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Simulating cardiac arrest events to evaluate novel emergency response systems

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ABSTRACT
This paper presents a simulation model approach to predict improvements in survival by new out-of-hospital cardiac arrest response systems. Poor cardiac arrest survival rates have motivated the exploration of new response system concepts to augment EMS systems, including citizen responders dispatched by a cell phone app, and the use of drones to deliver an AED to a cardiac arrest location. With few existing studies, the system effectiveness remains largely unknown. A predictive model was developed to understand the improvement these systems may have on cardiac arrest survival. The model uses a geospatial Monte Carlo sampling approach to simulate the random locations of cardiac arrests and the responding agents. The model predicts the response time of EMS, mobile dispatched responders, and drone AED delivery, based on the distance traveled and the mode of transit, while accounting for additional non-transit system factors. A logistic regression model is utilized to translate response times for CPR and defibrillation to a likelihood of survival. The model was developed to simulate and compare multiple response system concepts. The paper presents a case study to demonstrate the model’s utility.

1. Introduction and motivation
Sudden cardiac arrest is one of the leading causes of death worldwide, with over 350,000 out-of-hospital cases each year in the United States alone (Benjamin et al., 2018). Cardiac arrest survival requires a rapid intervention with cardiopulmonary resuscitation (CPR) and defibrillation. For each minute from the onset of cardiac arrest until treatment, the likelihood of survival decreases by 7 to 10% (Larsen et al., 1993)(About Cardiac Arrest, 2018). If not treated within the first 10 to 15 min, the outcome is nearly always fatal. The overall survival rate in the United States is about 10% (Abrams et al., 2013). Although a few communities have achieved significantly higher survival rates, many cities and rural areas are much lower.

1.1. Cardiac arrest treatment and current survival
Cardiac arrest occurs when the electrical activity of the heart fails to stimulate muscle contractions in an organized rhythm. Ventricular fibrillation and ventricular tachycardia are arrhythmias which result in loss of circulation to the lungs, brain, and vital organs. Treating these arrhythmias requires cardiopulmonary resuscitation (CPR) and defibrillation. For each minute from the onset of cardiac arrest until treatment, the likelihood of survival decreases by 7 to 10% (Larsen et al., 1993)(About Cardiac Arrest, 2018). If not treated within the first 10 to 15 min, the outcome is nearly always fatal. The overall survival rate in the United States is about 10% (Abrams et al., 2013). Although a few communities have achieved significantly higher survival rates, many cities and rural areas are much lower.

1.2. New response systems to augment EMS
New types of response systems are being developed with the objective to bring AEDs to the cardiac arrest locations, rather than rely on a bystander to locate and retrieve an AED located in the vicinity of the arrest. These systems utilize two new technologies that have emerged over the past decade: the GPS enabled smart phone, and Unmanned Aerial Vehicles (drones). One such category of system

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concepts is the use of a smartphone app to alert nearby responders of a cardiac arrest and provide the location and directions to the arrest. These “mobile responder” systems rely on a network of citizen volunteers, or off-duty first responders, to provide quick treatment. These systems have their origins dating back to the mid-2000s, when SMS message-based systems such as Heartrunner in Sweden, and the Northern Ireland Public Access Defibrillation study were started. However, the pervasiveness of the location aware smartphone over the past 8 years has led to substantial growth in these systems, with over 29 systems operating in Europe alone (Scquizzato et al., 2020). One of the early implementations of this type of system in the United States is PulsePoint (PulsePoint.org), a system which dispatches citizen volunteer responders to nearby cardiac arrests, to provide CPR until the arrival of EMS. Recent trials utilize verified responders, i.e. sanctioned off-duty first responders who carry AEDs at all times, to provide both defibrillation and CPR (PulsePoint.org | Off-Duty Professional Firefighters Partner with National Pilot Program to Save Lives). Other embodiments of this type of system utilize taxi drivers to carry AEDs and respond when dispatched to an arrest (Ng, 2019). These types of systems rely on the stochastic chance that a responder will be nearby the cardiac arrest location.

The second category of system utilizes drones to deliver an AED quickly to the cardiac arrest location. Drones have the advantages of a high speed and direct route of travel, without impairments such as traffic. The drones may be based at existing EMS stations, or located remotely, and dispatched by the 911 operator along with the ambulance. These systems rely on a bystander to retrieve the AED from the drone, or a dispatched mobile responder to meet the drone at the cardiac arrest location to apply the AED.

These new systems have varying levels of maturity, from PulsePoint, which has been in operation for a few years, to drone AED delivery, which is just beginning pilot studies under an FAA program, to completely untested concepts. There is a dearth of data to support the effectiveness of these systems, and their potential improvement in response time and survival over the traditional EMS response. Modeling and simulation can provide a method to predict the efficacy of these systems, as well as understand the effects of varying factors within these systems, more quickly and efficiently than real world experimentation. As public health and EMS decision-makers search for options to improve survival within their community, modeling and simulation can be an important tool to guide efficient use of resources.

1.3. Related work

Substantial research exists in the area of modeling and simulation for EMS response systems. The modeling can generally be divided into two objectives; optimal location of ambulance base stations, and simulation of EMS system performance. Optimal ambulance location models focused on finding the minimum number of ambulance base locations such that all demand locations were within a certain response radius (Toregas et al., 1971), optimizing service locations for maximum coverage under a constrained number of ambulance base locations (Church & Davis, 1992), optimizing overlapping coverage when ambulances may be unavailable for periods of time (Gendreau et al., 1997), and maximizing coverage with dynamically relocated ambulances (Gendreau et al., 2000). Discrete Event Simulation has been employed to model the performance of EMS systems. The approach has been applied to study redistribution of ambulances among base locations (Savas, 1969), the comparison of single start systems i.e. multiple ambulances based at a single location, to multiple start systems (Ingolfsson et al., 2003), and to develop operational strategies to minimize disruption of service due to ambulance unavailability (Wu & Hwang, 2009).

Although substantial work exists for ambulance response systems, limited simulation studies have been developed for mobile responder or drone delivery systems. Coverage models, similar to those applied to ambulance base locations, have been developed for the optimal location of public access AEDs (Chan et al., 2013, 2016) and for base locations for drone delivery of AEDs (Boutilier et al., 2017; Claesson et al., 2016; Pulver et al., 2016). Monte Carlo simulation models have been used to predict the performance of mobile responder cardiac arrest response (Marshall et al., 2006), and phone app based community responder systems for other medical conditions (Khalemsky & Schwartz, 2017). This work is either system specific, or location specific, lacking the ability to compare a diversity of systems operating in a specific location, or the flexibility to extend the model beyond the region of interest. These models also make some simplifications which could affect their predictive accuracy, such as neglecting the true distance required to travel in a road network, or the effects of reliability and availability of both machines and humans within the model.

2. Conceptual approach to cardiac arrest response simulation

Cardiac arrest survival is strongly correlated with the time-to-CPR treatment and the time-to-defibrillation. Our approach to predicting survival is to simulate these response times for various types of response systems. The cardiac arrest response time depends upon three primary factors: (1) the distance from the responding agent to the cardiac arrest location; (2) the velocity at which the responder travels to the location; and (3) additional system factors to account for non-transit time in the response. Our model concept simulates the transit distance using a 2-dimensional geographical space, applies a specific velocity for each type of transit mode, and uses average times for system factors. Out-of-hospital cardiac arrests are unpredictable events that can be represented by random locations within the geographical space. Although the origin locations of responding ambulances or drones are fixed, the locations of mobile responders at the time of the arrest are not predictable and can be represented by random locations. Although, generally,
the closest responder would have the shortest response time, that responder may be unavailable at the time of that event, so the next closest available responder is required. The influence diagram in Figure 1 depicts the relationship between these factors and how they are applied to predict survival.

We developed a flexible predictive model, conceptually based on the influence diagram in Figure 1, which can simulate response times to cardiac arrest events for different types of emergency response systems across a diverse set of regional attributes. The model applies a geo-spatial sampling approach to generate the cardiac arrest locations as well as the random origin locations of any responding agents (mobile responders). Responding agents with fixed origin locations i.e. ambulances and drones, are specified as model inputs.

The distance from these locations to the cardiac arrest location is influenced by the number of bases, as well as their specific locations. In contrast, mobile responders are randomly located at the time of the arrest. The likelihood of having proximate responders to the cardiac arrest is dependent on their density in the region, as well as how they are distributed throughout the region. Their distance to the cardiac arrest also dictates their transit mode. If the location is very close, e.g. within 150 meters, the responder would walk, whereas for greater distances they would choose to drive.

The model stochastically determines the availability of each responding agent within each system, based on operational availability and reliability factor inputs. Weather conditions are a factor which dictates the operation of the entire drone response system. Cardiac arrest events during non-permissible weather conditions rely on other responses, such as EMS.

Due to the variability in cardiac arrest response times from random locations and stochastic availability factors, we used Monte Carlo simulation to simulate a large number of cardiac arrest events, with the distribution of response times and survival likelihoods describing the macro-scale performance of the system. Summary statistics (mean, median, percentiles) are then used describe system performance.

The response times and survival rates are essentially functions of these random inputs. Because the time between different cardiac arrest events is large relative to the response time, the events can be seen as independent. Thus, our primary modeling concern was to propagate the variability in the random inputs to determine the variability in the response time and survival rate outputs, which suggested a Monte Carlo simulation approach instead of a discrete-event simulation approach.

2.1. Description of simulation logic and algorithm

2.1.1. Global parameter definition

Our model uses latitude and longitude coordinates (WGS84 Coordinate System) to define the region and specific location attributes. A simulation region boundary is defined by providing the northwest and southeast corner coordinates \((x_{NW}, y_{NW}, x_{SE}, y_{SE})\). The origin locations of fixed located responding agents, such as ambulance base locations \((E_i)\) or drone base locations \((D_i)\), are provided as model inputs. Additional global parameters include the number of mobile responders within a region \((N)\), the ambulance availability factor \((A_E)\), the mobile responder reliability \((A_R)\), the AED reliability \((A_{AED})\), the drone operational availability \((A_{DO})\), and the weather related flight availability \((A_{DW})\).
2.1.2. Generating cardiac arrest locations and responding agents locations

For each simulated event, the cardiac arrest location coordinates \((x_1, x_2)\) are generated from a bivariate distribution, with random samples providing the location’s latitude and longitude coordinates. The model can accommodate any finite, bivariate distribution. Ideally, the bivariate distribution would reflect the probability of future locations, which may correlate to population density. For the study described in this paper, we chose Beta distributions because they are finite and provide flexibility in simulating the distribution of cardiac arrests throughout the region, with a Beta \([1, 1]\) bivariate distribution providing a uniform geo-spatial sampling distribution. Other Beta distribution parameters can be used to simulate non-uniform distributions (Figure 2).

The coordinates \((y_{i1}, y_{i2})\) for each of the \(N\) mobile responders within the region are also sampled from a bivariate Beta distribution that may be different from the distribution for the cardiac arrest location. For example, this may be useful for modeling a region in which responders tend to aggregate in a city center while cardiac arrests tend to occur in that city’s suburbs.

2.1.3. Transit distance and time estimation

The transit distance from the responding agent’s origin to the cardiac arrest location depends upon the mode of transit. A responder who drives must follow the road network, a responder who walks can take a nearly direct route, and a responder that flies will take a direct route. To determine driving distance, our model can query the road network distance from the Google Maps API. Unfortunately, for a large number of simulations, with many responding agents, this approach requires excessive computational effort.

To achieve an operationally efficient model, we developed an approximation approach to the Google Maps road network distance using a Minkowski distance (Figure 3). This distance is a generalization of Euclidean and Manhattan distances, defined by the order value \(p\) in a space of dimension \(n\) (Rabe & Tietze, 2017; Shahid et al., 2009). The model uses the following two-dimensional version to estimate \(D_i\), the distance from responder \(i\) to the cardiac arrest location:

\[
D_i = \left( |x_1 - y_{i1}|^p + |x_2 - y_{i2}|^p \right)^{1/p}
\]  

(1)

The order value \(p\) must be tuned for the region’s road network. For the study described in this paper, we created a training set of randomly generated origin-destination coordinate pairs within the region (Bellevue, Washington). For each pair, we collected the driving distance from Google Maps and the Minkowski approximated distance for different values of \(p\). The value of \(p\) that minimized the Root Mean Squared Error (RMSE) over the entire training set was selected as the optimal value to approximate driving distances within the specific region (Figure 4). A separate validation set was created to evaluate the accuracy of the approximation. The method was applied to a variety of regions, with typical \(p\) values being 0.7 to 1.0, which is slightly longer than the Manhattan distance.

Responders who walk to the cardiac arrest location were assigned a Minkowski distance order of 1.8, which corresponds to a route that is nearly straight but navigates around obstacles on the route. The Euclidean distance, i.e. straight line of travel, was assumed for drone air travel.

There are three types of responders: (1) EMS, (2) drones, and (3) mobile responders. Consider a responder \(i\) of type \(j\); that is, \(i \in R_j\). The components of the response time are the responder’s travel time and \(C_j\), the fixed non-travel time for a responder of type \(j\). Let \(v_j\) be the speed of any responder of type \(j\). The response time \(t_i\) for responder \(i\) is the sum of these two times:

\[
t_i = \frac{D_i}{v_j} + C_j
\]

(2)

For each type of responder, the model determines the specific responder that will arrive first and determines the
The system response time is determined for the two types of cardiac arrest therapy. The CPR response time is the minimum of all responding agents capable of providing CPR. This includes mobile responders and EMS.

\[
t_{\text{CPR}} = \min\{t_E, t_B\} \tag{6}
\]

The time to defibrillation is the minimum time at which there is a defibrillator at the scene and a person to operate the defibrillator. The structure of this is dependent on assumptions in the modeled system. A system with mobile responders carrying AEDs, together with the EMS system follows a similar formula for CPR response time:

\[
t_{\text{defib}} = \min\{t_E, t_B\} \tag{7}
\]

A system which uses a drone delivered AED, and requires a cell phone dispatched mobile responder to operate it, together with the EMS response, follows the equation:

\[
t_{E} = \min\{t : i \in R_1\} \quad \text{(EMS)} \tag{3}
\]

\[
t_{D} = \min\{t : i \in R_2\} \quad \text{(drones)} \tag{4}
\]

\[
t_{B} = \min\{t : i \in R_3\} \quad \text{(mobile responders)} \tag{5}
\]

Figure 3. Google Maps image showing the road network distance, Euclidean distance (solid line), Manhattan distance (large dashed line), and optimized Minkowski approximation with \( p = 1.2 \) (small dashed line).
2.1.4. Survival prediction

For each simulated cardiac arrest event, the model estimates \( t_{\text{CPR}} \), the time-to-CPR, and \( t_{\text{defib}} \), time-to-defibrillation. The model can represent responders that can provide only CPR, such as the PulsePoint system, or both CPR and defibrillation. Several studies have provided survival predictions based on these response times (Larsen et al., 1993).

Valenzuela et al. developed a logistic regression survival prediction model (Valenzuela et al., 1997) in which \( P_s \), the probability of survival, is a function of the quantity \( L \):

\[
L = 0.26 - 0.106 \ t_{\text{CPR}} - 0.139 \ t_{\text{defib}}
\]

Our model uses this equation to predict the survival probability for each cardiac arrest event.

\[
P_s = \frac{e^L}{e^L + 1}
\]

2.2. Model logic, implementation, and mathematical operations

We used Microsoft Excel with the Oracle Crystal Ball add-in to implement the model in a spreadsheet. Crystal Ball was used to sample the random inputs and record the responses of the Monte Carlo simulations. Although a Visual Basic script was used initially to query distances between locations from the Google Maps API, we replaced this with the Minkowski road network approximation. Ambulance velocity was determined as 70 km/h using regression analysis of response time and distance data collected by the Bellevue Fire Department. Similar ambulance speeds are reported in simulation modeling of similar sized cities (Ingolfsson et al., 2003). The system response time constants for EMS include (1) the interval from the 911 call to dispatch, (2) the chute time (interval from dispatch to ambulance “wheels rolling”), and (3) time from arrival at the arrest location until patient treatment is started. The dispatch time and chute time together amount to 3.5 min, which was determined empirically from the Bellevue response time data. The time from arrival until treatment is assumed to be 1 min, a value used in published survival models (Larsen et al., 1993).

A stochastic factor is used to determine the availability of each ambulance for each simulation run. The availability \( A_E \) factor was assumed as 76%, a value reported as typical in literature (Powers, 2016). The EMS response time is determined by taking the minimum response time from all available ambulances.

2.2.1. EMS response time prediction

The EMS response time is predicted for all ambulances within the region using Equation (2). The transit distance for each ambulance is calculated using the Minkowski road network approximation. Ambulance velocity was determined as 70 km/h using regression analysis of response time and distance data collected by the Bellevue Fire Department. Similar ambulance speeds are reported in simulation modeling of similar sized cities (Ingolfsson et al., 2003). The system response time constants for EMS include (1) the interval from the 911 call to dispatch, (2) the chute time (interval from dispatch to ambulance “wheels rolling”), and (3) time from arrival at the arrest location until patient treatment is started. The dispatch time and chute time together amount to 3.5 min, which was determined empirically from the Bellevue response time data. The time from arrival until treatment is assumed to be 1 min, a value used in published survival models (Larsen et al., 1993).

A stochastic factor is used to determine the availability of each ambulance for each simulation run. The availability \( A_E \) factor was assumed as 76%, a value reported as typical in literature (Powers, 2016). The EMS response time is determined by taking the minimum response time from all available ambulances.

2.2.2. Mobile responder time prediction

Mobile responder time predictions also apply Equation (2), but, for each of the \( N \) responders, two possible response times are calculated; one assuming the responder walks to the location, a second assuming the responder drives. The walking velocity assumes a brisk walk of 7 km/h, while the driving velocity assumes an average suburban road velocity of 32 km/h (which includes time at stoplights). Additional
system time constants include a 1 min interval from 911 to cell phone alert activation, and an additional delay time from the alert activation until the start of transit (0.75 min was used when walking to the arrest location, and 1 min when driving). This delay may also include any delay from receiving an alert to accepting it. A responder reliability factor \( (A_R) \) of 30% was used, with each mobile responder’s availability stochastically determined for each cardiac arrest event. The reliability factor was obtained from an ongoing trial of a mobile responder system utilizing off-duty firefighters across five EMS districts in the United States.

The response time for each available mobile responder is then determined by the minimum of the calculated walking and driving response times. This approach presumes that the responder takes the optimal mode of transit to the cardiac arrest location.

### 2.2.3. Drone AED delivery time prediction

Drone response events likewise apply Equation (2), with the velocity of drone assumed at 100 km/h, a plausible value determined from review of performance specifications for commercial drones capable of carrying an AED size payload. The additional system constants in the drone time estimate account for the dispatch time (1 min), the vertical ascent time (0.5 min), the descent time, including AED deployment (1 min), and an additional 1 min from arrival until the start of treatment.

The availability of each drone in the system is determined by two factors. The operational availability \( A_{DO} \) accounts for the proportion of time a drone may be out on another call, or out of service for maintenance. Operational availability is stochastically determined for each drone independently for each cardiac arrest event. Weather availability \( A_{DW} \) is a factor that accounts for the proportion of time which the weather is conducive to drone flight. This is applied stochastically to the entire system of drones for each simulation. Thus, when a single drone is unavailable, the next closest available drone is used. However, no drones are available to respond when there are restrictive weather conditions.

![Diagram depicting model execution with EMS, mobile responders, and a drone response. Crossed out responders represent those that are stochastically determined as unable to respond.](image)
2.2.4. Survival prediction with multiple concurrent response systems

As previously discussed, these novel response systems augment the existing EMS ambulance response system. Thus, for each simulated cardiac arrest there occurs a parallel response, and the shorter response time determines the global system response time. Systems that provide only CPR (not defibrillation therapy), such as the Pulse Point system, could result in different response times for CPR and defibrillation. The minimum response time for each therapy provides the inputs to the survival logistic regression model, shown as Equation (3).

We present a brief description of the simulation algorithm with the following sequence of steps. Figure 5 provides a graphical view of the simulation region and responding agents.

1. Simulation run initialization. EMS responders (i.e. ambulances) and drones start at their input base locations $E_i$ and $D_i$.

2. A random latitude and longitude location $(x_1, x_2)$ is assigned for the cardiac arrest based on the geo-spatial input distribution within the region defined by $x_{NW}$, $y_{NW}$, $x_{SE}$, $y_{SE}$.

3. Random locations $(y_{i1}, y_{i2})$ are assigned for each of $i=1$ to $N$ mobile responders sampled from the responder geo-spatial distribution.

4. For each mobile responder, the model stochastically determines if they are “able and willing to respond” based on the responder reliability input $A_{RE}$.

5. The travel distance $d_i$ is calculated for each available mobile responder for both the walking and driving distance.

6. The response time $t_B$ is calculated for the 3 closest mobile responders using the minimum of the walking and driving transit times.

7. The operational state of the AED of each responder is stochastically determined based on the AED reliability input $A_{AED}$. The mobile responder time-to-CPR is defined by the first arrival, the time-to-defibrillation is defined by the first arrival with an operational AED.

8. For each EMS ambulance $E_i$, the model stochastically determines if it is available based on the ambulance availability input $A_{AE}$.

9. The travel distance $d_i$ is calculated for each available ambulance. The closest available ambulance is determined.

10. The response time $t_E$ is calculated for the closest available ambulance.

11. For each drone $D_i$, the model stochastically determines if it is available based on the drone operational availability input $A_{DO}$ and the drone weather availability input $A_{DW}$.

12. The travel distance $d_i$ is calculated for each available drone. The closest available drone is determined.

13. The response time $t_D$ is calculated for the closest available drone.

14. Response time-to-CPR is calculated; this equals the minimum of all agents’ response times.

15. Response time-to-defibrillation is calculated; this equals the minimum time from all agents capable of providing defibrillation.

16. The survival probability prediction is calculated using Equation (9).

17. The model output values are stored, and the model is returned to initialization step 1 for the next simulation.
Figure 7. Comparison of systems for (a) time-to-defibrillation distribution and (b) survival distribution. The marker indicates the mean predicted survival probability. The interval bar indicates the 5th and 95th percentiles of the predicted distribution.
repeating the process until all simulations are complete.

2.3. Model validation

Simulating novel response systems presents challenges for validating the predictive ability of the model. Although EMS response has significant history and data, and PulsePoint has been active for nearly 10 years, the remaining systems are in early-stage pilot studies and trials. Some are still concept proposals that have not yet been put into practice. As such, there is not sufficient data available from these systems to perform a global empirical validation of the model with concurrent responses from these systems. EMS response times were validated against available empirical data, while confidence in the novel systems simulation was built through a number of tests.

For our study of Bellevue, Washington, which is in King County, the King County Public Health department provided EMS response time statistics specific to cardiac arrest responses for the Bellevue Fire District. The mean and median response times were 4.9 and 4.8 min, respectively. Our simulations predicted a mean of 5.8 and a median of 5.6 min – the modest overestimation of actual response times. Figure 6 shows the validation distribution of EMS response times.

Sargent (2011) describes an iterative verification and validation process, consisting of conceptual model validation, computerized model verification, and operational validation. We employed this approach, using several validation techniques. Conceptual validation was accomplished through Face Validity, the review of the logic, relationships, and assumptions with domain experts. We reviewed the detailed conceptual model with emergency medicine experts who have experience directing emergency response systems and leading studies on mobile responder systems. Verification of the implementation employed (1) tracing of precedents and dependents in the model algorithm, (2) sensitivity analysis, (3) operational graphics, and (4) extreme value testing to assess the stability of the model over the entire range of inputs. The Operational Validation utilized Event Validity and Face Validity again. Although data were not available for an empirical validation of the global model responses, some specific events within the model could be validated with available data. We used this validation for the EMS response time in Bellevue, Washington, and the distribution of response times for a mobile responder network which involved both walk and driving responses. The domain experts provided valuable feedback on the model’s inputs and assumptions, and concluded that the model produced credible, well-grounded predictions that are suitable for the intended use.

3. Sensitivity analysis and factor experimentation

3.1. Methods

The city of Bellevue, Washington was chosen as an example region for the model experimentation presented here. We selected this region because we had access to EMS management and performance data. Bellevue, which is in King County, is a suburban city with a downtown core of with a few moderately tall buildings. This model application contains the five actual EMS ambulance stations located in the region, and the hypothetical drone bases were placed at the same locations as the ambulances.

Although the primary intended use of the simulation model is as a decision support tool, the objective of the model experimentation was to develop an understanding of how the system factors affect response times, such that these systems can be efficiently and effectively implemented. Our model incorporated a significant number of factors to predict response times and survival improvements. We used sensitivity analysis experiments to separate the highly influential factors from those with little effect. For factors that could be controlled, (e.g. dispatch delay times, drone ascension times), we chose the range of the analysis to represent the reasonable range under which a system may operate. For factors which are difficult to control, we applied a range of reasonable uncertainty within a specific system. For example, although drone weather availability may range from lower than 50% in harsh climates up to nearly 100% in others, we assumed the uncertainty of this factor within any specific climate would range as much as 10%.

After we identified the strongest factors from the sensitivity analysis, we selected five of these and ran a response surface design of experiments (DOE) to provide a deeper analysis of their effects. The DOE was structured using a central composite half factorial design so that it could identify non-linear model responses and main effect interactions. We used Analysis of Variance (ANOVA) and backward elimination stepwise regression with a p-value of 0.05 to identify significant factors and interactions.

3.2. Results and discussion

The experiments identified both factors that had a significant effect on the response and, also importantly, those with
little effect, for which the model is robust to variation. These findings are important when seeking to improve the predictive accuracy of the model or for identifying strategies that can improve system performance. Table 1 provides the range of each input setting used in the sensitivity analysis, as well as the R² value from ANOVA on the sensitivity response data. The R² value indicates the percentage of variation in the time-to-defibrillation distribution that is explained by each factor.

The sensitivity analysis identified the time between the 911 call and the dispatch of the responding agents as having significant effect on response time. This effect of this system specific constant is especially applicable to the drone response time, where this dispatch delay can constitute a significant portion of the overall response time. This insight provides motivation for a dispatch strategy that quickly dispatches the drone, such as immediately upon determination of a medical emergency call, even though the drone may be recalled upon determination that the call is not a cardiac arrest.

The sensitivity analysis also indicated factors for which the model is robust to error. The model is tolerant to moderate error in the regional and geospatial characteristics of a system. The Minkowski distance metric, used to approximate the road network distance, is robust to small errors in the selection of the optimum p value for a region. Similarly, the model is robust to uncertainty in the underlying spatial distributions of the cardiac arrest locations and mobile responder locations. Assuming a uniform distribution for both the cardiac arrest locations and the mobile responder distribution will result in only small predictive errors in the mean and 95th percentile response times even if the actual distributions are not uniform. The exception to this is that the model may underestimate the magnitude of the longest response times (i.e. upper tail of the distribution) in cases where the true mobile responder distribution is highly skewed or clustered.

It is intuitive that a higher density of mobile responders in the region, or a larger number of drones spatially distributed across the region, will decrease response times and improve survival rates. As the density of responders increases, the average distance of the closest responder to the cardiac arrest location decreases. Our results confirmed this effect but also revealed a non-linear relationship, indicating a range of preferable densities that a system should target. Below 2 responders per sq. km, the system has little measurable improvement over the baseline EMS response. Above this density, increasing the density reduces mean response time. Above 7 responders per sq. km, improvements continue, but with diminishing returns. The simulations showed notable differences in improvements between the mean response time and the 95th percentile of the distribution. Higher densities of responders resulted in both a decreased mean and reduced variance in the response times. Thus, while providing an overall benefit, the greatest benefit is the reduction in very long response times, which are those cases with very little chance of survival. The simulations demonstrated that improving the reliability of responders has the same effect as increasing the responder density. Thus, technological or motivational reliability improvements may be more economical than simply recruiting additional responders into a system.

Similarly, the response surface experiment showed that the number of drones within a region has a non-linear effect on response time. This is due to not only the improved spatial proximity to the cardiac arrest, but also the improved redundancy to unavailable drones. Due to the operational availability of drones, the greatest benefit is realized when the number of drones is increased from one to two, with additional marginal improvements as more drones are added. This suggests that any drone system should be equipped with at least two drones, regardless of the size of the region.

4. Example application of model

To illustrate the application of the model, we simulated the existing EMS system and four different types of response systems using the city of Bellevue, Washington as an example region. We chose systems that covered a range of both existing and proposed response concepts:

a. PulsePoint: a mobile responder system that uses a network of citizen volunteers to provide CPR;
b. ALERT: a derivative of PulsePoint that utilizes off-duty firefighters to provide CPR and defibrillations with an AED;
c. Drone-bystander use: a drone delivers an AED to the cardiac arrest location, and a bystander applies the AED to the cardiac arrest victim; and
d. Drone-mobile responder: a system that uses a drone to deliver the AED to the cardiac arrest location and dispatches mobile responders to apply the AED.

We simulated each system under several operational conditions. The systems utilizing mobile responders were simulated with 80, 200, and 320 responders (densities of 2 per sq. km, 5 per sq. km, and 8 per sq. km). The systems utilizing drone AED delivery considered the use of 1, 2, or 5 drones. The resulting time to defibrillation response distributions and survival distributions were compared to the simulated performance of the existing EMS only response. Figure 7 shows the mean, 5th, and 95th percentiles from the response distributions from 5,000 runs of the model.

The simulation results indicate that, in this case, the addition of these systems to an EMS response can improve both response time and survival rates, increasing the baseline EMS survival rate of 20% incrementally up to 30%. (The accuracy of these predictions depends upon whether appropriate input values were used and the influence of those factors, as discussed in Section 3.2.) The ALERT system and the drone-bystander use system achieve the greatest response time and survival improvements under the conditions of the simulation. The drone-mobile responder system provides a substantial improvement over EMS alone but suffers relative to other systems from the need for both the drone and
mobile responder to reach the cardiac arrest location before therapy is started. This system, however, has advantages over the ALERT and drone–bystander use because the mobile responders are not required to carry AEDs at all times, and the AED is always retrieved and applied by a trained responder.

5. Conclusions

Public health officials are searching for ways to improve survival from sudden cardiac arrest within their communities. With a diversity of novel response concepts proposed and piloted, but little conclusive data to date on the effectiveness of these systems, simulation modeling can be valuable tool to inform these decisions. Our model, which can be tailored to the specific attributes of a region, predicts response time and survival rates and supports the comparison of different types of response systems, as well as multiple system condition assumptions. Although we have focused on the model predictions of response time and survival here, when combined with cost models associated with each system, this provides for a cost-benefit analysis to support resource allocation decisions by public health officials.

5.1. Limitations of approach

The results presented in this paper are based on our model of a single region, with specific regional factors such as the road network distance approximation (Minkowski distance p value), EMS base locations, and EMS system constants, and weather conditions affecting drone flight. As neither mobile responder systems nor drone response systems currently exist within the Bellevue region, some of the model's input values (such as delay times before transit and drone and vehicle velocities) are estimates. As Section 3.2 discussed, some factors (inputs) have little impact on the response times (so inaccuracies are not critical to prediction accuracy), but incorrect values in the factors that have more impact make it more likely that the predictions are inaccurate. Clearly, changing the values of the inputs will affect the predictions of response times and survival improvements, and predictions based on uncertain input values must be considered uncertain. In addition, including other modes of transportation, such as bicycling, may change response times.

The Minkowski distance approximation works well in regions with consistent, relatively homogenous road networks. Geographic obstacles, such as lakes, rivers, and mountains, could result in loss of accuracy of the distance approximation. In such regions, using the Google Maps API or a similar road network routing algorithm would provide more accurate predictions.

The validation approach used multiple methods to compensate for the lack of available data for a global empirical validation. As such, the predictive accuracy of the simulations cannot be quantified. As real data becomes available from real world studies of these systems, an empirical validation would further support the credibility of the modeling approach.

5.2. Future work

Our model could be further enhanced to incorporate additional factors which influence survival rates in a community. These include the possibility of bystanders performing CPR, resulting in very short time-to-CPR responses, or the possibility of a public access AED being used on a cardiac arrest victim. Additionally, the use of a road network distance algorithm provides improved fidelity, particularly in regions with geographic obstacles. Although using a cloud-based routing engine, such as the Google Maps API, proved computationally inefficient for Monte Carlo simulations, implementing a local algorithm could reduce the computational effort.

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References


