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By:

Nishita Ardhapurkar, Undergraduate Department of Biomedical Engineering

Ryan K. Finley, Undergraduate Department of Biomedical Engineering

Sabin Ahmed, Ph.D., MITRE

Rob Lieberthal, Ph.D., MITRE

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Approved: ______________________ Date 5/11/2021
Sabin Ahmed, Ph.D., MITRE

Approved: Robert D. Lieberthal Date 05/11/2021
Rob Lieberthal, Ph.D., MITRE

Approved: ______________________ Date ______________
Shannon Barker, Ph.D., U.Va. Biomedical Engineering

Development of Optimization Framework for the Reallocation of Air Ambulance Base Locations in the United States

Nishita Ardhapurkar[a,1], Ryan K. Finley[a,2]

[a] Undergraduate Biomedical Engineering, University of Virginia

[1] Correspondence: nsa3av@virginia.edu

[2] Correspondence: rf2ub@virginia.edu

Abstract

Air ambulances are utilized to quickly and efficiently transport critically ill or injured patients to a treatment facility or hospital throughout the United States. Currently, based on the allocation of air ambulance bases in 2019, an estimated 42.5 million people live outside of a ten-minute fly circle from an air ambulance base.[1] Therefore, an optimization framework is necessary in order to redistribute air ambulance base locations to better meet the needs of the unserved population in the United States. In this research, a Greenfield Approach was utilized to reallocate the current number of air ambulance bases to serve a higher percentage of the population. The Maximal Covering Location Problem (MCLP) allows for a maximization of population coverage within a specified distance from the air ambulance base location and a specified number of air ambulance bases. To create the optimization framework, QGIS was used to provide geospatial analysis on demand points and flight circles based on the population by counties in a state. Allagash and Pulp Python programming modules were used to create the problem our team was attempting to solve by specifying the input of constraints into the model. To optimize the location of the air ambulance base locations, CPLEX Optimization Studio solved the problem created by the Python modules while continuing to use the demand points and flight circles from QGIS. The results optimization framework yielded a 3.05% increase in the population coverage compared to the existing coverage (an increase from 6,897,229 people to 7,157,853 people). The optimization framework presented in this paper successfully provides a novel approach to reallocating the air ambulance bases across the United States.

Keywords: Optimization, Maximal Covering Location Problem (MCLP), Greenfield Approach, Air Ambulance Base Location

Introduction

Air ambulances are utilized to carry critically ill or injured patients quickly and efficiently to a treatment facility or hospital throughout the United States. The air ambulance industry serves more than 550,000 patients per year with over 800 air ambulance fleet locations across the United States[2]. There are roughly 500,000 flights per year with a total revenue of $4.03 billion in 2019[3]. However, the air ambulance industry has to deal with a number of issues such as high cost, patient morbidity and mortality rates, and health equity. Our goal is to determine the locations where air ambulance bases should be placed in order to best cover and serve the needs of the United States population.

Based on the allocation of air ambulance bases in 2019, an estimated 42.5 million people live outside of a 10-minute fly circle from an air ambulance base[1]. This means that a twenty-minute response time, which is imperative in some emergency cases, cannot be achieved for 42.5 million people.

In the rural U.S., there are an estimated 85 million people who without air ambulances, would be unable to reach a health care facility within an hour after the injury or illness has occurred[4]. This is significant, especially in rural communities where patients are 14% more likely to die from trauma than patients in the urban U.S.[5] Trauma mortality rates can be reduced if there is a quick response once trauma has occurred. Studies show that a prehospital time of less than one hour can greatly increase the patient outcomes after severe head trauma, intra-abdominal bleeds, and severe thoracic injuries[6-8]. This one hour response time is known as the “golden hour”. This constraint of a golden hour is essential in lowering mortality and morbidity rates in patients.

Air ambulance providers need to meet the needs of both rural and urban patients. This is especially important due to hospital closings across the United States, especially in rural areas. Since 2010, over 100 hospitals have closed and another 430 are at risk, signifying a major issue within the healthcare system[9]. As these at-risk hospitals begin to close, the access to healthcare will continue to diminish for rural communities. As seen in Figure 1, there is a lack of coverage for air ambulance bases across the country. There are large areas in the country that are sparsely populated that do not require an air ambulance base near them if population coverage is the main goal. However, the population of the United States is constantly changing and certain areas are experiencing a rapid population increase. Thus, it is an important aim of our team’s work to ensure the air ambulance fleet locations are covering the largest population possible based on a twenty mile flight circle.

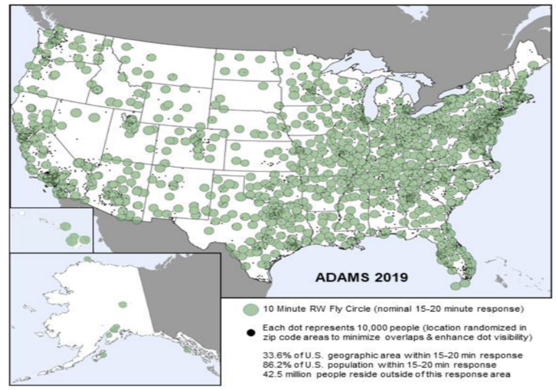


Figure 1. Current Allocation of Air Ambulance Bases. The green circles represent locations of ambulance bases as of 2019 with a 10 minute flight circle (response times of 15-20 minutes)[1].

Currently, extensive research has been done in the ground ambulance industry on optimizing ground ambulance locations. Many different types of frameworks have been created to optimize ground ambulance dispatching and many other issues within the industry. One such framework used the rolling-horizon optimization framework to minimize patient “tardiness” due to ambulance diversions[10]. Ambulance diversions are used when emergency rooms are overcrowded and cannot take any more patients. In these cases, the ambulances have to take patients to a different hospital. However, as mentioned before time is a critical factor in positive patient outcomes, so it is important to minimize ambulance diversions and tardiness due to them. Another framework used the recursive optimization-simulation approach to optimize ambulance location and dispatching[11]. Many different frameworks have been developed to optimize different aspects of the ground ambulance industry.

Air ambulances are used when traditional ground ambulances cannot be used due to rough terrain or long distances. In one study, patients transported by air ambulances were 57% less likely to die than patients transported by ground ambulances, due to the reduced transport times[12]. As mentioned previously, the current air ambulance system is not sufficient in providing optimal population coverage for each state. There is very little current research in the field, especially in optimization frameworks. One such optimization framework study on the air ambulance industry is based on the Norway healthcare system. In that study, the authors use the maximal covering location problem (MCLP) to allocate air ambulance bases such that the population of Norway is a desired service distance away from an air ambulance base. This was done by using population density data[13].

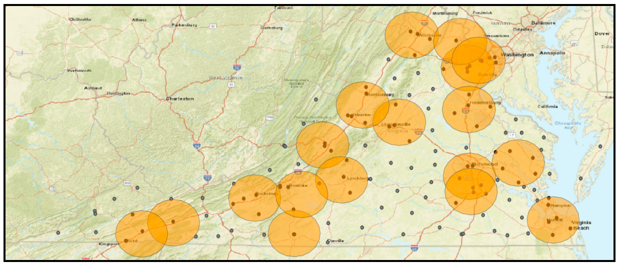
This is similar to the optimization framework that was created for this project. However, there are some key differences. The US is a much bigger country than Norway so the model will be on a much larger scale. Also, the air ambulance industry as a whole is different in Norway, so creating a framework for the industry in the U.S. requires different parameters. One key difference is that Norway has a national air ambulance system whereas in the U.S. air ambulances are siloed at the local and state level. Also, Norway is a much smaller country and therefore their air ambulance system is much simpler. The research will present a novel optimization framework for the air ambulance industry in the state of Virginia that will be expanded to the continental United States in future work. The optimization framework will be built on population by county in Virginia, rather than population per square kilometer as the Norway paper used. In this way, our team's optimization framework will build on and expand the work done in Norway. It will also incorporate some of the parameters used in existing ground ambulance optimization frameworks. The optimization framework created will allow for improved air ambulance dispatching systems that would improve ambulance base population coverage and response times. Instead of reallocating the current fleets, we will be utilizing an optimization model with a Greenfield approach to determine the best locations for air ambulance fleets to serve rural and urban communities across the country. A Greenfield approach involves not considering the current locations of air ambulances when building the optimization model. This will give us an idealized solution to the problem.

By placing the fleets in the right locations based on county population data, we will increase the total percentage of the population that is covered by air ambulance bases and decrease response times to patients through limiting the flight circles to twenty minutes. In addition, through optimization of the fleet locations, we would ensure that access to medical care is improved. Through designing and constructing an optimization model based on the maximal covering location problem (MLCP), we are able to accomplish maximum population coverage. Our project will ideally revolutionize the current air ambulance transportation network through the provision of an ideal allocation of air ambulances to optimize trade-offs between county population coverage and response times.

Results

A model with the optimized base locations in Virginia was created. Currently, there are 18 air ambulance bases in Virginia and these bases were reallocated to provide better population coverage in the state. Figure 2 shows the current allocation of air ambulance bases and the optimized allocation of air ambulance bases, respectively.

There are a few key differences that can be seen between the two. First, the optimized model better covers the population in Central Virginia. Second, the optimized model covers more population in the Appalachian Plateau region of Virginia.



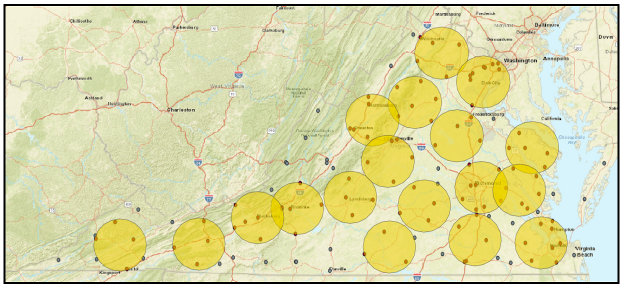


Figure 2: Current Air Ambulance Base Locations (top) and Optimized Air Ambulance Base Locations (bottom) in Virginia. Provides a comparison of the current allocation of air ambulance base locations and the optimized allocation of air ambulance base locations in Virginia.

Total Population of Virginia	Population Coverage in Current Allocation	Population Coverage in Optimized Model	Percentage Change in Population Coverage
8,566,397	6,897,229	7,157,853	3.05%

Table 1. Optimized Population Coverage Results. Provides an overview of the population coverage change based on the reallocation of the air ambulance bases with our team's optimization model.

As seen in Table 1, the optimization model was able to increase the percentage of the Virginia population that was covered by the optimized air ambulance base locations, with a twenty minute flight circle. The total population of Virginia covered with the optimized allocation would be 7,157,853 people, versus a population of 6,897,229 people who are covered under the current allocation. This accounts for a 3.05% increase in the number of people who would have access to air ambulances under the optimal allocation.

Discussion

The air ambulance optimization framework in this paper is effective in increasing the population coverage of air ambulance bases. As this is a new way of reallocating air ambulances, it can be considered a successful novel approach in optimizing air ambulance bases across the country. In addition, with the integration of an optimization framework for air ambulance bases across the state of Virginia, it allows for the reallocation of air resources as demand changes. The air ambulance industry needs to be a fluid industry where it is able to adjust based on population and demand changes. This is critical, due to the continued closure of hospitals around the country and the constant aging of the United States population. As the population across the United States continues to age, it will lead to an increase in the demand for air ambulances in new areas in order to quickly transport patients. Thus, this model can provide companies a solution for where air ambulance bases should be placed and built in the future.

Although successful in covering a larger population in Virginia, there were limitations to our team's approach. The software that was utilized for the model did not allow for a completely Greenfield approach. The software required an input of possible air ambulance locations. For a true Greenfield approach, all possible air ambulance base locations would have to be input, which is not possible. Therefore, a "more optimized" solution with a greater population coverage could be achieved if more possible air ambulance base locations were inputted. Also, the use of population density or disease/trauma data to create the flight circles, would add additional accuracy to the model since the flight circles would be better distributed by demand. Lastly, by utilizing population by county to allocate bases, it automatically favored urban areas, since they are generally more populated. Thus, the air ambulance bases are not fully aligned with the demand for these services.

In the future, the optimization model and approach used in our team's project could be extended to the rest of the continental United States. The reallocation and optimization of air ambulance bases around the country should occur in order to best serve the most patients possible. In addition, in future work researchers could utilize new parameters or constraints in the model in order to serve a greater number of people. New parameters that could be utilized instead of county population numbers could be population density or disease incidence and prevalence rates of common air transport patients. This could allow for air ambulances to serve where the highest need and demand are. A constraint that could be altered in future work could be the flight circle radius or the consideration of cost implications. Lastly, this framework could be used in the future to determine where new bases should be placed. This would allow the air ambulance industry to serve a greater number of patients, benefiting them in the long run.

Materials and Methods

Data Collection

The Atlas and Database of Air Medical Service (ADAMS) was used to find the current allocation of air ambulance bases in Virginia. A report by Booz Allen Hamilton was used to find information on the speed of air ambulances. This was used to determine the size of the flight circles surrounding the air ambulance bases. Population data was collected from the US Census.

Model Constraints

The optimization model developed by our team had to be constrained in a few ways in order to best serve the needs of the Virginia population, while still accomplishing the goal of improving air ambulance coverage and access for patients. The flight circles developed in the model were constrained to be no larger than twenty miles. This was included in order to serve patients in emergency scenarios, as oftentimes response times are critical in the mortality and morbidity rates of patients. In addition, the model is constrained by the current number of air ambulance bases present in Virginia. There were eighteen air ambulance bases located in Virginia in 2020. This allows for the work to be focused on reallocation of available resources, rather than creating resources that may or may not be accessible.

Model Development

In developing the optimization model, our team utilized various software and packages in order to successfully reallocate the air ambulance bases. QGIS, a geographic information system, allowed for the creation of the demand points and flight circles. This system allows for the analysis of geospatial data, thus we were able to manipulate the population data by county to create initial demand points and flight circles. Pulp and Allagash Python modules were then used to create the problem utilizing the constraints outlined. Then, CPLEX Optimization Studio was utilized to solve the problem set forth by the Pulp and Allagash modules. Lastly, QGIS was used to visualize the optimized flight circles and calculate population coverage before and after optimization.

End Matter

Author Contributions and Notes

N.A. and R.F. designed research, N.A. and R.F. performed research, N.A. wrote software, N.A. and R.F. analyzed data; and N.A. and R.F. wrote the paper.
The authors declare no conflict of interest.

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