Cornell University

Dispatch Policies for Out-of-Hospital Cardiac Arrest

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Executive Summary

Our team has modeled a volunteer based alerting system for Out-of-Hospital Cardiac Arrests (OHCAs), in Hendersonia – a city that currently does not have such a system in operation. In order to model this system, we analyzed a dataset with 15 years of data on OHCAs in Hendersonia. This dataset included information on when OHCAs occur in Hendersonia, their locations, the dispatch times for each, and the ambulance arrival times for each. Another dataset including information on the volunteer responses and response delays for a similar system in a different city was also analyzed.

With data analysis complete, we were able to model this volunteer alert system in Hendersonia for a single OHCA. We started by simulating a simple dispatch policy that notified all volunteers within 1 kilometer of the OHCA. After brainstorming various improvements to this basic dispatch policy, our team generated 100 random OHCAs with different volunteer locations. For each OHCA, we simulated and analyzed 800 different dispatch policies which varied in how many volunteers to alert and how often after the OHCA is dispatched. Furthermore, the policies were improved to alert volunteers by their proximity to the OHCA and to halt alerts if there was a 90% probability that the ambulance had already arrived at the scene.

Our dispatch policies not only considered maximizing the survival rate, but also minimizing the amount of total alerted volunteers. Over time, if too many volunteers accept an alert and arrive at the scene, volunteers will have a tendency to stop accepting alerts. Thus, our goal was to find the most efficient dispatch policy which will ensure volunteers will continue to accept alerts when our dispatch policy is implemented and operational.

After running our simulations for various amounts of volunteers and focusing on 9000 volunteers, we determined that a policy of notifying two volunteers every 39 seconds was the most efficient dispatch policy. The survival rate of this policy was on average 9.71%, the average number of alerted volunteers was 4.3, and the average number of acceptances per OHCA was 1.6. This policy is a massive improvement over a baseline survival rate of 3.8% when no alerting system is in place

Problem Description

OHCA calls are some of the most time-sensitive calls received by 911 operators because of the drastic impact that swift and quality cardiopulmonary resuscitation (CPR) and defibrillation has on the victim's survival rate. It is most imperative to initiate CPR as quickly as possible where the more time lost exponentially decreases survival rates. Ambulance arrival rates vary up to around 10 minutes in cities and it has been estimated that increasing ambulance capabilities will not be able to impact survival rates for OHCAs. This necessitates an alternative solution to this serious medical condition.

Phone enabled alert systems are currently being implemented with apps such as GoodSam and PulsePoint paving the way in recent years. These alert systems are directly connected with 911 operators and a network of medically trained individuals that will alert nearby volunteers of the location of an OHCA. The volunteers can respond to the alert and indicate to emergency services their intentions of going to the scene to perform urgent CPR.

Our team has been tasked with exploring a range of dispatch policies and recommending one that efficiently alerts volunteers. An ideal policy will optimize the number of volunteers alerted, in an attempt to guarantee an acceptance with minimal time to the scene, without compromising the survival rate of the patient. The timing and amount of people to notify has an impact on survival rate and is the tradeoff at the core of our model. We will describe our modeling approach, analysis, and verification in the following sections.

Modeling Assumptions and Approach

Our team based our dispatch policy simulation on a set of timing, city specific, and other logical assumptions to ensure its accuracy and replicability. Using historical data over the last 15 years, we used a statistical package to fit a probabilistic distribution over the timing of volunteer responses, ambulance response delay and arrival times, and the location density of OHCA calls across the city. These distributions generated the times used in our model and were validated as accurately reflecting OHCA emergency procedures using hypothesis testing, a reliable statistical verification test. We also modeled the volunteers arriving at the scene by assuming a straight-line path (though this is not likely possible due to city streets and blocks) and standard pace of 6 km/h. The volunteer program is currently being scaled with an estimated operating size of 12,000 individuals and so we analyzed dispatch policies in the range of 0 to 12,000, specifically focusing on the 9,000 to 12,000 range.

Under logical assumptions, we decided to model single instances of OHCAs given the extreme infrequence of two simultaneous occurrences, which we proved to have a 0.5%

probability over a span of one week. We also chose to treat volunteer acceptances as a confirmation that they will make their way straight to the scene of the cardiac arrest, without delay or abandonment, given their seriousness as medical professionals. This set of assumptions defines the framework of our model and allows for a justified simulation of uncertainties.

The basic flow of our simulation is as follows: First, *n* OHCAs are generated using the past 15 years of OHCA call locations. For each of the *n* OHCA locations, generate the time between cardiac arrest beginning and a bystander calling by assuming it usually takes around two and a half minutes for a bystander to call 911. Generate the random locations of volunteers in the entire city also by using the past 15 years of OHCA locations as an estimate for population centers. These locations are then narrowed down to volunteers within one kilometer radius of the OHCA call as these are the only volunteers we will alert. Then using these volunteers and our decided dispatch policy, we determine the arrival time of each volunteer notified by generating their response and response delay time modeled from given volunteer response data in a similar city. Of those that accept, we add the time of response of these volunteers and add how long it would take them to walk to the OHCA using a walking speed of six km/h and assuming they walk in a straight line towards the OHCA resulting in volunteer arrival times. Using all of this data we could find our major performance metrics which include: survival rate of OHCA calls (SR), total alerted volunteers (AV), the fraction of OHCAs with a volunteer within 200 meters (NF), the fraction of calls where a volunteer arrives first (VF), and the total number of volunteer acceptances (NA).

Model Verification

Since we assume that no two OHCA calls occur simultaneously, it is sufficient to generate the OHCA call locations beforehand and assume that each has the same resources available. We then generated various interarrival times for the dispatch delay, volunteer response delays, and ambulance arrival delay based on the distributions we estimated from the data. Since these are all independent processes we can assume that generating these values independently is sufficient for each simulation.

Furthermore, we wanted to ensure that our model has no look ahead bias. To do so, we kept track of time throughout our dispatch policy. For all of the volunteers that had been notified, we only checked if they had accepted by the current time *t* (i.e. if a volunteer accepts at 11 seconds but we are only at $t = 5$, we would not consider this an acceptance). When calculating the probability that the ambulance had already arrived, we only used the distribution of the ambulance arrival time (which is known by the system) – not the ambulance arrival time that we generated at the beginning – to inform whether or not more volunteers should be alerted.

As a "sanity check" we looked at historical data to see what the typical survival rate of an OHCA is. We found that typically, less than "10% of all patients with OHCA will survive" ("Out-of hospital cardiac arrest: a unique medical emergency"). Iterating over all simulations, the average survival rate at the corresponding optimal policy dispatch was 9.73%, which is within the cone of expectations.

Dispatch Policies

Recall that the given task is to create a dispatch policy that maximizes survival rate while minimizing the resources allocated per OHCA (the number of volunteers who were alerted per OHCA). Over time, if too many volunteers are notified and arrive at the scene to find other volunteers already there, they will become less likely to respond in the future. As a result, our policy must consider the tradeoff between survival rate and number of alerted volunteers.

Our team first implemented a simple dispatch policy: once we receive notice of an OHCA, the app notifies all volunteers within 1 km. While this policy is favorable to the survival rate of the OHCA victim, it is clear that this policy over utilizes resources. In examples where there are hundreds of volunteers within 1 km, we do not need to notify all customers to obtain an almost equivalent survival rate.

From this policy, our team brainstormed various ways to maintain relatively the same survival rate while decreasing the number of notified volunteers. First, we implemented a "roll-out" dispatch policy; we sorted our volunteers by distance closest to the OHCA location, and notified only a certain batch of volunteers at a time. We notified p amount of people every t seconds. After every t seconds, we checked if someone that we notified had accepted the OHCA alert. This significantly reduces the amount of notified volunteers; since our volunteers are sorted by distance to the OHCA victim, we no longer need to continue notifying more people once a singular volunteer accepts (everyone that would be notified after is farther from the OHCA victim and therefore is guaranteed to arrive at the scene after).

Next, to reduce the amount of alerted volunteers, we made time (*t*) and number of volunteers notified per wave (*p*) variable. For each OHCA, we created a matrix of survival rates indexed on *t* and *p* for various iterations of our dispatch policy. We created one matrix of average survival rate for each dispatch policy by averaging over each OHCA.

Lastly, to reduce the amount of the total alerted volunteers in every policy, we considered the ambulance arrival time. Before notifying the next volunteer, we found the minimum arrival time of that volunteer to the OHCA (i.e. this volunteer accepts and starts walking to the OHCA site immediately). We then checked the probability that the ambulance had arrived by that time, and if it was over 90%, we stopped notifying volunteers.

Results and Modifications

Following the modeling approach described above, we simulated our dispatch policy for varying *p* (number of people notified in each batch) and *t* (the number of times before checking if we should notify more people). For a fixed number of volunteers, we simulated 100 OHCAs and averaged the matrix results for each of our metrics. We followed this approach for different amounts of volunteers ranging from 1,000 to 12,000 (though our analysis focuses on the results between 9,000 and 12,000 people).

Once we obtained the results of our analysis, we found the optimal survival rate for each of our fixed number of volunteers ranging between 9,000 and 12,000. To do so, for a fixed number of volunteers, we found the maximum survival rate aggregated over all of the OHCAs. We then found all of the policies that have a survival rate within 1% of the maximum survival rate and selected the policy with the minimum number of alerted volunteers.

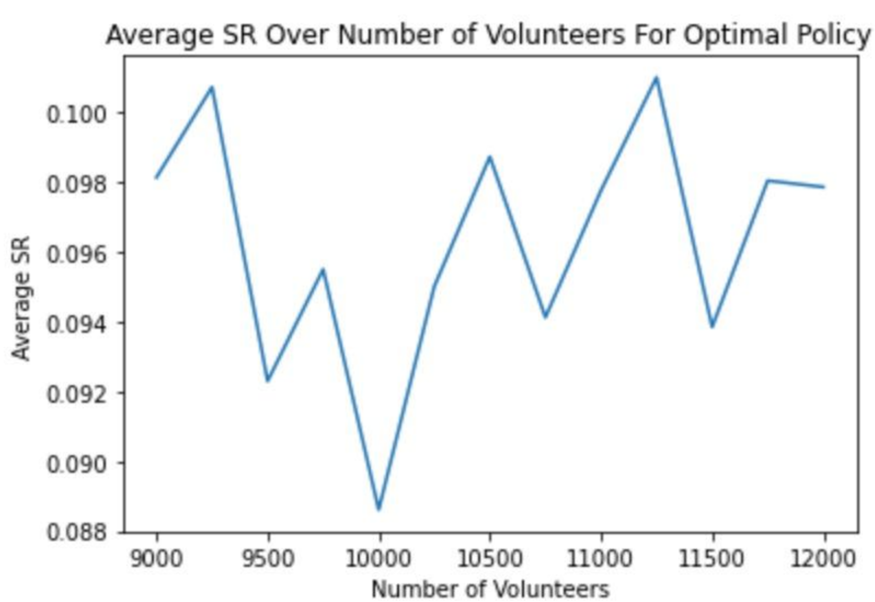
Figure 1: Most Efficient Policies for Varying Number of Volunteers

	# Volunteers	# Vols to Alert	Alert Interval (s)	Average Vols Alerted	Survival Rate (%)
0	9000	2	34	4.22	10.0
1	9250	1	16	4.57	9.8
2	9500	2	39	4.00	10.1
3	9750	2	37	4.14	9.3
4	10000	2	36	4.30	9.9
5	10250	2	40	3.90	9.1
6	10500	2	37	4.30	9.6
7	10750	2	31	4.90	10.1
8	11000	2	37	4.32	9.6
9	11250	2	39	4.10	9.8
10	11500	2	39	4.34	10.1
11	11750	2	31	4.36	9.8
12	12000	2	39	4.10	9.8

In **Figure 1** above, we can see that the optimal policies for between 9,000 and 12,000 volunteers are relatively the same (alerting 1 person every 16 seconds is relatively the same as alerting 2 people every 32 seconds).

For our system, we would ideally vary the optimal policy based on the number of volunteers signed up in the city. However, for the purposes of our research, we will fix the number of volunteers to 9,000 (the minimum number of expected volunteers) and focus on our optimal policy which alerts 2 people every 39 seconds.

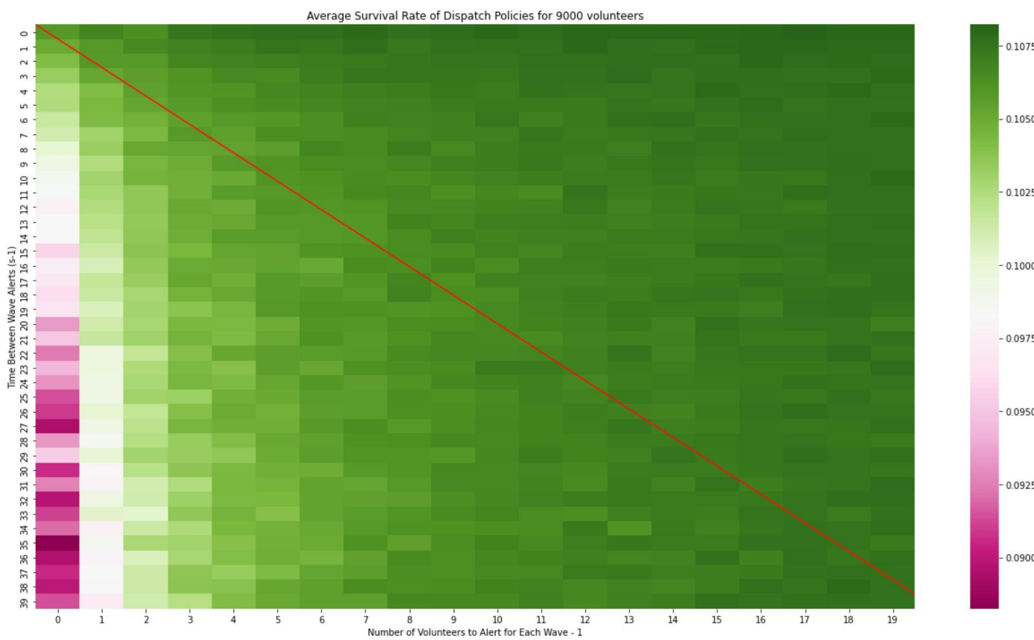
Figure 2: Average Survival Rate of Dispatch Policies for 9000 Volunteers



In **Figure 2,** we see how our average survival rate varies with the number of volunteers in Hendersonia. Note that this only varies ~1%, which is important since the number of volunteers is variable in the city, and we want our dispatch policy to produce relatively consistent results.

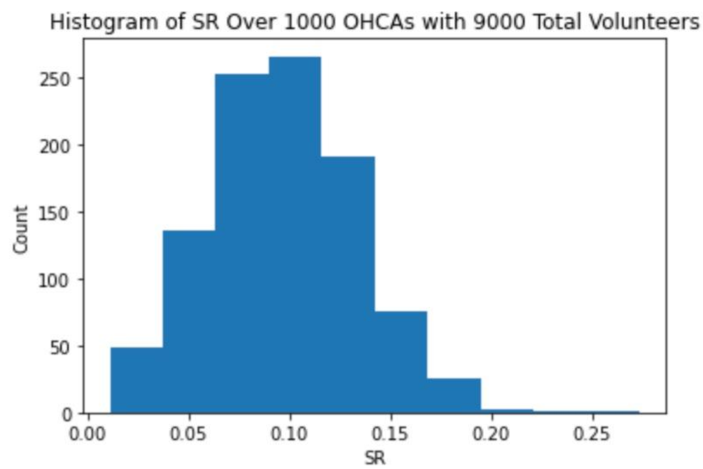
Before diving into the results of our selected dispatch policy, **Figure 3** is an example of the output of our survival rate matrix where the number of volunteers is fixed to 9,000. Note that the survival rate increases from the lower left corner (notifying 1 person every 40 seconds) to the top right corner (notifying 20 people every 1 second). However, it is clear from the heat map above that we do not need to notify 20 people every 1 second to obtain the optimal survival rate.

Figure 3: Average Survival Rate of Dispatch Policies for 9000 Volunteers



To further understand our selected dispatch policy – notifying 2 people every 39 seconds, we ran a simulation with 1,000 OHCAs fixed to 9,000 volunteers. We created a 95% confidence interval for the survival rate, which was 0.09707047774202365 +/- 0.002261794136893605. As seen in **Figure 4,** our 95% confidence interval is within 0.2% of the average survival rate of 9.71% (for an interval of 9.69% to 9.73%).

Figure 4: Histogram of Survival Rate Over 1000 OHCAs with 9000 Total Volunteers



We observed that the average number of alerted volunteers is 4.3, but as shown below in **Figure 5** we see that the vast majority of the time we are only alerting two or four volunteers. This is a number we want to keep down with our dispatch policy, as it will cause volunteers to be less open to accepting alerts in the future. This low number of alerts results in an average number of volunteers that accept at 1.6. The mode of total acceptances is 1 this is the most efficient possible value for volunteer acceptances. To keep volunteers engaged we want only one showing up to the scene and the most common occurrence is one person so this dispatch policy greatly increases survival rates without wasting the usage of volunteers

Figure 5: Histogram of Total Alerted and Number Accepted Volunteers Over 1000 OHCAs with 9000 Total Volunteers

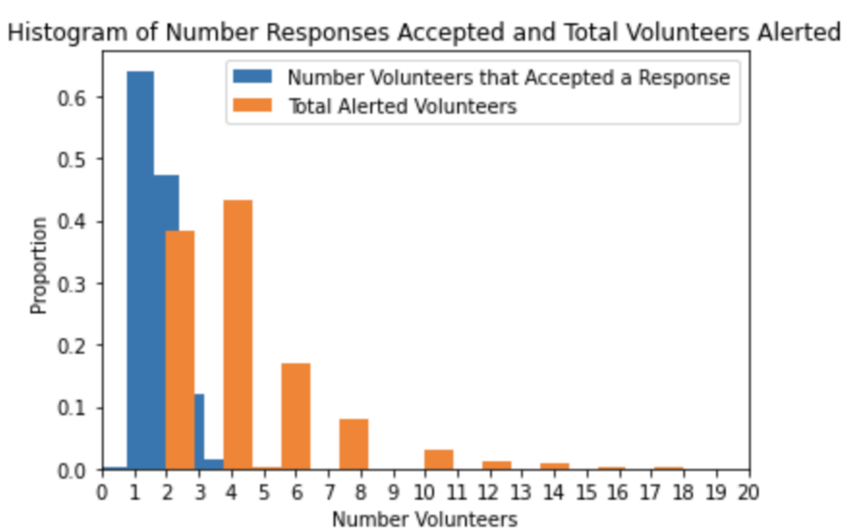
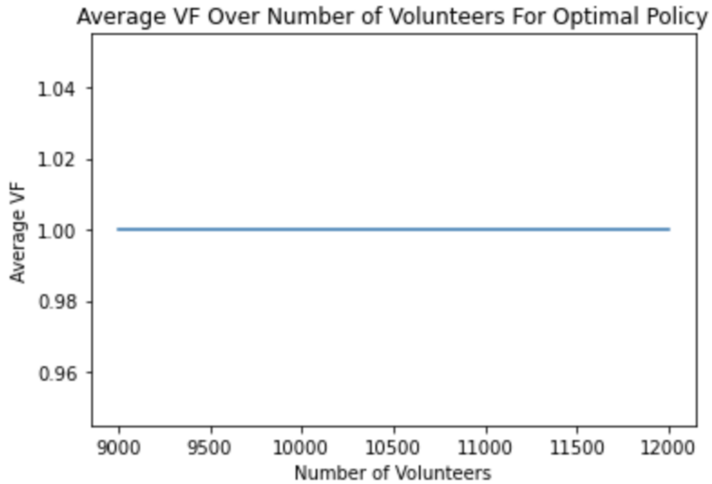


Figure 6: Average Volunteer First Measure Over Number of Volunteers For Optimal Policy



Additionally, as shown in **Figure 6,** the average fraction of time the volunteer arrives first is one for any number of volunteers; having a volunteer arrive on site first before the ambulance is extremely important to increasing the chances of survival for the patient. Combining this information with the number of accepted volunteers being 1.6, it is clear that we are notifying enough volunteers such that they beat the ambulance, but not too many that several volunteers arrive at the scene.

Our group thought of some improvements to our dispatch policy that we would have liked to test. To further improve our model, we could run a simulation that varies the number of people that we notify every rollout *within* a dispatch policy (i.e. we start by notifying 20 people, and if no one accepts we notify 15, and if no one accepts we notify 10…). Another improvement that could be made with the volunteer app is a way to cancel alerts for volunteers so that if we know a volunteer has accepted the alert and will arrive before anyone else, we cancel the alerts to everyone else, including others that may have accepted, to ensure only one person who accepted the alert will show up to the scene. Lastly, adding navigation capabilities would allow us to more accurately estimate the time until a volunteer arrives on the scene (due to our straightline assumption) and additionally would allow volunteers to follow directions taking them on the fastest route.

Conclusion

To conclude, we recommend implementing a dispatch alert policy of 2 individuals every 39 seconds. This optimal policy improves the survival rate from OHCAs from a no-policy baseline of 3.8% to 9.71% while alerting an average of 4.3 nearby volunteers with 1.6 average acceptances for each OHCA.

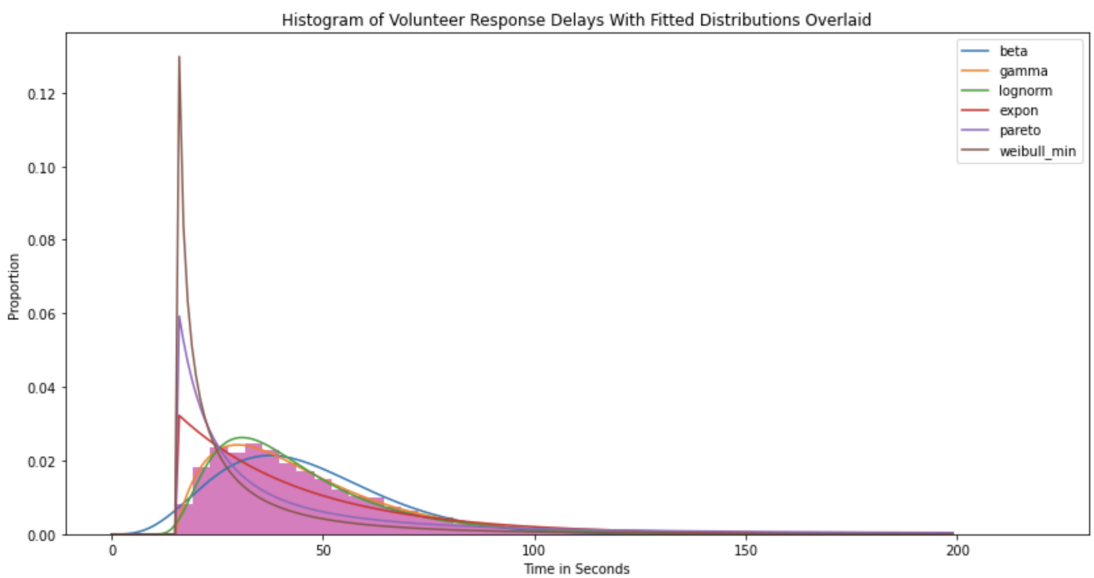
While the process of our system helps improve the survival rates of OHCAs that occur outside in the public, it fails to help OHCAs that occur when no bystander calls 911; without the bystander, there is no one to describe the scene, so the call center is unable determine if the victim is a suspected OHCA. With over 70% of OHCAs occurring within homes, this is a huge issue with the current process our system uses (“CPR Stats & Stats. How CPR is changing (and saving) lives.”). A future improvement to address this issue would be to connect the phone system to life alert buttons, which many OHCA prone people keep on them at all times in case of a cardiac arrest with no one home.

Appendix

Generating Volunteer Response Delays

To generate volunteer response delays, we fit a distribution to the response delay data from a similar system in a different city. We used the Python package scipy.stats to fit multiple probability distributions to the data and created QQ-plots to further enforce our choice of distribution. For the case of volunteer response delays, we determined that the gamma distribution was the best choice as shown in **Figure 7**.

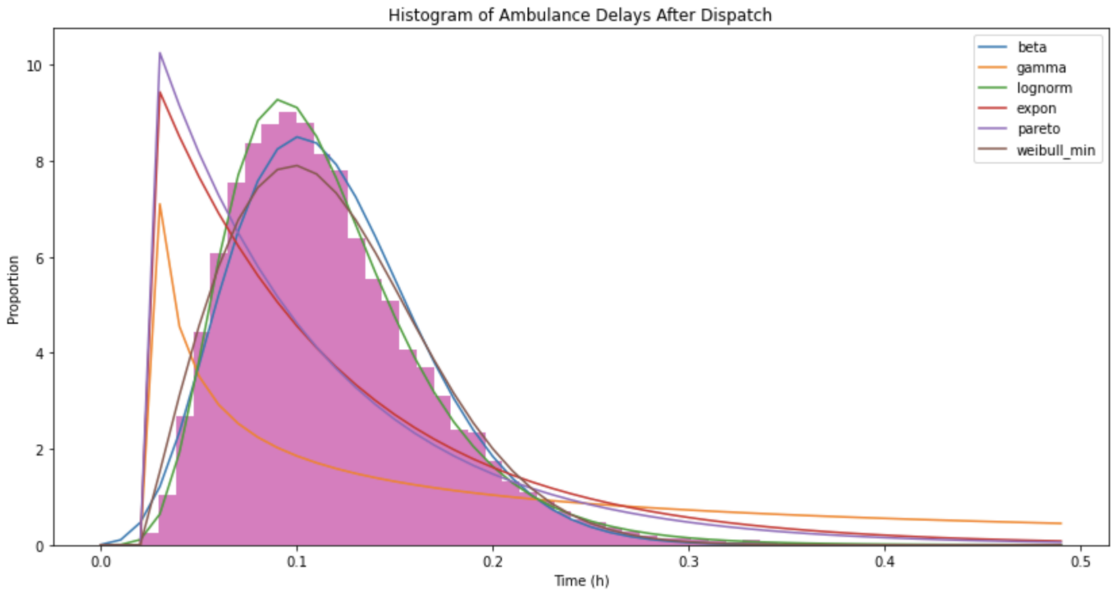
Figure 7: Histogram of Volunteer Response Delays With Fitted Distributions Overlaid



Generating Ambulance Response Delays

Similar to volunteer response delays, for ambulance arrival times we used scipy.stats to fit multiple distributions to the data and plotted QQ-plots to make our choice. In this case, the lognormal distribution fit the data the best as shown in **Figure 8**.

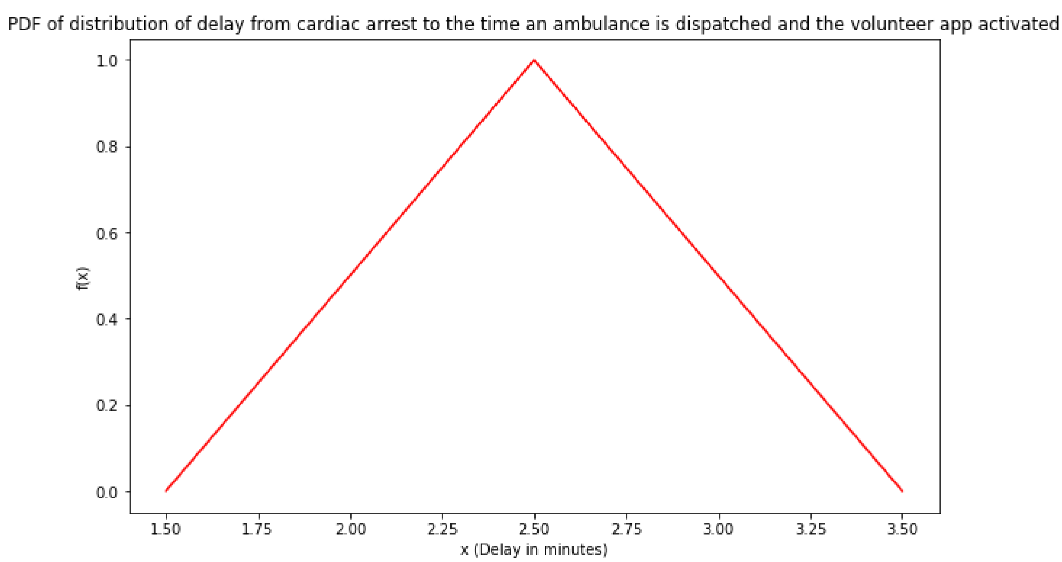
Figure 8: Histogram of Volunteer Response Delays With Fitted Distributions Overlaid



Generating Dispatch Response Delays

In order to simulate the call delay between cardiac arrest and bystander call to dispatch, we used the triangular distribution with min 1.5, mean 2.5, and max 3.5. We chose the triangle distribution because we have no other data about the distribution besides the minimum, mean, and maximum.

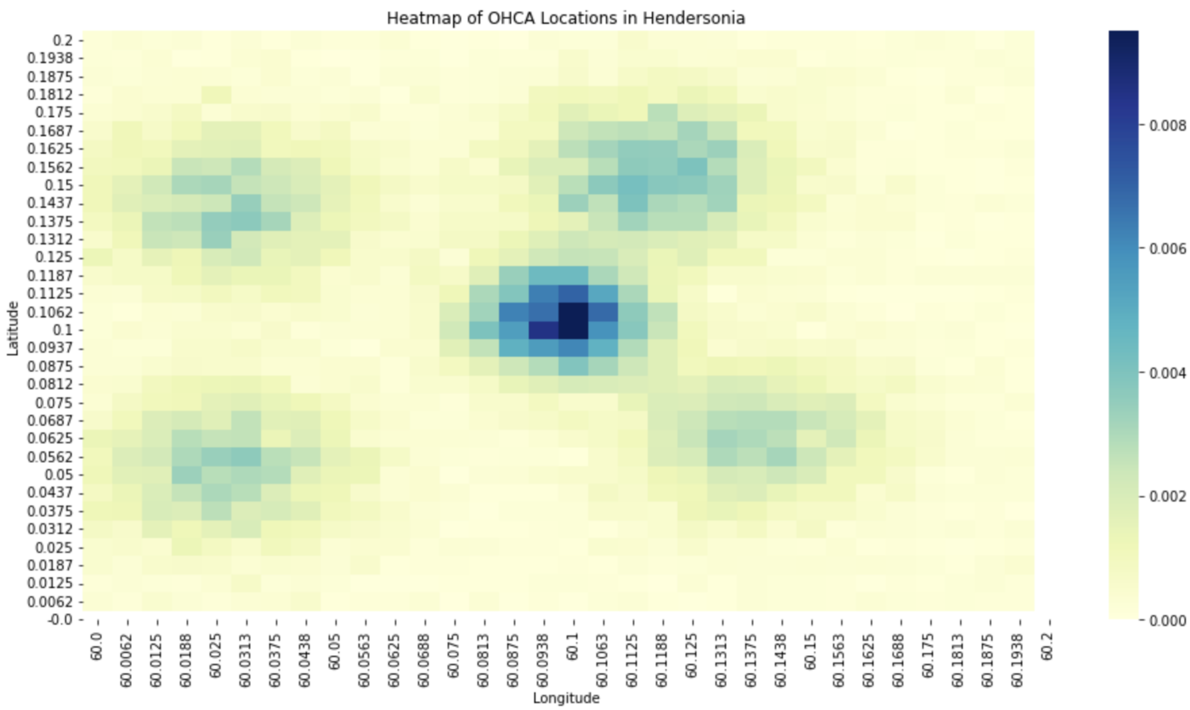
Figure 9: PDF of Distribution Dispatch Delay



Generating OHCA call locations

In order to generate the locations of the individual OHCA call locations, we split Hendersonia into squares of constant side length, and calculated the proportion of OHCA calls that fall in each square using the past 15 years of data. Then using these probabilities, we perform the acceptance/rejection method to generate the call locations to simulate on. The heatmap of these probabilities is shown below in **Figure 10**.

Figure 10: Heatmap of OHCA Locations in Hendersonia



Generating Volunteer locations

Similar to generating OHCA call locations, in order to generate the locations of volunteers within a kilometer of each call, we performed acceptance/rejection using the thinning method and the same heatmap proportions above to generate the volunteers across the entire city. Then, using latitude and longitude calculations we return the volunteers that are within one kilometer of the given OHCA.

Dealing with Look Ahead Bias in Dispatch Policy

In the creation of our “roll-out” dispatch policy, we needed to ensure there was no look-ahead bias. When creating the list of volunteer arrival times, we initially alert x amount of people and receive $n <= x$ responses from these volunteers. We then increment time by t, and check the generated response times of the volunteers who accepted. If any of these response times are less than time t, then we terminate the alert system and alert no more people. If none of these times are less than t, or there were no acceptances at all, we alert x additional volunteers and increment time by t. We continue this process, ensuring that we only consider the response times that are less than the current time t. This ensures that we have no look ahead bias, and maintains the real world dispatch flow.

Works Cited

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