)
  Volunteer which resulted in max survival chance set to AED permanently
end while
```

5.5 Simulation experiments

Table 5.1 shows all interventions that we simulate in the next chapter. First, we simulate these interventions group by group, using historical distributions of volunteers and AEDs. We first test all possible variable settings for the interventions in group 1 with settings for groups 2 and 3 as in the current Hartslagnu alerting method. We will then use the optimal intervention found for group 1 to simulate all possible variable settings for the interventions in group 2. Finally, we use the optimal strategies for both groups 1 and 2 to simulate all possible settings for the interventions in group 3. This results in a combination of interventions from all three groups that together form the best found strategy. We call this entire process Experiment 1.

In Experiment 2, we perform the same method of finding the best intervention for each of the three groups in order, but instead of using historical distributions for available volunteers and AEDs we perform this method for a number of different combinations in these two circumstances, ranging between 10 and 150 available volunteers and between 0 and 10 available AEDs. This will result in a best found strategy for each combination of available numbers of volunteers and AEDs. We then run the simulation again with historical numbers of volunteers and AEDs, but instead of using the same strategy in each case, we use the best found strategy based on the available number of volunteers and AEDs in each case. This way, we can determine whether differentiating the alerting strategy based on these circumstances will improve the outcomes.

It is possible that by going through each of the four groups in order, we miss certain combinations of interventions that perform better than the one we found. In Experiment 3, we test a number of combinations of interventions and settings from each of the groups, excluding interventions that were not optimal for any of the numbers of available volunteers and AEDs in Experiment 2. This will show any interactions between different alerting, canceling and AED allocation methods that could increase the survival chance.

In Experiment 4, we again simulate the interventions group by group, with different scenarios with changed circumstances or assumptions to see whether the optimal method found in the aforementioned steps is still optimal in these circumstances. We will determine whether it is better to adapt the strategy based on changes in the following circumstances:

- Probability of bystander resuscitation
- Percentage of volunteers alerted by app vs. sms

In addition to this we test the robustness of the solution we found against the changes in the following assumptions:

- Volunteer movement speed on foot, assumed 6 km/h
- Volunteer movement speed on bike, assumed 20 km/h
- Time from emergency call to activation of Hartslagnu system, assumed 90 seconds
- Time to collect an AED, assumed 15 seconds
- Time from collapse to bystander resuscitation, assumed 60 seconds

Lastly we will test the performance of the best found solution when using a different function to calculate survival chance or using different sets of 500 simulated cases.

	Intervention	Variables to change	Values
0	Current		
0a	Increased radius for AEDs used		
0b	Improved choice of AED per volunteer		
1a	Volunteer alerting radius	Alerting radius (m)	300, 350, 400,. . . ,1250
1b	Volunteer alerting number	Number to alert	10, 15, 20,. . . , 120
		Maximum alerting radius (m)	750, 800, 850,. . . ,1250
2a	Cancel limit	Maximum number of acceptations	1, 2, 3,. . . , 10
2b	Never cancel close volunteers	Radius in which alerts are not cancelled (m)	50, 100, 150,. . . , 500
		Maximum number of acceptations	1, 2, 3, 4, 5
2c	Cancel when closer volunteers have accepted	Maximum number of closer acceptations	1, 2, 3, 4, 5
2d	Switch task instead of cancelling	Maximum number of CPR acceptations	1, 2, 3, 4, 5
		Maximum number of AED acceptations	1, 2, 3, 4, 5
3a	AED Radius	Radius around volunteer to pick up AED (m)	50, 100, 150,. . . , 750
3b	AED Distance increase	Max distance increase via AED to patient (m)	50, 100, 150,. . . , 750
3c	AED Percentage	Percentage of volunteers sent to AED	0, 5, 10,. . . , 100
3d	Greedy algorithm		
3e	Dynamic greedy algorithm		

Table 5.1: All considered interventions and ranges of variables, divided in 4 groups.

Chapter 6

Results

In this chapter we describe the results of the 4 experiments described in the previous chapter.

To select the best setting we look at both survival chance and the number of volunteers that are alerted. We count a volunteer that was alerted, but cancelled before they replied, as not alerted. We take that an extra percentage point of survival chance is 100 times more important than alerting one fewer volunteer. In Experiment 1, we look at the interventions one group at a time for historical distributions of available volunteers and AEDs. In Experiment 2, we again look at the interventions one group at a a time, but with various volunteer and AED counts to find whether the optimal solution is different in these circumstances. In Experiment 3, we look at combinations of interventions from different groups. Lastly, in Experiment 4, we test a number of changes in circumstances and assumptions to see how the best found strategy performs in these cases.

All survival rates mentioned are the result of simulating 500 cases, which are exactly the same for each scenario. Survival rates mentioned are according to the Matinrad function.

6.1 Experiment 1, Group 0: Current algorithm and improvements

The current alerting strategy, as described in earlier chapters, can be summarized as follows:

- **AED area:** AEDs are used in a radius of 500 meter around the incident
- **AED choice:** If volunteers are sent to an AED, they are sent to one closest to their current location
- **Alerting Volunteers:** All volunteers are alerted within 750 meter from the incident
- **Cancelling the alert:** Volunteers are cancelled when 5 volunteers have accepted the alert
- **AED allocation:** Volunteers pick up an AED if one is available within 250 meter of their location

We first simulate this current model to create a benchmark to measure all alternatives against. For the current system we find a survival rate of 13.7%. In the current system, an average of 24.1 volunteers are alerted per incident and the alarm is cancelled in 1.6% of cases. For an AED selection radius of 250 meters plus the volunteer alert radius we find a survival chance of 14%. If we then minimize the distance for a volunteer to travel via an AED to the patient in cases with more than one available AED, we find a survival chance of 14.1%. This increase is very small, because this change only affects cases where more than one AED is available and in many cases the closest AED and the one which least increases distance to the patient are the same one.

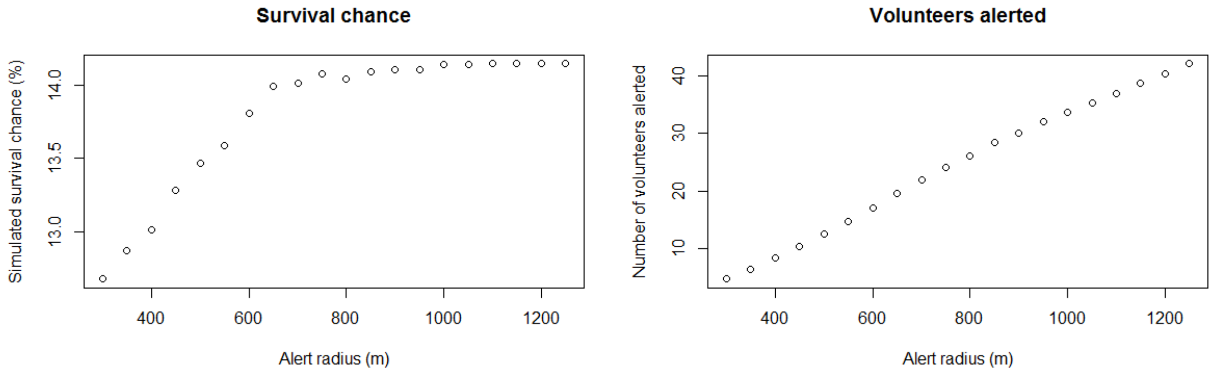

Figure 6.1: Simulated survival chance and number of alerted volunteers as a function of alerting radius (Intervention 1a).

6.2 Experiment 1, Group 1: Alternative methods of deciding which volunteers to alert

The current system alerts volunteers within a 750 meter radius around the incident. As the first step in finding a better alerting algorithm we test different alternatives for deciding which volunteers get alerted. We will then take the best result to test different methods for cancelling volunteers and allocating AEDs.

Intervention 1a: Adjusting the volunteer alerting radius

Figure 6.1 shows the effect of changing the alerting radius on survival chance. The figure shows that the increase in survival chance drastically slows down around 750 meter. The fact that survival chance stops increasing after 750 meter means that volunteers further away than this can rarely arrive at the scene before another volunteer of the ambulance. If we take into account that increasing the alerting radius results in more volunteers being alerted, we find that the current radius of 750 meter is optimal. Different settings for the alerting radius either result in a lower survival chance or in a marginally higher survival chance, but at the cost of alerting too many extra volunteers.

Intervention 1b: Alerting a set number of volunteers

Instead of alerting volunteers in a certain radius, the algorithm could be changed to alert a certain number of volunteers within a maximum radius. The actual number of volunteers based in both systems is not deterministic. The number of volunteers in the chosen radius varies and the predetermined number of volunteers may not be available in the chosen maximum radius. We test a large number of different combinations of settings for the number of volunteers to alert and the maximum radius in which to alert them. We find that an optimal situation is reached when alerting up to 70 people in a radius of a maximum of 1000 meter. This results in a survival chance of 14.2%. Figure 6.2 shows the effect of changing one of these variables while keeping the other at the best value found. It becomes clear that the survival chance stops increasing at a certain radius, as was the case for Intervention 1a, even though more people will be alerted. Increasing the number of volunteers to be alerted beyond 70 will not increase survival chance a lot because it is rare that more than 70 volunteers are available. Decreasing the number of volunteers to alert to around 45 has a very small influence on the survival chance, but the influence on the mean number of volunteers alerted is also relatively small.

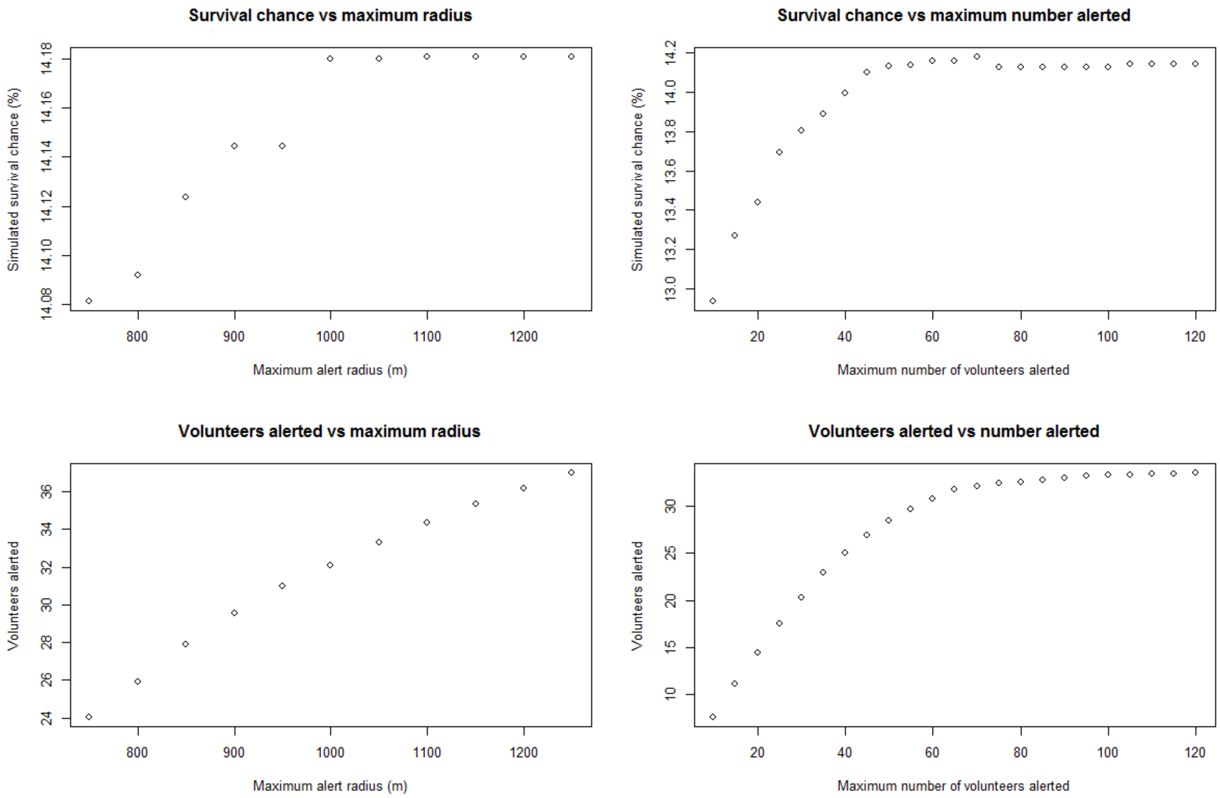

Figure 6.2: Simulated survival chance and number of alerted volunteers as a function of number of volunteers to alert and maximum alerting radius (Intervention 1b). Only one of the two variables is changed in each case while keeping the other at the value found to result in the best outcomes (70 volunteers to alert or a maximum radius of 1000 meter).

Comparing interventions for deciding which volunteers to alert

If we compare the optimal outcomes for interventions 1a and 1b we find that alerting a set number of volunteers (70 in a 1000 meter radius) results in a slightly more favorable outcome. Although the difference is very small with intervention 1a resulting in a survival chance of 14.1% by alerting 25 volunteers on average and intervention 1b resulting in a survival chance of 14.2%, but alerting 32 volunteers on average. We use the method of alerting up to 70 people in a radius of a maximum of 1000 meter to evaluate interventions in further sections.

6.3 Experiment 1, Group 2: Alternative methods of deciding when and how the alert is cancelled

In the current system the alert is cancelled when five volunteers have accepted it. In this section, we look into other options that could decrease the number of volunteers responding to an alert too late to impact the situation.

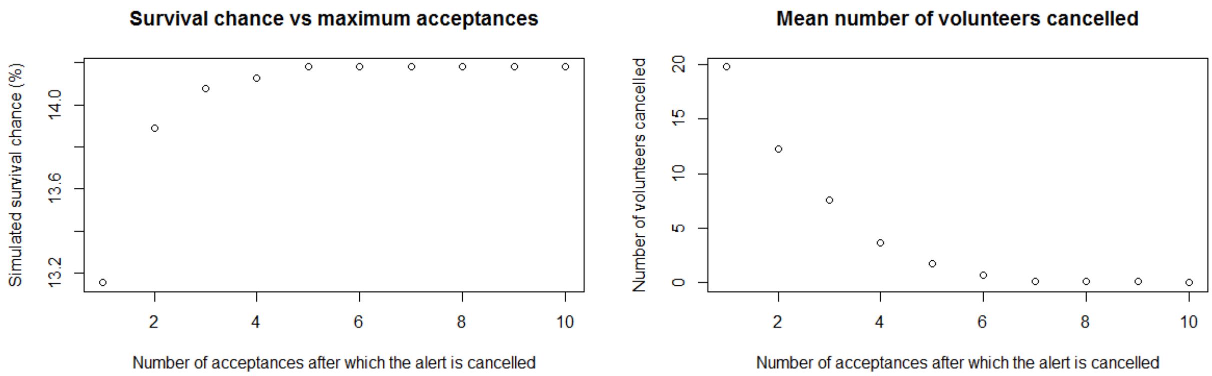

Figure 6.3: Patient survival chance and the mean number of volunteers cancelled as a function of the number of acceptances after which an alert is cancelled (Intervention 2a).

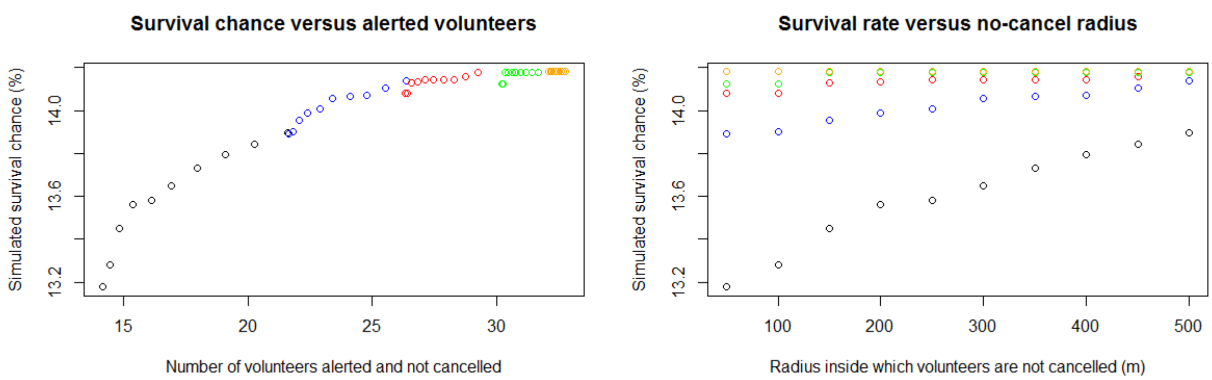

Figure 6.4: Patient survival chance as a function of the number of the radius within which volunteers are never cancelled. Volunteers outside this radius are cancelled after one (black), two (blue), three (red), four (green) or five (orange) acceptances (Intervention 2b).

Intervention 2a: Changing the number of acceptances after which an alert is cancelled in the current algorithm

Figure 6.3 shows that decreasing the maximum number of volunteers that can accept an alert below the current number of five volunteers would decrease patient survival chance. If we look at both survival chance and the number of alerted volunteers we find that a maximum number of 5 acceptances results in the optimal outcome with a survival chance of 14.2% and an average of 32.1 alerted volunteers.

Intervention 2b: Never cancel close volunteers

One obvious alternative to the current method is simply to never cancel the alert for volunteers within a certain radius. Figure 6.4 shows that this method can decrease the number of non-cancelled alerted volunteers without impacting survival chance. The optimal result is reached when alerts are cancelled after 3 acceptances, but not for volunteers within 500 meter from the incident. The survival chance will still be 14.2%, but only 29.3 volunteers are alerted on average.

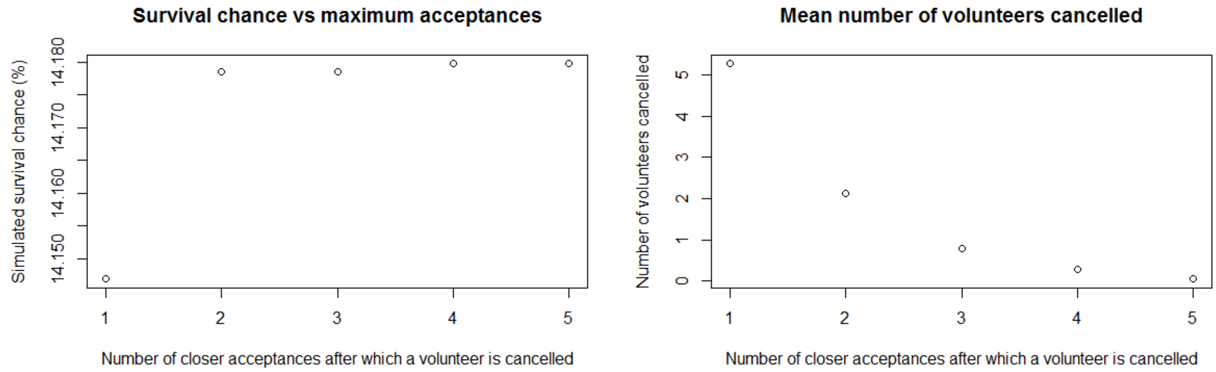

Figure 6.5: Patient survival chance and mean number of volunteers cancelled as a function of the number of acceptances after which an alert is cancelled (Intervention 2c).

Intervention 2c: Cancel based on number of closer volunteers that have already accepted

Figure 6.5 shows that cancelling the alert for volunteers based on the number of volunteers closer than them that have already accepted has almost no influence on survival chance, even if the alert is cancelled after one closer volunteer has accepted. However there is a significant impact in the number of volunteers cancelled, meaning this cancel method can decrease the number of volunteers that accept the alert late without impacting survival chance. We find that cancelling after two closer volunteers have accepted optimizes our outcomes with a survival chance of 14.2% and 31.7 volunteers alerted on average. The difference with Intervention 2a is very small, this is because, whichever value is taken for the number of closer volunteers, the number of volunteers that is cancelled using this method is very low.

Intervention 2d: Switch volunteer task instead of cancelling

Instead of cancelling volunteers when others have already accepted we can switch whether they are assigned to AED or CPR. For example, when two volunteer assigned to CPR have accepted, all volunteers that have not yet accepted are assigned to AED. When the maximum number for both tasks has been reached, all further volunteers are cancelled. In contrast to other methods of cancelling volunteers, this method has the potential to increase the survival chance. We find that switching volunteers after one volunteer has accepted for CPR or after four volunteers have accepted for AED results in the optimal outcome. This results in a survival chance of 14.9% with 32.1 volunteers alerted on average. Figure 6.6 shows that allowing more than one acceptance for CPR results in a strong decrease in survival chance. This is most likely connected to the high probability of CPR being performed by a bystander. If this is the case a volunteer without an AED can do little to improve the survival chance.

Comparing interventions for deciding when and how the alert is cancelled

Table 6.1 shows the outcomes of different methods to deciding when and how the alert is cancelled. It is clear that switching volunteers between the different task (Intervention 2d) is the optimal strategy as it is the only one that can result in an increased survival chance. We use this method to cancel alerts in testing the next interventions.

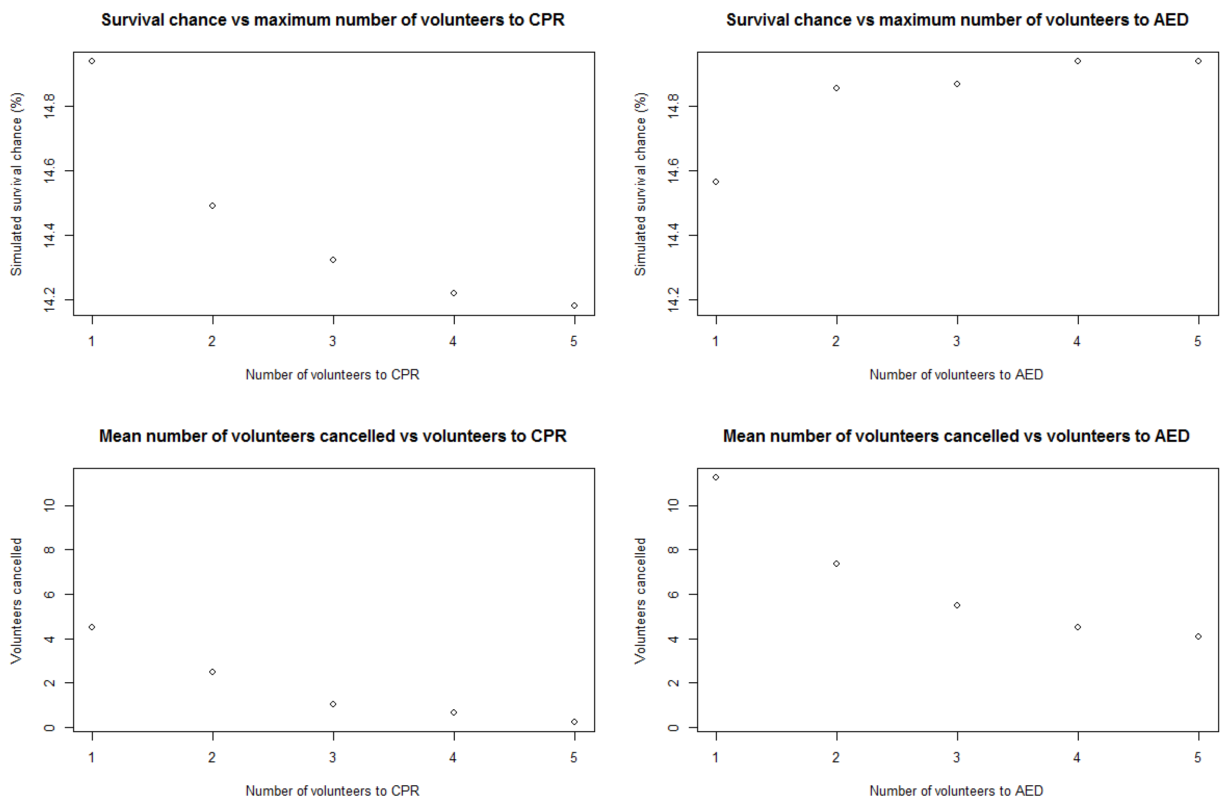

Figure 6.6: Simulated survival chance and number of volunteers cancelled as a function of the maximum number of acceptances for AED and CPR (Intervention 2d). Only one of the two variables is changed in each case while keeping the other at the value found to result in the best outcomes (1 for CPR and 4 for AED).

Intervention	Survival chance	Average number of volunteers alerted
2a	14.2%	32.1
2b	14.2%	29.3
2c	14.2%	31.7
2d	14.9%	29.3

Table 6.1: Survival chance outcome and number of alerted volunteers for each method of cancelling the alert.

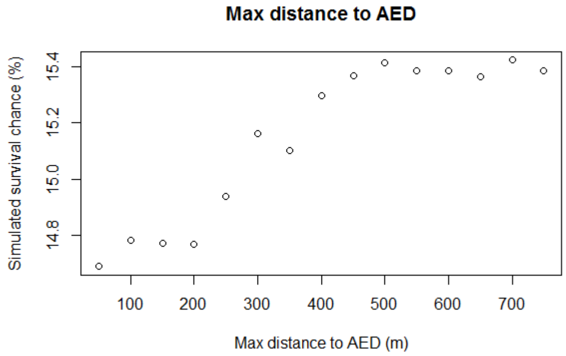

Figure 6.7: Patient survival chance as a function of the maximum distance from a volunteer to the nearest AED.

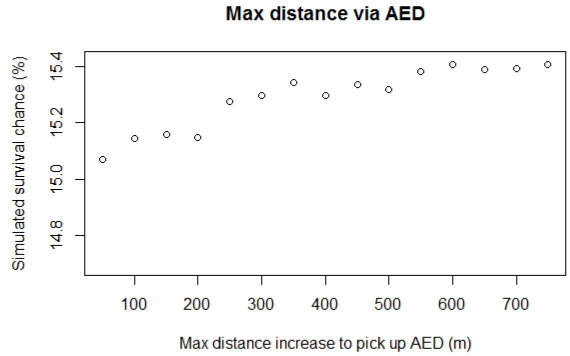

Figure 6.8: Patient survival chance as a function of the maximum increase in distance for a volunteer to pick up an AED.

6.4 Experiment 1, Group 3: Alternative methods of deciding which volunteers are sent to pick up an AED

In this section we look at the simulation outcomes for different methods of deciding which volunteers are sent to pick up an AED. Because this decision will not influence the number of volunteers that is alerted, the survival chance is the only objective to optimize for.

Intervention 3a: Changing the maximum distance from a volunteer to an AED

The first intervention to change the way in which the volunteers are assigned to AEDs is to change the maximum distance for a volunteer to travel to an AED. As shown in Figure 6.8, this setting has a significant impact on the survival chance. An optimal survival chance of 15.4% is found at a maximum distance of 700 meter, but the figure shows that any maximum distance over 400 meter returns similar results.

Intervention 3b: A maximum distance increase for a volunteer via an AED to the patient

The second way of determining which volunteers are sent to an AED is by limiting the increase in distance that results from the detour to an AED. Figure 6.8 shows the relation between this maximum distance increase and the simulated survival chance. The difference between different settings in this intervention is less stark than in intervention 3a, but a clear relation can be seen where sending more volunteers to an AED results in a higher survival chance, with the optimal survival chance of 15.4% being reached at a maximum distance increase of 600 meter.

Intervention 3c: Sending a set percentage of volunteers to an AED

A third method for determining which volunteers are sent to an AED is sending a predetermined percentage of volunteers to an AED, prioritizing volunteers with the minimum distance via an AED to the patient. Figure 6.9 shows the relation between the percentage of volunteers sent to an AED and the simulated survival chance. Any percentage above 30% results in very similar survival chances, but the optimal survival chance of 15.4% is reached at 70%.

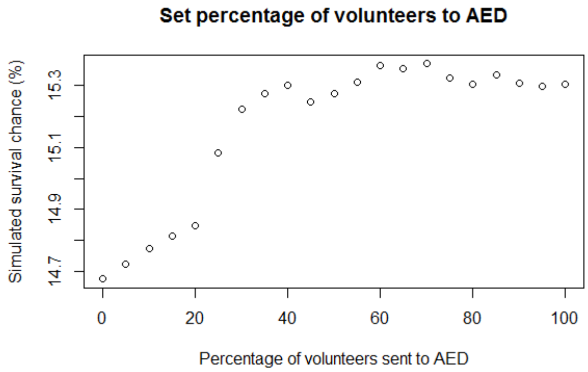

Figure 6.9: Patient survival chance as a function of the percentage of volunteers sent to an AED.

Intervention	Survival chance
3a	15.4%
3b	15.4%
3c	15.4%
3d	15.4%
3e	15.2%

Table 6.2: Survival chance outcome for each method of determining which volunteers are sent to pick up an AED.

Interventions 3d and 3e: The greedy algorithm

By implementing the greedy algorithm we find a survival chance of 15.4% if we run the algorithm only once at the time the alert is sent. If we rerun the algorithm every time a response is received, whether positive or negative, we find a survival chance of 15.2%. This means that the other interventions in this group, although much simpler, result in similar or even slightly better results than this algorithm.

Comparing interventions for deciding which volunteers to send to an AED

It is clear that the decision of which volunteers are sent to an AED has a significant impact on patient survival chance. Table 6.2 shows the outcomes of determining which volunteers are sent to pick up an AED. The performance of all of the options of all five interventions is very similar. Because the greedy algorithms are harder to implement and take up some calculation time, delaying the sending of the alerts to the volunteers, we do not advise implementing this method. Of the other three methods we advise maximizing the distance increase via the AED to the patient (Intervention 3b) as we believe this will lead to fewer cases where volunteers have to make weird routes to pick up an AED.

6.5 Best method found in Experiment 1

Multiple methods simulated in the previous section result in very similar outcomes. More specifically, different interventions for AED allocation result in almost equal outcomes. Out of these methods we believe minimizing the distance increase resulting from picking up an AED (Intervention 3b) results in fewer counter-intuitive routes for volunteers. For that reason we advise implementing that strategy. With that decision, the best method found by successively testing different alternatives for the three parts of the alerting algorithm consists of the following parts:

- **AED area:** Increase the radius for AED use to 250 meter above the volunteer alert radius
- **AED choice:** Send volunteers to the AED that minimizes their total distance to the incident, instead of the AED closest to the volunteer
- **Alerting Volunteers:** Alert up to 70 volunteers in a maximum radius of 1000 meters
- **Cancelling the alert:** Switch volunteers tasks after one volunteer has accepted for CPR or four volunteers have accepted for AED
- **AED allocation:** Let volunteers pick up an AED if this increases their distance to the patient by at most 600 meter

According to our simulation, this method can increase the mean survival chance of patients from 13.7% to 15.4%, while only increasing the mean number of volunteers alerted from 24.1 to 29.3.

6.6 Experiment 2: Influence of number of available volunteers and AEDs on best method

It is possible that a different strategy is optimal when different numbers of volunteers and AEDs are available. We therefore run simulations to find the best alerting strategy for different values of these variables.

We take a range between 10 and 150 available volunteers within 1250 meter from the incident and between 0 and 10 available AEDs within 1500 meter from the incident. These are the maximum distances at which volunteers and AEDs are alerted in our interventions.

All outcomes of testing these scenarios are shown in Appendix C. One thing that becomes clear from looking at these results is that in cases with no available AEDs the different interventions have little to no influence on the survival chance of patients, reinforcing the notion that increasing the number of available AEDs is crucial to improving the system. If we look at all scenarios where one or more AEDs are available we see that for the first two steps of the system, the alerting and cancelling methods, clear winners arise. Alerting a predetermined number of volunteers is preferable in most scenarios and switching volunteers between tasks instead of cancelling them is preferable in all scenarios with at least one available AED. For the AED allocation step, different methods are preferred in different scenarios, but as was the case in the previous section, outcomes for different interventions in this group are very similar.

We then run the simulation again for historical numbers of available volunteers and AEDs, but instead of using the same strategy for each case, we use the best found strategy for the number of volunteers and AEDs available in each case. Doing this we find a survival chance of 15.3%, compared to the survival chance of 15.4% when using the best found strategy for historical numbers of available volunteers and AEDs as found in the previous section. From this results we conclude that using different strategies based on the numbers of available volunteers and AEDs does not improve the system.

6.7 Experiment 3: Testing combinations of interventions from different groups

With our previous method of looking at the groups of interventions one by one, it is possible that certain combinations of interventions that work well together are overlooked. We therefore look at all possible combinations of interventions under historical distributions for the available numbers of volunteers and AEDs. Because Intervention 2d has proven to clearly outperform all other interventions for cancelling the alert in the previous section, we only simulate combinations including this intervention in this section. We simulate each combination of intervention with each possible combination of variables for these interventions as noted in Table 5.1. The best performing combination of variable settings and the simulated survival chance for each combination of interventions are shown in Table 6.3.

AED allocation→		3a	3b	3c	3d	3e
Variable→ ↓ Volunteer alert		Distance	Increase	%		
1a	Survival Chance:	15.4%	15.4%	15.4%	15.3%	15.2%
	Radius :	900	950	900	950	950
	2d max CPR count:	1	1	1	1	1
	2d max AED count:	2	2	2	4	4
	Variable Group 3:	700	700	95		
1b	Survival Chance:	**15.5%**	15.5%	15.4%	15.5	15.3%
	Number of volunteers alerted:	**60**	105	105	105	105
	Maximum radius:	**1000**	1000	1000	1050	1050
	2d max CPR count:	**1**	1	1	1	1
	2d max AED count:	**2**	2	2	4	4
	Variable Group 3:	**700**	700	100		

Table 6.3: Best performing variable settings and simulated survival chance for all combinations of interventions under historical distributions for numbers of available volunteers and AEDs.

The combination of interventions 1b, 2d and 3a slightly outperforms the other options, although the difference with other combinations is minimal. The first thing that becomes clear is that the best strategy found with this method is only slightly better than the one found in by testing the different intervention groups in order. The best found combination using this method results in a survival chance of 15.5%. This is a very small increase compared to the 15.4% we found using our previous method. Regarding possible interaction effects, the best settings for intervention 1b found here are almost the same as those found with the previous method. On the other hand, there seems to be a interaction effect between intervention groups 2 and 3. The best found number of AED acceptances after which volunteers are switched to CPR is now 2 in all cases, except for the Greedy algorithm. It does make sense that these things interact as this cancellation method also influences the AED allocation. Because the outcomes are so close, we again select Intervention 3b, like in previous sections, which means the best found alerting strategy is as follows:

- **AED area:** Increase the radius for AED use to 250 meter above the volunteer alert radius
- **AED choice:** Send volunteers to the AED that minimizes their total distance to the incident, instead of the AED closest to the volunteer
- **Alerting Volunteers:** Alert up to 105 volunteers in a maximum radius of 1000 meters
- **Cancelling the alert:** Switch volunteers tasks after one volunteer has accepted for CPR or two volunteers have accepted for AAED
- **AED allocation:** Let volunteers pick up an AED if this increases their distance to the patient by at most 700 meter

6.8 Experiment 4, Part 1: Testing of alternative circumstances

The are some circumstances that influence the outcomes of the Hartslagnu alerting system to such an extent, that it might be beneficial to change the alerting strategy under those circumstances. In this section we test whether that is the case for scenarios where it is known whether or not a bystander is available to perform CPR and for scenarios where all volunteers are alerted via app.

Probability of bystander resuscitation

In earlier sections we found that the best found strategies result in sending a lot more volunteers to AEDs than is the case in the current situation. This is likely linked to the high probability of CPR being performed by a bystander. If this is the case, sending a volunteer to perform CPR does not increase the patients survival chance. In some cases, it is possible that the emergency operator is aware of whether bystander CPR is being performed. We test whether adapting the strategy in this case will improve the outcomes of the system. Therefore we test one scenario with bystander CPR in all of the cases and one scenario with bystander CPR in none of the cases.

As expected, we find that in cases with a bystander performing CPR, the best outcome is achieved by sending all volunteers to an AED. When no bystander is available to perform CPR, the best strategy prioritizes CPR more than in the strategy for all scenarios. Roles are now switched after 2 acceptances for either CPR or AED and the maximum increase in distance is only 350 meter. When we run the simulation again with a probability of 61.7% for having a bystander available for resuscitation (Pijls et al., 2016), we find a survival chance of 16.3%. This result is not unexpected as the knowledge of whether or not a bystander is performing CPR changes which type of help is still needed for the patient. Based on this result we advise to implement the possibility to adapt the alerting strategy based on whether a bystander is available to perform CPR.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d
Variables→ ↓ Bystanders				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%	
Bystander CPR	18.6%	19.3%	19.4%	19.4% 750	**19.4%** **60** **1000**	19.4% 5	19.4% 3 500	19.4% 2	**20.4%** **1** **4**	21.5% 700	21.4% 750	**21.7%** **100**	21.3%
No bystander CPR	7.1%	7.3%	7.4%	7.4% 750	**7.4%** **70** **1000**	7.4% 5	7.4% 3 500	7.4% 1	**7.5%** **2** **2**	7.6% 400	**7.6%** **350**	7.5% 35	7.6%

Table 6.4: Best simulation outcomes for each intervention for cases with and without a bystander performing CPR. Best strategies for each set of interventions are bold.

Percentage of volunteers alerted by app vs. sms

We have seen that there are important differences in the acceptance rate and response time between volunteers that are alerted by app and volunteers that are alerted by sms. It is likely that more volunteer will switch to the app in the future. We simulate two different cases in which all volunteers are alerted by app. One in which we decrease the number of available volunteers per alert to account for the 53.6% of sms-alerted volunteers that are not actually in the area of the alert and one in which the number of volunteers equals the number of volunteers in the current system. We believe the first of these scenarios to be more likely. In both cases we assume all volunteers have acceptance rates and response times similar to current app-alerted volunteers. Table 6.5 shows the outcomes for these two scenarios.

As expected, the survival chance in these circumstances is higher that under the current mix of app and sms alerts. This is explained by the higher acceptance rate and shorter response time of app-alerted volunteers. This higher acceptance rate also means fewer volunteers need to be alerted. These scenarios do not result in a change in the best cancellation method. Remarkably, the greedy algorithm performs best in the scenario with an equal number of volunteers compared to the current system, but because the outcomes of Intervention 3b are very similar, that intervention is preferred because of its simplicity. The maximum distance increase for Intervention 3b is remarkably smaller than for the current mix of app and sms. Based

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d
Variables→ ↓ Volunteers				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%	
Fewer	14.5%	14.8%	14.9%	15.1% 1200	**15.1%** **45** **1200**	15.1% 6	15.1% 3 500	15.1% 2	**16.2%** **1** **4**	16.5% 500	**17.1%** **300**	16.7% 65	16.5%
Equal	15.8%	16.4%	16.5%	16.8% 1150	**16.9%** **55** **1200**	17.1% 9	17.1% 5 450	17.1% 4	**18.2%** **1** **4**	18.3% 350	18.5% 400	18.4% 35	**18.5%**

Table 6.5: Best simulation outcomes for each intervention for two scenarios where all volunteers are alerted by app. Best strategies for each set of interventions are bold.

on these results we conclude that in a scenario where all volunteers are alerted via the app, the alerting strategy should be adapted to the following:

- **AED area:** Increase the radius for AED use to 250 meter above the volunteer alert radius
- **AED choice:** Send volunteers to the AED that minimizes their total distance to the incident, instead of the AED closest to the volunteer
- **Alerting Volunteers:** Alert up to 45 volunteers in a maximum radius of 1200 meters
- **Cancelling the alert:** Switch volunteers tasks after one volunteer has accepted for CPR or four volunteers have accepted for AED
- **AED allocation:** Let volunteers pick up an AED if this increases their distance to the patient by at most 300 meter

6.9 Experiment 4, Part 2: Influence of certain assumptions

Wherever possible, we use data to support the numbers used in the simulation. However, in some instances no data exists and we have to use assumptions. In this section we test whether changing assumptions, related to volunteer movement speed, the duration of certain parts of the timeline, results in a different alerting strategy performing best. To do this we find an alerting method for a number of settings for these assumptions in the same way we found a solution in Experiment 1, i.e. by optimizing the four groups of interventions in order.

We then compare the outcome from using the alerting strategy found in this way to the outcome of using the alerting strategy found in Experiment 3 in the changed circumstances to see how this method performs in changed circumstances.

We do the same with different functions to calculate the survival chance as well as ten different sets of 500 randomly generated cases.

In this chapter we only report the survival chance outcome for the best found strategy per setting of the assumptions. More detailed outcomes per intervention as well as the best found intervention settings are reported in Appendix D.

Duration of certain parts in the timeline

We made a number of assumptions about the duration of certain part of the timeline, because no data on these parts of the timeline is available. We test a number of changes in these assumptions, more specifically we change the time between the call to the emergency number and the activation of the Hartslagnu system, the time it takes a volunteer to collect an AED after arriving at the location of the AED and the time it

Duration (seconds)			Simulated survival chance	
Activation	Collect AED	Connect AED	Best found	Experiment 3
60	10	40	17.8%	17.7%
90	10	40	16.9%	16.9%
120	10	40	16%	16.1%
60	20	40	17.5%	17.5%
90	20	40	16.7%	16.6%
120	20	40	15.8%	15.9%
60	30	40	17.3%	17.2%
90	30	40	16.5%	16.4%
120	30	40	15.6%	15.7%
60	10	67	16.3%	16.2%
90	10	67	15.4%	15.4%
120	10	67	14.6%	14.7%
60	20	67	16%	16%
90	20	67	15.2%	15.2%
120	20	67	14.5%	14.5%
60	30	67	15.8%	15.7%
90	30	67	15%	15%
120	30	67	14.3%	14.4%
60	10	90	15%	15%
90	10	90	14.3%	14.3%
120	10	90	13.5%	13.6%
60	20	90	14.8%	14.8%
90	20	90	14.1%	14.1%
120	20	90	13.4%	13.5%
60	30	90	14.6%	14.6%
90	30	90	13.8%	13.9%
120	30	90	13.3%	13.3%

Table 6.6: Survival chance outcomes of the best found alerting strategy for different values for the duration of three parts of the timeline, compared with survival chance outcomes of using the strategy found in Experiment 3.

takes to connect an AED. As shown in Table 6.6, the alerting strategy found in Experiment 3 performs roughly as well as the best strategies found for all different values of the assumptions. This means that the alerting strategy from Experiment 3 can be expected to perform well even if our assumptions regarding the duration of these parts of the timeline do not adequately reflect reality.

Volunteer movement speed

Because no data is available about the movement speed of volunteers we have used assumptions of a movement speed of 6 km/h for volunteers on foot and 20 km/h for volunteers on bike. In this section we test whether the alerting strategy found in Experiment 3 still performs well when we change this assumption. Table 6.7 shows the survival chance outcomes for both the best strategies found for each set of assumption values and the outcome for the strategy found in Experiment 3. This strategy again performs roughly as well as the

Speed (km/h)		Simulated survival chance	
Foot	Bike	Best found	Experiment 3
6	12	13.8%	13.8%
9	12	14%	14.1%
12	12	14.4%	14.4%
6	16	14.7%	14.7%
9	16	14.9%	15%
12	16	15.2%	15.3%
6	20	15.4%	15.5%
9	20	15.7%	15.4%
12	20	16%	16.1%

Table 6.7: Survival chance outcomes of the best found alerting strategy for different values volunteer movement speed, compared with survival chance outcomes of using the strategy found in Experiment 3.

	Simulated survival chance	
Function	Best found	Experiment 3
Larsen	16.3%	16.4%
Matinrad	15.4%	15.5%
Valenzuela	13.5%	13.7%

Table 6.8: Survival chance outcomes of the best found alerting strategy using three different function to calculate survival chance, compared with survival chance outcomes of using the strategy found in Experiment 3.

Survival chance function

In Chapter 4 we determined that the Matinrad survival function most closely fits the real world outcomes of the Hartslagnu system, as reported by Pijls et al. (2016). In this section we test how the alerting strategy found in Experiment 3 performs under the other survival functions. Table 6.8 shows the outcomes of this comparison. It shows that the alerting strategy found in Experiment performs well, regardless of which survival function is used in the simulation. We can conclude that this strategy will still perform well, even if the actual development of survival chance over time is closer to one of the other functions.

Different randomly generated cases

For all previous simulations we used the same set of 500 randomly generated cases. To test whether the alerting method we found will also perform well in cases other than the set it was trained on, we create ten more sets of 500 cases each. These sets are randomly created in the same way as the original set of 500 cases, but with different seed values for generating random numbers. As shown in Table 6.9, the performance of the alerting method found in Experiment 3 is very close to those of the best found alerting methods for each of the sets. We can conclude that the success of this alerting strategy is not a result of over-fitting on the original set of 500 cases and we can be confident that the strategy will keep performing well in new cases.

Conclusion

In this section we have shown that the alerting strategy we found in Experiment 3 is very robust against changes in a number of assumptions, specifically assumptions related to the duration of certain parts in the timeline and the movement speed of volunteers. In addition, the strategy performs well when using a different function to calculate the survival chance and for different sets of randomly generated cases.

	Simulated survival chance	
Set	Best found	Experiment 3
1	16.9%	16.7%
2	15.7%	15.7%
3	16.7%	16.6%
4	16.1%	16%
5	15.7%	15.7%
6	16.9%	16.7%
7	17%	16.9%
8	16.1%	16%
9	16.3%	16.2%
10	16.3%	16.2%

Table 6.9: Survival chance outcomes of the best found alerting strategy for ten different sets of 500 randomly generated cases, compared with survival chance outcomes of using the strategy found in Experiment 3.

Chapter 7

Conclusions and discussion

In this chapter we reflect on the results found in the previous chapters as well as the limitations of this research and the opportunities to extend and improve upon this research.

7.1 Conclusions

In this research, our aim was to find an alerting strategy that improves survival chance for patients of OHCA compared to the current strategy used by Hartslagnu.

We first analyzed historical data regarding the Hartslagnu system and found suitable distributions for the numbers of available volunteers and AEDs as well as volunteer acceptance rates and response times. The available data, however did not allow us to create useful prediction models to predict volunteer acceptance rates and response times. With the distributions found, we then created a Monte Carlo simulation. We found that the outcomes of this simulation, in regards to patient survival chance, are very close to those observed in the Hartslagnu system.

We simulated a number of scenarios and interventions in order to find an improved alerting strategy. We have compared these strategies on the predicted patient survival chance and the mean number of volunteers alerted under each of these strategies. We have found that a number of possible alerting strategies result in very similar outcomes when their parameters are optimized. We divided the alerting process into three steps: alerting volunteers, cancelling volunteers and allocating AEDs. We found that, for both the volunteer alerting step and the AED allocation step, the different methods we tested result in very similar outcomes. For the volunteer cancelling step we found that switching volunteers between tasks when a certain number has accepted for one of the tasks clearly performs better than all tested alternatives. This shows that the strategies we found to perform best put more emphasis on the use of AEDs compared to the strategy currently used by Hartslagnu. If one alerting strategy is to be used for all cases, the best results are to be expected with the following strategy:

- **AED area:** Increase the radius for AED use to 250 meter above the volunteer alert radius
- **AED choice:** Send volunteers to the AED that minimizes their total distance to the incident, instead of the AED closest to the volunteer
- **Alerting Volunteers:** Alert up to 105 volunteers in a maximum radius of 1000 meters
- **Cancelling the alert:** Switch volunteers tasks after one volunteer has accepted for CPR or two volunteers have accepted for AED
- **AED allocation:** Let volunteers pick up an AED if this increases their distance to the patient by at most 700 meter

This strategy can increases the mean simulated survival chance of patients from 13.7% to 15.5%, a relative increase of 13.1%, while only increasing the mean number of volunteers alerted from 24.1 to 29.3. For comparison, we also simulated a scenario with only ambulances and bystanders influencing survival, but without the Hartslagnu system. The simulated survival chance in this scenario is 11.5%. This means the proposed improvements can increase absolute increase in survival chance by the Hartslagnu system from 2.2% to 4.0%.

Because these survival rates are calculated over all patients instead of dividing the patients in groups according to the Utstein template (Jacobs et al., 2004), these numbers should not be used to compare the Hartslagnu system to other OHCA CRS systems.

We found that different strategies for determining which volunteers are alerted and determining which volunteers are sent to an AED result in a similar increase in survival chance.

We have found that changing the alerting strategy based on the number of volunteers and AEDs available per case does not increase the survival chance.

In cases when the status of bystander CPR is known at the moment the system is activated, we found that outcomes are increased when the strategy is adapted to this information.

In addition, we have found that in a situation where all volunteers are alerted via app, a different alerting strategy performs better. In this case, fewer volunteers will need to be alerted, as acceptance rates among app-alerted volunteers are higher.

We have shown that the proposed alerting strategy still performs well, when we change assumptions related to the duration of parts of the timeline and volunteer movement speed.

Lastly we found that the proposed strategy performs well under different functions to calculate patient survival chance as well as in other sets of randomly created cases.

7.2 Limitations

In order to create our simulation, we had to make a number of assumptions. Although we have shown that the alerting strategy we propose is robust when changing a number of these assumptions, the simulation is still a simplification of reality. Assumptions related to the way the probability of a shockable rhythm degrades over time as well as other factors influencing patient survival chance might limit the validity of the simulation outcomes.

Other than that, we have treated a number of variables as independent, even though it is likely that these variables are not actually independent, because the lack of quantitative data on these relationships. We know, for example, that ambulance response times are lower in denser populated areas.

In this research, we have focused only on implementing different alerting strategies and not looked into other ways the survival chance can be improved. One important factor determining survival chance is the availability of AEDs. Research on this subject already exists and many initiatives are running to increase the number of available AEDs. It has also become clear in this research that the low acceptance rate among volunteers is a limitation on the effectivity of the system. Increasing volunteer commitment and thus acceptance rate could thus be another way to improve the system.

7.3 Opportunities for further research

More research is required to better understand the survival chance of OHCA patients and how this changes over time. In the current model, administering CPR does not influence the probability of a shockable rhythm, only the survival chance directly. If a better understanding is reached of the behavior of OHCA over time, CRS systems can be adjusted more precisely to improve survival chance.

As mentioned earlier, increasing volunteer acceptance rate and lowering volunteer reaction time can be another way to improve the system. Research in what can motivate volunteers to do this can be valuable in improving OHCA CRS systems.

7.4 Opportunities with further expanding of Hartslagnu technology

The system of Hartslagnu is very young and many projects are planned to improve the system. In this section we mention a few of these projects and how they could interact with the alerting strategy.

Monitoring high-risk patients

Technology exists to monitor patients with a high risk of OHCA. This technology is not yet used to automatically alert the Hartslagnu system. This could make it possible to use the Hartslagnu system in cases where it cannot currently be used, because no witnesses are around to call the emergency number. As shown in this research, the alerting strategy should be different for these cases, as it can be assumed that no bystander is available to administer CPR.

Tracking volunteers after they accepted

In the future, Hartslagnu plans to track volunteers after they have accepted the alert. The data from this tracking will provide valuable insights into the timeline from the moment the alert is sent to the moment a volunteer arrives to administer aid. These insights can be used to improve upon the simulation, to better inform decisions regarding the alerting strategy.

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Appendix A

Goodness of fit tests for used distributions

In this appendix we show the statistical test behind the distributions used in the simulation.

A.1 Number of volunteers and AEDs per alert

For both the number of volunteers and the number of AEDs per alert. The probability that none are available is significantly larger than any distribution would predict. We will first look at how the probability of finding at least one volunteer or AED depends on the alerting radius and then fit a distribution to the cases with one or more volunteers or AEDs respectively.

Because we will not simulate cases where the alerting radius will be lower than 300 meter, we analyze the probability of finding at least one volunteer between 300 and 750 meter. In 72.8% of cases, at least one volunteer is found within 300 meters and in 21.1% of cases. This leaves only 6.1% of the cases where the closest volunteer is found between 300 and 750 meter from the incident. Figure A.1 shows how the probability of finding at least one volunteer changes on this interval as well as a fitted truncated exponential distribution ($\lambda = 0.2378$, lower limit $= \pi * 0.3^2$, upper limit $= \pi * 0.75^2$, the areas of a 300, respectively 750 meter alerting radius). The outcome of the Kolmogorov-Smirnov (p = 0.151) together with the relatively close fit between historic and estimated probabilities gives us enough evidence to assume this distribution is a good enough fit. For simulation purposes we assume this distribution holds for an alerting radius larger than 750 meter.

In 24.3% of the cases, an AED was available within 300 meter and in 36.1% of the cases, no AED was available within 1000. This means in 39.6% of the cases the closest AED was between 300 and 1000 meters

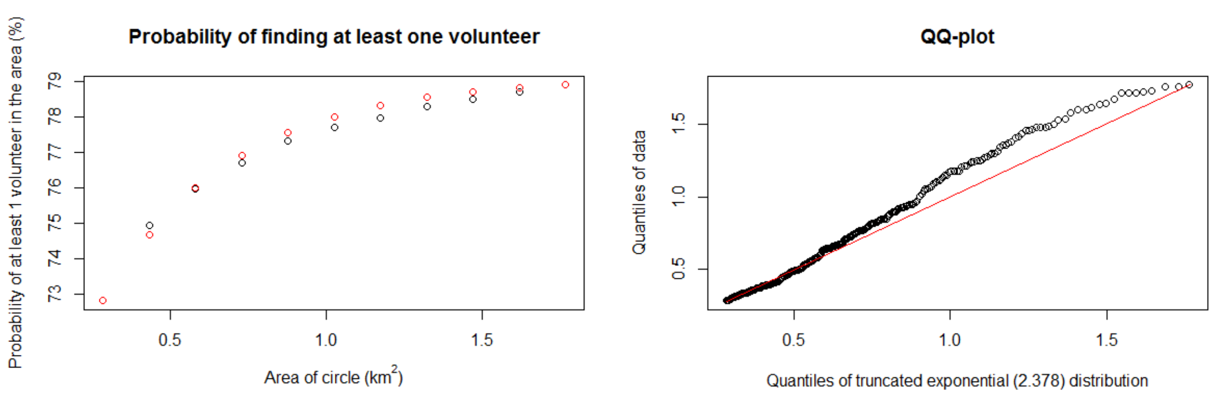

Figure A.1: Historical probability of finding at least one volunteer in a radius between 300 and 750 meter and fitted truncated exponential (2.378) distribution and QQ-plot for this distribution.

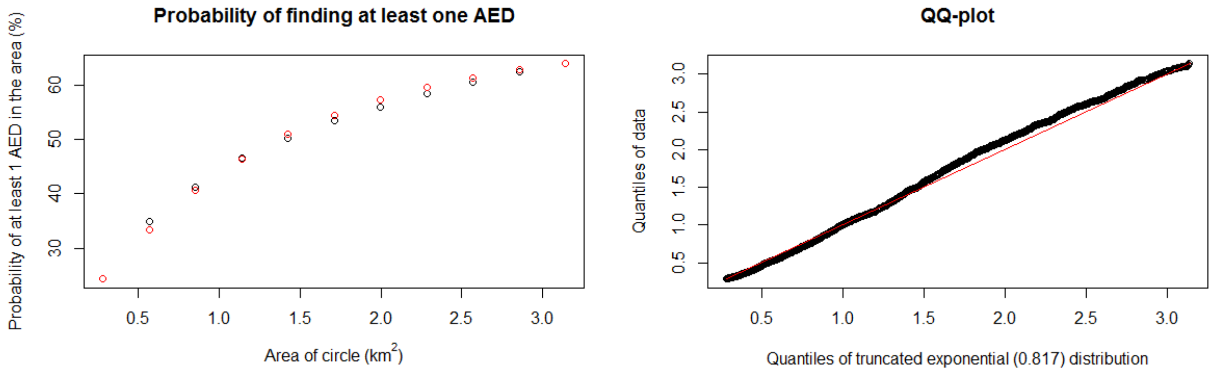

Figure A.2: Historical probability of finding at least one AED in a radius between 300 and 1000 meter and fitted truncated exponential (0.871) distribution and QQ-plot for this distribution.

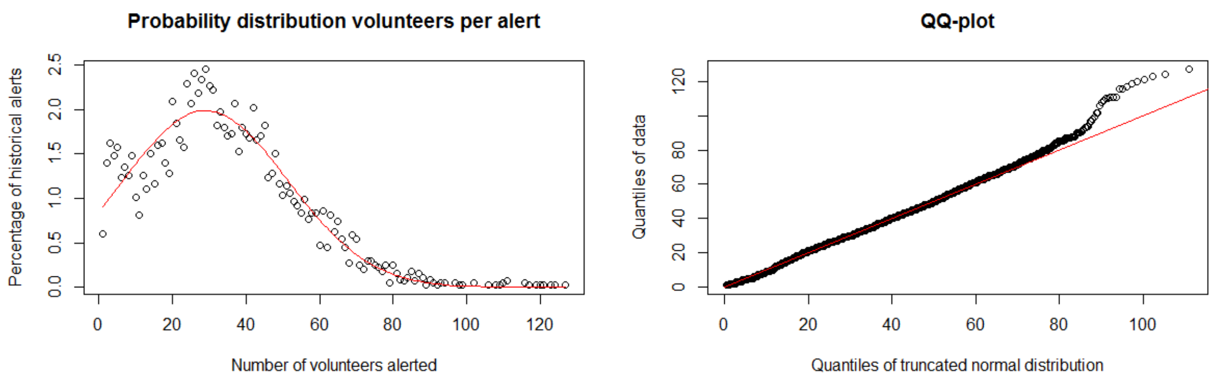

Figure A.3: Historical distribution of all volunteer counts for cases with one or more available volunteer (black) and fitted truncated normal distribution (red) and QQ-plot for this distribution.

from the incident. Figure A.2 shows how the probability of finding at least one AED changes on this interval as well as a fitted truncated exponential distribution ($\lambda = 0.871$, lower limit $= \pi * 0.3^2$, upper limit $= \pi$, the areas of a 300, respectively 1000 meter alerting radius). The outcome of the Kolmogorov-Smirnov (p = 0.005) does not show definitive results, but both graphs show a very close fit, which gives us enough evidence to assume this distribution is sufficiently accurate to be used in the simulation. For simulation purposes we assume this distribution holds for an alerting radius larger than 1000 meter.

Figure A.3 shows the historical distribution for the number of volunteers in cases with at least one available volunteer and fitted truncated normal distribution ($\mu = 28.940, \sigma = 22.351$, lower limit = 0.5) and the QQ-plot for this distribution. It becomes clear from the QQ-plot that this distribution is not a good fit for the data as it significantly underestimates the probability of large numbers of available volunteers. Predictably, the χ^2-test shows that this distribution does not fit the data ($p < 0.001$). Because the number of cases with high volunteer counts are very low (fewer than 1% of cases have more than 80 available volunteers) and because the distribution predicts lower volunteer counts reasonably well, we still opt to use this distribution to estimate the overall effectiveness of this system. When comparing different alerting algorithms we will run simulations for different volunteer counts without using this distribution.

Figure A.4 shows the observed probabilities for the number of available AEDs per alert within a 1000 meter radius as well as the expected probabilities according to a truncated exponential distribution ($\lambda =$

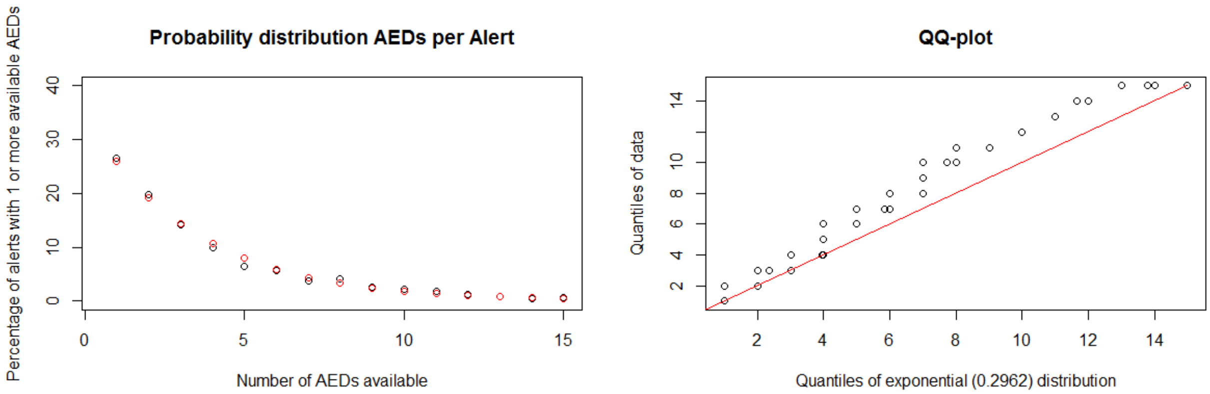

Figure A.4: Historical distribution of all AED counts for cases with one or more available AED (black) and estimated probabilities according to fitted truncated exponential (0.2962) distribution (red) and QQ-plot for this distribution.

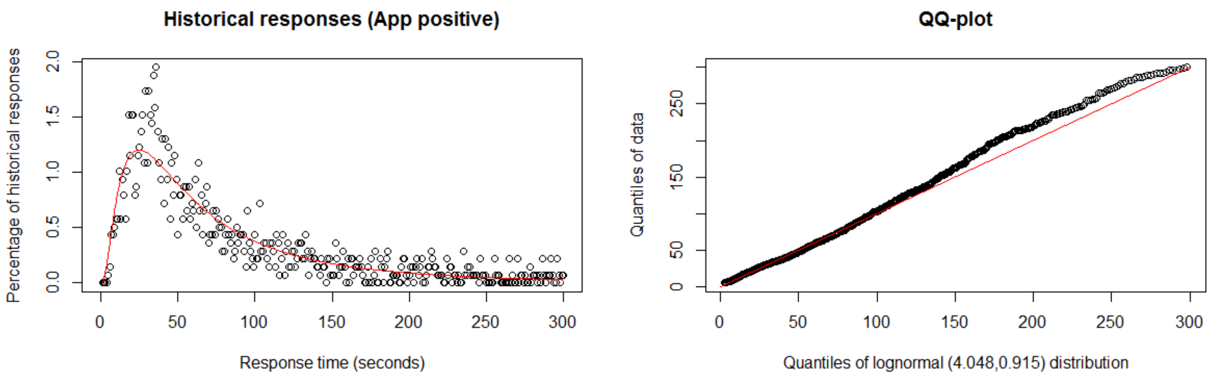

Figure A.5: Historical distribution or response times of positive responses to app alerts with fitted truncated lognormal (4.048,0.915) distribution and QQ-plot for this distribution.

0.2962, lower limit = 0.5, upper limit = 15.5). Although the χ^2-test shows that the data does not fit this exact distribution ($p = 0.001$).

A.2 Response times

Figure A.5 shows the historical distribution for the number of available AEDs in cases with at least one available AED with fitted truncated lognormal distribution ($\mu = 4.048, \sigma = 0.915$, upper limit = 300) and the QQ-plot for this distribution. The Kolmogorov-Smirnov test gives no reason to reject this distribution (p = 0.3008). The QQ-plot shows that the distribution slightly overestimates the probability of an average to high response time and slightly underestimates the probability of a very high response time. The distribution does accurately predict the probabilities for low response times. Because low response times are the majority of responses and because low response times are the most important for determining the survival chance, we find this distribution is sufficiently accurate to be used in the simulation.

Figure A.6 shows the historical distribution with fitted truncated lognormal distribution ($\mu = 4.273, \sigma = 0.736$, upper limit = 300) and the QQ-plot for this distribution. The Kolmogorov-Smirnov test does not show conclusive evidence to accept or reject this distribution (p = 0.0236). It is known that tests for goodness

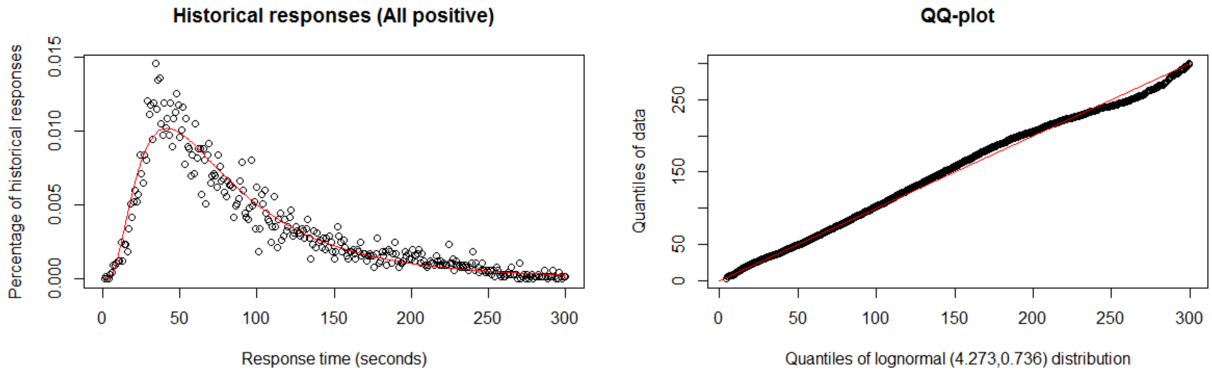

Figure A.6: Historical distribution of all response times of positive responses with fitted truncated lognormal (4.273,0.736 distribution and QQ-plot for this distribution.

of fit gravitate towards low p-values for large sample sizes (in this case: n = 6472). If we take 100 random samples of 10% of the data and perform a Kolmogorov-Smirnov test on each of these samples we find an average p-value of 0.3650, with 94 out of 100 samples showing a p-value over 0.05. In combination with the QQ-plot, which shows a very close fit, especially for lower response times, this gives enough evidence this distribution is sufficiently accurate to be used in the simulation.

A.3 Distribution of volunteers and AEDs over alerting radius

Figure A.7 shows that volunteer count does not linearly increase with the alerting area, but that volunteers are more likely to be closer to the alert. This can be explained by the fact that most cardiac arrests happen within residential areas, where many volunteers are available. Areas further from the patient are increasingly less likely to still be in a residential area with many available volunteers. The QQ-plot shows that the data very closely fits a truncated exponential distribution ($\lambda = 0.3$, upper limit $= \pi * 0.75^2$, the area of a 750 meter alerting radius). The Kolmogorov-Smirnov test suggest that the data does not fit this distribution ($p < 0.001$), but this could again be a result of the large sample size (n= 136,210). If we take 100 random samples of 1% of the data and perform a Kolmogorov-Smirnov test on each of these samples we find an average p-value of 0.2856, with 87 out of 100 samples showing a p-value over 0.05. In combination with the very close fit shown in the QQ-plot, this gives enough evidence this distribution is sufficiently accurate to be used in the simulation. For simulation purposes we assume this distribution holds for an alerting radius larger than 750 meter.

Figure A.8 shows that AED count does not linearly increase with the alerting area, but that AEDs, just like volunteers, are more likely to be closer to the alert. The QQ-plot shows that the data very closely fits a truncated exponential distribution ($\lambda = 0.225$, upper limit $= \pi$, the area of a 1000 meter alerting radius). The Kolmogorov-Smirnov test suggest that the data does not fit this distribution ($p < 0.001$), but the very close fit shown in the QQ-plot gives enough evidence this distribution is sufficiently accurate to be used in the simulation. For simulation purposes we assume this distribution holds for an alerting radius larger than 1000 meter.

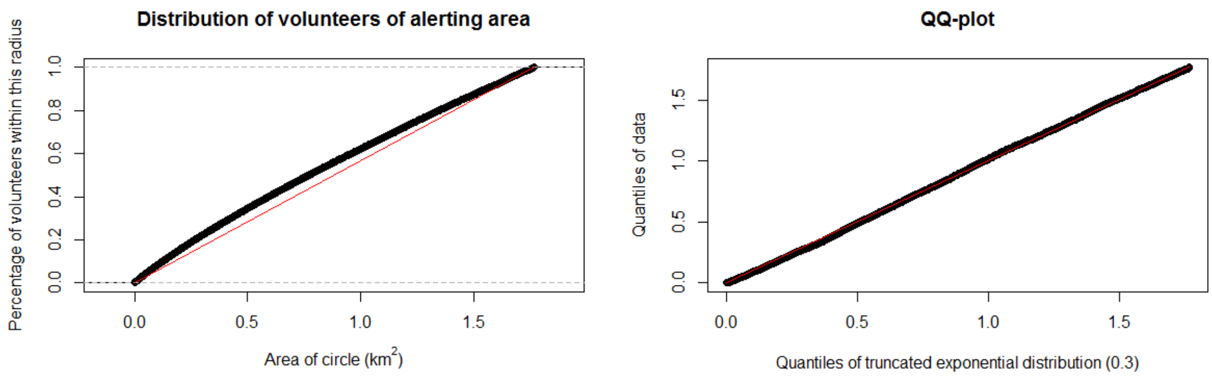

Figure A.7: Empirical cdf for distribution of volunteers over alerting area and QQ-plot for fitted truncated expontential distribution (0.3)

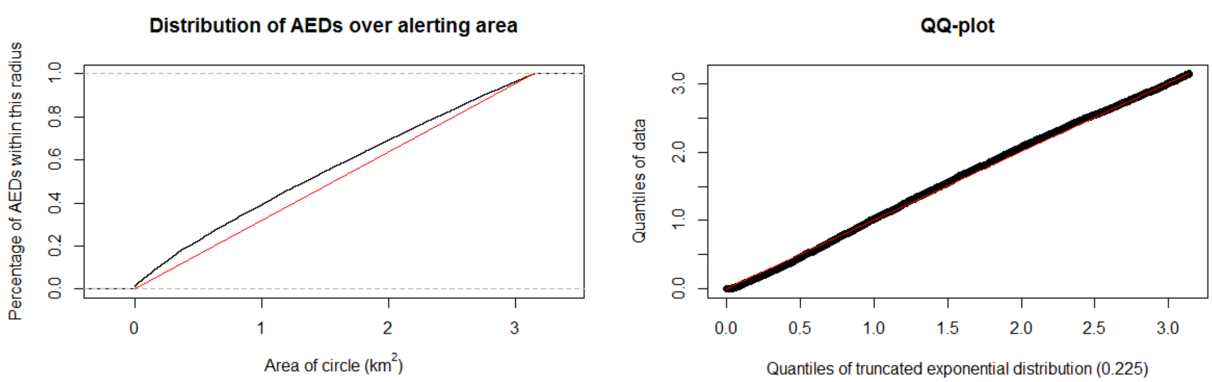

Figure A.8: Empirical cdf for distribution of AEDs over alerting area and QQ-plot for fitted truncated expontential distribution (0.225)

Appendix B

Prediction models for volunteer acceptance rates and response times

Classified as→:			Random chance			Random tree			Simple model			ANN		
↓ Actual	Count	Share (%)	0	1	2	0	1	2	0	1	2	0	1	2
0	7,096	58.6%	4,156	801	2,139	4,528	729	1,839	4,247	805	2,044	5,534	148	1,400
1	1,367	11.3%	801	154	412	673	235	459	797	165	405	890	68	462
2	3,652	30.1%	2,139	412	1,101	1,916	462	1,274	2,133	405	1,114	2,218	86	1,308
Correcly predicted (%):			58.6%	11.3%	30.1%	63.8%	17.2%	34.9%	59.9%	12.1%	30.5%	78.0%	5.0%	35.8%

Table B.1: Outcomes for several methods of classification to predict volunteer acceptance rates for app alerts.

Classified as→:			Random chance			Random tree			Simple model			ANN		
↓ Actual	Count	Share (%)	0	1	2	0	1	2	0	1	2	0	1	2
0	113,033	95.6%	108,034	4,846	153	107,989	4,878	166	107,927	4,975	131	112,711	523	15
1	5,070	4.29%	4,846	217	7	4,611	452	7	4,774	289	7	4,763	82	3
2	160	0.01%	153	7	0	142	15	3	153	7	0	158	21	0
Correcly predicted (%):			95.6%	4.3%	0.01%	95.5%	8.9%	1.9%	95.5%	5.7%	0.0%	99.9%	1.6%	0.0%

Table B.2: Outcomes for several methods of classification to predict volunteer acceptance rates for sms alerts.

Appendix C

Simulation outcomes for different numbers of available volunteers and AEDs

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ ↓ Volunteers				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%		
Historical distribution	13.7%	14%	14.1%	14.1% 750	**14.2%** **70** **1000**	14.2% 5	14.2% 3 500	14.2% 2	**14.9%** **1** **4**	**15.4%** **700**	15.4% 600	15.4% 70	15.4%	15.2%
10	12.2%	12.2%	12.3%	12.4% 850	**12.4%** **60** **850**	12.4% 2	12.4% 1 500	12.4% 1	**12.4%** **1** **1**	**12.8%** **550**	12.8%	12.8% 400	12.7%	12.6%
20	12.8%	12.9%	12.9%	13% 1050	**13%** **15** **1050**	13% 4	13% 2 350	13% 1	**13.2%** **1** **2**	14% 700	14% 750	**14.1%** **100**	13.7%	13.4%
30	13.3%	13.6%	13.6%	13.7% 10000	**13.7%** **25** **1000**	13.7% 4	13.7% 3 350	13.7% 1	**14.3%** **1** **3**	14.9% 700	15% 650	**15.1%** **95**	14.6%	14.5%
40	13.2%	13.7%	13.8%	13.8% 800	**13.8%** **30** **800**	13.8% 3	13.8% 3 50	13.8% 2	**14.5%** **1** **2**	15.5% 750	15.5% 750	**15.6%** **100**	15.2%	15%
50	14.1%	14.6%	14.7%	15% 1050	**14.9%** **40** **1050**	14.9% 5	14.9% 4 250	14.9% 3	**15.8%** **1** **2**	**16.5%** **500**	16.4% 550	16.4% 70	16.3%	15.9%
60	14.5%	15.1%	15.2%	15.4% 900	**15.4%** **45** **900**	15.4% 5	15.4% 4 250	15.4% 3	**16.5%** **1** **2**	17% 500	**17%** **550**	17% 70	16.8%	16.5%
70	14.8%	15.4%	15.5%	15.8% 1000	**15.8%** **60** **1000**	15.8% 5	15.8% 4 350	15.8% 3	**17.2%** **1** **4**	17.6% 650	**17.7%** **500**	17.6% 50	17.4%	17.2%
80	15.3%	16%	16.1%	16.3% 900	**16.3%** **60** **950**	16.4% 8	16.3% 3 450	16.4% 4	**18.1%** **1** **4**	**18.4%** **450**	18.4% 450	18.3% 60	18.4%	18.2%
90	16%	16.8%	16.8%	16.9% 800	**16.9%** **50** **850**	16.9% 6	16.9% 3 450	16.9% 3	**18.3%** **1** **4**	18.7% 600	**18.8%** **550**	18.7% 90	18.7%	18.4%
100	16.2%	17.1%	17.2%	17.4% 850	**17.4%** **65** **900**	17.4% 5	17.3% 3 400	17.4% 3	**18.9%** **1** **4**	19.3% 450	**19.4%** **550**	19.3% 75	19.3%	19.1%
110	16.5%	17.4%	17.5%	17.6% 800	**17.6%** **65** **800**	17.7% 7	17.7% 5 500	17.7% 4	**19.1%** **1** **4**	19.6% 600	19.6% 550	**19.6%** **70**	19.4%	19.2%
120	16.9%	17.7%	17.8%	17.9% 900	**17.8%** **70** **800**	18.1% 6	18% 3 500	18% 2	**19.6%** **1** **3**	19.9% 700	**19.9%** **350**	19.8% 60	19.9%	19.7%
130	17.1%	17.9%	18%	18.4% 1000	**18.4%** **105** **1050**	18.4% 5	18.5% 5 350	18.5% 3	**20.2%** **1** **3**	20.4% 600	**20.6%** **600**	20.5% 40	20.4%	20.25
140	17.4%	18.1%	18.2%	18.3% 850	**18.4%** **95** **950**	18.6% 8	18.6% 5 400	18.6% 3	**20.4%** **1** **4**	20.8% 750	**21%** **500**	20.9% 45	20.8%	20.5%
150	17.8%	18.6%	18.7%	**18.9%** **950**	18.9% 105 900	19.1% 6	19.1% 4 500	19% 2	**21.2%** **1** **4**	21.3% 600	**21.5%** **500**	21.2% 35	21.4%	21.2%

Table C.1: Simulation outcomes for different numbers of available volunteers, with available AEDs according to the historical distribution.

Intervention→	0	1a	1b	2a	2b	2c
Variables→ ↓ Volunteers		Radius	Number Radius	Limit	Limit Radius	Limit
Historical distribution	12.5%	**12.4%** **600**	12.5% 60 750	12.4% 2	**12.4%** **1** **350**	12.4% 1
10	11.9%	11.9% 850	**11.9%** **60** **850**	11.9% 2	**11.9%** **1** **500**	11.9% 1
20	12.1%	12.1% 800	**12.1%** **15** **800**	12.1% 1	**12.1%** **1** **500**	**12.1%** 1
30	12.3%	**12.3%** **700**	12.3% 20 750	12.3% 2	**12.3%** **1** **300**	12.3% 1
40	12.5%	12.5% 700	**12.5%** **20** **750**	12.5% 2	**12.5%** **1** **400**	12.5% 1
50	12.7%	12.7% 800	**12.6%** **20** **750**	12.6% 1	**12.6%** **1** **250**	12.6% 1
60	12.8%	12.8% 750	**12.8%** **35** **750**	12.8% 2	**12.8%** **1** **450**	12.8% 1
70	12.9%	12.9% 650	**12.9%** **30** **750**	12.9% 2	**12.8%** **1** **300**	12.9% 1
80	13.1%	**13.1%** **650**	13% 30 1000	**13.1%** **2**	13.1% 2 200	13.1% 1
90	13.2%	**13.1%** **600**	13.1% 30 1000	**13.1%** **2**	13.1% 2 50	13.1% 1
100	13.3%	**13.2%** **550**	13.2% 35 1000	13.1% 2	**13.1%** **1** **200**	13.2% 1
110	13.3%	**13.2%** **500**	13.3% 40 1000	**13.2%** **2**	13.2% 2 50	13.2% 1
120	13.4%	**13.3%** **500**	13.3% 40 1000	13.3% 2	**13.2%** **1** **200**	13.3% 1
130	13.5%	**13.4%** **550**	13.4% 40 1000	13.3% 2	**13.3%** **1** **150**	13.4% 1
140	13.6%	**13.4%** **450**	13.4% 40 1000	13.3% 1	**13.3%** **1** **200**	13.4% 1
150	13.6%	**13.4%** **450**	13.5% 40 1000	13.3% 1	**13.3%** **1** **150**	13.4% 1

Table C.2: Simulation outcomes for different numbers of available volunteers, for cases with no AEDs available.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ ↓ Volunteers				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%		
Historical distribution	12.9%	13%	13%	13% 750	**13%** **60** **750**	13% 5	13% 2 200	13.6% 1	**13.6%** **1** **3**	**14%** **750**	13.9% 750	14% 50	13.8%	13.7%
10	12%	12%	12%	12% 1000	**12%** **60** **1000**	12% 2	12% 2 50	12% 1	**12.1%** **1** **1**	12.4% 750	12.3% 700	**12.4%** **75**	12.2%	12.2%
20	12.3%	12.4%	12.4%	12.4% 800	**12.4%** **15** **800**	12.4% 2	12.4% 2 50	12.4% 1	**12.6%** **1** **2**	13% 750	13% 700	**13.1%** **90**	12.7%	12.6%
30	12.7%	12.7%	12.7%	12.7% 750	**12.7%** **20** **750**	12.7% 3	12.7% 3 50	12.7% 1	**13%** **1** **2**	13.4% 750	13.5% 700	**13.6%** **90**	13.3%	13.2%
40	12.9%	13.1%	13.1%	13.2% 800	**13.2%** **30** **800**	13.2% 3	13.2% 2 250	13.2% 1	**13.7%** **1** **3**	**14.2%** **750**	14.1% 750	14.2% 40	14%	13.8%
50	13%	13.1%	13.1%	13.2% 800	**13.2%** **35** **800**	13.2% 5	13.2% 3 250	13.2% 2	**13.9%** **1** **2**	14.4% 600	**14.5%** **750**	14.4% 85	14.3%	14%
60	13.2%	13.5%	13.5%	13.6% 850	**13.6%** **40** **850**	13.6% 5	13.5% 1 500	13.6% 1	**14.8%** **1** **4**	15.3% 700	**15.4%** **750**	15.2% 35	15%	14.8%
70	13.8%	14%	14%	14% 800	**14%** **50** **800**	14% 5	14% 3 400	14% 2	**15.3%** **1** **4**	15.6% 500	**15.6%** **650**	15.5% 60	15.6%	15.5%
80	13.6%	14%	14%	14% 750	**14%** **50** **750**	14% 5	14% 2 400	14% 1	**15.6%** **1** **5**	16% 650	**16.1%** **750**	15.9% 25	16%	15.7%
90	13.8%	14.1%	14.1%	**14.1%** **650**	14.2% 60 900	14.1% 8	14.1% 2 450	14.1% 3	**15.4%** **1** **5**	15.8% 550	**15.9%** **750**	15.7% 45	15.7%	15.5%
100	14.2%	14.3%	14.3%	14.5% 850	**14.5%** **70** **850**	14.5% 10	14.4% 2 500	14.5% 2	**16.3%** **1** **4**	**17%** **750**	16.9% 750	16.9% 55	16.8%	16.6%
110	14.4%	14.7%	14.7%	14.9% 800	**14.9%** **65** **800**	14.9% 75	14.8% 3 300	14.8% 1	**16.6%** **1** **4**	16.9% 700	**17%** **750**	16.8% 40	16.9%	16.8%
120	14.1%	14.4%	14.4%	**14.3%** **600**	14.3% 50 750	14.3% 8	14.3% 3 200	14.3% 2	**16%** **1** **5**	16.3% 600	**16.2%** **750**	16.2% 50	16.2%	16.1%
130	14.4%	14.8%	14.8%	14.7% 700	**14.8%** **70** **800**	14.8% 5	14.8% 4 250	14.8% 4	**16.8%** **1** **3**	**17.4%** **500**	17.3% 700	17.3% 55	17.3%	17.2%
140	14.7%	15%	15%	15% 700	**15.1%** **80** **850**	15.3% 8	15% 2 400	15.2% 2	**17.3%** **1** **4**	**17.7%** **550**	17.7% 750	17.7% 30	17.6%	17.6%
150	14.8%	15.3%	15.3%	**15.4%** **900**	15.3% 85 750	15.3% 4	15.5% 3 450	15.4% 1	**18.1%** **1** **3**	18.3% 700	**18.4%** **750**	18.3% 40	18.3%	18.2%

Table C.3: Simulation outcomes for different numbers of available volunteers, for cases with 1 AED available.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ ↓ Volunteers				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%		
Historical distribution	13.2%	13.5%	13.5%	13.5% 750	**13.5%** **60** **800**	13.6% 8	13.5% 3 200	13.6% 2	**14.7%** **1** **4**	**15%** **600**	14.8% 450	15% 85	14.9%	14.8%
10	12%	12.1%	12.1%	**12.2%** **850**	12.2% 60 850	12.2% 2	12.2% 1 500	12.2% 1	**12.2%** **1** **1**	**12.8%** **650**	12.6% 700	12.8% 65	12.5%	12.4%
20	12.3%	12.5%	12.5%	12.5% 1050	**12.6%** **15** **1050**	12.6% 2	12.6% 2 50	12.6% 1	**12.9%** **1** **2**	13.8% 750	13.8% 750	**14%** **85**	13.3%	13.1%
30	12.6%	12.7%	12.7%	12.7% 750	**12.7%** **20** **750**	12.7% 3	12.7% 2 400	12.7% 1	**13.3%** **1** **3**	14.5% 700	14.4% 700	**14.6%** **100**	14%	13.9%
40	13%	13.6%	13.6%	13.7% 850	**13.7%** **30** **850**	13.7% 3	13.7% 2 500	13.7% 1	**14.6%** **1** **4**	**15.5%** **750**	15.3% 750	15.5% 85	15.1%	14.7%
50	13.5%	13.9%	13.9%	14.1% 850	**14.1%** **35** **850**	14.1% 5	14.1% 3 250	14.1% 2	**15.2%** **1** **4**	**16.1%** **700**	16% 700	16% 60	15.8%	15.5%
60	13.6%	13.9%	13.9%	14.1% 950	**14.1%** **45** **1000**	14.1% 6	14.1% 2 400	14.1% 1	**16.2%** **1** **4**	**16.9%** **600**	16.8% 700	16.7% 60	16.5%	16.4%
70	14%	14.4%	14.4%	14.6% 950	**14.6%** **55** **950**	14.6% 6	14.6% 4 250	14.6% 5	**17%** **1** **4**	**17.6%** **650**	17.6% 600	17.4% 45	17.2%	17.1%
80	14.6%	15.4%	15.5%	15.5% 750	**15.5%** **50** **750**	15.5% 6	15.5% 4 250	15.5% 3	**17.2%** **1** **4**	17.7% 650	**17.7%** **750**	17.6% 55	17.5%	17.2%
90	14.5%	15.2%	15.2%	15.2% 750	**15.2%** **50** **750**	15.3% 7	15.3% 5 350	15.3% 5	**17.6%** **1** **5**	**18.3%** **650**	18.3% 750	18.1% 55	18%	17.7%
100	14.6%	15.2%	15.3%	15.4% 850	**15.4%** **65** **850**	15.5% 7	15.5% 5 400	15.5% 3	**18.4%** **1** **5**	**19.3%** **700**	19.2% 750	19.2% 60	18.9%	18.6%
110	15.1%	15.9%	15.9%	16.1% 900	**16.1%** **85** **900**	16.3% 7	16.3% 5 450	16.1% 1	**18.9%** **1** **5**	**19.6%** **650**	19.4% 550	19.5% 50	19.3%	18.9%
120	15.3%	16%	16%	16.1% 900	**16.1%** **75** **1000**	16.3% 8	16.2% 3 500	16.3% 3	**19%** **1** **4**	19.7% 700	19.5% 700	**19.7%** **40**	19.6%	19.3%
130	15.4%	16.2%	16.2%	16.2% 800	**16.3%** **80** **850**	16.4% 7	16.3% 4 450	16.4% 2	**19.3%** **1** **4**	19.9% 450	19.7% 750	**19.9%** **40**	19.7%	19.3%
140	15.6%	16.4%	16.5%	**16.4%** **650**	16.5% 750 800	16.5% 6	16.5% 5 150	16.5% 4	**18.9%** **1** **3**	**19.8%** **500**	19.6% 750	19.7% 40	19.6%	19.3%
150	15.5%	16.3%	16.3%	**16.6%** **950**	16.5% 105 900	17% 7	16.7% 3 500	17% 5	**20.7%** **1** **4**	21.1% 600	21.1% 500	**21.2%** **45**	20.9%	20.4%

Table C.4: Simulation outcomes for different numbers of available volunteers, for cases with 2 AEDs available.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ ↓ Volunteers				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%		
Historical distribution	13.5%	14%	14%	14.1% 900	**14.1%** **85** **900**	14.1% 4	14.1% 3 500	14.1% 2	**15.4%** **1** **4**	15.9% 450	**15.9%** **700**	15.9% 40	15.9%	15.8%
10	12.1%	12.3%	12.3%	12.3% 1000	**12.3%** **60** **1000**	12.3% 2	12.3% 2 250	12.3% 1	**12.5%** **1** **1**	13% 750	12.9% 700	**13.1%** **65**	12.7%	12.6%
20	12.7%	12.8%	12.8%	12.9% 850	**12.9%** **15** **850**	12.9% 2	12.9% 2 50	12.9% 1	**13.1%** **1** **2**	14% 750	13.9% 750	**14.2%** **95**	13.6%	13.4%
30	13%	13.1%	13.1%	13.3% 850	**13.3%** **25** **850**	13.3% 3	13.3% 2 250	13.3% 1	**13.9%** **1** **2**	15.2% 850	15.2% 850	**15.5%** **100**	14.8%	14.6%
40	13.3%	13.7%	13.7%	13.8% 950	**13.8%** **35** **950**	13.8% 4	13.8% 2 350	13.8% 1	**14.9%** **1** **4**	**16.4%** **750**	16.3% 750	16.3% 85	15.9%	15.7%
50	13.8%	14.2%	14.2%	14.5% 1000	**14.5%** **45** **1000**	14.5% 4	14.5% 4 50	14.5% 2	**16.1%** **1** **4**	17% 700	**17%** **750**	17% 85	16.7%	16.5%
60	14.2%	14.7%	14.7%	15% 950	**15%** **50** **950**	15% 4	15% 4 50	15% 3	**17.1%** **1** **4**	17.8% 600	**17.8%** **750**	17.7% 60	17.6%	17.3%
70	14.7%	15.3%	15.3%	15.5% 950	**15.5%** **50** **950**	15.5% 6	15.5% 3 500	15.5% 2	**17.9%** **1** **4**	18.6% 550	**18.6%** **750**	18.4% 50	18.6%	18.4%
80	15.2%	16.2%	16.2%	16.4% 950	**16.4%** **65** **950**	16.4% 5	16.4% 5 350	16.4% 3	**18.9%** **1** **4**	19.3% 550	**19.4%** **350**	19.4% 55	19.3%	19.1%
90	15.7%	16.6%	16.6%	16.7% 900	**16.8%** **70** **1000**	16.9% 6	16.8% 5 400	16.9% 5	**19.4%** **1** **5**	20% 650	**20.1%** **700**	19.9% 50	19.9%	19.7%
100	15.4%	15.7%	15.8%	16.1% 950	**16.1%** **75** **1000**	16.2% 7	16.1% 3 400	16.2% 3	**19.4%** **1** **5**	20.2% 700	**20.3%** **750**	20.1% 55	20.3%	20%
110	16%	16.6%	16.6%	16.8% 800	**16.8%** **70** **850**	16.8% 5	16.9% 5 400	16.9% 2	**19.8%** **1** **4**	20.5% 550	20.5% 700	20.6% 50	**20.6%**	20.4%
120	16.1%	16.7%	16.7%	17% 950	**17%** **105** **950**	17.2% 8	17.1% 4 450	17.1% 2	**20.3%** **1** **3**	21.3% 700	**21.3%** **700**	21.1% 60	20.9%	20.6%
130	16.1%	17.1%	17.1%	17.5% 950	**17.5%** **105** **950**	17.7% 8	17.7% 5 500	17.7% 3	**20.9%** **1** **4**	**21.6%** **600**	21.6% 750	21.5% 55	21.5%	21.2%
140	16.9%	17.8%	17.8%	17.9% 850	**18%** **95** **950**	18.4% 9	18.3% 5 350	18.4% 5	**21.5%** **1** **4**	**22.2%** **450**	22.2% 750	22.2% 35	22.2%	22%
150	16.9%	18.2%	18.3%	18.7% 900	**18.7%** **115** **900**	19.1% 9	19.5% 5 500	19.1% 4	**22.1%** **1** **4**	22.6% 550	22.6% 750	22.6% 55	**22.6%**	22.2%

Table C.5: Simulation outcomes for different numbers of available volunteers, for cases with 3 AEDs available.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ ↓ Volunteers				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%		
Historical distribution	13.8%	14.3%	14.4%	14.5% 1000	**14.6%** **70** **1000**	14.6% 6	14.6% 5 50	14.6% 5	**16%** **1** **4**	16.7% 700	16.7% 700	**16.7%** **65**	16.6%	16.5%
10	12.2%	12.3%	12.3%	12.3% 900	**12.3%** **60** **900**	12.3% 2	12.3% 2 250	12.3% 1	**12.4%** **1** **1**	13.2% 750	13.2% 700	**13.3%** **95**	12.8%	12.6%
20	13.1%	13.2%	13.2%	13.3% 1000	**13.3%** **60** **1000**	13.3% 2	13.3% 2 50	13.3% 1	**13.5%** **1** **2**	14.9% 750	14.7% 750	**15%** **100**	14.3%	14.1%
30	13.2%	13.5%	13.6%	13.7% 950	**13.7%** **20** **950**	13.3% 4	13.7% 2 350	13.7% 1	**14.4%** **1** **3**	16.1% 750	16% 750	**16.2%** **100**	15.5%	15.4%
40	14%	14.4%	14.4%	14.6% 950	**14.6%** **35** **950**	14.6% 4	14.6% 3 350	14.6% 1	**15.5%** **1** **2**	17.1% 750	17% 700	**17.1%** **95**	16.4%	16.1%
50	14.4%	15.4%	15.2%	15.3% 850	**15.4%** **35** **950**	15.4% 4	15.4% 4 50	15.4% 3	**16.9%** **1** **3**	**17.9%** **750**	17.8% 700	17.8% 80	17.5%	17.3%
60	15%	15.5%	15.5%	15.8% 900	**15.8%** **40** **900**	15.9% 6	15.9% 3 500	15.9% 2	**17.8%** **1** **4**	18.6% 650	**18.6%** **600**	18.5% 75	18.3%	18.1%
70	15.3%	16.1%	16.2%	16.5% 950	**16.5%** **50** **1000**	16.5% 6	16.5% 5 300	16.5% 4	**19%** **1** **4**	19.8% 550	**19.9%** **550**	19.5% 85	19.6%	19.4%
80	16%	17%	17.1%	17.3% 850	**17.3%** **50** **850**	17.5% 7	17.3% 4 500	17.4% 5	**19.6%** **1** **5**	20.4% 550	**20.4%** **750**	20.3% 85	20.2%	20%
90	16.2%	17.3%	17.4%	17.5% 850	**17.5%** **65** **850**	17.6% 8	17.6% 5 400	17.6% 4	**20.5%** **1** **5**	20.9% 6060	**21%** **700**	20.8% 55	20.8%	20.5%
100	16.6%	17.7%	17.8%	18.2% 850	**18.2%** **70** **850**	18.3% 7	18.3% 4 500	18.3% 3	**20.9%** **1** **4**	21.7% 650	**21.9%** **750**	21.5% 80	21.6%	21.4%
110	17.1%	18.6%	18.7%	18.9% 800	**18.9%** **80** **900**	19.1% 7	19.1% 5 450	19.1% 4	**21.6%** **1** **5**	22.4% 600	**22.5%** **750**	22.3% 60	22.3%	22%
120	17%	18.4%	18.4%	18.7% 950	**18.7%** **95** **1000**	19.1% 8	19% 5 500	19.1% 4	**21.9%** **1** **5**	22.8% 500	**22.9%** **700**	22.8% 40	22.9%	22.7%
130	17.8%	19.1%	19.3%	19.8% 1000	**19.8%** **100** **1000**	20% 7	19.9% 5 500	20% 1	**22.6%** **1** **3**	**23.6%** **400**	23.5% 650	23.3% 75	23.3%	23.1%
140	17.7%	19.2%	19.4%	19.5% 850	**19.5%** **95** **950**	20.1% 9	19.9% 5 350	20.1% 5	**23.3%** **1** **4**	**23.7%** **500**	23.7% 700	23.7% 40	23.6%	23.2%
150	18.2%	19.6%	19.7%	20.1% 950	**20.1%** **120** **950**	20.3% 6	20.4% 5 500	20.5% 5	**23.8%** **1** **4**	24.1% 550	**24.2%** **650**	24.1% 35	24.1%	23.7%

Table C.6: Simulation outcomes for different numbers of available volunteers, for cases with 5 AEDs available.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ ↓ Volunteers				Radius	Number Radius	Limit	Limit Radius	Limit	CPR AED	Radius	Increase	%		
Historical distribution	14.5%	15.5%	15.6%	15.8% 1050	**15.8%** **105** **1050**	15.8% 5	15.8% 5 50	15.8% 3	**16.8%** **1** **4**	17.7% 600	**17.7%** **650**	17.7% 100	17.5%	17.3%
10	12.5%	12.7%	12.8%	13% 1000	**13%** **60** **1000**	13% 2	13% 2 250	13% 1	**13.1%** **1** **1**	13.8% 700	13.7% 750	**13.8%** **95**	13.4%	13.2%
20	13.2%	13.6%	13.7%	13.8% 1000	**13.8%** **60** **1000**	13.8% 4	13.8% 3 350	13.8% 1	**14.1%** **1** **2**	15.7% 750	15.5% 700	**15.7%** **100**	15%	14.8%
30	14.4%	15.1%	15.2%	15.6% 1050	**15.6%** **60** **1050**	15.6% 4	15.6% 3 350	15.6% 1	**16.1%** **1** **2**	**17.7%** **750**	17.6% 700	17.7% 100	16.9%	16.7%
40	14.7%	15.5%	15.7%	16% 1050	**16%** **35** **1050**	16% 4	16% 4 50	16% 2	**16.7%** **1** **4**	18.5% 650	**18.5%** **750**	18.5% 100	17.9%	17.5%
50	15.2%	15.9%	16%	16.6% 1100	**16.6%** **40** **1100**	16.6% 4	16.6% 4 50	16.6% 3	**18%** **1** **3**	19.3% 750	**19.4%** **550**	19.4% 95	18.9%	18.6%
60	16.1%	17.2%	17.3%	17.8% 900	**17.8%** **45** **900**	17.8% 5	17.8% 4 100	17.8% 3	**19.3%** **1** **3**	20.2% 650	**20.4%** **700**	20.3% 85	19.9%	19.7%
70	16.9%	18.2%	18.4%	18.7% 950	**18.7%** **55** **950**	18.7% 5	18.7% 4 300	18.7% 2	**20.7%** **1** **5**	21.3% 550	**21.5%** **650**	21.2% 100	21.1%	20.9%
80	18%	19%	19.2%	19.7% 950	**19.7%** **60** **950**	19.8% 6	19.8% 5 500	19.7% 2	**21.5%** **1** **5**	22.3% 550	**22.6%** **500**	22.3% 100	22.3%	22%
90	18.2%	19.5%	19.8%	20.2% 950	**20.2%** **70** **1000**	20.1% 5	20.2% 4 450	20.3% 3	**21.9%** **1** **4**	22.8% 550	**23%** **550**	22.9% 65	22.9%	22.6%
100	18.9%	20.5%	20.7%	21.1% 950	**21.1%** **70** **950**	21.2% 6	21.2% 4 500	21.2% 3	**23%** **1** **4**	23.7% 500	**24%** **400**	23.6% 85	23.9%	23.5%
110	18.8%	20.3%	20.6%	21% 850	**21%** **70** **900**	21% 5	21% 5 450	21% 4	**23.1%** **1** **4**	24% 450	**24.1%** **650**	23.9% 80	23.8%	23.6%
120	19.9%	21.4%	21.7%	22.1% 900	**22%** **80** **900**	22.1% 6	22.2% 5 450	22.2% 3	**24%** **1** **4**	24.9% 450	**25%** **550**	24.7% 100	24.9%	24.7%
130	20.6%	22.4%	22.6%	23.1% 950	**23.1%** **100** **1050**	23.1% 5	23.2% 5 350	23.2% 4	**24.7%** **1** **3**	25.4% 550	**25.6%** **550**	25.4% 95	25.5%	25.3%
140	20.8%	22.8%	23.1%	23.7% 950	**23.7%** **110** **950**	23.9% 6	23.8% 5 200	24% 5	**25.4%** **1** **3**	25.8% 450	**26.1%** **350**	25.7% 90	26.1%	25.9%
150	21.1%	22.7%	22.9%	23.3% 850	**23.3%** **115** **850**	23.5% 6	23.5% 5 500	23.6% 5	**25.6%** **1** **4**	26.1% 500	**26.3%** **450**	26% 40	26.3%	26%

Table C.7: Simulation outcomes for different numbers of available volunteers, for cases with 10 AEDs available.

Appendix D

Simulation outcomes for changes in certain assumptions

Intervention→			0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ Duration (seconds						Radius	Number Radius	Limit	Radius Limit	Limit	CPR AED	Radius	Increase%			
*1:	*2:	*3:														
60	10	40	15.4%	15.9%	16%	16.1% 1000	**16.1%** **70** **1000**	16.1% 5	16.1% 3 500	16.1% 2	**17.1%** **1** **4**	**17.8%** **700**	17.7% 750	17.7% 70	17.7%	17.5%
90	10	40	14.9%	15.3%	15.4%	15.4% 750	**15.5%** **70** **1000**	15.5% 5	15.5% 3 500	15.5% 2	**16.3%** **1** **4**	**16.9%** **700**	16.9% 750	16.8% 70	16.8%	16.6%
120	10	40	14.5%	14.8%	14.9%	14.9% 750	**14.9%** **60** **750**	14.9% 5	14.9% 3 500	14.9% 2	**15.4%** **1** **3**	**16%** **500**	15.9% 600	16% 70	15.9%	15.8%
60	20	40	15.3%	15.7%	15.8%	15.8% 750	**16%** **70** **1000**	16% 5	16% 3 500	16% 2	**16.9%** **1** **4**	17.5% 700	17.5% 750	17.4% 70	**17.5%**	17.3%
90	20	40	14.8%	15.2%	15.3%	15.3% 750	**15.4%** **70** **1000**	15.4% 5	15.4% 3 500	15.4% 2	**16.1%** **1** **4**	16.7% 700	16.6% 750	16.6% 70	**16.7%**	16.4%
120	20	40	14.4%	14.7%	14.8%	14.8% 750	**14.8%** **60** **750**	14.8% 5	14.8% 3 500	14.8% 2	**15.2%** **1** **3**	**15.8%** **500**	15.8% 600	15.8% 70	15.7%	15.6%
60	30	40	15.2%	15.6%	15.7%	15.7% 750	**15.8%** **70** **1000**	15.8% 5	15.8% 3 500	15.8% 2	**16.7%** **1** **4**	17.2% 500	17.2% 600	17.2% 70	**17.3%**	17%
90	30	40	14.8%	15.1%	15.2%	15.2% 750	**15.2%** **70** **1000**	15.2% 5	15.2% 3 500	15.2% 1	**16%** **1** **4**	16.4% 700	16.4% 600	16.4% 70	**16.5%**	16.2%
120	30	40	14.3%	14.6%	14.7%	14.7% 750	**14.7%** **60** **750**	14.7% 5	14.7% 3 500	14.7% 2	**15.1%** **1** **3**	**15.6%** **500**	15.6% 600	15.6% 70	15.4%	15.4%
60	10	67	14.1%	14.5%	14.6%	14.7% 1000	**14.8%** **70** **1000**	14.8% 5	14.8% 3 500	14.8% 2	**15.7%** **1** **4**	16.2% 500	16.2% 600	16.1% 70	**16.3%**	16%
90	10	67	13.7%	14%	14.1%	14.1% 750	**14.2%** **70** **1000**	14.2% 5	14.2% 3 500	14.2% 2	**14.9%** **1** **4**	**15.4%** **700**	15.4% 600	15.4% 70	15.4%	15.2%
120	10	67	13.3%	13.5%	13.6%	13.6% 750	**13.6%** **60** **750**	13.6% 5	13.6% 3 500	13.6% 2	**14.1%** **1** **3**	**14.6%** **500**	14.6% 600	14.6% 70	14.4%	14.3%
60	20	67	14.1%	14.4%	14.5%	14.5% 750	**14.6%** **70** **1000**	14.6% 5	14.6% 3 500	14.6% 2	**15.5%** **1** **4**	16% 500	16% 600	15.9% 60	**16%**	15.8%
90	20	67	13.6%	13.9%	14%	14% 750	**14.1%** **70** **1000**	14.1% 5	14.1% 3 500	14.1% 1	**14.8%** **1** **4**	**15.2%** **500**	15.2% 600	15.2% 70	15.1%	15%

Table D.1: Simulation outcomes for changing the assumptions about duration of parts of the timeline, part 1/2. *1: Time from call to emergency number to activation of Hartslagnu system. *2: Time to collect an AED. *3: Time to connect an AED.

Intervention→			0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ Duration (seconds						Radius	Number Radius	Limit	Radius Limit	Limit	CPR AED	Radius	Increase%			
*1:	*2:	*3:														
120	20	67	13.2%	13.4%	13.5%	13.5% 750	**13.5%** **60** **750**	13.5% 5	13.5% 3 500	13.5% 2	**14%** **1** **3**	**14.5%** **500**	14.4% 600	14.4% 70	14.3%	14.2%
60	30	67	14%	14.3%	14.4%	14.4% 750	**14.5%** **70** **1000**	14.5% 5	14.5% 3 500	14.5% 2	**15.3%** **1** **4**	**15.8%** **500**	15.7% 600	15.7% 60	15.8%	15.5%
90	30	67	13.5%	13.8%	13.9%	13.9% 750	**14%** **70** **1000**	14% 5	14% 3 500	14% 1	**14.6%** **1** **4**	**15%** **500**	15% 600	15% 60	14.9%	14.8%
120	30	67	13.1%	13.4%	13.4%	13.4% 750	**13.4%** **60** **750**	13.4% 5	13.4% 3 500	13.4% 2	**13.9%** **1** **3**	**14.3%** **500**	14.3% 600	14.3% 70	14.2%	14.1%
60	10	90	13.1%	13.5%	13.6%	13.7% 1000	**13.7%** **70** **1000**	13.7% 5	13.7% 3 500	13.7% 2	**14.5%** **1** **4**	**15%** **500**	15% 600	15% 60	15%	14.7%
90	10	90	12.7%	13%	13.1%	13.1% 750	**13.2%** **70** **1000**	13.2% 5	13.2% 3 500	13.2% 1	**13.9%** **1** **4**	**14.3%** **500**	14.3% 600	14.2% 60	14.2%	14.1%
120	10	90	12.3%	12.5%	12.6%	12.6% 750	**12.6%** **60** **750**	12.6% 5	12.6% 3 500	12.6% 2	**13.1%** **1** **3**	**13.5%** **500**	13.5% 600	13.5% 70	13.4%	13.3%
60	20	90	13%	13.4%	13.5%	13.5% 750	**13.6%** **70** **1000**	13.6% 5	13.6% 3 500	13.6% 2	**14.4%** **1** **4**	**14.8%** **500**	14.8% 600	14.7% 60	14.8%	14.6%
90	20	90	12.6%	12.9%	13%	13% 750	**13.1%** **70** **1000**	13.1% 5	13.1% 3 500	13.1% 1	**13.7%** **1** **4**	**14.1%** **500**	14.1% 600	14.1% 60	14%	13.9%
120	20	90	12.2%	12.5%	12.5%	12.5% 750	**12.5%** **60** **750**	12.5% 5	12.5% 3 500	12.5% 2	**13%** **1** **3**	**13.4%** **500**	13.4% 600	13.4% 70	13.2%	13.1%
60	30	90	13%	13.3%	13.4%	13.4% 750	**13.5%** **70** **1000**	13.5% 5	13.5% 3 500	13.5% 2	**14.2%** **1** **4**	**14.6%** **500**	14.6% 350	14.5% 60	14.5%	14.5%
90	30	90	12.6%	12.8%	12.9%	12.9% 750	**12.9%** **60** **750**	12.9% 5	12.9% 3 500	12.9% 2	**13.4%** **1** **3**	**13.8%** **500**	13.8% 600	13.8% 70	13.7%	13.6%
120	30	90	12.2%	12.4%	12.5%	12.5% 750	**12.5%** **60** **750**	12.5% 5	12.5% 3 500	12.5% 2	**12.8%** **1** **3**	**13.3%** **500**	13.2% 600	13.2% 70	13.1%	13%

Table D.2: Simulation outcomes for changing the assumptions about duration of parts of the timeline, part 2/2. *1: Time from call to emergency number to activation of Hartslagnu system. *2: Time to collect an AED. *3: Time to connect an AED.

Intervention→		0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ Speed (km/h) Foot:	 Bike:				Radius	Number Radius	Limit	Radius Limit	Limit	CPR AED	Radius	Increase	%		
6	12	13%	13.1%	13.2%	13.2% 650	**13.2%** **60** **750**	13.2% 5	13.2% 2 500	13.2% 1	**13.5%** **1** **4**	13.8% 500	**13.8%** **600**	13.7% 70	13.7%	13.7%
9	12	13.2%	13.3%	13.5%	13.4% 650	**13.5%** **60** **750**	13.5% 5	13.4% 2 500	13.4% 1	**13.7%** **1** **4**	14% 500	**14%** **600**	14% 70	13.9%	13.9%
12	12	13.3%	13.5%	13.6%	13.6% 650	**13.7%** **60** **850**	13.7% 5	13.7% 3 200	13.7% 2	**14.1%** **1** **2**	**14.4%** **450**	14.4% 600	14.4% 75	14.2%	14.4%
6	16	13.4%	13.6%	13.7%	13.7% 750	**13.7%** **60** **750**	13.7% 5	13.7% 3 500	13.7% 2	**14.1%** **1** **4**	**14.7%** **500**	14.6% 600	14.6% 70	14.5%	14.4%
9	16	13.6%	13.8%	13.9%	13.9% 750	**14%** **60** **850**	14% 5	14% 3 500	14% 2	**14.6%** **1** **4**	**14.9%** **500**	14.9% 600	14.9% 70	14.8%	14.8%
12	16	13.7%	14%	14.1%	14.1% 750	**14.2%** **60** **850**	14.2% 5	14.2% 3 500	14.2% 2	**14.8%** **1** **2**	15.2% 700	15.2% 750	**15.2%** **75**	15%	15%
6	20	13.7%	14%	14.1%	14.1% 750	**14.2%** **70** **1000**	14.2% 5	14.2% 3 500	14.2% 2	**14.9%** **1** **4**	**15.4%** **700**	15.4% 600	15.4% 70	15.4%	15.2%
9	20	13.8%	14.2%	14.3%	14.3% 750	**14.4%** **70** **1000**	14.4% 5	14.4% 3 500	14.4% 2	**15.2%** **1** **4**	15.7% 700	15.7% 600	15.6% 70	**15.7%**	15.5%
12	20	14%	14.4%	14.5%	14.6% 1000	**14.6%** **70** **1000**	14.6% 5	14.6% 3 500	14.6% 2	**15.5%** **1** **4**	15.9% 700	15.9% 750	15.9% 70	**16%**	15.8%

Table D.3: Simulation outcomes for changing the assumptions about volunteer movement speed.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ Function:				Radius	Number Radius	Limit	Radius Limit	Limit	CPR AED	Radius	Increase	%		
Larsen	15.4%	15.6%	15.6%	15.6% 750	**15.7%** **60** **800**	15.7% 5	15.6% 2 500	15.6% 1	**16%** **1** **2**	**16.3%** **700**	16.3% 600	16.3% 75	16.2%	16.1%
Matinrad	13.7%	14%	14.1%	14.1% 750	**14.2%** **70** **1000**	14.2% 5	14.2% 3 500	14.2% 2	**14.9%** **1** **4**	**15.4%** **700**	15.4% 600	15.4% 70	15.4%	15.2%
Valenzuela	12.1%	12.4%	12.5%	12.5% 750	**12.5%** **60** **800**	12.5% 5	12.5% 3 500	12.5% 1	**13%** **1** **4**	**13.5%** **500**	13.5% 700	13.5% 95	13.4%	13.3%

Table D.4: Simulation outcomes for simulating when calculating survival chance with different functions.

Intervention→	0	0a	0b	1a	1b	2a	2b	2c	2d	3a	3b	3c	3d	3e
Variables→ Case:				Radius	Number Radius	Limit	Radius Limit	Limit	CPR AED	Radius	Increase	%		
1	14.5%	15.1%	15.2%	15.3% 900	**15.3%** **60** **900**	15.4% 6	15.4% 4 350	15.4% 3	**16.2%** **1** **3**	15.8% 550	**16.9%** **750**	16.7% 100	16.6%	16.5%
2	13.8%	14.2%	14.3%	14.4% 850	**14.4%** **90** **850**	14.3% 3	14.3% 3 50	14.4% 2	**15.1%** **1** **2**	**15.7%** **750**	15.7% 750	15.7% 1000	15.5%	15.2%
3	14.4%	14.9%	14.9%	15.1% 1100	**15.1%** **70** **1100**	15.1% 5	15.1% 4 200	15.1% 2	**16.3%** **1** **3**	16.7% 500	**16.7%** **700**	16.6% 85	16.3%	16.6%
4	14.2%	14.6%	14.6%	14.7% 850	**14.7%** **50** **1000**	14.8% 7	14.8% 3 450	14.8% 2	**15.5%** **1** **3**	16% 750	**16.1%** **700**	16% 80	16%	15.8%
5	13.9%	14.2%	14.3%	14.4% 1000	**14.4%** **90** **1000**	14.4% 5	14.4% 3 500	14.4% 4	**15.4%** **1** **4**	**15.7%** **750**	15.7% 700	15.6% 100	15.4%	15.5%
6	14.5%	15%	15%	15.3% 1050	**15.2%** **60** **1050**	15.3% 6	15.2% 2 500	15.3% 4	**16%** **1** **5**	16.8% 750	**16.9%** **700**	16.8% 95	16.6%	16.5%
7	15.1%	15.6%	15.6%	15.8% 1000	**15.8%** **85** **1000**	15.8% 5	15.8% 3 450	15.8% 2	**16.6%** **1** **4**	17% 550	**17%** **750**	16.9% 40	16.8%	16.7%
8	14%	14.4%	14.5%	14.7% 1100	**14.7%** **95** **1100**	14.7% 5	14.7% 5 50	14.7% 3	**15.5%** **1** **4**	**16.1%** **600**	16.1% 400	16.1% 100	15.9%	15.8%
9	14.1%	14.5%	14.5%	14.7% 1000	**14.7%** **80** **1000**	14.7% 5	14.7% 4 400	14.7% 2	**15.8%** **1** **4**	16.3% 700	16.3% 600	16.2% 85	**16.3%**	16.2%
10	14.4%	14.6%	14.7%	14.9% 950	**14.9%** **75** **950**	14.9% 4	14.9% 4 50	14.9% 3	15.7% 1 4	16.3% 650	**16.3%** **750**	16.2% 85	16%	16%

Table D.5: Simulation outcomes for simulating with ten different sets of 500 scenarios each.