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Joint planning of drones and volunteers in emergency response to out-of-hospital cardiac arrest ☆

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ABSTRACT

Various initiatives are in place worldwide to reduce the time from the occurrence of an out-of-hospital cardiac arrest to the start of cardiopulmonary resuscitation (CPR) and defibrillation using an Automated External Defibrillator (AED). In addition to optimizing the management of emergency medical services and other professional emergency response resources, these include utilizing close-by volunteers using mobile phone dispatching, and delivering AEDs using Unmanned Aerial Vehicles (UAVs), commonly known as drones. The latter two examples have previously been studied separately, and it has been proved that the time to administer CPR and AED delivery can be reduced. In this paper, the potential of joint planning and dispatching of volunteers and AED delivering drones is investigated. Optimization models are used to determine good locations for drones. These are then evaluated, together with new, adapted dispatch strategies for the volunteers, using a simulation model. Results of a case study, with data for the county of Västra Götaland in Sweden, show that drones can indeed help reduce the time to defibrillation, and, by adaptive dispatching, the time to CPR can be reduced as well. Thus, it is shown that by joint planning of drones and volunteers, it may be possible to improve the survival probability from out-of-hospital cardiac arrest.

1. Introduction

Each year, more than 350,000 people suffer from out-of-hospital cardiac arrest (OHCA) in Europe, making it the third highest cause of death overall (European Resuscitation Council, 2017). A cardiac arrest is a sudden heart failure where the heart dramatically reduces its pumping of blood and, therefore, stops the circulation of blood to the body. The symptoms of cardiac arrest are unconsciousness, with absent or abnormal breathing. Within minutes of cardiac arrest, the patient risks permanent neurological deficiencies (brain damage) or death if early treatment with cardiopulmonary resuscitation (CPR) and defibrillation using an Automated External Defibrillator (AED) are not initiated. In Sweden, and most of Europe, a person witnessing an OHCA occurrence will typically call 112 to reach the public safety answering point. This is operated by the company SOS Alarm AB in Sweden, and an SOS operator will answer and conduct an interview with the witness (in some regions, the call may be transferred to a nurse in case of medical emergencies), establishing that it is a suspected OHCA. This triggers a set of different actions, which may differ a bit depending on the region, but typically the closest available ambulance will always be dispatched to the patient. Furthermore, fire services or other first response units may be dispatched if they can reach the patient quicker, volunteer responders may be alerted through the SMS lifesavers initiative (more info on this below), and the SOS operator may give instructions to the witness to start CPR, or use an AED if one is available.

In AED, "automated" refers to the unit's ability to analyze the patient's condition autonomously. With its electrodes attached to the patient, the device determines whether a shock is warranted, and consequently charge an internal capacitor ready to provide the defibrillation. On a signal from the device, the bystander is instructed to clear away from the patient and to press a button, which initiates a shock (Kerber et al., 1992).

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During cardiac arrest, four types of arrhythmias are seen upon attaching an AED, two of which are shockable. These are ventricular fibrillation and pulseless ventricular tachycardia (Jasmeet et al.). The etiology of OHCA is most often cardiac related, about 70%, but regardless of cause, it is vitally important that the patient receives CPR as soon as possible. Additionally, for shockable rhythms, early electrical defibrillation treatment increases the survival probabilities considerably. The chances of surviving a cardiac arrest quickly diminish with time, where after only three minutes of untreated, the probability of survival of the patient has decreased by 50% (Waalewijn et al., 2001). It is estimated that less than 10% of all patients suffering from OHCA survive globally (Wong et al., 2019). However, many efforts have been made to increase this number. In many industrialized cities, AEDs can be found in public buildings and street corners. However, these are often not used even when a person suffers from a cardiac arrest nearby.

To combat this challenge, several academic and medical communities have launched initiatives in which volunteers are alerted when an OHCA occurs in their immediate vicinity. The volunteers are asked to find the patient and begin CPR or administer an early shock to the patient's heart by retrieving a nearby AED.

Another approach to increase the survival probability of OHCA is to use an Unmanned Aerial Vehicle (UAV), also known as a drone, to deliver the AED directly at the patient. In this way, bystanders or volunteers can potentially give defibrillation sooner than having to find a stationary AED themselves. In the event of an OHCA case, the drone flies autonomously to the patient to provide the bystander with an AED. Sometimes, the drone would have to fly to a nearby location, for example, if the patient is inside a building. Then someone has to pick up the AED from the street, potentially causing some CPR hands-off time if only one bystander is present. Especially in rural areas, where the response time of the Emergency Medical Services (EMS) is often long, drones have a high potential to significantly decrease the time to defibrillation (Claesson et al., 2016), which may significantly increase the probability of survival of the patient (Van de Voorde et al., 2017).

Combining the use of drones and volunteers is a relatively new approach to increase the effectiveness of response in cases of OHCA. Drones ensure that volunteers do not waste time by first picking up a stationary AED before heading to the patient, as the AED is delivered directly. This causes the arrival time of the volunteers to the patient to decrease. In single-bystander situations, volunteers provide help in picking up the drone-delivered AED, which means that a bystander does not have to leave the patient. The volunteers also have training in CPR and use of defibrillators and thus provide comfort and better usage of the drone-delivered AED.

This article aims to evaluate the potential of improving the emergency response to OHCA patients through the combined use of drones and volunteers dispatched by mobile phones, hereafter called volunteers. The evaluation is done by combining optimization models for drone location and different volunteer dispatch strategies. These are then tested in a simulation environment with the goal of providing insight into which models and strategies are most efficient.

We study the combination of two Swedish initiatives, here called SMS lifesavers and the Everdrone project. SMS lifesavers started as a research project by Karolinska Institutet in Sweden, and is now run by the company Heartrunner Sweden AB. In the event of an OHCA, a Mobile Phone Positioning System (MPS) is used to locate the volunteers within a predetermined distance from the patient and a notification is automatically generated and sent to those volunteers. This is done simultaneously with the dispatch of EMS to the patient. The volunteers then respond whether they are available or not. Those available are given one of two possible assignments: either to go directly to the patient and perform CPR or to find a stationary AED and bring it to the patient. The location of the patient and the AEDs are provided in the instructions.

Everdrone is the company that operates the drones that are used to deliver AEDs to OHCA cases around the Västra Götaland area in Sweden. Together with Karolinska Institutet, SOS Alarm (Swedish public safety answering point) and Region Västra Götaland among others, they have participated in a number of studies and trials, as well as real, live deliveries of AEDs. In this paper, the Everdrone project refers to these activities.

The outline of the paper is as follows. Section 2 contains a comprehensive literature review and positions this work in relation to previous studies. The two models used to optimize the location of the drones are presented in Section 3 followed by the volunteer dispatch strategies in Section 4. The simulation used to evaluate the locations and dispatch strategies is presented in Section 5 and data related to the area studied in Section 6. The results of the location analysis and the simulation study are discussed in Sections 7 and 8 respectively. The paper ends with a discussion in Section 9 and conclusions in Section 10.

2. Previous literature and contributions

One of the first studies designed to assess the feasibility of drone delivery of AEDs was conducted in Sweden in 2016 (Claesson et al., 2016). The study used GPS locations of historical OHCA events in the Stockholm area and estimated EMS response times to optimally locate drones. By different weightings of objective functions, they generated two separate solutions, each with ten drones. One solution focused on the delivery of AEDs to the most populated urban areas, while the other focused on rural areas with a long response time to EMS. Their experiments indicated that the delivery of AED was feasible and faster than the EMS, especially in rural areas. They also concluded that delivery by landing the drone or by low altitude drop of the AED was superior to a parachute drop. The same research team conducted tests on actual flight times compared with calculated flight times and EMS (Claesson et al., 2017). Both studies argued that the time to deliver an AED decreased significantly when using drones.

As drones are battery-operated and have a limited service range, a network of drones is required to provide adequate service to a larger area. Questions arise regarding how many drones are needed to fulfill the demand for AEDs and the optimal location of each drone's base. Claesson et al. (2016) used a GIS model to locate the drones. Several other studies have tried other approaches. Pulver et al. (2016) used GIS to simulate the travel times of EMS in Salt Lake County and used a Maximum Coverage Location Problem (MCLP) model with response time as the service standard. The model proposed the optimal locations of the drones to maximize the coverage of OHCA demand. Later, Pulver and Wei (2018) extended this work by explicitly integrating backup coverage and continuously distributed demand.

The same concept was applied in North Carolina, where researchers developed a mathematical model to locate candidate drone stations based on existing infrastructure and assessed the expected increase in survival probability that this would result in Bogle et al. (2019). Over the estimated four-year lifespan of the drone, the study concluded that the drones could double the survival rates and that an AED drone network remained cost-effective.

A similar study was conducted in Toronto, where a mathematical model was used to determine the optimal number and location of drones. This was done to quantify the number of drones needed to deliver an AED one, two or three minutes faster than the historical median EMS response times (Boutilier et al., 2017).

A more recent study was performed by Schierbeck, Nord, et al. (2021). They extended the work by Claesson et al. (2016), but this time at a national level in Sweden. The model maximized the coverage of OHCAs reached within 8 min.

In Sanfridsson et al. (2019), simulated OHCA cases on mannequins were used to analyze the experience of bystanders. The main findings were that bystanders perceived the delivery of the drone as positive and helpful and reported that they felt relief upon drone arrival.

One crucial drawback was that with only one bystander available, significant hands-off time occurred when retrieving the AED-drone. This emphasizes the importance of having at least two bystanders and showcases the potential effect of having volunteers to retrieve the drone instead.

A recent study further developed the optimization of drone location, this time in Northern Ireland Mackle et al. (2020). This model, in addition to the standard EMS response times, also included the response times of lay volunteers who would bring publicly accessible AEDs. In this study, OHCA cases, ambulance response times, and lay volunteers response times were simulated, and the need to consider real cases with locations and response times was expressed.

In EMS facility location problems, multiple researchers have questioned the use of traditional models such as the Maximum Coverage Location Problem (MCLP) (Church & ReVelle, 1976) and the p-median (Hakimi, 1965) with linear objectives. The argument is that these objectives do not properly differentiate between the consequences of different response times. Therefore, Erkut et al. (2008) introduced the Maximum Survivability Location Problem (MSLP), which considers the locations by taking into account medical research on the relationship between response times and survival rates. The MSLP is an extension of the p-median problem by incorporating a survival function into the objective to emphasize the importance of short response times in emergency response.

One of the first studies to develop a survivability function for OHCA was by Larsen et al. (1993). They used multiple linear regression based on data obtained from 1,667 OHCA cases in King County (Washington, USA). Other studies include Valenzuela et al. (1997), Waalewijn (2001) and De Maio et al. (2003). Matinrad et al. (2019) used the survival function from Valenzuela et al. (1997) for optimizing the dispatch of lay volunteers. However, to reflect the increased survival probabilities since 1997 and Swedish conditions, the parameters of the regression model were updated based on the extensive study population data in Waalewijn (2001).

The first comprehensive volunteer-dispatching system in OHCA was established in 2006 in Switzerland (Roman et al., 2013). Since then, several other countries have implemented similar systems but with slight variations. A study by Scquizzato et al. (2020) compared twelve existing volunteer systems worldwide. Their calculations showed that volunteers arrive before EMS in a median of 47% of the occasions, performed CPR in a median of 24% of occasions, and attached an AED in a median of 9% of occasions. The same study also performed a pooled analysis of the results from Ringh et al. (2015), Pijls et al. (2016) and Lee et al. (2019) to evaluate the acquired survival probability. It showed that survival after hospital discharge or after 30 days is 14.4% in the volunteer group vs 9.4% in the control group. This result indicates that the implementation of a volunteer response system can significantly improve patient survival outcomes.

Valeriano et al. (2020) identified 25 existing systems in 23 different countries, and Caputo et al. (2017) revealed that a mobile app outperforms a text message system. The median arrival time of the volunteers in the app-based system was 3.5 min compared to 5.6 min in the SMS-based system.

The manner in which volunteers are dispatched varies greatly between the various systems. Most systems focus on the enhanced CPR performance and therefore dispatch all volunteers directly to the patient. Only seven of the 25 systems identified by Valeriano et al. (2020) assign roles to the volunteers. Some of the systems have incorporated a feature in which the volunteers register their level of first-aid training. In this way, in case of an OHCA, the CPR-trained volunteers are dispatched directly, while others are dispatched to find an AED. Other systems decide on the assignments of the volunteers based on their location and time to respond to the notification.

One of the first studies to evaluate a quantitative model on volunteer management was performed by Falasca and Zobel (2012). They proposed a multi-criteria optimization model for task assigning both individual volunteers and groups in humanitarian organizations. Although the model is general and applicable for several situations, it lacks the specificity of assigning volunteers in OHCA cases. Matinrad et al. (2019) developed another multi-criteria optimization model for task assignment specifically in OHCA. Their model took the travel time directly to the patient and via an AED for each volunteer as input parameters and then determined who should receive which assignments. The model is, however, based on an assumption that all volunteers are available and will accept the notification, and that their travel times are predetermined and fixed. These assumptions are challenged in Matinrad et al. (2021), where the dispatch model takes into account that the volunteers may not follow their assignment, but instead do something else. Recently, Paz et al. (2022) studied logistic coordination in systems with controlled agents (ambulances) together with volunteers. They considered the spatial location and response propensity of volunteers and showed in a simulation study that the proposed system outperformed a system where information about volunteers was not considered.

In relation to previous work, we present two new mathematical extensions of general location models, specialized for the drone delivery of AEDs in OHCA that assess the achieved survival probability, instead of the response time, as the service standard. This is done using the function by Matinrad et al. (2019), which contributes to the literature by applying the function in a new situation of drones, volunteers and EMS, and by evaluating its suitability in the multi-tier EMS system.

Most of the previous literature on drone location problems only considers the EMS as the other existing response unit. The paper by Mackle et al. (2020) also considers the effect of lay volunteers when finding optimal drone locations, but uses simulated input data. The authors express the need for historical data in future research, which we provide, thus extending their work and contributing to the existing literature.

We further expand the research on volunteer performance by developing new methods for dispatching volunteers and evaluating their performance. This is done using a new simulation environment for OHCA cases, extending current work by including simulated locations of patients and volunteers, extended task compliance, and spatiotemporal entity relationships between drones, volunteers, AEDs, and EMS. This allows the simulation to evaluate the synergetic effects of combining volunteers and AED-delivering drones, something no studies have done before, to the best of our knowledge.

3. Drone location

We use two location problems for placing the drones, a Maximum Coverage Location Problem (MCLP) and a Maximum Survivability Location Problem (MSLP). Both problems are formulated as deterministic integer linear models. We make the following assumptions

- The drone utilization rate is 100%, which means drones are unaffected by weather conditions, battery life or other circumstances reducing their operative ability.
- All OHCA cases are independent and do not occur simultaneously, which results in all nearby drones and volunteers being considered available for each case evaluated.
- All additional time is included in the flight time of the drone, and the AED can be used instantly by a bystander after the drone arrives with it. A volunteer does not have to be on site.
- The survival probability is measured using the survivability function by Matinrad et al. (2019):

$$S(T_C, T_D) = (1 + e^{-1.3614+0.3429T_C+0.18633T_D})^{-1} \tag{1}$$

where T_C is the time to CPR and T_D is the time in minutes to defibrillation.

We introduce $\mathcal{J}$ as the set of OHCA location nodes and $\mathcal{I}$ as the set of candidate drone location nodes, where P drones are to be located. The number of OHCA cases in node j is denoted D_j.

The time a drone in node i needs to reach node j is denoted T_{ij}^D, while T_j^{AED} and T_j^{CPR} are the shortest times to an AED and a CPR arrival at node j by either EMS or volunteers, respectively. If the first responding volunteer carries an AED, the time to CPR equals the time to AED.

The binary variable x_{ij} is 1 if a drone in node i delivers an AED to node j, and 0 otherwise. The binary variable y_i is 1 if a drone is located in node i, and 0 otherwise.

To facilitate presentation, we introduce the set $\mathcal{A}$ of all pairs (i,j) of candidate drone location nodes i and OHCA location nodes j such that it is beneficial for a drone at node i to deliver an AED at node j. In the MSLP, $\mathcal{A} = \{(i,j) \in \mathcal{I} \times \mathcal{J} | D_{ij} \leq R\}$, where D_{ij} is the distance from node i to node j and R is the range of the drone expressed in this distance. In the MCLP, in addition to $D_{ij} \leq R$, (i,j), the pair (i,j) must also meet the criteria

$$\left(S(T_j^{AED}, T_j^{CPR}) < B\right) AND \left(S(T_{ij}^D, T_j^{CPR}) \geq B\right)$$

where B is the desired survival probability, termed the threshold value. This criterion states that the survival probability must be below the threshold value when no drones are used, and above the threshold value if a drone is sent from a drone at node i.

Now we can formulate the constraints of the models.

$$\sum_{(i,j)\in\mathcal{A}} x_{ij} \leq M y_i \qquad i \in \mathcal{I} \tag{2}$$

$$\sum_{(i,j)\in\mathcal{A}} x_{ij} \leq 1 \qquad j \in \mathcal{J} \tag{3}$$

$$\sum_{i\in\mathcal{I}} y_i \leq P \tag{4}$$

$$x_{ij} \in \{0,1\} \qquad (i,j) \in \mathcal{A} \tag{5}$$

$$y_i \in \{0,1\} \qquad i \in \mathcal{I} \tag{6}$$

Constraints (2) ensure that only drones at bases are used while constraints (3) state that each OHCA location node can be covered at most once. Constraint (4) limits the number of bases, and constraints (5) and (6) define the variables.

MCLP maximizes the demand covered and can be formulated as

$$z^{MCLP} = \max \sum_{(i,j)\in\mathcal{A}} D_j x_{ij} \tag{7}$$

The objective of the MSLP is to maximize the total survival probability. We introduce the change function

$$\Delta S(T_{ij}^D, T_j^{AED}, T_j^{CPR}) = \begin{cases} S(T_j^{CPR}, T_{ij}^D) - S(T_j^{CPR}, T_j^{AED}) & \text{if } T_{ij}^D < T_j^{AED} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

and formulate the objective function of MSLP as

$$z^{MSLP} = \max \sum_{(i,j)\in\mathcal{A}} D_j \Delta S(T_{ij}^D, T_j^{AED}, T_j^{CPR}) x_{ij} \tag{9}$$

Note that all objective function coefficients are calculated a priori and used as parameters in the model.

4. Volunteer dispatch

Volunteers can significantly improve the survival probabilities for an OHCA patient through an early start of high-quality CPR or by providing early defibrillation. With multiple volunteers, good coordination of these is important to achieve an improved overall response. With various locations of stationary AEDs and volunteers and uncertainties about when volunteers respond and how they behave, the problem of finding an overall good dispatch is rather complex.

4.1. Current dispatch strategy

Today, the dispatch of OHCA volunteers in Sweden is made using simple assignment patterns. Each active region has a specified pattern that controls the order in which accepting volunteers are given assignments. The pattern in Västra Götaland, which is the case study area in this work, is 00011, where 0 indicates that the volunteer should go directly to the patient and 1 indicates that the volunteer should pick up an AED. This means that the first, second, and third volunteer to accept the notification is dispatched directly to the patient. The fourth and fifth are dispatched to the AED giving the shortest total Euclidian travel distance to the patient via the AED. The pattern then repeats itself, so the sixth candidate is again dispatched directly, until either a maximum number of volunteers have been notified or until there are no more volunteers inside a predefined radius surrounding the patient.

4.2. Individual dispatch strategy

The current dispatch strategy ignores any information on the position of the volunteers. Although the distance via an AED could be much greater than the distance directly to the patient for a volunteer, a given pattern might assign an AED to that person. Inspired by Slaa (2020), a method is introduced to exclude bad dispatches. This method dispatches each volunteer individually based on his or her distance to the patient and distance via an AED. If the distance via an AED is not longer than the direct distance to the patient plus a threshold, the volunteer is sent via an AED. Otherwise, the volunteer is sent directly to the patient. If a drone is available for the specific case, all volunteers are instead sent directly to the patient.

5. Simulation

To evaluate the drone locations and the dispatch strategies in a stochastic setting, a two-part simulation environment is created. The first part is the OHCA case simulation, where all the random number selections in the simulation occur. This part of the simulation consists of five main agents: the patient, volunteers, AEDs, drones, and EMS. All of these agents are simulated, and the results are stored for evaluation in the second part of the simulation, called the dispatch simulation. The purpose of the dispatch simulation is to find the outcomes of each case given the simulated OHCA case data, a dispatch strategy, and a drone location solution. The outcomes calculated in the dispatch simulation are the shortest time to CPR and AED.

The simulation environment is a grid system consisting of square zones with information about the population and the expected EMS response time in each zone. The first step of the simulation is to generate an OHCA incident with a patient. The patient's zone is drawn based on the population of the zones, where higher population zones yield a higher probability of OHCA occurrence. Finally, the exact position of the patient is drawn uniformly within that zone. Having identified the patient's position, the relevant stationary AEDs are those within a predefined radius around the patient. The availability of the AEDs is uncertain and is drawn from a binary probability distribution. All drones within the drone range of the patient are included in the simulation. The availability of the drones is uncertain and is drawn from a binary distribution. The uncertainty in availability is due to poor weather conditions, flight regulations, maintenance, and simultaneity in OHCA cases. Each zone in the simulation also has an expected deterministic EMS response time.

Given the position of the patient, the simulation draws the number and location of volunteers relative to the population in the surrounding zones, where higher population zones have a greater chance of getting a volunteer. With a zone determined, the exact location of the volunteer is uniformly drawn within that zone, but still within the predetermined radius from the patient. The dispatcher sends notifications to each volunteer in the vicinity of the patient. A volunteer then either accepts or

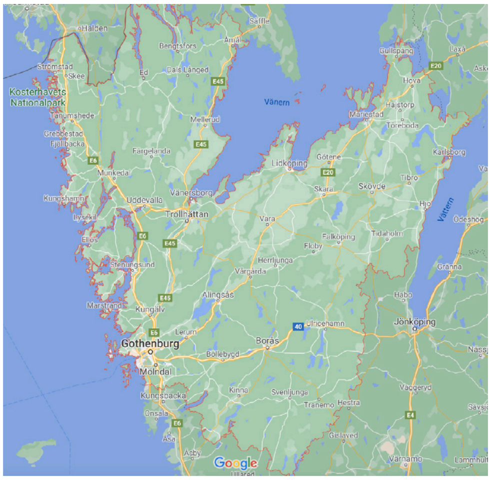


Fig. 1. The county of Västra Götaland.

rejects the assignment. All accepting volunteers receive an assignment either to go directly to the patient or via an AED. After the volunteer gets an assignment, they either comply or choose to do the other task. During the completion of the task, they may also fail to reach the AED and/or the patient.

Thus, for each OHCA case, the response times for drones with AEDs, volunteers with or without AEDs, and EMS are calculated. The time for start of CPR is set as the minimum of all volunteer response times and EMS response time. Only volunteers can use drone-delivered AEDs, so first defibrillation time is when a volunteer carrying an AED arrives, or when both a volunteer and a drone has arrived, or when EMS arrives.

6. Data

The area used for testing is the county of Västra Götaland in Sweden. Västra Götaland is the second largest county in Sweden in terms of population, with 1.7 million inhabitants, and has an area of 25,247 km^2. It consists of large and medium sized cities, such as Gothenburg, Borås, and Trollhättan, and rural areas. Fig. 1 shows a map of the county.

6.1. Location model data

The data used in the location models are based on a grid system representing the area of Västra Götaland that divides the area into 3897 rectangles, each with a longitudinal distance of 2175 m and a latitudinal distance of 2450 m. The information within each zone was aggregated into its center and is represented as a node in the mathematical models, both as an OHCA location node and as a potential location for a drone. In the cases when the potential locations for a drone are restricted, i.e. to a fire station or to controlled airspace, the zones covering the fire stations and the zones with the center inside the controlled airspace are considered as potential drone locations.

Using Västra Götaland ambulance call data for 2019, the number of suspected OHCA cases per year, as well as estimated EMS response times, was calculated for each zone. The number of OHCA cases in a zone becomes the demand D_j in the model. The EMS response time to a zone was calculated as the median response time of the ambulance to priority 1 emergencies (the most urgent type) within the zone during 2019. For zones that had no ambulance call during 2019, the time was set as a smoothed value based on the neighboring zone's response times.

Response times for volunteers were found using data from the area provided by Heartrunner, from 15,089 volunteer alerts sent out for a total of 796 OHCA cases from February 2019 to February 2020. The data was preprocessed and linear regression was used to obtain the expected volunteer response time, for CPR and via AED respectively, as a function of the population in the zone. A logistic regression was then used to obtain the probability that at least one volunteer would reach the patient. The final CPR and AED times for each zone were calculated as the probability weighed times of the volunteer response and the EMS response.

To obtain the expected arrival time of the drone, the total travel time was calculated using

$$T_{ij}^{D} = T^{TO} + \frac{D_{ij}}{S} + T^{L} \tag{10}$$

where T_{ij}^{D} is the expected travel time from node i to node j, T^{TO} is the take-off time, D_{ij} the distance from i to j, S the flight speed of the drone and T^{L} the drop-off time.

The specifications were provided or approximated based on the experiences from the ongoing Everdrone project. The take-off time of the drone, which includes getting approval to fly by the ATC and all other pre-flight activities, was set to 2 min. Drop-off time, which includes selecting exactly where to drop the AED and winching it down, was set to 1.5 min. The flight speed was set to 65 km/h based on the specs of the drone DJI M600 Pro. The range of the drone was set to 6 km as it is capable of flying 12 km on one charge. The distances between the nodes were calculated using Euclidean distance.

6.2. Simulation model data

The geography used in the simulation environment is a grid system with smaller squares compared with the grid system used for the location problems and partitions Västra Götaland into 36,924 zones. The grid system consists of two types of zones, large squares with dimensions 1000 m by 1000 m and small squares with dimensions 250 m by 250 m. This gives a more fine-grained description of the region suitable for the simulation since it is easier to get a good representation of the population density. The EMS and drone response times are calculated in the same way as in the location models, but drone availability is set to 80% based on experience from the Everdrone project. The Defibrillator Register in Sweden provided the positions of all 3170 AEDs in the area. All AEDs have an availability of 70% based on data from Heartrunner.

The number of responding volunteers was based on the population surrounding the patient within a 2 km radius, the same radius used to alert volunteers in the SMS-lifesaver project. The volunteer data was placed in five buckets based on the surrounding population, where more volunteers typically responded in zones with a large surrounding population. In the simulation, the number of responding volunteers was then sampled from the corresponding bucket. Fig. 2 shows the distribution of the number of volunteers by the surrounding population. The buckets are color-coded and for each simulated OHCA case, the surrounding population is calculated and then the number of volunteers is sampled from the corresponding bucket. The answer time for volunteers, i.e. the time from alert until they reply, was sampled from the 9256 times recorded in the historical data. The probability of answering the notification was set to 61.34% based on the data, and the probability of accepting (given an answer) to 46.24%.

Volunteers do not always follow the instructions given, some abort the mission, and others do the opposite of what they are told, e.g., travel directly to a patient even though they are told to find an AED first. Based on 2495 responses to a survey completed by volunteers who had responded to an alert, the conditional probabilities of different actions are calculated and presented in Table 1. A direct dispatch to a patient is denoted D and a dispatch via an AED is denoted A. $\bar{D}$ and $\bar{A}$ are actions started by the volunteer, while P^* and A^* is a successful arrival to the patient and the AED respectively, while $-A^*$ is a failed arrival at the AED. Finally, A^+ denotes an available AED and A^- an unavailable.

The two dispatch strategies presented in Section 4 are used. The current Västra Götaland dispatch of 00011 is called "Current VGR".

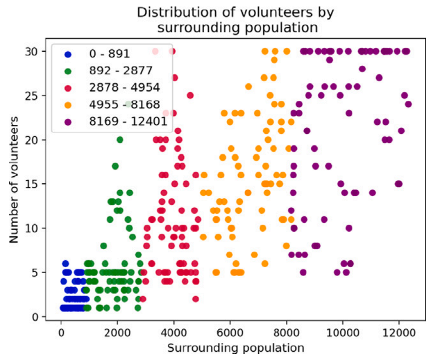


Fig. 2. The distribution of the number of volunteers by the surrounding population. The buckets are color-coded.

Table 1
Volunteer probabilities given dispatch and sequence of events.

Name	Probability
P($\bar{D}\|D$)	0.70
P($\bar{D}\|A$)	0.36
P($\bar{A}\|D$)	0.07
P($\bar{A}\|A$)	0.39
P($P^*\|\bar{D}$)	0.51
P($A^*\|\bar{A}$)	0.75
P($P^*\|A^*\&A^+$)	0.56
P($P^*\|A^*\&A^-$)	0.36
P($P^*\|-A^*$)	0.24

The second is the Individual Dispatch strategy using the direct distance and the distance via AED as the metric for assigning a task. To choose the threshold, all values from 50 to 1000 m with increments of 50 m were tested. Fig. 3 shows the results and we concluded that 500 m is a good threshold.

To determine the necessary number of replications in the simulation runs, the algorithm by Hoad et al. (2008) was used. The number of replications n is increased until a predetermined precision criteria is met. This precision criteria is the one-sided confidence interval, defined as a percentage of the cumulative mean. If $d_{required}$ is the user-determined precision criteria and d_n is the observed precision after n replications, the algorithm states that n should be increased until d_n converges to $d_{required}$. d_n is calculated according to Eq. (11), where $\bar{X}_n$ is the cumulative mean with n replications, $t_{n-1,\alpha/2}$ is the student t-distribution quantile with $n-1$ degrees of freedom and significance level of $\alpha/2$, while s_n is the sample standard deviation.

$$d_n = \frac{100 t_{n-1,\alpha/2} s_n / \sqrt{n}}{\bar{X}_n} \tag{11}$$

We use resulting survivability values as the dependent variable from which the precision criteria is set. Using a significance level of 5% and precision criteria of 5%, it was found that 5395 replications are necessary to satisfy the precision criteria for evaluation purposes. In evaluating the drone location and the dispatch strategies, 10,000 OHCA cases were used.

7. Location results

The optimization models are implemented in Python 3.7 using Gurobi 9.0.3 as the optimization solver. The implemented models are run on a 64-bit Apple Macbook Pro with the following specifications: Intel Core i5 (5th generation) with 2.7 GHz Dual-core processor and 8 GB installed RAM memory.

The Maximum Coverage Location Problem (MCLP) and the Maximum Survivability Location Problem (MSLP) are first tested without the simulation. The first parameter to calibrate is the number of drones, P. The results of running MSLP with varying number of drones are shown in Fig. 4.

The marginal improvement of one extra drone is diminishing and, based on this, 20 drones are selected as the base case parameter. It is considered a reasonable balance between covering a high part of the demand, yet not requiring an unreasonably high number of drones.

The second parameter to determine is the survivability threshold, i.e. the lowest survival probability a patient should have for it to be considered covered. Selecting the right threshold value can be tricky. By selecting a low value, most cases will already be covered by the existing EMS system, so no additional drone assistance is considered needed. However, with a high threshold, even with the use of drones, the desired survival probability cannot be reached, and the case can never be considered covered.

Fig. 5 shows how many of the input data cases that can potentially get help from drones for given survivability thresholds. From this, 0.02 was chosen as the threshold value. Here, the number of cases that can be pushed above the threshold by using drones is the largest. Note that this value is not a realistic desired survival probability. This is further discussed later.

MCLP and MSLP are tested with no restrictions on where the drones can be located. In addition, MCLP is tested with two different restrictions on where the drones can be located, at fire stations and within controlled airspace. The only difference when solving the controlled airspace MCLP and the original MCLP is that the candidate grid zones in the original MCLP are reduced to those within controlled airspace and outside of restricted airspace, as provided by Luftfartsverket Sweden (Luftfartsverket, 2021). When the drones can be located only at fire stations, the actual location of the fire stations within the region is used. The reason for testing this is to see how more restrictive and possibly realistic locations will affect the results. The solutions from the four models are shown in Fig. 6.

All solutions focus the locations around the larger cities, and the drones overlap considerably more in the MSLP solution compared with the MCLP solutions. The total population within the area covered by the MCLP solution is 1.12 million out of 1.7 million. Thus, by locating 20 drones, more than 65 percent of the population in Västra Götaland can be covered. For the other solutions, the coverage is 1.02 million and 1.06 million for the MSLP and the MCLP restricted to fire stations, respectively. The solution of the MCLP restricted to controlled airspace covers 537,000 of a total possible population of 583,000 within the controlled airspace. Interestingly, each of the controlled airspaces gets at least one drone, but the main cluster is in the Gothenburg area.

Of the drones located by MCLP restricted to fire stations, 15 of the locations are very similar to those suggested by the MSLP. This reflects the fact that fire stations are strategically located to meet high demand and indicates that the drone locations suggested by the MSLP are realistic.

New response times to the historical OHCA cases can be estimated for the locations from the four models. With only the dispatch of volunteers and EMS, the average "time to CPR" of the historical cases was 11 min and 11 s, and the average "time to AED" was 15 min and 59 s. Only the "time to AED" is affected by the additional dispatch of drones. The average "time to AED" achieved with the additional dispatch of drones for the various models are listed in Table 2.

According to these response times, the best performing model is the MSLP which reduces the average "time to AED" to 10 min and 7 s. Interestingly, the location at fire stations also results in a lower average "time to AED" than the MCLP. But, as mentioned, restricting the locations to fire stations results in most of the locations being very similar to those of the MSLP. Thus, the performance in most cases should also be similar. Location within controlled airspace results in a slower response than the other methods, which is expected as much fewer cases can be reached. However, the drones help reduce the time to AED by almost four minutes on average, compared to not having any drones.

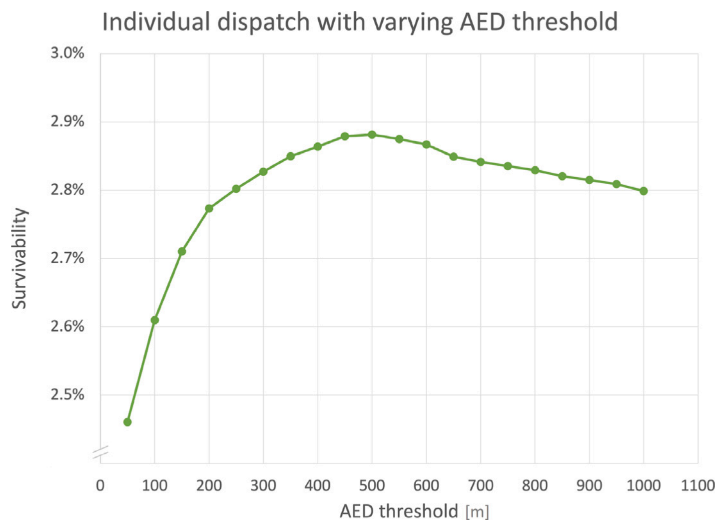


Fig. 3. Individual dispatch with varying AED threshold values tested on 10,000 simulated OHCA cases with no drones included. Note that the y-axis does not start at zero.

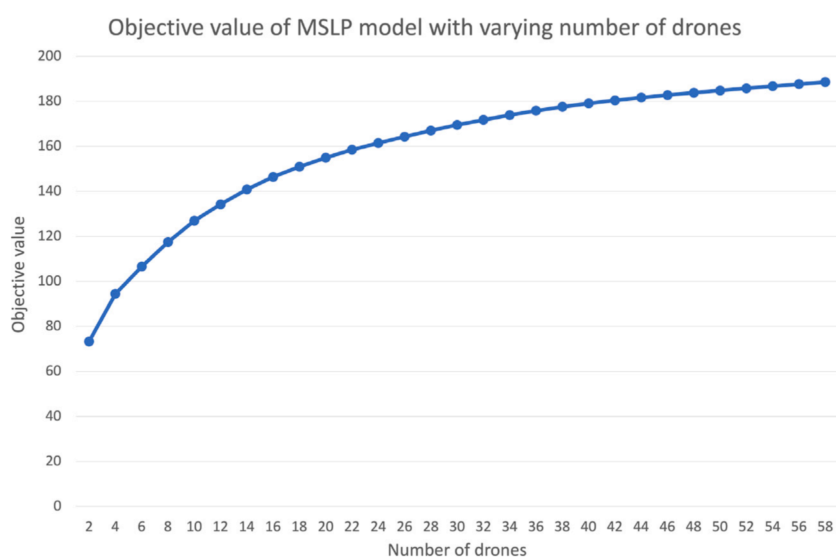


Fig. 4. MSLP model objective value with varying number of drones.

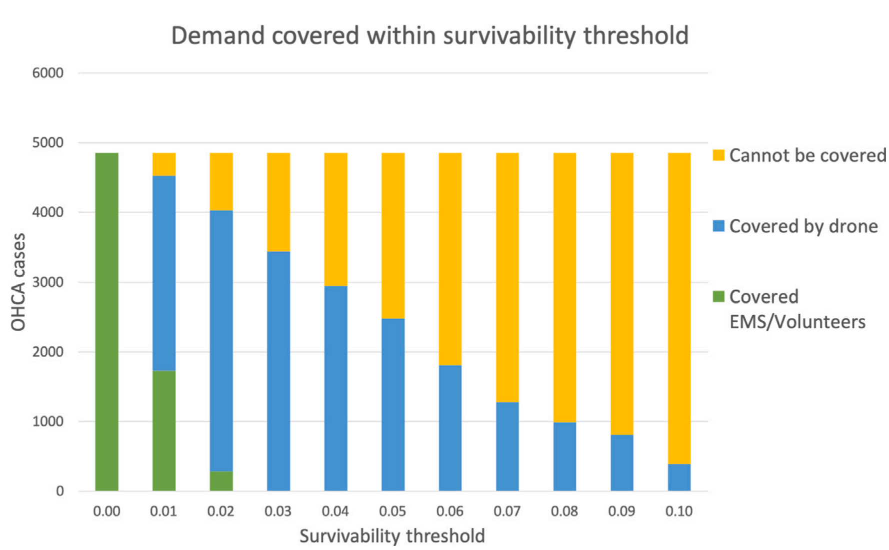
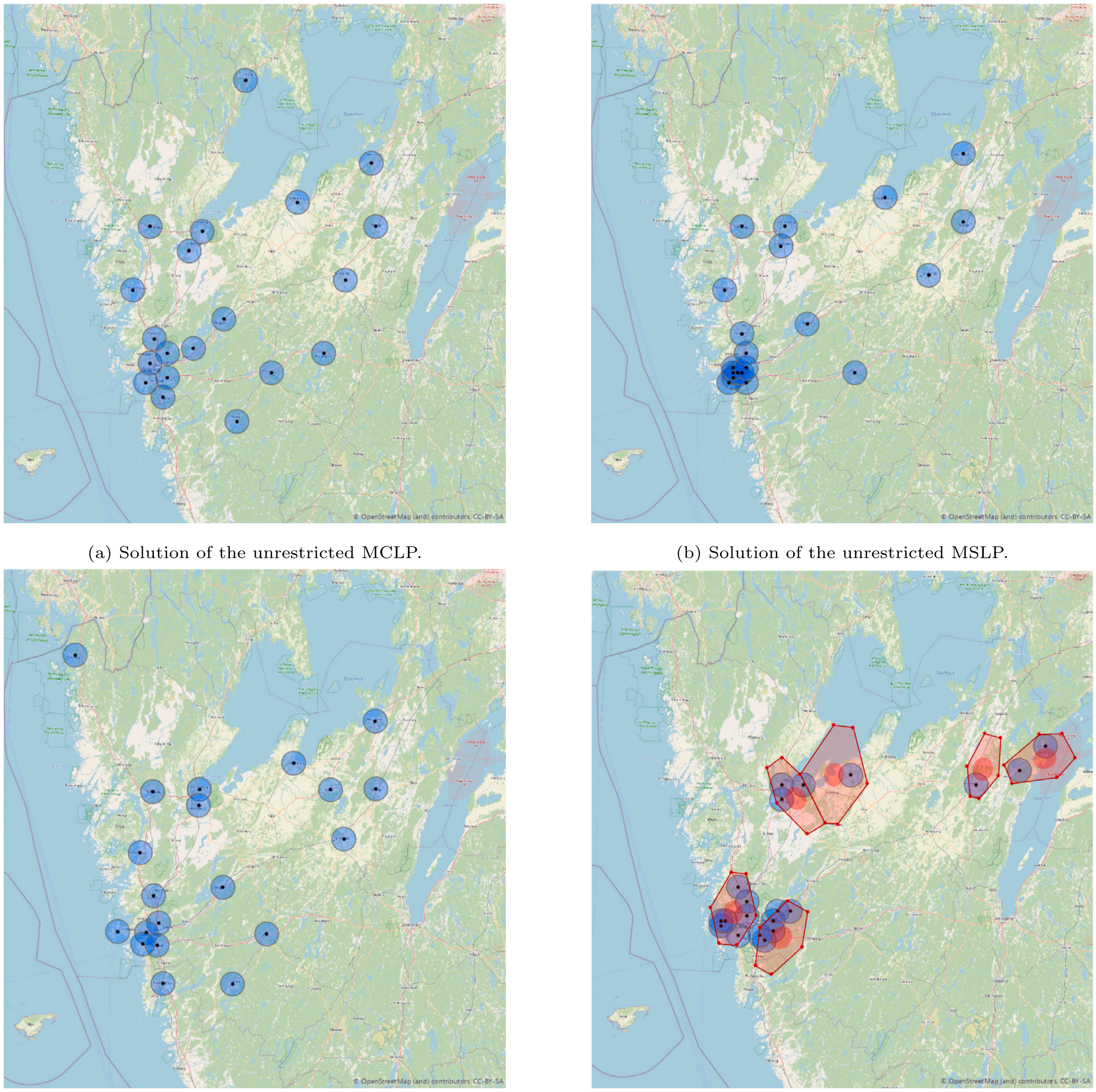


Fig. 5. OHCA cases that are already covered by EMS and volunteers, those that can be covered by drone, and those that cannot be covered by a drone for different survivability thresholds.



(a) Solution of the unrestricted MCLP.

(b) Solution of the unrestricted MSLP.

(c) Solution of the MCLP restricted to fire stations.

(d) Solution of the MCLP restricted to controlled airspace.

Fig. 6. Solutions from four different location models. Blue circles represent the range of the drone from its base.

Table 2
The average times for AED delivery for all drone location methods.

	Time to AED (mm:ss)
Volunteers & EMS only	15:59
MCLP	10:30
MSLP	10:07
Fire stations	10:24
Controlled Airspace	12:09

8. Simulation results

The simulation model is implemented in Python 3.7. The implemented model runs on a 64-bit Apple Macbook Pro with the following specifications: Intel Core i5 (5th generation) with 2.7 GHz Dual-core processor and 8 GB installed RAM memory.

The run time of the simulation can be divided into two parts. The first part is the OHCA case simulation, where the cases are generated. The second part is the dispatch simulation, where the outcome of each case is simulated. The runtime of the two parts was 20 s and 5 s for 1000 unique cases respectively.

8.1. Survivability results

The optimal locations from the four different location models are tested with both volunteer dispatch strategies in a total of 10,000 unique, simulated incidents. For each test, the incidents and stochastic outcomes remain the same. The results from these tests are presented under the Base case columns in Table 3. The table shows the survivability results of the combinations of dispatch strategy and location. The columns contain the dispatch strategies; No volunteers [Only EMS], the current strategy used in Västra Götaland [Current VGR] and the Individual Dispatch strategy [Individual Dispatch]. The rows show the case without drones [No Drones], MCLP restricted to controlled airspace [Controlled Airspace], unrestricted MCLP [MCLP], MCLP restricted to fire stations [Fire Stations] and unrestricted MSLP [MSLP]. Each cell

Table 3
The survivability results using the drone location solutions from the rows and dispatch strategies in the columns on the same simulated data. Cells marked N/A represent invalid cells where drones cannot be used as no volunteers are present to utilize them. The left columns are without bystander initiated CPR and the right with bystander initiated CPR included in 63% of the cases.

	Base case			Bystander initiated CPR		
Dispatch / Drone	Only EMS	Current VGR	Individual Dispatch	Only EMS	Current VGR	Individual Dispatch
No Drones	0.10%	2.20%	2.91%	7.38%	9.60%	11.5%
Controlled Airspace	N/A	3.82%	4.40%	N/A	13.3%	14.6%
MCLP	N/A	4.94%	5.45%	N/A	15.8%	16.7%
Fire Stations	N/A	5.39%	5.88%	N/A	16.5%	17.4%
MSLP	N/A	5.62%	6.14%	N/A	16.7%	17.7%

contains the average survival probability and N/A represent infeasible combinations.

An initial assessment suggests that including drones and volunteers could potentially increase the probability of survival. The solutions from the location models are sorted in ascending order. Among the dispatch strategies, the Individual Dispatch is better than the current method for all drone locations (and if there are no drones).

The survivability results of the base case in Table 3 are notably low, considering the Swedish average OHCA survival probability of 11% (Svenska Hjärt-Lungräddningsregistret, 2020). There are several explanations for this. As previously described, the effects of bystanders are intentionally disregarded in the simulations as a way to exclusively focus on the volunteer effects. Since the evaluation is based on a survivability function that only uses the response time to CPR and AED, bystanders needed to be excluded for there to be any reason to dispatch volunteers directly to the patient. This causes the resulting survival probability values to be considerably lower than realistic, as the time to CPR assumes no bystanders.

In the simulation performed by Slaa (2020), it was assumed that a bystander initiated CPR after 30 s in 63% of OHCA incidents. To test the results of this assumption, each of the 10,000 simulated incidents had a 63% chance of having a "time to CPR" of 30 s. The recalculated results of these tests are shown in Table 3 under Bystander initiated CPR, which gives more realistic values.

Including bystanders has a major impact on the survival probability values since it drastically reduces one of the input values in the survivability function. Although these results show increased survival probabilities across all cells, the figures are still low. Especially the values under "Bystander initiated CPR" and "Only EMS and "Current VGR/No Drones" were expected to be around the national average of 11% since they include EMS and/or volunteers, similar to the current conditions in VGR. One possible explanation is the deterministic use of median EMS response times. If the response times were drawn from a distribution, the shorter response times would have a larger positive impact on the survival probability than the longer response times' negative impact. This is due to the convex shape of the survivability function.

Although there is a large difference in the resulting survival probabilities when including the bystander effect, the sequential dominance between the strategies remains the same. With this in mind, the original predicted values, without the bystander effect, are still valid when used for comparative purposes.

8.2. Controlled airspace

As drones are required to fly inside controlled airspace today, the location of drones in controlled airspace is the most foreseeable solution. Thus, it is interesting to evaluate the performance of this solution compared with not having drones. For this comparison, the individual dispatch strategy is used as it is simple, yet it already has proved a good performance. The results show an increase from 2.91% to 4.40% when including drones. However, the value 4.40% is the average survival probability of all 10,000 cases. Only 2706 of these cases had a successfully arriving drone.

Fig. 7 shows the absolute survival probability changes for cases receiving a drone. The green bars represent the number of cases with a positive change in survival probability, making up most of the cases. The yellow bar is the number of cases with no improvement, even if a drone was available. Many of these cases do not improve as there are no volunteers available to use the drone-delivered AED. The red bars illustrate incidents where the survival probability actually decreases with the use of drones. When simulating the compliance of volunteers, some volunteers will arrive if they are dispatched to an AED, but fail to arrive if given a direct dispatch instead, due to the stochastic setting. With drones included, the dispatch of some volunteers might change, resulting in them failing to arrive, potentially reducing the survival probability.

8.3. Fire stations

The next drone location solution is where drones can only be located at an existing fire station. Since this includes all fire stations in the entire county of Västra Götaland, the solution ignores current aviation restrictions. However, the possible drone locations are more constrained than the MCLP and MSLP as there are fewer candidate locations. It should be considered a proposal for a future solution if the aviation restrictions are liberalized for emergency drone usage. It therefore also serves as a proof of concept, suggesting what might be accomplished if the restrictions are alleviated.

The average survival probability using the Individual Dispatch shows an increase from 4.40% when using the controlled airspace locations to 5.88% when using the fire station drone locations. Thus, expanding the possible locations of drones has a considerable effect on increasing the potential survival probability. Furthermore, this drone location solution is also capable of serving considerably more cases. Of the 10,000 simulated cases, the fire station solution was able to dispatch a drone to the patient in 5232 cases, compared with only 2706 for the controlled airspace solution. Simply put, the possible benefits that can be obtained by alleviating the emergency drone flight restrictions are substantial.

8.4. Sensitivity analysis

Having presented the main results, it is interesting to study whether these results are sensitive to changes in the parameters. Note that the sensitivity analysis is based on the base case, i.e. without bystander initiated CPR.

8.4.1. Varying number and availability of drones

Allowing more drones is intuitively expected to produce better results, as there are more drones to cover the patients. However, having more drones would also increase costs, so it is interesting to study the marginal improvement to find an appropriate balance between survival probability and cost. Fig. 8 shows how the probability of survival increases with an increasing number of drones. It is apparent

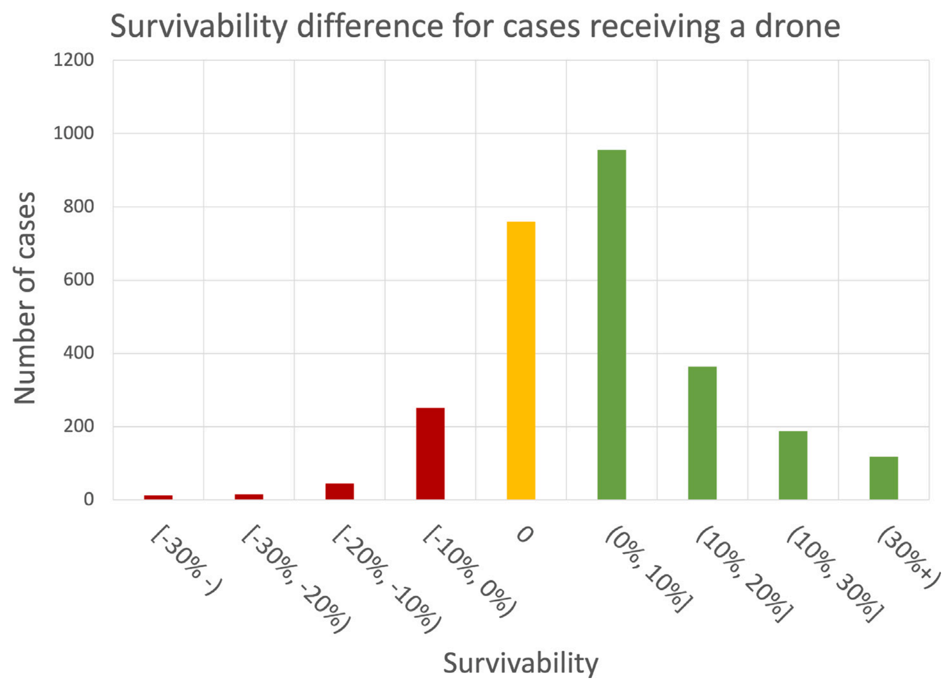


Fig. 7. Number of cases receiving drones within intervals of absolute change in survival probability compared when no drones were available.

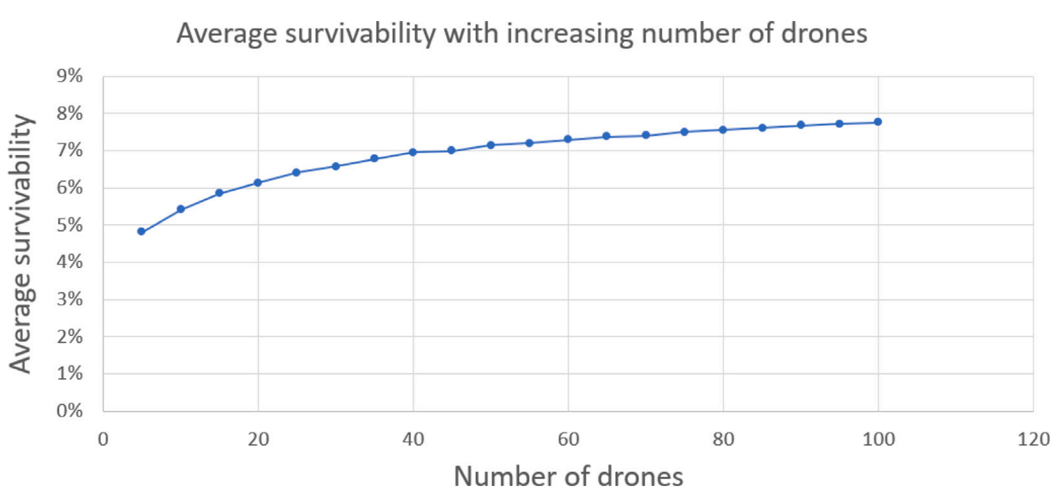


Fig. 8. Survival probability results when increasing the number of drones using the MSLP for drone location and the individual dispatch strategy.

how the total survival probability increases but with a diminishing factor. In other words, the incremental gain of each additional drone decreases. Unlike the analysis in Fig. 4, the number of drones is evaluated in a stochastic setting, where drones may be unavailable and only the volunteers can use the drone-delivered AED. However, the effects of changing the number of drones in the deterministic models resemble the change in the stochastic data. Another interesting consequence when increasing the number of drones is how the demand coverage changes. Quite intuitively, having more drones available leads to drones covering the previously uncovered areas. This results in an increase in the total demand covered, as shown in Fig. 9.

Another interesting aspect to study is how the performance of the drones varies with their availability. As previously described, the availability of the nearby drones is assumed to be known at the time of determining volunteer assignments. Therefore, the availability of drones directly affects not only the time to AED, but also the assignments given to the volunteers.

Table 4 shows how varying the availability of drones affects the demand served and the survival probabilities. It is clear that the marginal gain of increasing the availability diminishes. For example, increasing the availability from 10% to 20% increases the demand served from 1336 to 2294 and the survival probability from 3.66% to 4.20%. On the other hand, increasing the availability from 90% to 100%, increases the demand served from 5518 to 5784 and the survival probability from 6.37% to 6.59%.

9. Discussion

There are many practical obstacles to overcome before launching any type of drone service, even if systems for managing unmanned aerial vehicles are emerging, including the European U-space. The case studied in this paper is based on the successful trials in Västra Götaland, described in Schierbeck, Hollenberg, et al. (2021), where the drones are allowed only to fly beyond visual line of sight in the controlled airspace around the airport Säve. As more U-space services become available, it will become possible to operate drones over larger areas, e.g. the whole of Västra Götaland county, as tested in our paper. But more freedom and flexibility to operate drone services also means more

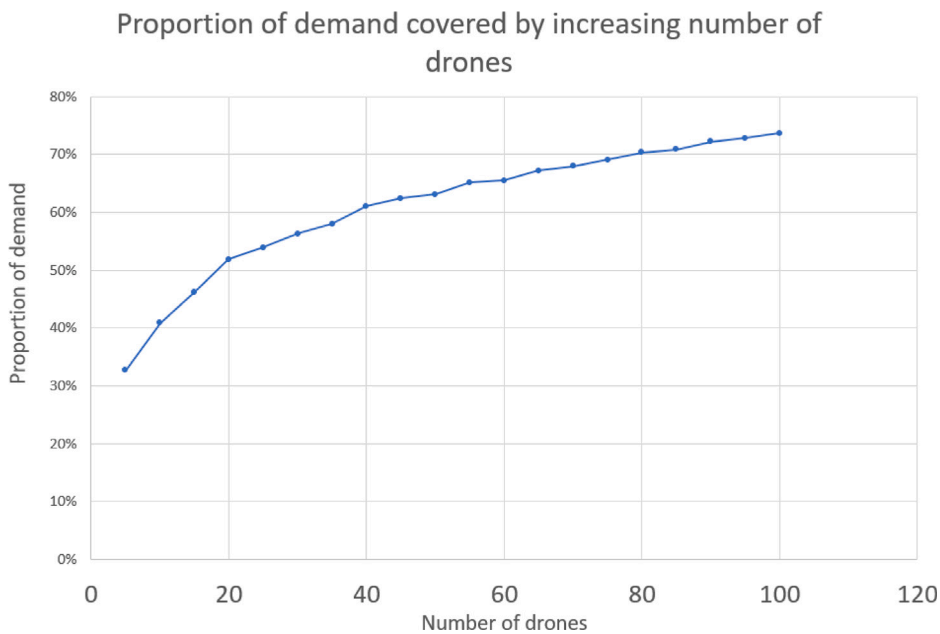


Fig. 9. Demand covered when increasing the number of drones using the MSLP for drone location and the individual dispatch strategy.

Table 4
Sensitivity analysis on varying the drone availability.

Drone availability	Demand served	Survival probability
10%	1336	3.66%
20%	2294	4.20%
30%	2999	4.64%
40%	3603	5.04%
50%	4091	5.38%
60%	4479	5.63%
70%	4860	5.86%
80%	5191	6.17%
90%	5518	6.37%
100%	5784	6.59%

difficult decisions, e.g. regarding how many drone stations to build, how many drones that should be allocated to each station, and where the stations should be located. Choosing where to locate drones and which demand to cover are political questions that are not answered directly in this paper, but it is of course a trade-off between costs and the benefits of the service. Hopefully, decision support tools like the models we present here, can help make informed decisions.

The aim with this paper is to illustrate how the performance of a multi-tier EMS system including volunteers and drones can be improved by selecting good locations and dispatch strategies. Placing seven drones in neighboring zones in the Gothenburg area, as the MSLP suggests, might not be a realistic implementation. However, compared with spreading them out, as suggested by the MCLP, it is estimated that the overall average survival probability will be better. This is due to the weighting of the large population in this area and the sensitivity of the survivability function to short response times, which are achievable in the cities.

The survivability function is a topic of discussion itself. It inputs the time to CPR and the time to AED. With the assumptions made here, ignoring the initiation of CPR by a bystander, the function fails to estimate realistic values of survival probability. However, when including the bystander initiated CPR, the additional benefit of arriving volunteers is not reflected by the function. Ideally, a survivability function that inputs additional parameters might be used, having a "time to bystander CPR", "time to arrival of first volunteer", "time to first defibrillation" and "time to EMS arrival". In this way, realistic values could be produced while also reflecting the benefit of volunteers. However, reliable data for the start (and quality) of bystander CPR is today very challenging to obtain. When evaluating the volunteer data, it was observed that some volunteers carried their own personal AED. Using this information when dispatching could potentially provide additional dispatch improvements as these would then not be sent via an AED. With an increasing number of volunteers carrying personal AEDs, the impact would increase. All dispatch strategies are static in the sense that the dispatch is predetermined when a volunteer answers the notification, and the method is not updated with additional information when such is revealed. A dynamic dispatch instead could make a decision on an assignment at the moment a volunteer answers, based on the currently available information. Consider the situation where two volunteers already have arrived directly to the patient; then the remaining volunteers should be told to find an AED.

The simulation includes some simplifying assumptions and does not differentiate volunteers, apart from their positions. If data exists, it may be possible to include properties such as age, medical proficiency, speed, whether they would bring a personal AED, and their previous dispatch history. This could increase the accuracy of the simulation. The EMS arrival time is derived directly from historical data, greatly simplifying the arrival time. In reality, the EMS arrival time varies greatly as the closest responding EMS unit is not always at its base. The availability of each drone is drawn independently from a binary distribution. However, this simplification does not include weather conditions or real-time flight restrictions caused by other air traffic. Another limitation is that we do not include is real-time case dependency. In reality, if a drone is busy with a case, it must be rendered unavailable for other cases until it returns to the base and is refitted with an AED and fully charged.

In practice, the realism of a simulation could be improved indefinitely. However, increasing the complexity might not change the overall results by much. In the historical data, only 66 out of 2561 (2.6%) volunteers stated that they had a personal AED when dispatched to an OHCA. The data also showed that the number of incidents that occurred simultaneously was close to zero in the region. Therefore, we can assume that the inclusion of these possibilities will not affect the overall outcome of all simulated cases by much. Some properties, such as the quality of CPR, cannot be modeled using available data. For the purpose of comparing the performance of the drone location and dispatch strategies, the proposed simulation model is sufficient.

Finally, the data used to calculate the probabilities in the simulation study are gathered from different registers and might therefore be subject to reporting and selection bias. We have not extensively validated register data vs. source data.

10. Conclusion

In this work, the potential of improving emergency response to OHCA patients using a multi-tiered response, including volunteers and drones, is investigated. The volunteers can perform CPR or bring an AED and perform defibrillation, while the drones can transport the AED faster than the volunteers. Using historical data on volunteer responses in the Swedish county of Västra Götaland as input to four different location models, optimal drone locations were produced. These were evaluated, together with two different volunteer dispatch strategies, using simulation.

The results show that the survival probabilities of OHCA patients increase significantly when using volunteers, especially when volunteers are combined with drones. When including 20 drones to a system of volunteers, the AED response time was reduced by 4 min 22 s and the CPR response was reduced by 28 s on average when tested on 10,000 simulated cases.

The main contribution of this work is the proof of concept analysis of a combined dispatch of drones and volunteers. Although it has previously been established that volunteers and drones independently can help decrease the time to start of AED (and CPR) in OHCA cases, it is shown here that by carefully combining and managing these resources, an even better outcome may be achieved.

As already mentioned in the discussion, there are many avenues for future research, including using stochastic multi-objective location models to get better drone locations, taking individual volunteer qualities (like travel speed, compliance probability, and expected quality of care) into account both in dispatching and in the simulation, utilizing dynamic dispatch models that are updated based on the latest available information, and developing better response time models for volunteers, drones and EMS.

CRediT authorship contribution statement

Lasse Frigstad: Study conception and design, Material preparation, Data collection and analysis, Work is based on the Master's thesis, Commented on previous versions of the manuscript. **Vegard Furu:** Study conception and design, Material preparation, Data collection and analysis, Work is based on the Master's thesis, Commented on previous versions of the manuscript. **Sigve Kristiansen Svenkerud:** Study conception and design, Material preparation, Data collection and analysis, Work is based on the Master's thesis, Commented on previous versions of the manuscript. **Andreas Claesson:** Study conception and design, Commented on previous versions of the manuscript. **Henrik Andersson:** Study conception and design, Supervised the Master's thesis, Wrote the first draft of the manuscript, Commented on previous versions of the manuscript. **Tobias Andersson Granberg:** Study conception and design, Material preparation, Data collection and analysis, Wrote the first draft of the manuscript, Commented on previous versions of the manuscript.

Data availability

The authors do not have permission to share data.

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Ethics approval

No ethics approval was needed for this research.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Andreas Claesson is shareholder in Heartrunner Sweden AB

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