ORIE 4580/5580: Simulation Modeling & Analysis

A Volunteer Dispatch Policy for Out-of-Hospital Cardiac Arrests

Julia VanPutte [NetID: jhv42, Class: **4580**] jhv42@cornell.edu
Rafael Chaves [NetID: rvc29, Class: **4580**] rvc29@cornell.edu
Tara Khanna [NetID: tmk82, Class: **5580**] tmk82@cornell.edu
Gloria Zhang [NetID: gyz2, Class: **5580**] gyz2@cornell.edu
Nick Kunz [NetID: nhk37, Class: **5580**] nhk37@cornell.edu

December 9, 2022

Executive Summary

An Out-of-Hospital Cardiac Arrest (OHCA) requires urgent medical attention. OHCAs are one of the most serious medical emergencies, as patients require both cardiopulmonary resuscitation (CPR) and automatic external defilbulation (AED) within minutes to survive. Survival rates generally average around 7%. As the time the patient does not receive emergency medical treatment increases, the likelihood of a fatal outcome increases.

An emergency alert system has been established, which notifies volunteers to respond to an OHCA via their mobile device. Volunteers are mostly off-duty healthcare professionals such as nurses, paramedics, or anyone with CPR training. They are dispatched according to their geographic proximity to a OHCA location. After an alert has been sent, volunteers decide whether or not to respond. In the case that they agree to respond, they travel to the OHCA location and conduct CPR until an ambulance arrives.

This study proposes a volunteer emergency dispatch policy to maximize the chance that a patient survives the event of an OHCA, while minimizing the number of alerted volunteers for each OHCA. We estimated that the probability an alerted volunteer would agree to respond or will attend an OHCA event was 39.2%. We found that the optimal number of alerted volunteers to an OHCA event that were likely to arrive before an ambulance was 7, when there were 12,000 total volunteers in the system.

Therefore, our emergency dispatch policy recommends that the 7 nearest volunteers are alerted to any given OHCA. In the case that 7 volunteers were notified, the average chance that a patient survived increased by 11.1% when compared to the case where there were no volunteers. Additionally, the average survival rate for patients when alerting 7 volunteers was 17.8%. When compared to the case where every volunteer was alerted, the average survival rate was 18.1%. The recommended dispatch policy reduces the number of alerted volunteers, while marginally reducing survival rates by 0.3% or about 3 patients for every 1,000 people, when compared to alerting all volunteers.

We also discovered that the probability of a volunteer responding had a proportionate effect related to the number of alerted volunteers. In other words, the chances of a OHCA patient surviving were roughly equal given the same change in either case where the probability of a volunteer agreed to respond increased or the number of alerted volunteers increased. What this means is that if fewer volunteers agree to respond, more volunteers are needed. It should be noted that the alert sent to volunteers should encourage them to accept to respond, so that a fewer number of volunteers are required within the total network of volunteers.

1 Problem Description

An Out-of-Hospital Cardiac Arrest (OHCA) is a potentially fatal medical emergency where the heart enters an atypical rhythm due to blood flow being restricted from the heart. Minimizing the time until medical attention can be rendered is especially important in the event of an OHCA, as the patient survival rate drops precipitously as the emergency response time increases.

There are two primary ways that OHCA events are treated, they are: 1) an automatic external defilbulator (AED), and 2) cardiopulmonary resuscitation (CPR). Treatment involves both CPR and AED, and must be rendered within minutes in order to exhibit a material increase in patient survivability. Although an ambulance service can perform both AED and CPR, it can take upwards of 10 mins for an ambulance to arrive to the OHCA location.

Therefore, in order to reduce the time between when an OHCA occurs and when emergency medical attention can be rendered, a volunteer system has been established, where volunteers are alerted of the OHCA on their mobile device and elect whether or not to respond. Again, volunteers are typically off-duty healthcare professionals such as nurses, paramedics, etc. and are notified according to their geographic proximity to the location of the OHCA.

The goal of this study is to design an optimal emergency volunteer dispatch policy, such that the number of alerted volunteers is minimized, while maintaining substantively similar patient survival rates. The policy seeks to minimize the effect of alerting too many volunteers and therefore crowding the scene of the OHCA and increasing that chances that volunteers will not respond in the future. Volunteer response rates are critical, as they must remain high to increase the chances that a patient will survive a OHCA.

When an OHCA happens, we define the process as such:

1. A patient experiences an OHCA and either themselves or a bystander calls 911.
2. The dispatcher at the 911 call center determines that the emergency is an OHCA and alerts the closest ambulance and activates the system to alert volunteers.
3. The system determines if any volunteers are within a 1 km radius of the patient. If so, the system alerts 7 of the closest volunteers.
4. Volunteers then decide whether they will attend. If they choose to attend, the volunteer will walk to the OHCA after either responding to the alert with an acceptance or just walking straight to the scene. If they do not choose to attend, they will either not respond or respond with a denial.
5. When the first volunteer arrives, they initiate CPR and defibrillation if they have an AED, although this is rare. Other volunteers may arrive at the scene.
6. The ambulance arrives and renders patient care. Volunteers leave the scene.

Taking this into consideration, we built a simulation model of the OHCA events, volunteer alert system, emergency dispatch policy, and tested it under various conditions. We identified the optimal number of volunteers to alert based on the criteria outlined in following sections.

2 Data Analysis

As a precedent to our model, we conducted the following analyses to guide our simulation. Considering the data taken from a similar city that established a similar volunteer alert system, we analyzed their observations over a 15-year time-horizon.

2.1 Patient Locations

The patient locations were modeled in order to generate OHCA event locations. OHCA event locations were generated with a random point process (Poisson) based on the historical data of OHCA emergencies in the city. This data was important for determining both volunteer locations and OHCA locations, since OHCA locations generally represent population density.

2.2 Volunteer Response Agreement

The volunteer response agreement was modeled to estimate whether or not a volunteer would agree to respond to an OHCA event after they have been notified of one. The volunteer response agree was modeled using our precedent, which indicated the proportion of volunteers that agreed to respond was 36.2%.

Roughly 19.9% of the volunteers do not respond to the alert, of which it was estimated that about 2.985% of the time they still arrive at the scene. We applied this proportion to estimate the probability that the alerted volunteers would agree to respond to the OHCA event, which was 39.2%.

Although data from a comparable city was useful, we recommend that the new volunteer emergency dispatch policy is reviewed based on the city's observed volunteer response rate.

2.3 Volunteer Response Time

The volunteer response time was modeled to estimate the delay between the time between an OHCA event and the calling of emergency services and the time a volunteer arrives at the patient's location. This includes both the time it takes for the volunteer to travel to the patient's location and the overall delay prior to travel. There are three time intervals nested in this regard, they are:

1. **Dispatch Delay**

   Dispatch Delay is the time between an OHCA event and the alert delivered to the volunteer's mobile device. Given the provided information regarding emergency dispatch procedures, this delay is typically 2.5 minutes with a minimum of 1.5 and a maximum of 3.5 minutes. We used this information to create a simple distribution model based on most likely occurrence.

2. **Acceptance Delay**

   Acceptance Delay is the time between the volunteer dispatch and start of travel. To model the Acceptance Delay, we utilized data from a similar city that has already instituted a similar volunteer policy for responding to OHCA's. We found that the Volunteer takes on average 45 seconds to respond to the alert based on over 11,000 OHCA's from a similar city. This varies based on a Gamma probability distribution and incorporated this randomness into our analysis.

3. **Travel Delay**

   Travel Delay is the time between the start of travel and arrival to the patient location. To model the Travel Delay, we assumed that volunteers walk to the scene at the rate of 6km/h. We simplified our model by not taking buildings or other obstacles into account. Additionally, we require that volunteers are not allowed to drive to the scene. This is because it is possible that a volunteer might make poor judgements while driving and increase the chances of an additional emergency.

These three time intervals represent the total time from the OHCA and the emergency call to 911, until to the volunteer arrives at the OHCA location.

2.4 Ambulance Dispatch Delay

The ambulance dispatch delay is defined to be the time between an OHCA event and the dispatch of a nearby ambulance. In our model, we assume that a 911 dispatcher calls an ambulance to the scene at the same time that they send a notification into the volunteer system. Thus, we used the same distribution for this as for the volunteer dispatch delay.

2.5 Ambulance Response Time

The time between the OHCA event and the ambulance arriving at the scene is defined as ambulance response time. This is the sum of ambulance dispatch time and ambulance travel time. The ambulance travel time was modeled to estimate the time from when the ambulance is dispatched to the time that it arrives to the location of the OHCA. This data modeling was performed on OHCA data from historical data over the last 15 years from a comparable city. It was concluded that it typically takes around 7 minutes for the ambulance to drive to the scene of the OHCA. We fit a lognormal probability distribution in this regard.

3 Modeling Assumptions

There were two broad categories of assumptions made in this study. The first were our primary considerations. The second was existing estimations of whether or not a patient would survive a OHCA, given when CPR is initiated and the time when AED is initiated.

3.1 Primary Considerations

The following modeling assumptions were made:

1. The geocoordinates were projected in the WGS84 reference system. This allowed us to account for the curvature of the earth using longitude and latitude, and computing the haversine distance between points.

2. Volunteers travel to OHCA locations at an effective rate of 6km/hr. We assume that all volunteers walk to OHCA locations and that their direction of travel is a straight-line, unaffected by obstacles such as buildings, barricades, etc.

3. Response delay was taken into account for volunteers that attend the OHCA but do not respond to the alert. We assume that volunteers will have a similar delay between the time of the alert and the departure of their current location. This fraction is 15% for those that do not respond to the alert.

4. There 12,000 volunteers in the system at operational capacity. We determined our model based on 12,000 volunteers which is the operational capacity goal for our locus. We consider fewer volunteers later in this report.

5. Only 1 OHCA event occurs at any given time and location. This is because it is extremely rare that two OHCA's would occur at the same time and call upon the same set of volunteers. Therefore, we neglect this complication from our model.

6. Volunteers do not respond to OHCA events with defibrillators. Although some volunteers can provide defibrillation, this is rare and is ignored in our model.

7. The historical data used to create our distributions are reasonable for this city. We assume that the city we have data for is similar enough to our city to model our proposed volunteer dispatch policy.

8. The probability a volunteer arrives to the scene is constant regardless of proximity. We acknowledge that if a volunteer is further away from the OHCA, there is a greater chance that they will decline the alert. Similarly, if a volunteer is very close to the OHCA, they will likely accept the alert. However, in order to simplify our analysis we assume constant probability for attendance regardless of proximity.

3.2 Patient Survival Rate

The probability that a patient survives has been estimated to be:

$$S(t_1, t_2) = (1 + e^{0.04+0.3t_1+0.14(t_2-t_1)})^{-1} \tag{1}$$

where:

$$t_1 = \text{time in minutes until CPR is initiated}$$
$$t_2 = \text{time in minutes until AED is initiated}$$

such that t_1 and t_2 are measured from the time of cardiac arrest to the time that treatment is initiated. We consider only volunteers that can arrive before the dispatched ambulance.

4 Modeling Verification

The accuracy of our model relies on reasonable simulations of patient and volunteer locations. Moreover, when comparing different policies, we compute the average survival rate based on the same OHCA and volunteer locations, response times, and dispatch times. This increases the precision of our comparisons between different numbers of volunteers alerted.

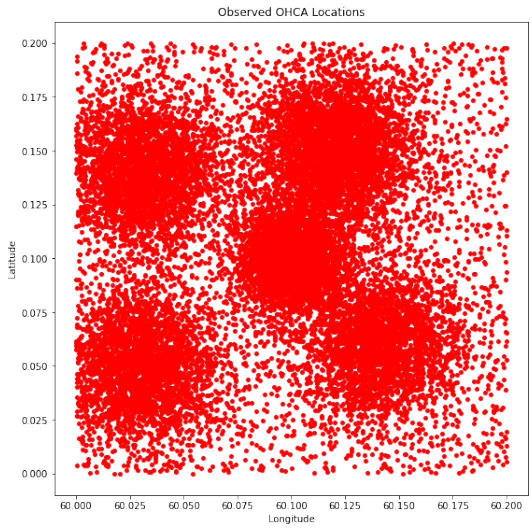
After establishing how to reasonably generate locations and response times, it is important to determine the lowest and highest average survival rates possible, regardless of policy. We used these benchmarks to assess the credibility and quality of recommended policies.

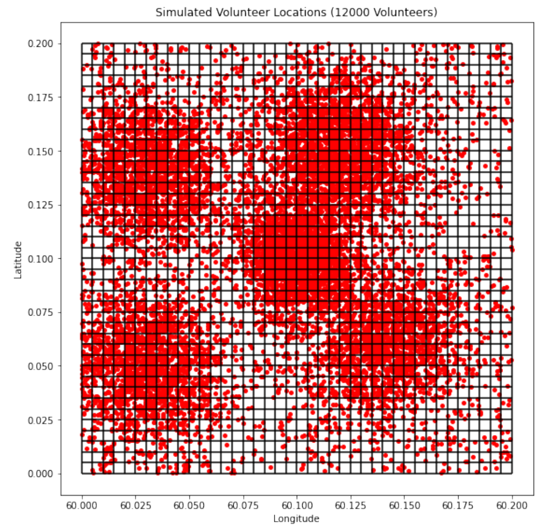
We determined the lowest average survival rate by simulating the scenario where we alert no volunteers. Conversely, we determined the highest possible average survival rate by simulating the scenario where we alert every volunteer after an OHCA.

4.1 OHCA and Volunteer Locations

As previously mentioned, we used historical data to simulate the location of OHCAs. Since we lack data regarding the position of volunteers, we used OHCA data to also simulate the location of volunteers. This approach is reasonable because areas with a high concentration of OHCAs likely align with densely populated regions. Therefore, we also expected to have a high number of volunteers in areas with many OHCA's.
The hypothetical volunteer locations were generated by partitioning the city into many square grids, and using the fraction of OHCA's that occurred in a particular grid to estimate the probability that a volunteer falls in that square.

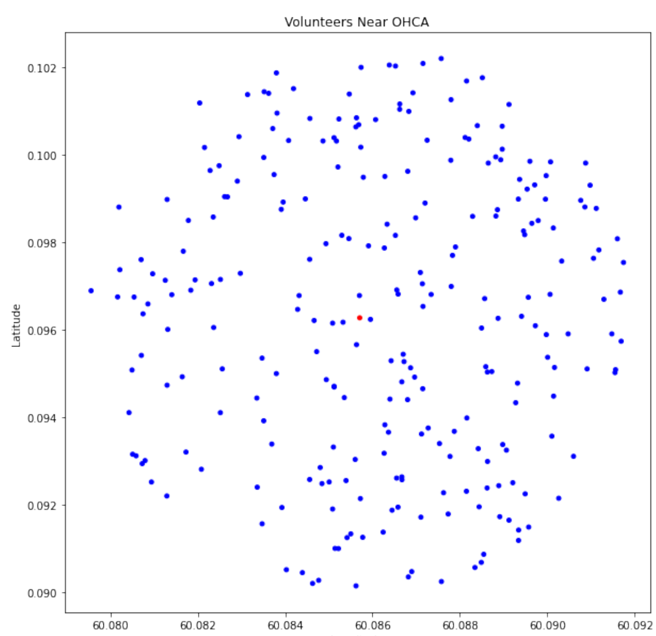
We assessed the accuracy of our volunteer and OHCA simulations by inspection in the following two figures, which illustrate the location of 12,000 hypothetical OHCA's (left) and 12,000 hypothetical volunteer locations (right). Since we used OHCA historical data over a 15-year time-horizon to generate the locations of OHCAs and volunteers, the figures bare visual similarity.





We expected several areas to have a high concentration of OHCA's and volunteers corresponding to locations within our city that have a high population density. As expected, the figures exhibit clusters with a high concentration of OHCA's and volunteers, which indicated that our simulation of OHCA locations were reasonable.

If a volunteer fails to arrive before the ambulance, ambulance personnel will initiate CPR and defibrillation. In this case, we assume the time until CPR and the time until the initiation of defibrillation to be equivalent. So only volunteers that arrive before the ambulance will impact the patient's survival. Therefore, upon generating an OHCA and an ambulance dispatch time, our model determines the number of volunteers who are in close proximity to the OHCA and generates their locations, instead of generating the locations of all volunteers. By only considering volunteers that are able to arrive before an ambulance, we are alerting less than 7 volunteers in some scenarios. Additionally, the generations of much less than 12,000 volunteers in each simulation replication improves the runtime of our code. The plot below illustrates the location of a randomly generated OHCA in blue. The red dots correspond to the location of volunteers who are likely to reach the patent before an ambulance. We see a "circle" centered at an OHCA, filled with volunteers. This plot suggests that given an OHCA, we are correctly generating volunteers in close proximity to the patient.



4.2 Using Common Random Numbers

For more accurate comparisons, we computed the average survival rate under different scenarios based on the same simulations of OHCA/volunteer locations, response times, and dispatch times. We used a different random stream for each source of uncertainty. That is, we used a different stream to generate OHCA locations, a different stream to generate volunteer locations, etc. In other words, we generated the same locations, response time, etc. every time we estimate the average survival rate under a different scenario.

4.3 Alerting No Volunteers

The survival rate of a single OHCA achieves a minimum when a volunteer fails to arrive before an ambulance. That is, for any OHCA, the survival rate will be lowest if we decide not to alert any volunteers. We simulated the average survival rate for an OHCA provided we alert no volunteers. With $1,000$ replications, we received the following results:

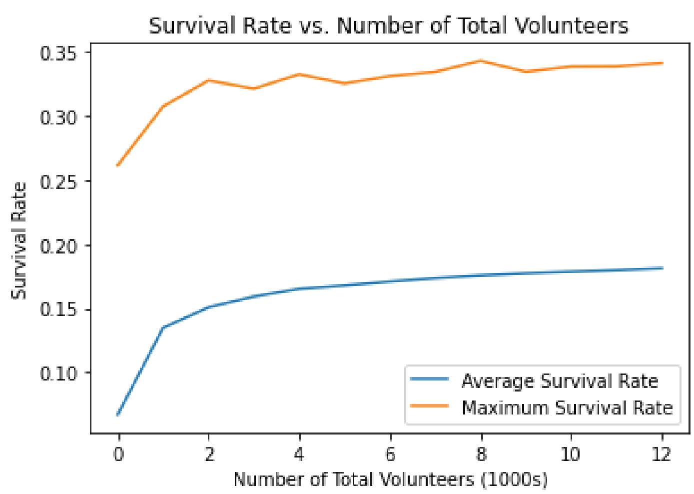
- **Average Survival Rate**: 6.7%, with a 95% confidence interval (CI) of $(0.064, 0.070)$
- **Maximum Survival Rate**: 26.2%

These results indicate that when testing different policies, we should expect to see an average survival rate of at least 6.7%. A lower average survival rate would suggest that our policy performs worse than the policy of alerting no volunteers and would be indicative of errors in our model.

4.4 Alerting all Volunteers

With any OHCA, a patient is more likely to survive if a volunteer arrives to the scene promptly. In order for a volunteer to arrive, we need to alert volunteers of the OHCA. Since volunteers can choose to decline, the more volunteers we alert, the higher chance we have of a volunteer reaching the patient. Therefore, the policy that achieves the highest average survival rate is to simply alert every volunteer in the system upon receiving an OHCA.

We determined the average survival rate with 1,000 replications each under a simulation with for $0 - 12,000$ total volunteers (in increments of 1,000). The figure below illustrates the average and maximum survival rate as we vary the number of total volunteers.

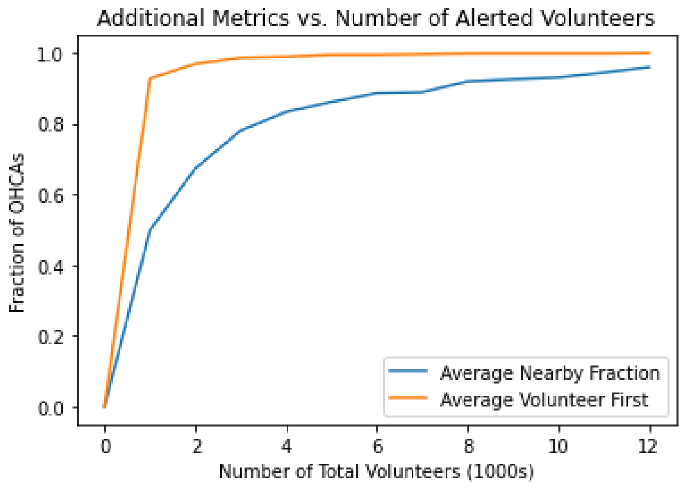


The average survival rate and maximum survival rate increases as we increase the total number of volunteers, achieving a maximum with 12,000 total volunteers. If average the mean survival rates across each number of total volunteers we get an average of 16%. We are primarily interested in the average survival rate with 9,000-12,000 total volunteers as 12,000 is the assumed eventual size of the volunteer network.

- **9,000 volunteers**: Average SR = 17.7% with 95% CI: $(0.174, 0.181)$, maximum SR = 33.5%.
- **12,000 volunteers**: Average SR = 18.1% with 95% CI: $(0.178, 0.185)$, maximum SR = 34.1%.

This implies that regardless of our policy, our average survival rate should not exceed 19%. If we see higher average survival rates after adjusting our model to implement different policies, we will know we have made an error. Moreover, these insights indicate that with our policy, we should aim to alert the fewest number of volunteers possible while keeping our average survival rate near 18%.

The figure below indicates the fraction of OHCA's where we had a volunteer arrive before the ambulance (volunteer first) and the fraction of OHCA's with a volunteer within 200 meters (nearby fraction).



With over 2,000 total volunteers we see that a volunteer arrives before the ambulance in approximately 90% of OHCA's (Average Volunteer First). Clearly, it is unnecessary to alert all volunteers of an OHCA to ensure one arrives before the ambulance. We also noted that with over 4,000 total volunteers, around 80% of OHCAs had a volunteer within 200 meters (Average Nearby Fraction). This suggests that we can achieve high survival rates by simply alerting volunteers in close proximity to an OHCA. Thus, in the following section, we focused on determining the optimal number of closest volunteers to alert for each OHCA, such that survival rates were substantively similar to alerting all volunteers.

5 Modeling Analysis

In order to determine the optimal number of nearby volunteers to alert, we developed a simulation model (see appendix) to generate an OHCA location within the city. The model randomly generates a time for the 911 officer to dispatch the ambulance. We computed the random time that the ambulance would take to get to the scene (t_2). Using this time, we generated volunteers within a fixed radius around the OHCA location. To generate volunteers, we only generated volunteers that could arrive before an ambulance (assuming they walk at 6km/hr) and are also less than 1km away from the OHCA location. This represented the portion of our recommendation where the model is used to only alert volunteers that could arrive at the scene before the ambulance, up to our recommended maximum 7 alerted volunteers within this radius.

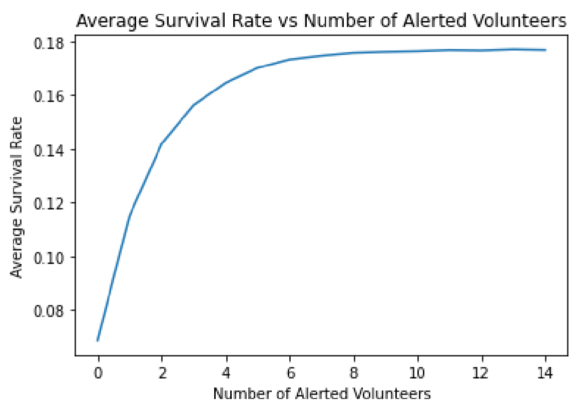
After generating volunteers around the OHCA location, we alerted up to 7 volunteers within this radius or if there are less that 7 volunteers that could arrive before the ambulance, we alert all within the radius. We then randomly generate a response delay for these volunteers and use our probability of volunteer attendance based on a similar city to determine if these volunteers will respond to the OHCA. For the alerted volunteers that choose to respond, we computed the travel time based on our assumed walking speed of volunteers of 6km/hr. We then compute t_1 for the time it took the first volunteer to arrive at the scene (dispatch time +

response delay + walking time).

Our model outputs various performance metrics to determine how many volunteers to alert. In order to determine the best model for this situation, we selected models that alerted 1,2,. . . ,20 of the closest volunteers that were within 1km and could arrive before the ambulance. We then evaluated these models based on the below discussed performance metrics and resulted in a policy of alerting the 7 closest volunteers to the OHCA that are within 1km and could arrive before the ambulance.

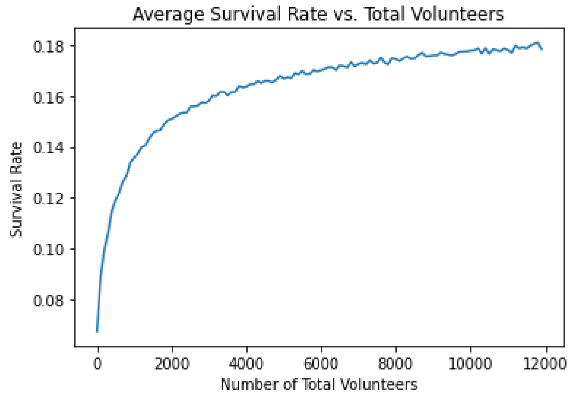
5.1 Performance Metrics

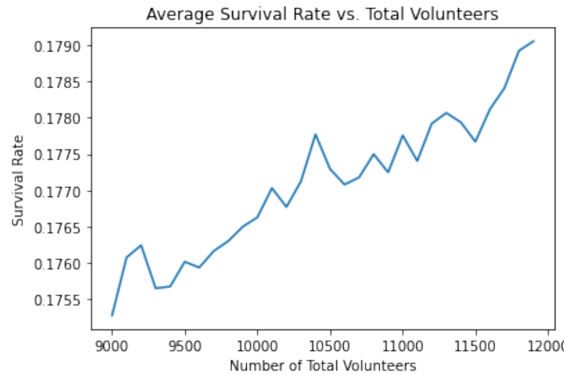
The figure below exhibits the average survival rate vs number of alerted volunteers for a simulation of 1,000 replications with 12,000 total volunteers in the system. The survival rate does not exhibit a material increase after 7 volunteers. Between alerting 6 and 7 volunteers, we observed an increased survival rate of 0.25% and between 7 and 8 alerted volunteers, the difference is only 0.08%. We elected to alert 7 volunteers because an increase in 0.25% on average corresponds to about 2.5 patients surviving out of 1,000 OHCA's. However, an increase in 0.08% only corresponds to 0.8 patients out of 1,000 surviving (on average). Thus, our specification of 7 volunteers was motivated by the average survival rate, based on our chosen significance level, which was substantively sufficient. Note that the average survival rate for 7 volunteers is 17.8% with a 95% CI of (0.174, 0.182).



Based on the analysis contained later in the sensitivity analysis section, further solidified alerting the 7 closest volunteers. With this policy, we observed that with 12,000 total volunteers, the average survival rate has a 95% likelihood of being in the interval $(0.174, 0.182)$. This was greater than the survival rate of $(0.064, 0.070)$ in the scenario where the volunteer system was not implemented. Finally, if every volunteer was notified, the survival rate was $(0.178, 0.185)$, which overlaps with the confidence interval of our proposed plan.

We also analyzed how the survival rate increased as more total volunteers were added to the system. We observed that the average survival rate for alerting the 7 closest volunteers, given the total volunteers in the system, focusing on the near full system of 9,000 to 12,000 volunteers, we observed a small increase in the survival rate linearly dependent on the number of total volunteers with the addition of noise from the model.





5.2 Additional Performance Metrics

Our model that alerts 7 volunteers of the total 12,000 volunteers in the system has the following additional performance metrics:

- **Average Number of Alerted Volunteers = 6.88**

  This describes the average number of alerted volunteers in the system. Note that this does not equal our proposed 7 alerted volunteers. When volunteers are alerted, only alerted volunteers that can arrive prior to the ambulance are counted. We observed that on average, about 6.88 volunteers are alerted meaning that typically there are 7 volunteers that can arrive prior to the ambulance. This is important because it maximizes survival rates.

- **Average Number of Attending Volunteers = 2.662**

  This describes the average number of volunteers that will arrive at the OHCA location by either responding or arriving without responding. While having 2 or 3 volunteers may appear unreasonable, the goal here was to minimize the total proportion of OHCA's where no volunteers arrive or show up after the ambulance (which appears to be 3.7% of the time in our simulation). The result of about 2.7 volunteers arriving at the OHCA is a sufficient performance metric, as it appears that our model did not cause overcrowding at the scene of the OHCA while still maximizing the patient survival rate.

- **Average Nearby Fraction = 95.2%**.

  This metric defined the proportion of OHCA's that have a volunteer within 200m of the OHCA location. It did not change based on the number of volunteers alerted, as long as we alert at least 1 volunteer. This is because we only alert the closest volunteers and above 1 alerted, that closest will always be simulated. Therefore, we did not place a priority on this metric. However, note that across the city, there was about a 95.2% chance that a volunteer will be within 200m. Note that this metric was location-based and did not take into account that volunteers may or may not arrive.

- **Average Volunteer First = 96.3%**.

  This metric is the proportion of OHCAs where the volunteer arrives before the ambulance in our model. This changed based on the number of volunteers alerted and is defined as out of the volunteers within 200m that *can* arrive before the ambulance, the fraction of OHCA's that actually *have* the volunteer arriving before the ambulance. This metric was relatively high, which supported the validity of our model.

- **Maximum Survival Rate = 34.13%**

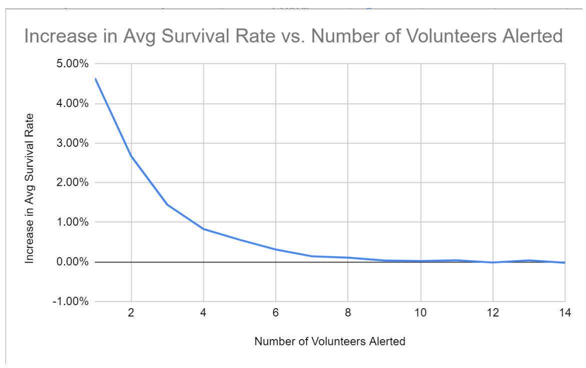
  This is the maximum survival rate for all simulations. This metric was roughly around 34% for all numbers of alerted volunteers and describes the best-case scenario for volunteer notification. It described the case in which the volunteer alerted is in close proximity to the OHCA, responds to the alert that they will respond to the OHCA, and therefore minimizes t_1. In this case, the ambulance was likely to also be near to the scene and therefore minimize t_2. We hypothesized that this might likely be the case in a densely populated area.

5.3 Sensitivity Analysis

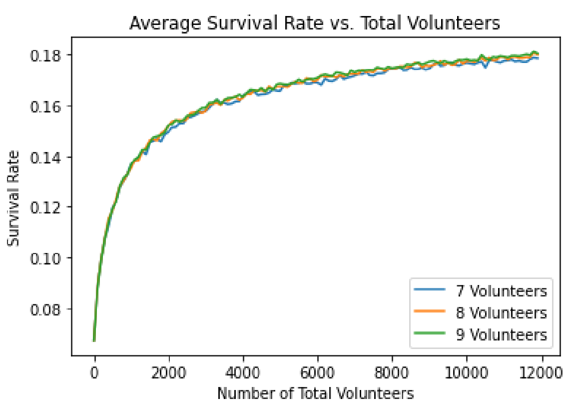
Based on our model analysis, we recommended alerting the 7 closest volunteers. However, this solution depended on some important assumptions. First, we noted that the survival rate changed incrementally as more volunteers were alerted, as well as the addition of more volunteers in the system. Additionally, we tested how external factors might affect the solution.

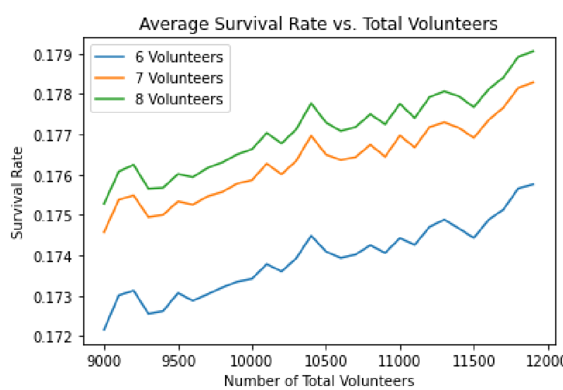
We specified a survival rate increment to determine the survival rate increase with 1 additional volunteer. We specified a cutoff of 0.1%, so that for every 1,000 patients with an OCHA emergency, one additional life could be saved. Since there were slightly under 1,000 emergencies in a year, this was a sufficient threshold. Between alerting 6 and 7 volunteers, we noted an increased survival rate of 0.25%, whereas between 7 and 8 alerted volunteers, we noted an increased survival rate of .08% which is below our threshold of 0.1% - an increase of 1 of 1,000 people saved, which is a marginal trade-off between the number of alerted volunteers and the survival rate.

This cutoff is exhibited in the figure below. It illustrates the increase in survival rate affected by alerting more volunteers from a replication of 1,000 simulations.



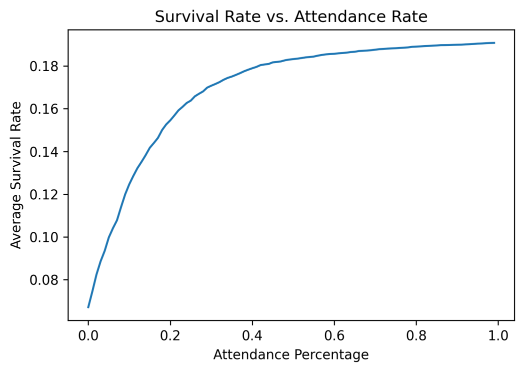
In addition, we illustrated how the survival rate changed as more volunteers joined the system prior to reaching the operational capacity goal of 12,000 total volunteers. Above we observed how the survival rate changed, as more volunteers entered the system. In this regard, we analyzed how the average survival rate changed with a special focus on alerting 6, 7, and 8 volunteers.





Based on inspection from 0 to 12,000 volunteers, we noted that the survival rate appeared roughly similar when alerting 6, 7, and 8 volunteers until about 2,000 total volunteers, after which survival rates began to diverge. Specifically, 9,000 to 12,000 total volunteers had a material difference in survival rates which appeared to increase in general regardless of noise in the model. Broadly, 7 alerted volunteers lead to a greater chance of survival, as opposed to 6 alerted volunteers. Additionally, with 8 alerted volunteers, there was a smaller increase in survival rates, when compared to 7. These values were consistent with our specified cutoff.

Finally, to report the incremental change between different numbers of alerted volunteers to total volunteers, we illustrated the survival rate change based on the percentage of volunteers that arrive at the OHCA location. Considering 7 alerted volunteers, we noted that on average 39.185% of volunteers arrived at the OHCA. This was calculated by the historical data, indicating that 36.2% of volunteers respond, combined with the 2.985% of volunteers that did not respond, but arrive anyways. We also noted a large increase in survival rates as the volunteer attendance rates jump from 0% to 30%, but slowly starts to plateau past 30%. Therefore, we further justified alerting more volunteers if the attendance rate was lower than 30%. If the attendance rate was greater than 50%, it might be prudent to potentially amend the volunteer dispatch policy by reducing the number of alerted volunteers, as 3 or more volunteers at any given OHCA location, might cause over-saturation.



6 Conclusion

This study proposed an volunteer emergency dispatch policy to maximize the chances that a patient survives the event of an OHCA, while minimizing the number of alerted volunteers to each emergency. We recommended that a dispatch policy be implemented that alerts the 7 closest volunteers to any given OHCA. We estimated the probability an alerted volunteer would agree to respond or attend to an OHCA event was 39.2% when there were 12,000 total volunteers in the system. In the case that 7 volunteers were notified, the average chance that a patient survived increased by 10.7% when compared to the case where there were no volunteers.

We also discovered that the probability of a volunteer responding had a proportionate effect related to patient survival rates and to the number of alerted volunteers. In other words, the chances of a OHCA patient surviving were roughly equal given the same change in either case where the probability of a volunteer agreed to respond increased or the number of alerted volunteers increased. What this means is that if fewer volunteers agreed to respond, more volunteers were needed.

As an extension of our recommended volunteer emergency dispatch policy, we also recommend that additional steps be taken in the future to encourage volunteers to accept to respond to an OHCA emergency, so that a fewer number of volunteers are alerted, while simultaneously increasing the total number of volunteers within the network to improve the chances they will be near an OHCA. This would be an important and natural next step in this analysis dedicated for future work.

Appendix

Distribution Fitting

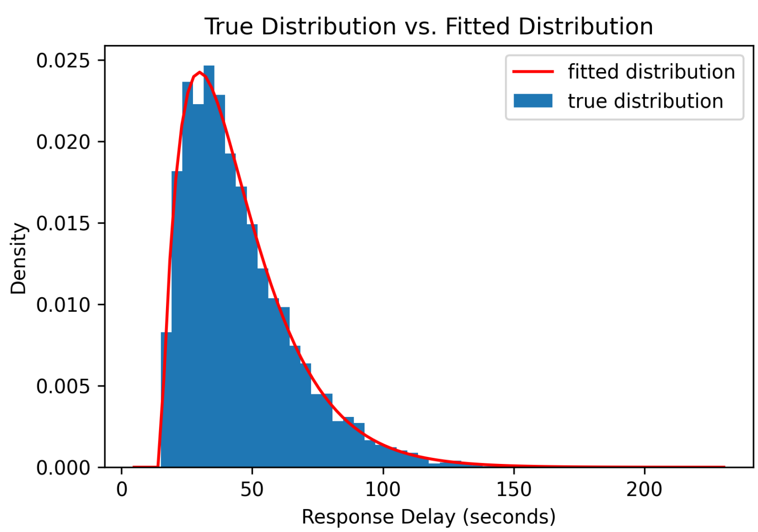
Given historical data on both the volunteer response delay and the ambulance delay, we inspected the fit of the following distributions on both datasets, using a Kolmogorov–Smirnov test:

- Gamma
- Log-normal
- Beta
- Exponential
- Weibull
- Pareto

To validate our results, we also plotted the histogram of the true data against the probability density function of the hypothesized distribution. We show our results below.

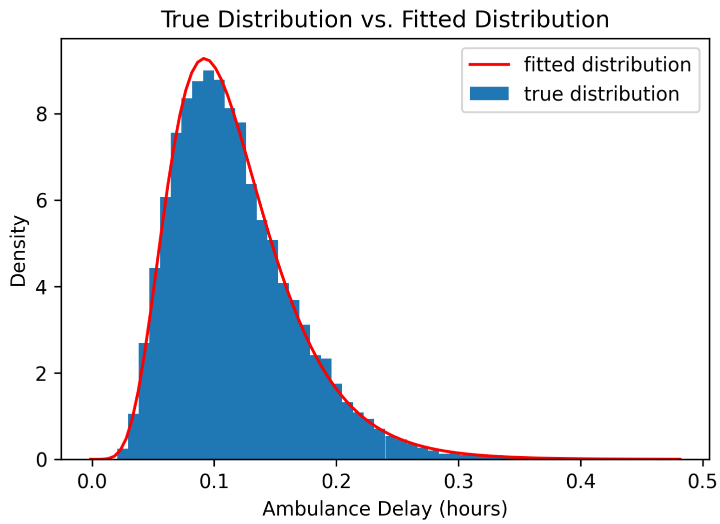
Volunteer Response Delay

Our response delay dataset provides many observations of whether a volunteer responded to an alert, and how long it took for the volunteer to respond after the alert was sent. We cleaned the data by filtering out the observations in which volunteers did not respond. From our set of tested distributions, we observed that a shifted gamma distribution yielded by far the largest p-value (0.84). Below is the density function of this distribution overlaid on histogram of the response data.



Ambulance Delay

For ambulance delay time, we used a dataset containing all OHCAs over the last 15 years, with information about the date/time that an ambulance was dispatched, and the time that it arrived. We removed outliers in the dataset where the ambulance delay was reported to be over 24 hours. Fitting the same distributions to this dataset, we found that the log-normal distribution yielded by far the largest p-value (0.32). Again, the theoretical density function is overlaid on the true data below.



Generating Volunteer Locations

Pseudocode for generating volunteer locations around a certain radius of an OHCA location is provided below. As discussed in section 4.1, we modeled the volunteer locations by dividing the city into an $N \times N$ grid (we found that $N = 40$ provided a good estimate of the true distribution). Within a grid cell, we assume that the probability density is uniform across the cell. From this, we generated a probability matrix $P \in \mathbb{R}^{N \times N}$, where P_{ij} is computed as the fraction of OHCAs in our dataset that fell into cell (i, j).
Our volunteer generation algorithm computes the subset of grid cells that fall within a square of side length $2r$ centered at the OHCA location (using the auxiliary function GetBoundaries). It then generates a Poisson point process in this square, which is proportional to the probability density of the volunteers. The mean, λ of this point process is assumed to be the sum of the probabilities within the desired area multiplied by the total number of volunteers in the city. Within the square, locations are generated through the acceptance-rejection method. Once a set of candidate locations are determined, the locations that actually fall outside the desired radius of the OHCA are filtered out, as determined by the Haversine Distance. This approach is preferred to a much more inefficient (but simpler) implementation where a point process is generated over the entire city for each OHCA location rather than within a square.

Algorithm 1 Generate Volunteer Locations Around OHCA Location

Input:
n: Total number of volunteers in city
(x, y): Longitude and Latitude of OHCA Location
r: Radius to generate locations in, in km
P: Volunteer probability matrix

Output: $\mathcal{N}$: generated volunteer locations within radius

$\mathcal{N} \leftarrow \emptyset$
$(x_\ell, x_h, y_\ell, y_h) \leftarrow \mathsf{GetBoundaries}(x, y, r)$
$i_\ell \leftarrow \mathsf{IndexOf}(x_\ell)$
$i_h \leftarrow \mathsf{IndexOf}(x_h)$
$j_\ell \leftarrow \mathsf{IndexOf}(y_\ell)$
$j_h \leftarrow \mathsf{IndexOf}(y_h)$
$R \leftarrow \{(i, j) \mid i_\ell \leq i \leq i_h \wedge j_\ell \leq j \leq j_h\}$
$\lambda \leftarrow n \cdot \sum_{(i,j)\in R} P_{ij}$
$m \leftarrow \mathsf{Poisson}(\lambda)$
$M \leftarrow \max_{(i,j)\in R} P_{ij}$

while $i < m$ **do**
  $accepted \leftarrow \mathsf{false}$
  while not $accepted$ **do**
    $X \leftarrow \mathsf{Uniform}(x_\ell, x_h)$
    $Y \leftarrow \mathsf{Uniform}(y_\ell, y_h)$
    $Z \leftarrow \mathsf{Uniform}(0, M)$
    $i \leftarrow \mathsf{IndexOf}(X)$
    $j \leftarrow \mathsf{IndexOf}(Y)$
    $accepted = Z < P_{ij}$
  end while
  $\mathcal{N} = \mathcal{N} \cup \{(X, Y)\}$
  $i = i + 1$
end while
$\mathcal{N} = \mathcal{N} \setminus \{(x', y') \in \mathcal{N} \mid \mathsf{HaversineDistance}((x, y), (x', y')) > r\}$

Simulation Model - Alerting k Volunteers

Our model logic for simulating the survival rate of an OHCA provided we alert the k closest volunteers is as follows:

- Generate OHCA location, dispatch delay, and ambulance delay. The time of defibrillation (t_2 in expression for survival rate) is the sum of dispatch delay and ambulance delay
- Based on time of defibrillation, generate volunteers that can arrive before the ambulance. We refer to these volunteers as nearby volunteers.
- If there are no nearby volunteers: the time of CPR is same as the time of defibrillation. Set volunteer first, which indicates whether a volunteer arrived before the ambulance, to 0. The nearby fraction is 1 if there is a volunteer within 200 meters of the OHCA and 0 otherwise.
  If there are nearby volunteers, determine which volunteers will go to the OHCA and calculate their arrival times. Determine the arrival time of the volunteer that is closest. Their arrival time is the time of CPR (t_1). Additionally, set volunteer first to 1.
- Calculate survival rate given time of CPR and defibrillation.

The pseudocode below describes the logic of our simulation model where we alert k volunteers.

Algorithm 2 Alert k Volunteers Simulation

Input: The number of alerted volunteers $k \geq 0$
Output: Survival Rate (sr)
Nearby Fraction (nf): indicates whether a volunteer was within 200 m of the OHCA
Volunteer First (vf): indicates whether a volunteer arrived before ambulance

$\text{ohca} \leftarrow \mathsf{GenOHCA}()$
$\text{DispatchDelay} \leftarrow \mathsf{GenDispatchDelay}()$
$\text{AmbDelay} \leftarrow \mathsf{GenAmbulanceDelay}()$
$\text{WalkSpeed} = 0.1$
$t_2 \leftarrow \text{DispatchDelay} + \text{AmbDelay} * 60$
$\text{radius} \leftarrow \mathsf{min}(t_2 * \text{WalkSpeed}, 2)$
$\text{NearbyVol} \leftarrow \mathsf{GenerateVolunteersAround}(\text{ohca}, \text{radius}, k)$
if $\mathsf{len}(\text{NearbyVol}) == 0$ **then**:
  $nf = 0$
  $t_1 = t_2$
  $vf = 0$
  $av = 0$
else:
  $nf = (\min\{\text{NearbyVol}\} \leq 0.2)$
  $av = \mathsf{len}(\text{NearbyVol})$
  $\text{AttendVol} = \text{NearbyVol}[\mathsf{AttendProb}(av)]$
  $av = \mathsf{len}(\text{AttendVol})$
  $\text{WalkTime} = \text{AttendVol} * 10$
  $\text{ArrivalTime} = [\text{DispatchDelay} + \mathsf{ResponseDelay}() \text{ for i in } \mathsf{range}(\mathsf{len}(\text{AttendVol}))] + \text{WalkTime}$
end if
if $\mathsf{len}(\text{ArrivalTime}) > 0$ and $\mathsf{min}(\text{ArrivalTime}) < t_2$ **then**:
  $t_1 = \mathsf{min}(\text{ArrivalTime})$
  $vf = 1$
else:
  $t_1 = t_2$
  $vf = 0$
end if
$sr \leftarrow \mathsf{CalcSurvivalRate}(t_1, t_2)$