Simulating Metro Manila Ambulance Response Time

Introduction

For this assignment, I chose to model the emergency response network. Then I chose the National Capital Region of the Philippines which consists of multiple cities that are highly congested and with the presences of bridges (see Figure 1). The current simulation is exploring how the different amounts of ambulance stations affect the response time of ambulances across the city and also the effect of strategical position of ambulance stations. From these simulations, I want to examine how the network structure reflects the emergency response efficiency in the area and hopefully come up with a strategic recommendation to improve the emergency service.

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Figure 1. Map of NCR

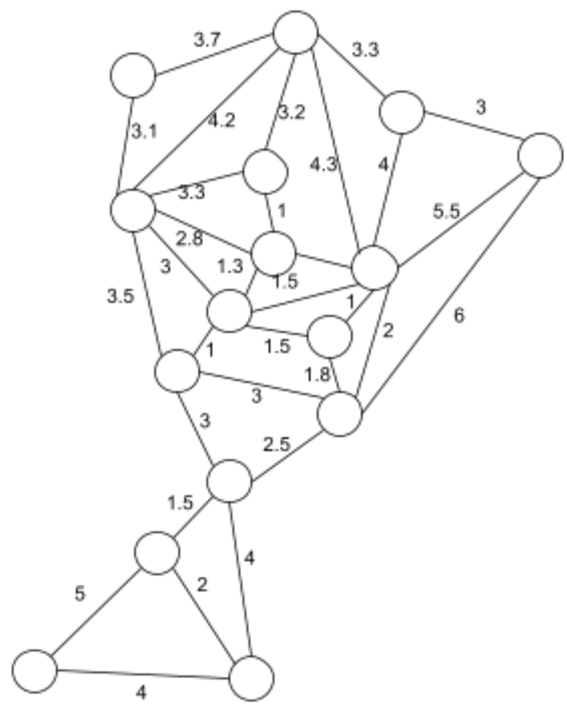


Figure 2. Network diagram of NCR along with the estimated edge weights based on the length that was created using the NCR map. The edge weights were just estimated.

The rules of the simulation are as follows:

1. Once a call has been made, the call center will immediately assign the closest available ambulance to the destination.
2. Ambulances can only respond one area and cannot go to two areas between transit to and from their station
3. Each node represents one city and one city can only have 1 ambulance station.
4. The operation is 24/7

The assumptions of the simulation are as follows:

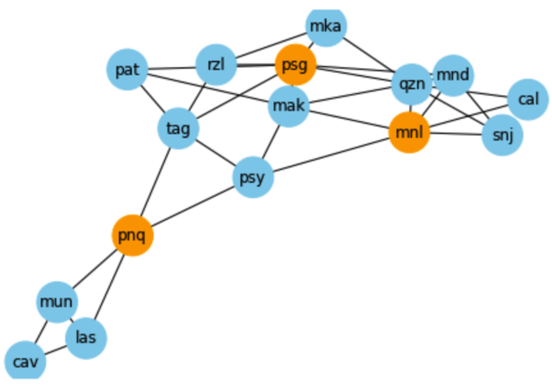
1. There is only one ambulance station per city
2. Calls for emergency services are modeled with a poisson distribution while the service time was modeled with a normal distribution.
3. There are no highways or freeways. Therefore, city regions that touch are the ones with nodes connected. If an ambulance wishes to travel to a location 3 cities away, they have to pass through this city.
4. Emergency responders and call center agents are constantly working

The current parameters that were estimated are the following:

1. Arrival time: data was not available online. Thus, I estimated based on the model's scale (city-based and assuming that there is only 1 station per city). An emergency call is expected every 20 minutes and was modeled with an exponential distribution to be used for the scheduling function. This variable is crucial since it sets the level of need for responses in the entire region. The whole simulation will be building upon this variable.
2. The number of ambulances are set to 2 per station as it is considered as the average per hospital. This variable affects the availability of a station and can highly affect nodes with high degrees as they are expected to encounter more calls.
3. Service time: the service time of the responders are modeled with a normal distribution with a mean of 7 and a standard deviation of 2 since these are trained individuals and consistency in speed should be exhibited. The variability accounts for the different types of assistance that is required in the location of the situation.

For our empirical analysis, we would be investigating two concepts: strategic mapping and strategic capacity planning.

Strategic Mapping



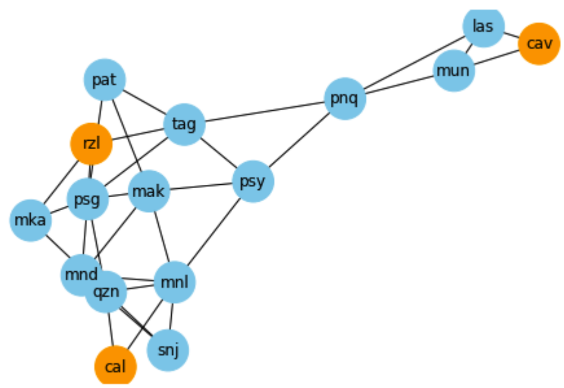


Figure 3. Good mapping of ambulance stations

Figure 4. Bad mapping of ambulance stations

Here, we are investigating if choosing the location with the highest degree and ease of connection will have an effect in the average response time of ambulances.

Constraints and constants:

1. Number of stations and ambulances per station
2. Arrival and service rates
3. Node Structure

The strategically chosen nodes are of high degrees and act as bridges to clusters (Paranaque). The poorly chosen nodes are the ones that have long edges, low degrees, and are located at the very corners of the map.

Good mapping: Manila, Paranaque, Pasig

Bad mapping: Rizal, Cavite, Caloocan

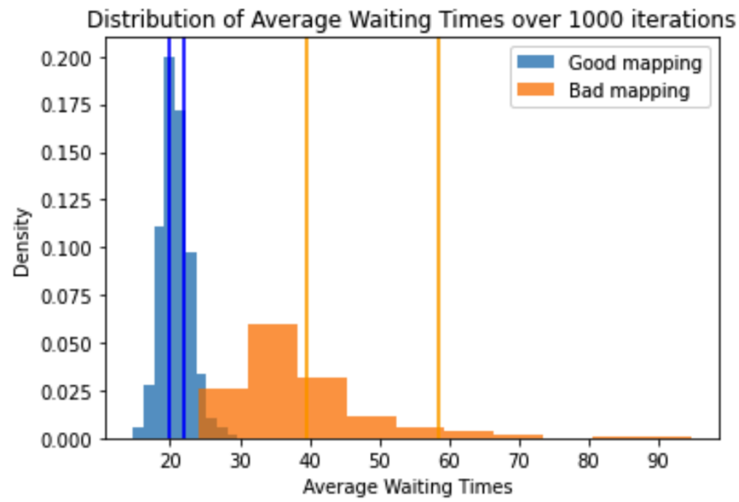


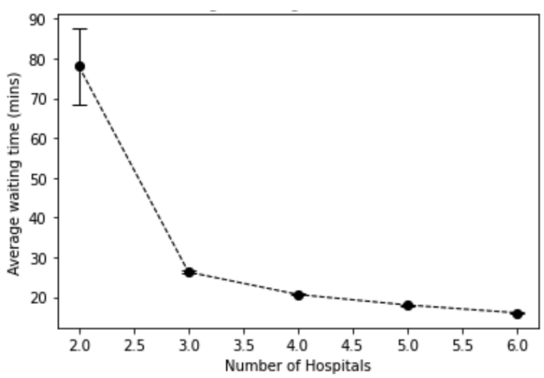
Figure 4. Distribution of Average Waiting Times over 1000 iterations. The good mapping has a significant difference compared to the bad mapping with respect to average waiting times for the emergency response. The confidence interval was calculated using the quantile function in Python.

Based on our results, the location of hospitals are very significant when it comes to reducing average waiting times. In the good mapping scenario where we focused on putting the 3 hospitals to nodes with the highest degrees and also performing as a bridge between clusters have a significantly lower average waiting time compared to the badly mapped set of hospitals that are placed at low degree nodes and high edge weights. Given the confidence intervals, it further strengthens the significance of properly mapping the hospital locations.

One of the main reasons is the travel time between nodes. The travel time is the sum of edge weights of the shortest path between the station to the target node. Therefore, we need to assign hospitals to where it would have the least distance from all nodes. This can be placed at nodes with high degrees or center of the network.

Capacity Planning

Here, we look into the different variations of the number of ambulance stations and ambulances allocated to the city and see how it affects the waiting times. For the changing number of stations, we are randomly allocating the ambulance k times for every simulation. For the changing number of ambulance counts. We will only be focusing on one set of ambulance stations. Here, we will use the bad mapping example.



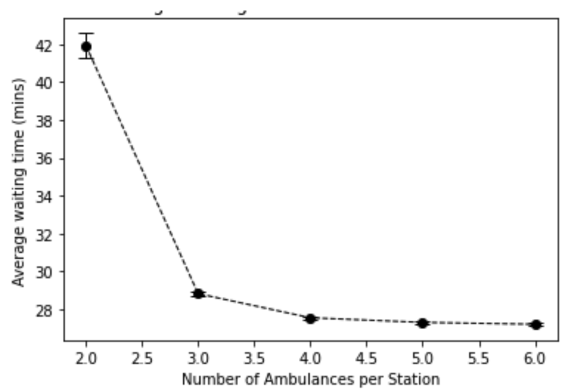


Figure 5. Error bar plot for the average waiting time with varying number of hospitals in network. The simulation was repeated 500 times with a simulation term of 5000 mins. The assignment of hospitals for each node is arbitrary. The number of ambulances per hospital in this simulation is 2. The default value was 3 hospitals. The error bar represents the 95% confidence interval.

Figure 6. Error bar plot for the average waiting time with varying number of ambulances in the network. The simulation was repeated 500 times with a simulation term of 5000 mins. The default value was 2 ambulances per station. The number of hospitals for this simulation was 3. The error bar represents the 95% confidence interval.

Given the number of 500 simulations, the results show a decent convergence of data. What I did is that for every simulation, there are 5000 steps since sometimes it takes longer for the model to reach a stable state. Meaning, the scale of the parameters makes the early results of each simulation not different from one another. Achieving that stable state at every simulation helps a lot in differentiating the different variables.

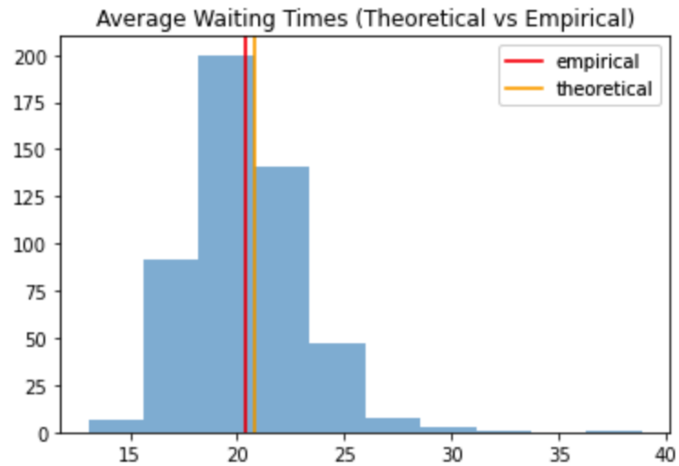
Starting with the number of hospitals, there is a huge decrease in average waiting times for responses as we increased from 2 to 3. Further than that did not show any more significant improvements. The way this simulation was set-up is that for each trial, it will randomly allocate k amount of hospitals across the system. We see that the confidence interval for 2 hospitals is considerably bigger than the other since we can have more ways to move our hospitals around. We already saw how the mapping of hospitals greatly affects the average waiting time (see Figure 4). The default setting in our simulation was 3 hospitals so there is not much difference we can provide in this area.

Looking into the number of ambulances, we see a significant decrease from the default set-up of 2 to 3 ambulances per hospital. An increment of 1 ambulance per hospital improves our ability to attend more calls because it increases our capacity by 3 more ambulances. Given our set of parameters in this model, we can fairly say that incrementing the number of ambulances would be preferred in improving the emergency operations.

Theoretical Analysis

$$\frac{\sum \text{weight of network}}{N_{nodes}} - \text{avg. service time} = \text{avg. waiting time}$$

Based on our prior empirical results, the edge weights have a high effect on the waiting time of the individuals. We can get the average edge weight of the network and subtract the average service time. We can predict the average waiting time of patients for responders.



Here, we simulated 500 results for the empirical approach and calculated its mean. We compare it with the theoretical value and both seemed to show the same results. However, this is only limited to the current parameters that the model has. This can change drastically since the number of hospitals and number of ambulances can also affect the waiting times. All in all, this model is not very good but it can be further improved.

Recommendation and Conclusion

Based on our two investigations in strategic mapping and capacity planning, we can say that properly allocating the hospitals based on the network topology and increasing one more ambulance per hospital will reduce our response time.

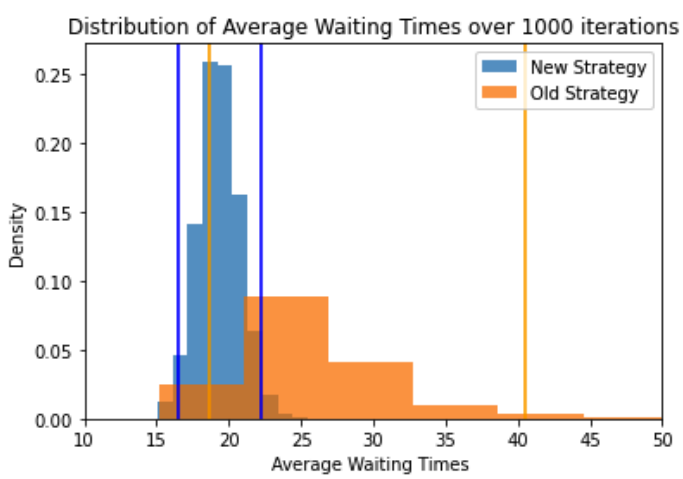


Figure _. Comparing the New and Old Strategy based on waiting times. The new strategy shows a strong improvement compared to the old model.

The old model still follows a random allocation of hospitals, 2 ambulances per hospital. The new model has the strategic locations for the hospitals and 3 ambulances are allocated per hospital.

These results are only limited to the assumptions and rules set by the researcher. Further analysis on more realistic models, inclusion of highways, and skyways should be included since edge weights do have a strong influence on the average response times of ambulances.