Helicopter Emergency Transport in Upstate New York

ORIE 4580 Project Report

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Executive Summary

For specific cases of medical emergencies, helicopters are used to transport emergent patients from their current location to a medical facility. Across the state of New York, there are nine helicopter bases located at medical facilities in Buffalo, Rochester, Elmira, Ithaca, Watertown, Syracuse, Binghamton, Utica and Albany. In this analysis, the medical facility in Sayre, Pennsylvania is also included due to its proximity to the border of New York. The goal of this report is to determine the optimal number of helicopters to use and which bases to place them at to minimize the average response time between a call being received at the Helicopter Dispatch (HD) and the helicopter arriving at the scene.

To begin this process, we built a model that accurately represents the real-life call arrival and helicopter transport process. We used a dataset containing statistics for 16,993 calls requiring helicopter transportation over the course of one year, from January 1st to December 31st. From this historical data, we were able to determine the appropriate input parameters for our model that mimics the behaviors we would expect to see from emergency calls and helicopter operations.

We investigated two cases to support our final recommendation, one in which the number of bases used is unlimited, another in which a maximum of five bases are used; in both of these cases, the maximum number of helicopters that could be supported was twelve. To better understand performance, we tracked the following metrics: average response time, response fraction, helicopter utilization, time to definitive care, and percentage of call dispatched.

In the case of an unlimited number of bases, we believe that it is optimal to have ten helicopters assigned across seven bases as follows: two in Rochester, two in Albany, two in Syracuse, one in Watertown, one in Ithaca, one in Sayre, and one in Utica. This set of bases and helicopters gives an average response time of 32.12 minutes, 3.47 successful transportations per helicopter per day, and a response fraction of 82.58%. Furthermore, we believe that helicopter utilization is important here because it implies that over the course of a year, a greater number of helicopters are not being used when they are available which does not justify their cost. With twelve helicopters in use, the performance metrics showed minimal differences in improvement, and an

overall cost inefficiency due to the lower utilization. Therefore, we believe 10 helicopters is preferable.

In the case of a maximum of five bases, we believe that it is optimal to have nine helicopters assigned as follows: two in Rochester, two in Albany, one in Syracuse, one in Ithaca, and one in Utica. This yields an average response time of 34.65 minutes, 3.7 successful transportations per helicopter per day, and a response rate of 81.92%. Similar to the first case, we see minimal improvement in average response time as we increase the number of helicopters to twelve and a decrease in helicopter utilization. Therefore, to avoid inefficient usage of funds, we recommend nine helicopters.

When we compare these two results, we can see that having more bases with helicopters does improve the performance metrics. We expect to see these results because employing more bases across the state allows for helicopters to reach patients faster in remote parts of the state. Additionally, having more helicopters in bases that are located in heavily populated areas, such as Rochester, Syracuse, and Albany, allows the HD to more efficiently handle the higher frequency of calls in those areas. Therefore, if there are no financial constraints, it is best to implement our strategy of utilizing ten helicopters and seven bases located in Rochester, Albany, Syracuse, Watertown, Ithaca, Sayre, and Utica.

Problem Description

For emergency calls that require helicopter transportation, the location of the helicopter bases and the number of helicopters at each base can greatly affect the quality of care that a patient receives. If not enough bases are used, or there are too few helicopters in circulation, then a helicopter may take too long to arrive at the scene or, in the worst case, there may not be enough available helicopters to transport the patient. However, there is a significant financial cost associated with maintaining and operating each helicopter. Therefore, we will assess how many helicopters should be employed and where they should be located to minimize the average response time while also keeping in mind the respective cost of adding new helicopters and bases.

Additionally, since ambulance crews want to live in a reasonable-sized population center, helicopter bases are only being considered in Buffalo, Rochester, Elmira, Ithaca, Sayre PA, Watertown, Syracuse, Binghamton, Utica, and Albany. We consider employing a maximum of twelve helicopters across these locations. We investigate two cases, one in which an unlimited number of bases may be used, and another in which a maximum of five bases may be used. This constraint is placed in the second case to avoid the fixed costs associated with operating an additional helicopter base.

To analyze the success of our results, we track five performance metrics: average response time, response fraction, helicopter utilization, time to definitive care, and percentage of call dispatched. Although the main objective is to minimize the average response time, the other metrics will be used to understand the overall success of each simulation. By analyzing these metrics across all of the simulations, we can determine the optimal operating conditions to provide the best service for urgent patients in need of helicopter transfer while keeping in mind the financial constraints.

Modeling Approach and Assumptions

Our model is based on the analysis of the helicopter transport operations in the upstate New York area. There are multiple events that occur that our simulation works to replicate in order to more accurately understand the decision making process.

The events that occur are:

1. An emergency call is generated
2. The HD decides whether it is safe to fly or not and, if so, dispatches the closest available helicopter.
3. If the flight is canceled when the helicopter is en-route, the crew returns back to its base.
4. If the helicopter reaches the incident scene, the ambulance crew decides which medical facility to transport the patient to.
5. The helicopter transports the patient to the receiving facility.
6. The helicopter completes the route and returns to its base

Modeling Approach

Helicopters are dispatched to respond to emergency patients, however the availability, flight conditions, and patient condition affect the utilization and placement of helicopters. Our model works to determine the most efficient assignment of helicopters and bases in order to best meet the helicopter transport operations needs. In addition to determining how to place up to twelve helicopters in the upstate New York area, we also analyze a system that only supports up to five different helicopter bases.

Based on our understanding, an emergency call is generated once a first responder determines the patient needs further medical attention. Given that our access to real-world data is limited, we utilized the sample data to develop a heat plot of the call locations to see where most of the calls were concentrated. To mimic the call location density, we divided upstate New York into 10-by-10 mile blocks and calculated the probability of a call occurring in each region. We then generated the longitude and latitude coordinates uniformly at random for each call within the ranges of the blocks.

With the knowledge of the location of the call, the HD needs to decide whether it is safe to fly and where the nearest available helicopter is located. If the weather conditions do not allow a helicopter to be dispatched, the emergency call is recorded as “not serviced - unsafe.” If there are no helicopters available within range, the call is recorded as “no helis”, and we flag this as an area for us to further investigate. However, if it is safe to fly and the HD finds an available helicopter, an active call is created, and the helicopter is dispatched. The HD tracks whether the helicopter completes its route and whether the helicopter is canceled and no longer needed for the active call. If the call is canceled when the helicopter is en-route, the ambulance crew returns to its base. Modeling this helps us keep track of which helicopters are available to take a new active call assignment. In addition, knowing where the available helicopters are located is important for when we determine the ideal base locations for the helicopters.

Apart from keeping track of the available helicopters in upstate New York, our model also aims to make flight paths efficient. If a helicopter reaches the incident scene, the crew has to decide which medical facility to transport the patient to. The receiving facility is not always the closest hospital since some injuries require specialized treatment. Therefore, the ambulance crew has to determine whether the patient needs to be transported to a trauma center or the nearest medical center. There are four trauma centers in upstate New York: one in Rochester, one in Albany, one in Syracuse, and one in Sayre PA. After the crew makes the decision, the helicopter transports the patient to the receiving facility and returns to its base. With the knowledge of the location of the receiving facility, we can allocate the travel time of the helicopter.

Modeling Assumptions

Based on the helicopter transport operations in the upstate New York area, we were able to observe that the helicopters travel at a speed of 160 km/hr and that they can respond to calls within 180 km of their base. This helps us keep track of the time needed for a helicopter to reach the location of an incident, the time needed for the crew to transport the patient from a scene to a medical facility, and the time needed for the helicopter to return to its base. In addition, knowing the range within helicopters can fly helps us decide whether or not a helicopter is available to take an emergency call assignment.

While building the simulation model, we assumed that helicopters do not require refueling and servicing between calls and that the ambulance crews do not have restrictions on the number of hours they can fly in a single shift. This means that helicopters can be dispatched at any time. However, the helicopters must first reach their base before they are being considered available for another call.

Because calls requiring the transport of multiple patients are very rare, we assumed in our model that each emergency call requires transport of only one patient. This means that we do not have to worry about transporting patients to different hospitals depending on their injury. In our simulation model each helicopter crew transports a single patient to only one medical facility.

In addition, the decision on whether it is safe to fly or not usually depends on the path the helicopter takes from its base to the scene. However, in our model, we assume the decision is made without regard to the location of the base or the incident scene.

Data Analysis

For our model, we used a sample set of data of 16,993 calls to help determine the best fit distribution for input values. The analysis was run in order to understand the randomness patterns within the system to help build a more well-rounded simulation model. Our appendix describes in more details the conclusions we made about the sample data and what distributions were used.

Understanding Call Arrivals

For calls, we needed to understand the arrival rate, location, and cancellation time. For the simplicity of the model when analyzing the hourly rate of call arrivals, we decided to ignore day-of-week and seasonality effects in order to get a general sense of the call patterns. On average, there was a higher frequency of calls during mid-day.

In addition, we needed to understand where the calls were coming in from; we created a heat map to highlight areas where there was a high density of calls generated. This allowed us to generate the location of calls based on their likelihood of occurring within the upstate New York region, and it helped us in understanding how to begin selecting helicopter base locations.

The final component of analysis related to calls was finding the maximum time allowance before a cancellation occurred. The time until cancellation was fitted to a distribution and helped us better understand the behaviors and external factors that affect the completion of a trip.

Understanding Helicopter Operations

Furthermore for our model, we need to understand the helicopter operations. The data allowed us to determine the probability of events occurring. We noticed that about 10% of the time, flights were unsafe; typically we would assume there is some level of correlation between time and effect like weather, but for feasibility purposes, we treated each call independent of this. In determining patient facility transfer location, we saw that about 80.7% of patients would be flown to the hospital, the other 19.3% would be flown to the nearest trauma center. This was important to note so that our model would consider helicopter allocation and helicopter base placement to maximum flight coverage for all possible needs.

Moreover, we analyzed the time taken by each helicopter to measure key metrics for our final recommendation. The time taken at different stages of the helicopters' route would determine if the helicopter could sufficiently help the patient before a cancellation occurred. The sample dataset estimated the amount of time spent on scene was about 24.5 minutes, and about 17.1 minutes at the medical facility; we also needed to be mindful of helicopter preparations like dispatch delays and flight checks, which averaged about 7-7.5 minutes. Each of these components in the helicopter's timeline helped with mapping helicopter availability throughout the simulation.

Model Verification

In order to ensure that our model accurately reflects the call arrival and helicopter transportation system in real-life, we employed a variety of simulation techniques.

When generating the locations of calls, we chose to use the probability of a call arriving in a 10-by-10 mile block generated from the historical data. Once the block has been selected, we then randomly select a longitude and latitude within that block. This is preferable to resampling because unlike resampling where we would only generate calls in locations that exist in the dataset, we are able to generate new locations that may occur in real-life while maintaining the probability of a call arriving there.

Additionally, for many simulation models, it takes a certain amount of time for the model to reach conditions that are “normal” operating conditions. For example, when we first start the simulation, there are no call arrivals and all helicopters are available. These start-up conditions are unique to the beginning of the simulation and do not represent the system as a whole because over the course of many years, there is a continuous flow of calls and helicopters in use. Therefore, we chose to allocate a two-week warm up period. This means that we let the simulation run for two-weeks without collecting any statistics. Our performance metrics are then calculated from the data generated after the warm up period until the end of the simulation run. By doing this, we avoid factoring in results that skew our performance metrics.

Finally, we chose to use batch means for our simulations. We ran each simulation over the course of a year and split the year into twenty batches, where each batch is approximately 2.6 weeks long. This means that, including our warm up period, each simulation ran for a total of 54 weeks. For each batch, we calculated the five performance metrics. The performance metrics of the entire simulation are then calculated as the average of each of the batch results with a 95% confidence interval generated by the variation in results across all of the batches. By using twenty batches that span for about 2.6 weeks, we sufficiently minimize the impact of the dependence between the batches as the simulation runs from one batch to the other.

Model Analysis

In our model analysis, we simulated two different scenarios each considering a variation of one to twelve helicopters placed for operations. In the first case, we wanted to understand what would be the optimal helicopter to base assignments without any limitations on the number of bases a helicopter could be placed at. In the second case, we wanted to understand what would be the optimal helicopter to base assignment if we were only able to use up to five bases due to financial constraints.

For the analysis of our model, we wanted to understand what the environment looks like. We ran a simulation for five years, and over the five years, we averaged the total annual distribution of flights beginning from a helicopter base. In order to see the distribution, we had no limit on the maximum number of bases utilized and unlimited helicopters available. In figure 1, there is a higher percentage of calls being made closer to Albany, Rochester, Syracuse, and Buffalo. This created the foundations to how we initially chose helicopter base selections.

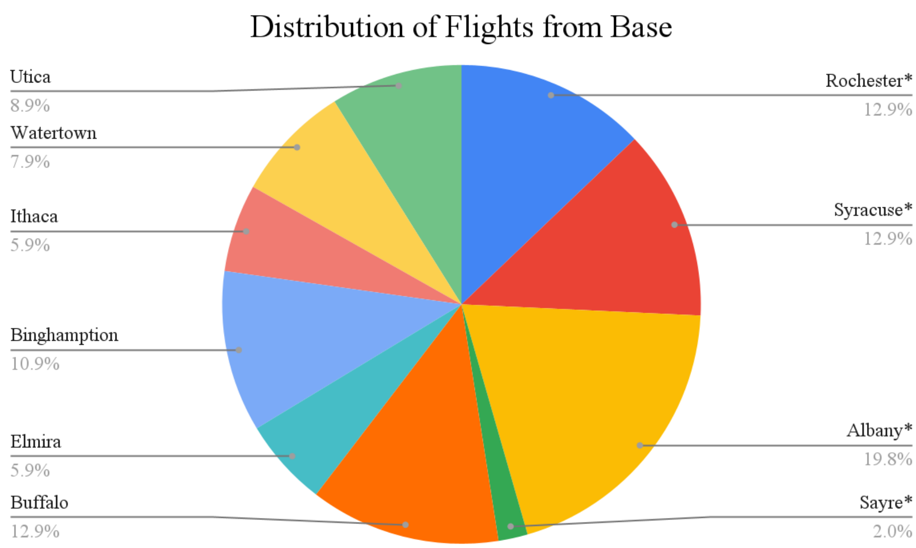

Fig. 1 Pie chart of the distribution of flights from a given base

In addition to utilizing the distribution of flights from base, we visualized the reach of 180 kilometer circumference from cities with the highest frequency of calls. This visualization allowed us to understand the coverage overlap and where we were willing to make tradeoffs in "time to definitive care". It also helped us group call locations in order to reduce the number of bases we use in helicopter operations.

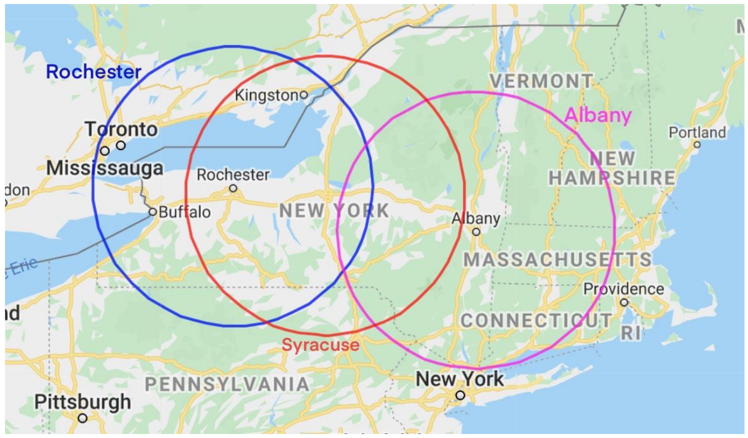

Fig. 2 Radius circumference of reach from bases in high call frequency areas

With the understanding we gained from figure 1 and figure 2, we began mapping helicopters to different bases assignments. While we had more metrics, we focused on comparing the average response time, utilization, and response fraction across the same number of helicopters but different active base combinations. Average response time was weighted highest in our analysis because we considered the importance of getting patients to care in a timely manner.

Case 1 - Unlimited Bases

In the first scenario, where we did not have a limit on the number of bases, we started testing our simulation model by using a single helicopter, and then iterated up to twelve possible helicopters in operation. By comparing the different metrics for the case with only one helicopter, we were able to notice that the best result was when we had a helicopter placed in Ithaca. From there we had to start adding more helicopters in the other locations. To choose a location for the second helicopter we first visualized the reach of 180 km circumference from each city (fig. 2), and then we tested those configurations of bases that covered most of the area with emergency calls. Cases such as placing all helicopters in one base or in bases that are very close to each other and cover almost the same region did not perform as well.

By analyzing figure 2, we were able to see that if we had bases in Rochester, Syracuse, and Albany, the helicopters would be able to cover almost the whole upstate New York area. Taking this into account, we ran simulations with various helicopters to base assignments and compared the metrics. We were able to notice that possible solutions occurred when we had a helicopter in Rochester, Albany, Syracuse, Ithaca, Watertown, or Utica (table 1, Appendix A).

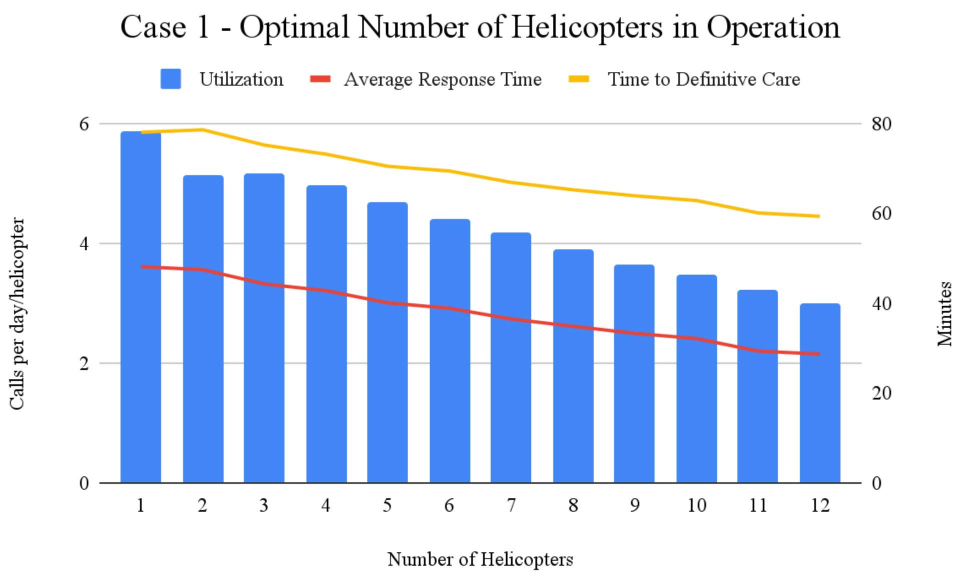

Fig. 3 Number of helicopters metrics with unlimited bases

Looking at figure 3 and table 1 (Appendix A), we can see that as the number of helicopters increases the average response time decreases. Therefore, if we consider only that metric, twelve helicopters should be employed. However, by further analyzing our model and the various simulations we ran, we noticed that utilization decreases as the number of employed helicopters increases. This suggests that using all twelve helicopters might not be the most optimal solution. Even though metrics such as time to definitive care, response fraction, and average response time improved as the number of helicopters in use increased, the overall improvement of the system was not that significant at each step. The most notable changes in the metrics occurred when we employed eight, nine, and ten helicopters.

Even though the average response time decreased when we had eleven and twelve helicopters, we had to add an additional base in Elmira, which increases the fixed costs. In addition, moving from ten to eleven helicopters, the average response time and the response rate only improved by 2.79 minutes and 0.76% respectively. Similarly, from ten to twelve helicopters, these metrics only improved by 3.45 minutes and 0.92%. Given that the overall improvement is not significant and that adding more helicopters and bases increases the fixed costs, we decided that the most efficient solution would be to use ten helicopters in upstate New York. We should employ two helicopters in Rochester, two in Albany, two in Syracuse, one in Watertown, one in Ithaca, one in Sayre, and one in Utica.

Case 2 - Up to Five Bases

In our model analysis of using only up to 5 bases, we noticed very quickly that our metrics showed the best results when we narrowed down bases to Rochester, Albany, Syracuse, Ithaca, and Utica. From there we ran simulations on our model with different allocation amounts of helicopters at each of these bases. We collected data on the top performing base subsets to analyze and determine the optimal number of helicopters to keep in operations.

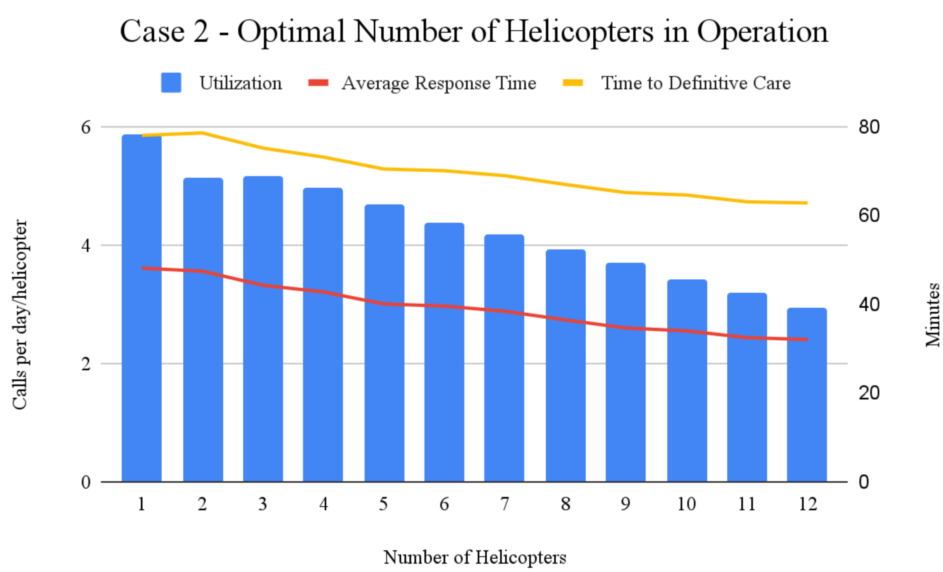

Fig. 4 Number of helicopters metrics with up to five bases

In figure 4 and table 2 (Appendix B), initially we see that utilization decreases as the number of helicopters in use increases. This means that while we can use up to twelve helicopters, it may not be the most favorable choice when considering all the tradeoffs. From our performance analysis we know that having more than nine helicopters is ideal because it provides sufficient coverage and satisfactory operation times. With nine helicopters we would have two helicopters in Rochester, Albany, Syracuse, and Ithaca, and one in Utica.

However, we see that average response time and time to definitive care steadily improved as the number of helicopters in operation increases. If we utilize ten helicopters, we would add another helicopter to Utica; this only improves the average response time by 0.657 minutes and the response rate by 0.001%. We do not believe the cost of adding another helicopter is worth this minimal improvement in the performance metrics. Similarly, for twelve helicopters, the average response time and response rate improve by only 2.60 minutes and 0.005%. Therefore, we did not think all twelve helicopters need to be in use.

Furthermore there was a decrease in the number of helicopters not available each day as we increased the number of helicopters, but a notable change occurred when we used nine to ten helicopters. Around that point we also see the response fraction start to standardized. Therefore, with nine helicopters we believe we are maintaining a high quality of patient care while also efficiently using the financial resources of the HD.

Conclusions

After running the simulations for the case with unlimited bases and the case with a maximum of five bases, we are able to conclude that both more bases and more helicopters lead to a faster average response time. Additionally, the results show that it is best to have the bases spread out across New York so that the helicopters can quickly reach calls in any part of the state.

Case 1 - Unlimited Bases

In this scenario, we were able to add helicopters to any of the bases as long as the total number of helicopters did not exceed twelve. We expected it to be optimal to have at least one helicopter in each of the bases and multiple in only one or two bases, however this was not the case. In all of our simulations, the best outcome never exceeded more than eight bases being used. The maximum number of helicopters at the same base also never exceeded more than three. This suggests that the optimal solution, based on average response time and utilization, requires a tradeoff between the number of bases and the saturation of helicopters there. Specifically, Rochester, Albany, and Syracuse all benefit from having at least two helicopters at their base.

We believe the best solution is to have ten helicopters located across seven bases as follows: two in Rochester, two in Albany, two in Syracuse, one in Watertown, one in Ithaca, one in Sayre, and one in Utica. This set of bases and helicopters gives an average response time of 32.12 minutes, 3.47 successful transportations per helicopter per day, and a response fraction of 82.58%.

Case 2 - Up to Five Bases

In this scenario, we could allocate up to twelve helicopters in a maximum of five bases to avoid the fixed costs associated with adding a new base. From the results of all the simulations, it is evident that having helicopters located in Rochester, Albany, and Syracuse are essential to keeping average response time low and helicopter response rate high.

We believe that the best approach would be to have nine helicopters located in five bases as follows: two in Rochester, two in Albany, two in Syracuse, two in Ithaca, and one in Utica. This leads to an average response time of 34.65 minutes, 3.70 successful transportations per helicopter per day, and a response rate of 81.92%.

Final Recommendations

With unlimited financial resources, it is clear that utilizing all twelve helicopters in more than five bases leads to the lowest average response time. The optimal allocation would be three in Rochester, two in Albany, two in Syracuse, one in Watertown, one in Ithaca, one in Elmira, one in Binghamton, and one in Utica for a total of twelve helicopters and eight bases. This leads to an average response time of 28.66 minutes, 3.00 successful transportations per helicopter per day, and a response fraction of 83.50%. However, it is unlikely that the HD has unlimited resources, so this solution would be in an ideal scenario.

Therefore, looking at the optimal results between the case with unlimited bases and the case with up to five bases, if the HD has the financial capacity to afford more than five bases, we would recommend having two in Rochester, two in Albany, two in Syracuse, one in Watertown, one in Ithaca, one in Sayre, and one in Utica for a total of ten helicopters across seven bases.

Furthermore, if we had the time and resources to add more complexity to our model, we would have liked to look into the impact of requiring helicopters to stop for refueling and servicing between calls, since we expect that would increase average response time and decrease the number of available helicopters. Additionally, we would like to have added the ability for helicopters to reroute on their way back to a base to answer a call that may have arrived nearby. This would ideally decrease the average response time and increase the helicopter response rate.

Appendix A - Table of Metrics from Unlimited Bases

The table below includes the results from the model simulation where we used up to twelve helicopters and could assign them to any number of bases. While we ran various subsets of bases, the table only includes the top performers of those subsets by number of helicopters in order to help with the recommendation on how many helicopters should be employed.

Number of Helicopters	Heli Bases	Average Response Time	Response Fraction	Utilization	Time to Definitive Care
1	Ithaca	48.105	0.77395	5.864	78.006
2	Rochester, Albany	47.433	0.785	5.143	78.552
3	Rochester, Albany, Syracuse	44.262	0.7881	5.162	75.147
4	Rochester, Albany, Syracuse, Syracuse	42.753	0.7969	4.955	73.116
5	Rochester, Albany, Syracuse, Syracuse, Ithaca	40.056	0.8004	4.678	70.428
6	Rochester, Albany, Syracuse, Watertown, Ithaca, Utica	38.85	0.8026	4.399	69.381
7	Rochester, Albany, Syracuse, Watertown, Ithaca, Binghamton, Utica	36.456	0.8125	4.178	66.843
8	Rochester, Albany, Syracuse, Syracuse, Watertown, Ithaca, Binghamton, Utica	34.836	0.81425	3.895	65.202
9	Rochester, Rochester, Albany, Syracuse, Syracuse, Watertown, Ithaca, Binghamton, Utica	33.276	0.82205	3.633	63.873
10	Rochester, Rochester, Albany, Albany, Syracuse, Syracuse, Watertown, Ithaca, Sayre, Utica	32.115	0.8258	3.474	62.817
11	Rochester, Rochester, Albany, Albany, Syracuse, Syracuse, Watertown, Ithaca, Elmira, Binghamton, Utica	29.325	0.8334	3.218	60.057
12	Rochester, Rochester, Rochester, Albany, Albany, Syracuse, Syracuse, Watertown, Ithaca, Elmira, Binghamton, Utica	28.662	0.83495	3.006	59.304

Table 1 Metrics from Unlimited Bases

Appendix B - Table of Metrics from Up to Five Bases

The table below includes the results from the model simulation where we used up to twelve helicopters, but were limited to utilizing up to five bases. While we ran various subsets of bases, the table only includes the top performers of those subsets by number of helicopters in order to help with the recommendation on how many helicopters should be employed.

Number of Helicopters	Helicopter Bases	Average Response Time	Response Fraction	Utilization	Time to Definitive Care
1	Ithaca	48.105	0.77395	5.864	78.006
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3	Rochester, Albany, Syracuse	44.262	0.7881	5.162	75.147
4	Rochester, Albany, Syracuse, Syracuse	42.753	0.7969	4.955	73.116
5	Rochester, Albany, Syracuse, Syracuse, Ithaca	40.056	0.8004	4.678	70.428
6	Rochester, Rochester, Albany, Syracuse, Syracuse, Ithaca	39.573	0.8075	4.378	70.044
7	Rochester, Rochester, Albany, Syracuse, Syracuse, Ithaca, Utica	38.412	0.8119	4.172	68.922
8	Rochester, Rochester, Albany, Syracuse, Syracuse, Ithaca, Ithaca, Utica	36.45	0.8136	3.918	66.945
9	Rochester, Rochester, Albany, Albany, Syracuse, Syracuse, Ithaca, Ithaca, Utica	34.647	0.81915	3.704	65.124
10	Rochester, Rochester, Albany, Albany, Syracuse, Syracuse, Ithaca, Ithaca, Utica, Utica	33.99	0.8201	3.407	64.578
11	Rochester, Rochester, Albany, Albany, Syracuse, Syracuse, Ithaca, Ithaca, Ithaca, Utica, Utica	32.472	0.8252	3.187	63.051
12	Rochester, Rochester, Rochester, Albany, Albany, Syracuse, Syracuse, Syracuse, Ithaca, Ithaca, Utica, Utica	32.043	0.8242	2.927	62.781

Table 2 Metrics from Unlimited Bases

Appendix C - Model Construction & Implementation

Our model is a discrete event simulation based model that relies on a system state and a series of interconnected events. In terms of the system state, in order to fully encompass our system, we must keep track of each helicopter (and some related information), each call (and some related information), the current time, and all upcoming events. For each call, its location, time received, time it would be cancelled, and the index of the helicopter that is handling the call. For each helicopter, we want to keep track of its current status, its destination, the active call associated with it (if any), and its base location. The current time should represent the time that each event is initiated and should be updated as we pass through the simulation. Lastly, we need a list of all upcoming events (namely what they are, when they start, and what call / helicopter is associated with the event).

In terms of the interconnected events within our simulation, there are nine distinct events. The events are *CallArrival, CallCancelled, CallFinishesAtHD, HeliDepartsForCall, HeliArrivesAtScene, HeliDepartsFromScene, HeliArrivesAtHosp, HeliDepartsHosp, HeliArrivesAtBase.* Each of these events and its key components or aspects are discussed by state below in subsequent appendices.

Model Implementation

Now, we shall discuss a few of the details of our implementation in more concrete detail.

If your model chooses to use a status indicator, set each helicopter to be at base and set the list of active calls to be empty. Initialize the event list with the first CallArrival event at a time obtained using the interarrival time logic outlined above.

Our model utilized global dictionaries for the variables associated with the system state (call state and helicopter states). Depending on your implementation, the scope of your variables can be tricky, and global variables may be necessary so that variables can be accessed by other methods. This could also be avoided by using a functional programming methodology that passes state variables into each method and updates them locally.

In terms of our events, we used a global list for the event list. Then, we created a function for each of the nine events discussed in detail above. Certain events required helper functions in our implementation, although they are not necessary as long as each event does the required tasks outlined above. As we do events, be sure to modify the event list as outlined and select the appropriate event to initiate next (the event that is happening soonest).

Lastly, outside of our system state or model, we had to keep track of various statistics or metrics of our model to help with model optimization. In our opinion, this is one of the trickiest (and also most important) aspects of the model. In our implementation, we utilized two global dictionaries that held the stats that we found relevant. Our implementation used batch means to reduce the amount of time spent running our model, so we had to keep track of each of the K batch's statistics in one of our dictionaries, while we had another dictionary keep track of the statistics within the batch. In order words, if we use 20 batches, one list has 20 entries corresponding to the statistics from the dictionary of the statistics of the batch's given timeframe (maybe week 3 to week 5). While batch means is not required, this is a general challenge that should be well planned out and discussed. Regardless of the method for statkeeping or simulation optimization, it is very tricky to account for stat-keeping while using any of these methods and building these as you go and repeatedly checking their validity is important to a correct implementation .

Appendix D - Call State Model Components

The call state in the model triggers the following events: *CallArrival, CallCancelled, and CallFinishesAtHD.* These events will be discussed in more detail below.

Call Arrival

CallArrival pertains to a call being placed that is in need of attention. Within this event, a random time and location must be generated probabilistically. Through investigating prior call arrivals, we see that calls arrive with the following rates throughout the day (fig. 5).

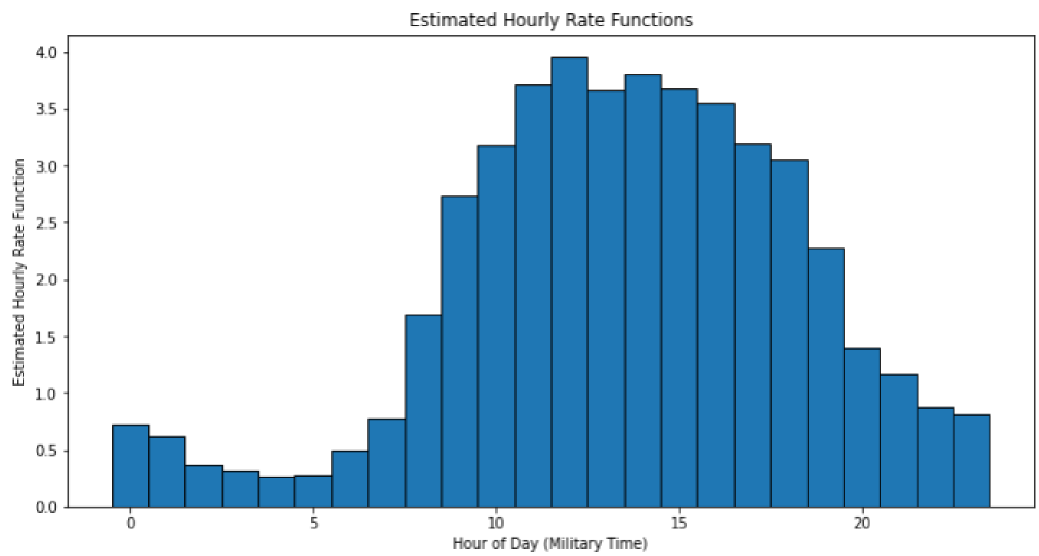

Fig. 5 Call Arrival Hourly Rate Distribution

Using these rates, we can implement a nonhomogeneous Poisson process to generate call arrivals. One tricky part of this is to ensure that a method like thinning or order statistics is used to generate such arrivals accurately. While this is trickier than resampling from past data, it allows more flexibility in terms of ramping up the number of calls in a year. Another tricky part is to ensure that throughout your implementation, all time-based values are on the same scale (minutes, hours, days, etc.), so be sure to keep that in mind.

Next, we need to generate the location of a call randomly. This can be done using an Inversion-like or Acceptance/Reception-like method. First, we can determine the probability of a call within a certain part of New York state by gridding the state and determining the probability of a call falling within that grid. A method like this results in gridded densities like in figure 6.

From these densities, we can generate calls uniformly at random throughout the grid. Similar to generating random call times, while this method is trickier it allows more flexibility and is worth doing.

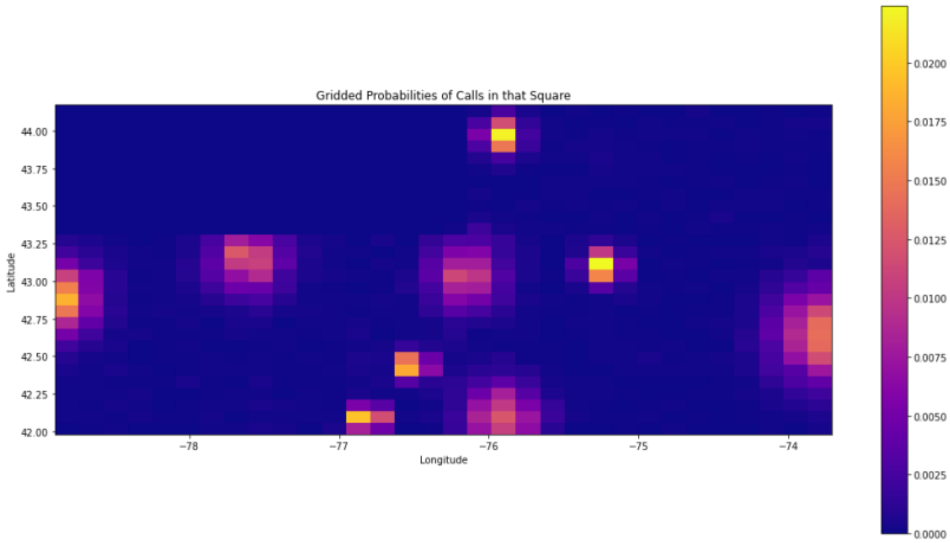

Fig. 6 Call location heat map plot

Within the *CallArrival* event, we also determine if the call finishes at dispatch or is cancelled before then. Thus, we must generate a random amount of time for each call to get cancelled. By investigating past data, we see that using an exponential distribution with parameter λ = 0.205 fits the distribution of cancel times well (fig. 7). Next, we are instructed that the delay at dispatch follows the triangular distribution with minimum 5 minutes, mode 7 minutes, and maximum of 10 minutes. Then, depending on which finishes first, we either schedule a cancellation for that call or that it finishes at dispatch.

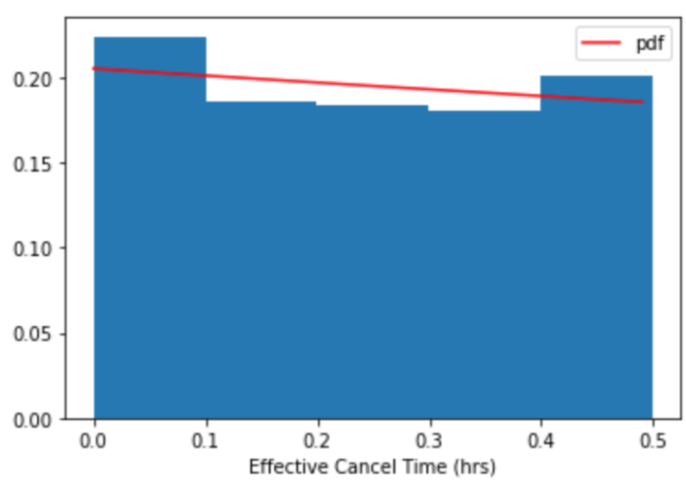

Fig. 7 Call cancellation time distribution

Lastly, within this event, we have to decide which helicopter to assign to a helicopter. In order to be feasible given the constraints of the problem, the helicopter must be within 180km of the caller's location, and must be available for assignment. In our implementation, we chose just to use the closest such helicopter, where available for assignment meant they were currently at base. If there is no such helicopter, note that. Ensure that at this point, the helicopter's status states that it is awaiting clearance and that the helicopter is pointing to that call. Going forward, we neglect to mention these types of status updates as they are dependent on one's implementation (and certainly not necessary to implement the simulation), but they are important to consider within each event.

Call Cancelled

CallCancelled pertains to handling the cancellation of a call (fig. 7). If the call's helicopter hasn't left yet, cancel the call and modify the helicopter's status to at base (available for another call). If they're en route, determine when they would return home, and use this information to schedule an event for the helicopter arriving at base. Determining when they would return home is tricky, but it is also equivalent to the amount of time the call has spent in the air. This quantity is equal to the call's cancellation time minus the sum of its call arrival time, time at dispatch, and prep time.

Call Finishes at Helicopter Dispatch

CallFinishesAtHD pertains to determining whether it is safe to dispatch a given call. By investigating past calls, we estimated from our 95% confidence interval that about 10.1% of calls are unsafe. Thus, we must randomly decide whether a call is safe or unsafe. If it is unsafe, cancel the call and set the helicopter's status to being at base. If it is safe, there is a prep time that we know is triangularly distributed with a minimum of 5 minutes, mode of 7.5 minutes, and maximum of 10 minutes. If the call would be cancelled before prep time, cancel it at the end of the prep time. Otherwise, after this prep time, schedule the helicopter leaving for the call at the end of prep time.

Appendix E - Helicopter State Model Components

The helicopter state in the model triggers the following events: HeliDepartsForCall, HeliArrivesAtScene, HeliDepartsFromScene, HeliArrivesAtHosp, HeliDepartsHosp, and HeliArrivesAtBase. These events will be discussed in more detail below.

Helicopter Departs for Call

HeliDepartsForCall pertains to handling the call being in flight towards the scene. In this event, only two things can happen. Either the call is cancelled before the helicopter arrives at the scene or the helicopter arrives at the scene. If the call gets cancelled, determine where its helicopter would be when it's cancelled based on its flight speed (180 km) and actual flight time (current time minus time departed from base), and set that as its destination and cancel the call. Otherwise, schedule the helicopter arriving at the scene at the time it will arrive on scene (which should be calculated using the distance from the base to the call location)

Helicopter Arrives at Scene

HeliArrivesAtScene pertains to the helicopter arriving at the scene of the call location. Once this point happens, cancellations are not possible. By investigating past data, in figure 8 we know that the time spent at the scene can be modelled by a Gamma random variable with parameters a = 2.95 and scale = 0.12. Thus, generate a random scene time, and at this time, schedule an event for the helicopter leaving the scene.

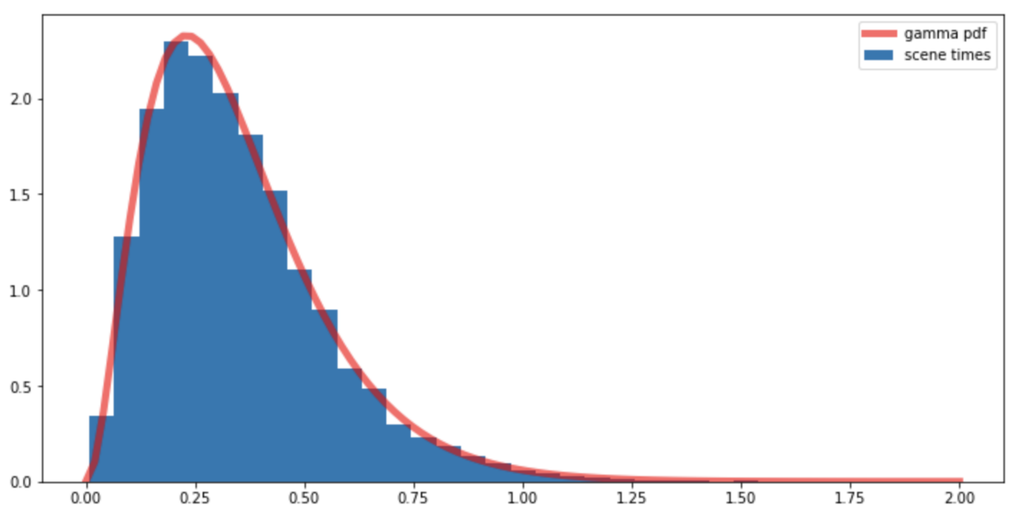

Fig. 8 Helicopter time spent on scene distribution

Helicopter Departs from Scene

HeliDepartsFromScene pertains to what happens as the helicopter leaves the scene. By investigating past data, we know that 80.7% of calls go to their closest medical center (assuming the closest isn't a trauma center). Thus, we can use this to estimate the fraction of calls that don't require transport to a trauma center. If it requires a trauma center, send the helicopter to the nearest trauma center, otherwise send it to the nearest medical facility. Determine when the helicopter will arrive at its destination, and schedule the helicopter arriving at the hospital at that time.

Helicopter Arrives at Hospital

HeliArrivesAtHosp pertains to the helicopter arriving at the hospital and the time its crew spends there. By investigating past data, we know that the time the crew spends at the hospital can be modeled by a Gamma distribution with parameters a = 2.91 and scale = 0.17. Then, schedule a departure from the hospital at this time.

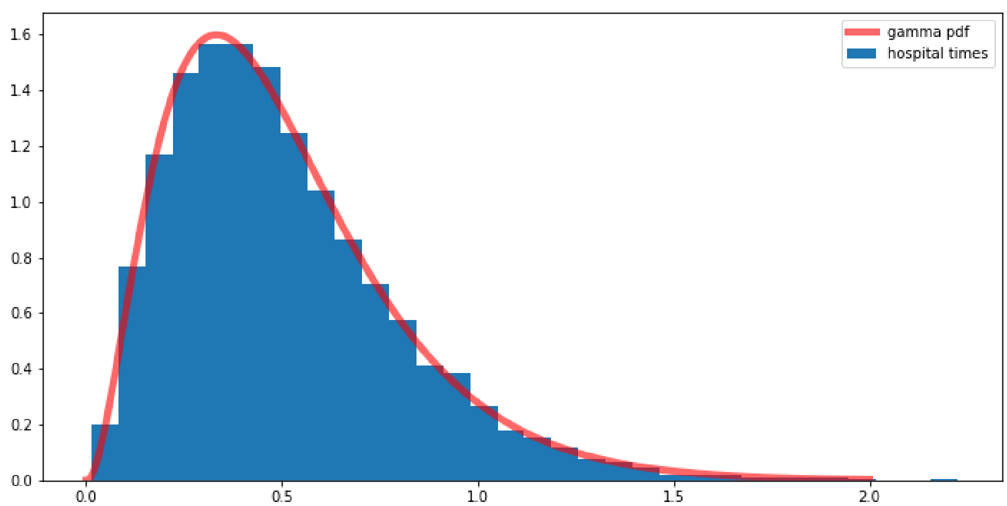

Fig.9 Helicopter time spent at hospital distribution

Helicopter Departs Hospital

HeliDepartsHosp pertains to sending a helicopter back to its base. At this point, note any final statistics about the call, then send the helicopter back to its base. Note that the time it arrives at its base must be computed from the distance between the hospital and its base and the speed of the helicopters.

Helicopter Arrives at Base

HeliArrivesAtBase pertains to the helicopter arriving back at its base. If you are updating a helicopter's status, at this point the helicopter should be marked as at base.

Appendix F - Performance Metric Calculations

The performance metrics we analyzed within our simulation model to support our final recommendation. The performance metrics are listed by order of importance.

Average response time

This is the time from when a call is received at dispatch to when the helicopter arrives at the scene (and thus is only calculated for calls that arrive at the scene). Thus, within the event handling a helicopter arriving at the scene, we calculate this by taking the current time minus the time that call was received, and append this to our existing list of response times.

Utilization of helicopters

This is computed by finding the average number of calls satisfactorily transported per day and dividing by the number of helicopters. Thus, when a helicopter arrives at the hospital, we increment the number of calls satisfactorily transported in that given day. Then, at the end of our simulation, we take the average over all days in our simulation, and divide that by the number of helicopters.

Time to definitive care

This is the time from when a call is received by dispatched to when the patient arrives at their care facility. Thus, within our event handling the helicopter arriving at the hospital, we should append this time to our existing list of times to definitive care.

Percentage of calls dispatched

This is the percentage of calls where a helicopter is dispatched. For clarity, a call is not dispatched if it is unsafe to fly or if no helicopters are available within range. Thus, we have to keep track of the number of calls that occur within our simulation, the number of calls where it is deemed unsafe to fly, and the number of calls where there are no helicopters available. We can keep track of the number of calls that occur by looking at the last call's call index. Then, the number of unsafe calls can be incremented during the event handling the call finishing at HD if it is deemed unsafe. Lastly, within the call arrival event, if there is no helicopter available within range, we can increment the number of calls with no helicopter available.

Response fraction

This is the fraction of calls received at dispatch where a helicopter eventually arrives at the scene. Thus, within the event handling the call finishing at HD, we can increment the number of calls that are received at dispatch. Then, within the event handling a helicopter arriving at the scene, we can increment the number of helicopters that have arrived at the scene. Using these quantities, we can then compute the response fraction at the end of the simulation.