

Modeling Ambulance Service for High-risk Epidemic Patients in Ho Chi Minh City During COVID-19

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Abstract: As the recent fourth-wave pandemic in Ho Chi Minh City (HCMC) started in June 2021 we see that scheduling and modeling for call center and ambulance service are critical to successfully delivered COVID-19 severe illness patients to their suitable hospitals. The modeling process is developed by using the ARENA application, as the result, the simulation model suggests that considering the severity of each area during the pandemic before distributing emergency vehicles to ambulance base across the city helps reduce response time as well as increase utilization rates of such vehicles. The proposed method highly shows efficiency and could be applicable in any cases of this kind of pandemic

Keywords: Ambulance service, Crowdedness Index, Discrete-Event Simulation, Rerouting strategy

1 Introduction

The study deals with transferring patients to a suitable hospital depending on their epidemic conditions at the time of emergency vehicle arrival to maximize the number of epidemic patients that could be arrived at hospitals. Additionally, the study will also incorporate a rerouting strategy to redirect patients to the next hospital to balance the load of emergency medical system during the pandemic. Figure 1 present the general modeling process of the Ambulance Service (AS) system of HCMC during COVID-19

Modeling AS is applicable, which is useful for decision makers have better view of the current performance of a system and provide appropriate improvements for the EMS system at the managerial level and increase the healthcare system's ability to cope with future pandemics.

One of the problems regarding high-risk epidemic patients is that they are scattered around the city. The transportation capacity of the ambulances is limited when the number of patients who need special medical care increases every day as the outbreak continues. Therefore, scheduling and enhancing emergency service to effectively transfer these patients to the suitable hospitals within the limited time to minimize the risk for COVID-19 patients

This paper considers high-risk epidemic patients are COVID-19 infected individuals whose symptoms become worsen and have higher-risk of fatality need to be transferred immediately to hospitals. There are three urgency levels based on guidelines [8], [9]

- Urgency level 1: patients with average level of COVID-19 symptoms with underlying health conditions.
- Urgency level 2: patients with serious levels of COVID-19 symptoms with or without underlying health conditions.
- Urgency level 3: patients with critical level of COVID-19 symptoms who need immediate medical interventions.



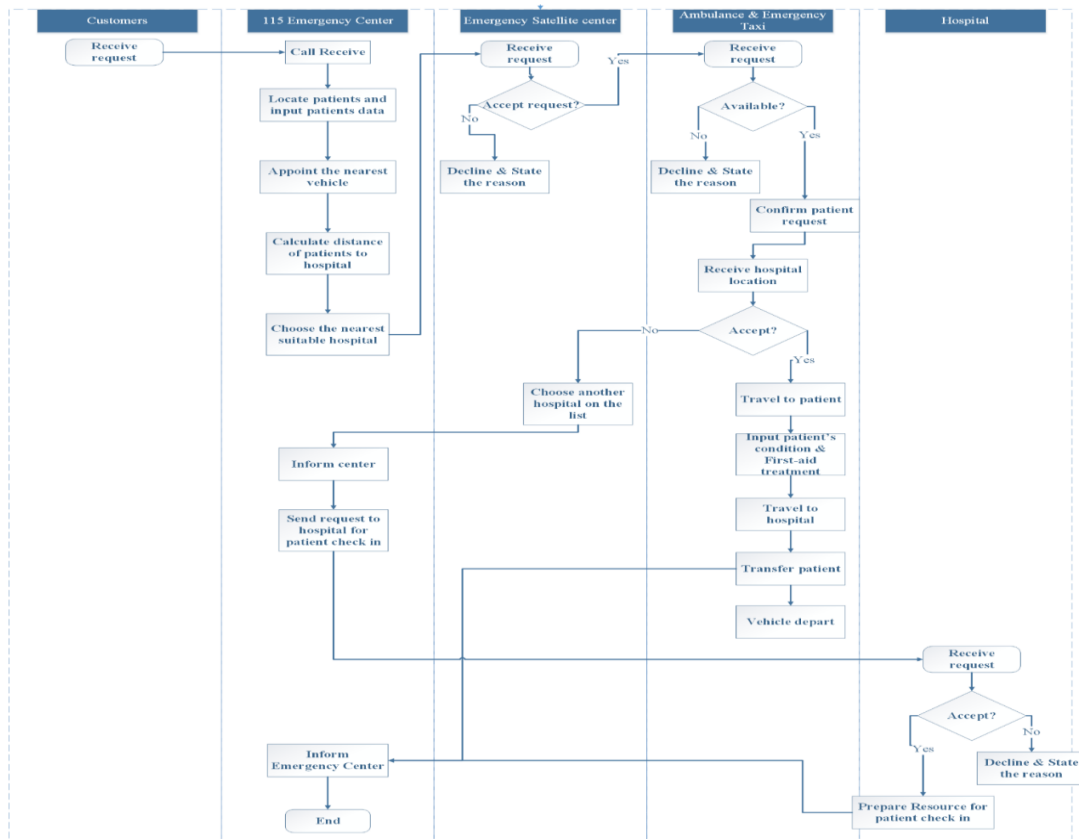


Figure 1: Operational process at Emergency Medical Service.

Regarding AS, this study considers activities from receiving calls from Emergency Center 115 of HCMC to successfully deliver patients to their suitable hospital in HCMC. The only vehicles this study used are official emergency taxis provided by corporations such as Me Linh (a taxi company) and Grab for patients' transportation and ambulances from Emergency center 115 and other hospitals in HCMC area.

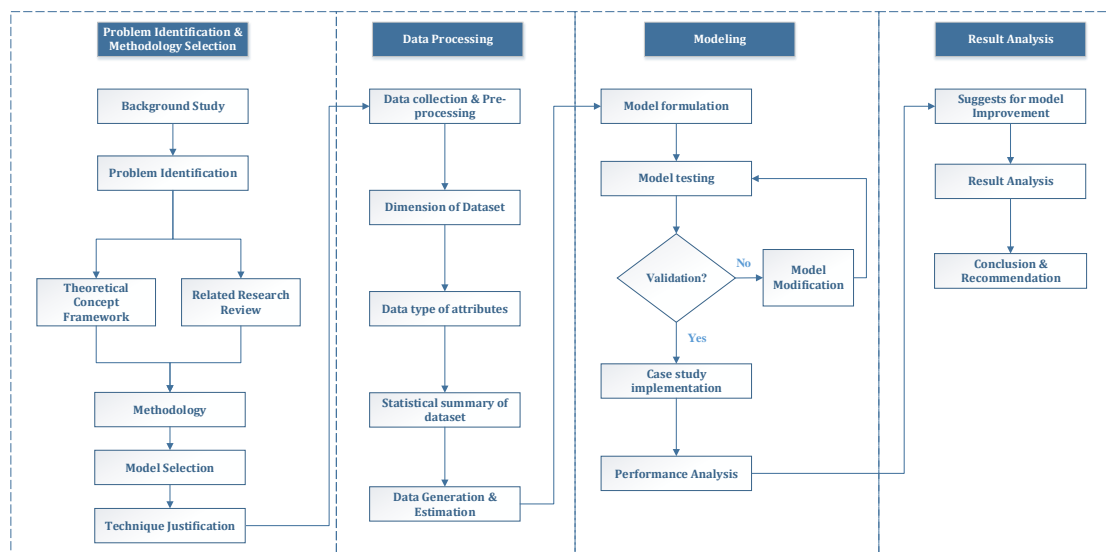


Figure 2: Flowchart of the study

2 Literature Review

Different approaches are optimizing AS system to increase the number of patients reached hospitals. Pinto *et al.* proposed a genetic simulation model to answer the question of how to improve emergency service in general, with a case study of an Emergency Medical Service (EMS) in Belo Horizonte city, Brazil. In the paper, they proved why simulation is an important method to study EMS, firstly tasks perform in an EMS are pre-defined and finished in a brief period, it is easy to model series of tasks in simulation. Secondly, although uncertainties remain a question to EMS system, they can be separated and defined during modeling of AS. Thirdly, simulation AS can help organization modifies changes easily and the model can be used many times and thus, help exploring the geographical information system. Fourth, because of the substantial number of variables to consider and the random nature of demand arrivals, analyzing for decision making with complex problem like AS with high number of alternatives and hybrid deterministic methods become less attractive compared to easy modified simulation models. Lastly, simulation modeling allows setting appropriate metrics for assessing complex alternatives rather than providing measures that have been derived from the primary principle [1]. Additionally, some simulation models of AS that allow ambulance to transfer patients to the most suitable hospitals based on their conditions, rather than the nearest hospital [2]. Object-oriented C++ programming was performed to simulate the AS of this paper. It was proved that transporting patients to hospitals that are more suitable to treat their conditions can prove to be as effective in terms of cost and efficiency as the traditional way of AS. Yang *et al.* used a simulation-based approach to describe and optimize an ambulance allocation problem, this approach can evaluate the performance of AS in Shanghai Songjiang District with an uncertain environment [3].

The Gaussian mixture model clustering was conducted to analyze the uncertainty of spatial demands while the simulation model generated demands based on the obtained spatial distribution. For optimization, the paper used a Gaussian-process-based search algorithm and combined with the simulation model to find the most suitable solutions to ambulance allocation.

Metaheuristic approaches [4] considered a quarantine vehicle scheduling problem for epidemic patients of COVID-19, this was a variant of a traditional vehicle routing problem. In this study, a hybrid algorithm between Water Wave Optimization metaheuristic and neighborhood search was performed and this model's result was reported to significantly outperformed some other well-known existing algorithm such as Tabu Search, Simulated Annealing, Genetic Algorithm and obtain high accuracy results in real-life COVID-19 problems for AS optimization. Although many data-driven approaches were used for modeling AS discrete-event simulation through [5] is still considered as one of a most popular methods for EMS. Such method can easily be modified and perform experimental design more effectively and less time consuming. Many applications are considered to perform simulation on EMS, such as ARENA, Simul8, FlexSim/FlexSim Healthcare, ProModel/MedModel, Simio, AnyLogic, TreeAge, ExtendSim.

3 Methodology

3.1 COVID-19 AS modeling process

In this AS model, Call center (sub-model 1), Ambulance dispatch (sub-model 2), AS on scene (sub-model 3), Transportation to hospitals (sub-model 4), Rerouting strategy (sub-model 5), COVID-19 hospitalization (sub-model 6), Ambulance going back to base (sub-model 7) or receive new request at hospital (sub-model 8) are the main operational activities as presented in Table 3.1.

The following description is the main function for these sub-models of AS. First, the Call center main functions are to receive calls and screen these calls into COVID-19 or non-COVID-19 requests, where each COVID-19 request is categorized based on 3 urgency levels, and the patient's information is recorded at Call center sub-model.

Table 1: Summary of AS model through 8 sub-models in this study.

AMBULANCE SERVICE MODEL	Sub-model	KPIs	Control factors
1. Call center Call arrivals follow Poisson distribution with 4000 calls/day	1	- %Trunk line utilization at call center - % of calls exit the system - Time in call center - Waiting time before trunk line available	- Number of trunk lines at call center (number of operators at call center)
2. Ambulance Dispatching Dispatching rule: highest urgency level first	2	- %Dispatcher utilization at ambulance base - %Ambulance utilization - Request waiting time at ambulance base	- Number of dispatcher at each ambulance base - Ambulance distribution at 22 ambulance bases
3. Ambulance serve on scene Time serve on scene: GAMM(0.22222, 3.1) minutes	3	- Average time serve-on-scene - Ambulance response time at each districts - Number of patients dead-at-scene	- Expiration time of each urgency level
4. Transport to Hospital Hospital selection: shortest distance & accept_patient = 1	4	- Average ambulance task time	- Hospital distance calculation - Hospital selection strategy
5. Rerouting Hospital selection: shortest distance & accept_patient = 1	5	- Waiting time at hospitals - Average number of rerouting times at each ambulance - Number of times hospitals applied redirect strategy	- Number of rerouting times an ambulance can have per trip - Number of times hospitals can apply redirect strategy per day
6. Patient receive medical attention Urgency level 1 & 2 LoS: LOGN(12.3, 11.6) days Urgency level 3 LoS: WEIB(25.1, 1.14) days *Length of stay at hospital (LoS) If (Hold request.queue = 0)	6	- %Hospital beds utilization	- length of stay distribution at hospital for each urgency level
7. Back to base	7&8	- Percentage of requests fulfilled at each district	
8. Receive new request			

Send the requests to the suitable ambulance base according to the location of patient, available ambulance will dispatch at the second sub-model, where the rule is to dispatch ambulance for the highest urgency level first. Once the ambulance arrives at the scene, which indicates sub-model 3 and in this sub-model, ambulance will perform its tasks by checking for the COVID-19 status and help the patient before loading onto ambulance. In sub-model 4, its main function is to decide the which hospital to transport patient to which is based on the urgency level, the shortest distance from patient's location to the hospital and whether the hospital is applying redirect strategy. However, during the pandemic, the ambulance may have to reroute several times before a hospital is willing to accept patient hospital admission. This is where sub-model 5 does its job. Its main function is to help ambulances decide which hospitals to reroute next based on the shortest distance from the current to the next hospitals and whether the considered hospital is applying redirect strategy. When a hospital is willing to accept the patient, the COVID-19 patient will go through sub-model 6, where its function is to describe the simplified process of hospitalization for COVID-19 patients and the estimation of hospitalized period for each urgency level. After dropping off patients at hospitals, the ambulance will have to decide their next action in sub-models 7 and 8, where their main functions are used to describe the process of ambulance after dropping patients at hospitals to either return to base or immediately go to next location if new requests available

3.2 Parameter table

Table 2: Parameter for simulation of AS model

Parameters	Value	Units
Average ambulance speed (both ambulance and taxi)	50	Km/h
Number of trips restocking materials for ambulance	1	Trip
Number of operators at Call center	40	People/Call center
Number of resource dispatchers at ambulance base	8	People/Call center
Number of urgency level 1 hospitals	57	Hospitals
Number of urgency level 2 hospitals	17	Hospitals
Number of urgency level 3 hospitals	5	Hospitals
Number of Ambulance bases	22	Bases
Expiration time for urgency level 1 patients	UNIF(72,144)	Hours
Expiration time for urgency level 2 patients	UNIF(72,96)	Hours
Expiration time for urgency level 3 patients	TRIA(12,24,48)	Hours
Expression for spent time by Operator for each call	TRIA(2,3,6)	Minutes
Time spends preparing at base after receiving request at ambulance	4	Minutes
Total number of ambulances in the city	287	Ambulances
Expression for spent time to replenish first aid materials and products [2]	5.02	Minutes
Average time for preparation and check resources before heading to patient's location [3]	4	Minutes
Average time to inform the emergency Call center by the patient or patient relatives [2]	1.15	Minutes
The time allowed to reject patient admission at hospitals (redirect strategy)	2	Hours
the first intervention of the ambulance authorities and the departure time of the patient for the hospital [2]	UNIF(1.08, 4.911)	Minutes
Load/Unload patient onto vehicle	2.15	Minutes
Length of stay in hospital beds	LOGN(12.3, 11.6)	Days
Length of stay in ICU beds	WEIB(25.1, 1.14)	Days
Probability of patients having urgency level 1	0.6	%
Probability of patients having urgency level 2	0.32	%
Probability of patients having urgency level 3	0.08	%

3.3 Redirect strategy

According to [10], in re-routing strategy, the study defined the Crowdedness Index (CI) as:

CI = current loading of ED/full capacity of ED

Hence, a CI larger than 1.0 implies that: (1) additional beds are being used or (2) a full or almost full department with patients of greater than average. Regarding the interval of ambulance diversion, the recommended interval is 2 hours with maximum time of 8 hours/day for each hospital. From [10] result, the 2-hour ambulance diversion segment strategy has the lowest average percentage of adverse patients and thus may avoid preventable delay of essential medical treatment. This strategy also keeps the CI slightly below 1.0 for most of the day, which implies that the Emergency Department efficiently operates in a sustainable fashion. In the study, a patient is referred to as an adverse patient when the patient's waiting time for service exceeds the upper limit of waiting time for his or her acuity level)

4 Result Analysis

4.1 Ambulance utilization

Upon analyzing the performance of the current AS, ambulance utilization rates across 22 districts must be reviewed. From Figure 3, the percentage of emergency vehicle usage vary over the bases. The gap between the maximum and minimum utilization is approximately 65 percent, while there has been a positive correlation between the ambulance utilization rates and infected cases distribution of 22 districts. Areas provide higher infected rate during the outbreak will have higher ambulance utilization rates, this is a crucial information for further improvements of the AS, where the number of ambulances at each area should be re-distributed with the consideration of the COVID-19 severity across HCMC.

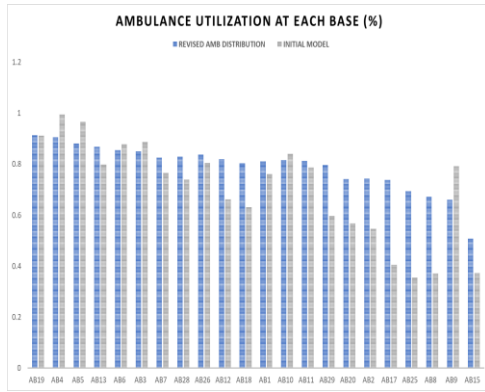


Figure 3: Comparison of utilization at ambulance bases between initial and revised ambulance distribution

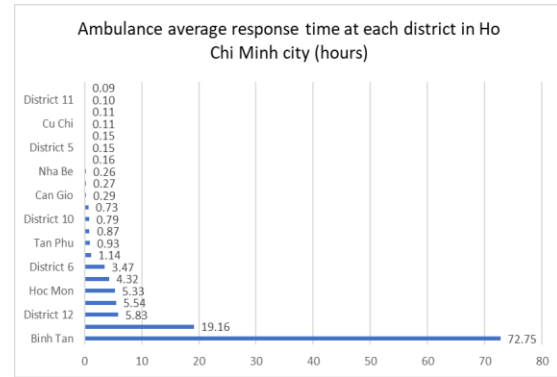


Figure 4: Ambulance average response time at each district in HCMC (hours)

4.2 Response time

As demonstrated in Figure 4, most of the response time in districts in HCMC is within 1 hour, which is acceptable when the number of calls spikes during the epidemic. However, the time for ambulance to response in Binh Tan and Binh Chanh was 70 and 19 times higher than in other areas. This is explained by the fact that the number of cases in these two areas was recorded to be the highest in the city, with Binh Tan accounting for about 6.32% and Binh Chanh accounting for more than 3% of the total number of cases in the city, which leads to the number of severe cases due to the Delta variant also increased at that time since the vaccine mass campaign during the fourth epidemic had not proved their effectiveness in time.

4.3 Waiting time at hospital

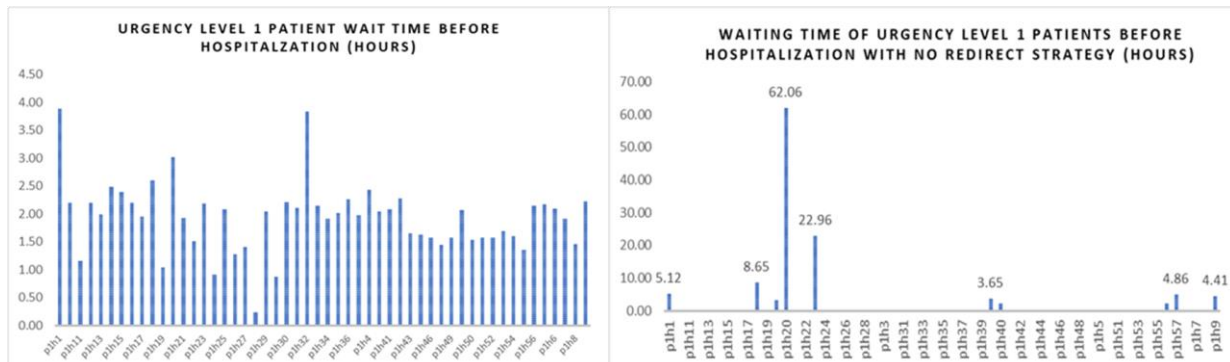


Figure 5: Waiting time of urgency level 1 patients at hospital before hospital admission (hours) with redirect strategy (left figure) and without redirect strategy (right figure)

The waiting time of urgency level 1 patients admitted to hospitals suggests a large variation, ranging from 12 minutes to 4 hours. This indicator shows that the redirect strategy provided for urgency level 1 is not highly effective when applying to pandemic situation. Furthermore, when looking at the

graph, the average waiting time is approximately 2 hours. Again, this reflects the overload of the health system during the recent epidemic.



Figure 6: Waiting time of urgency level 2 patients at hospital before hospital admission (hours) with redirect strategy (left figure) and without redirect strategy (right figure)

At patient with urgency level 2 wait times in Figure 6, the average waiting time is longer than those of urgency level 1, but more evenly spread with a gap between the minimum and maximum time of 30 minutes in 17 COVID-19 treatment hospitals. This shows that the redirect strategy for this kind of urgency is effective. However, waiting too long will lead to not being able to save the patient's life in time, or skip the golden period to treat the disease, ensuring a faster recovery. To save as many lives as possible during the pandemic, not only the medical system requires improvement from the AS, but also from the hospital in ensuring there are enough beds and equipment to deal with unusually high patient admissions.

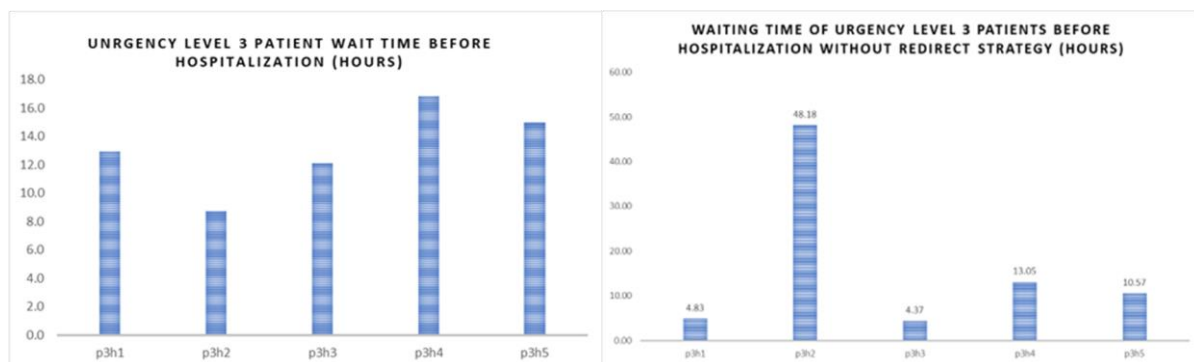


Figure 7: Waiting time of urgency level 3 patients at hospital before hospital admission (hours) with redirect strategy (left figure) and without redirect strategy (right figure)

For patient with urgency level 3 in the Figure 7, waiting time to hospital is the longest, this shows:

- Ambulance utilization will not be high if the waiting time is too long, even there are places where it takes more than half a day before admitting to the hospital.
- The number of hospital beds for this type of urgency is lacking, along with the long hospital stay, due to ICU treatment, the ICU stay time for urgency level 3 patients is expressed by WEIB(25.1,1.14) days (Weibull distribution), which means that each patient needs almost one month to be discharged from the hospital.

5 Model Improvements

We can suggest the following improvements to increase the number of hospital admissions:

Improvement 1: Change the number of ambulances at each base

Improvement 2: Change the redirect strategy at hospitals by not limiting the number of times an ambulance can be rerouted. The redirect strategy only comes from the hospital when the capacity has reach maximum level. In practice, especially during the pandemic, the number of times an ambulance can be rerouted does not considered in the system, provided that a patient will be received at the suitable hospital, ambulance driver is willing to drive to many hospitals until they have found one that accept the patient.

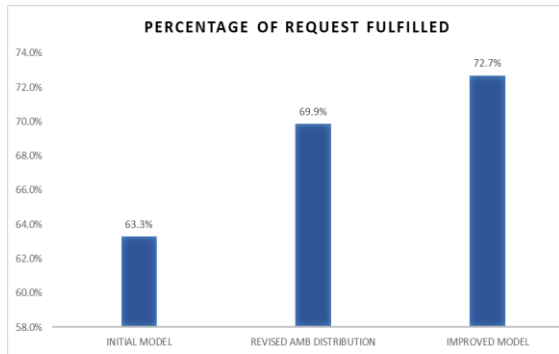


Figure 8: Percentage of request fulfilled of AS model of initial model, revised ambulance distribution and the improved model.

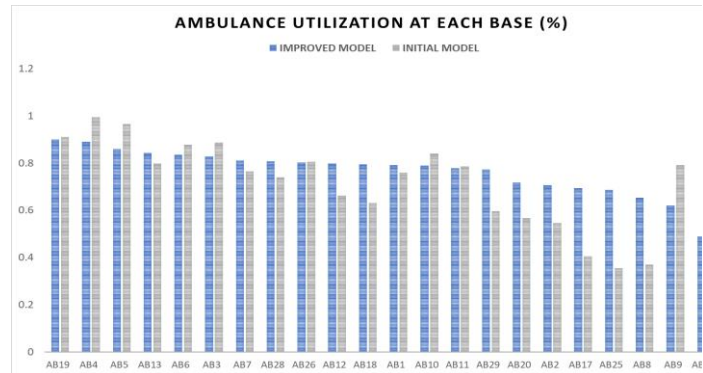


Figure 9: Percentage of ambulance utilization of the improved model and the initial model.

From the Figure 8, we can observe that the application of model improvements 1 and 2 has significantly improved the percentage of requests fulfilled of AS developed in this study. Specifically, when revising the ambulance distribution, the number of requests that can be fulfilled increase approximately 7% while this value is at 10% when applied both improvements into the model. We can see that re-distribute ambulance at 22 districts across HCMC based on the distribution of infected cases can significantly increase the number of patients who were able to transport into hospitals for treatment. To further understand the benefits these improvements, we need to take a closer look at the percentage of ambulance utilization at each base presented in Figure 9. When comparing to the initial model, the gap between the maximum and minimum utilization of the improved model is around 35% while this gap at the initial model is 65%. This means across the 22 ambulance bases from the improved model, although ambulances had to operate at high capacity, this level of performance is balance across the city, leaving less idle ambulances

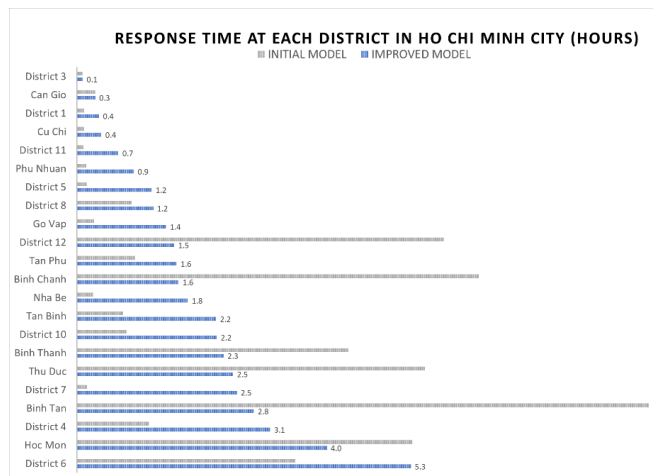


Figure 10: Ambulance response time at each district in HCMC (hours) of the improved model and the initial model.

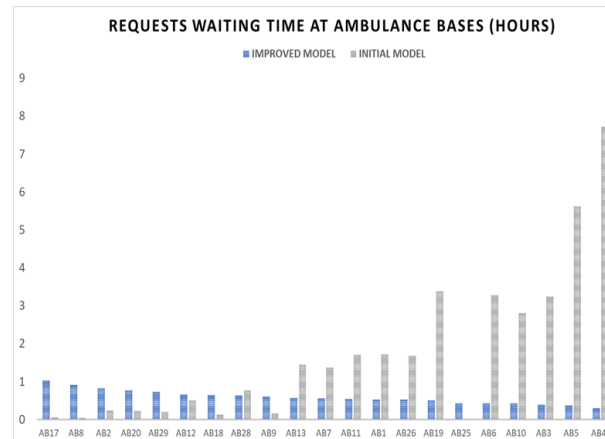


Figure 11: Request waiting time at 22 ambulance bases in HCMC (hours) of the improved model and the initial model.

Additional to the improvements in ambulance utilization, the waiting time of requests (response time of ambulances) across districts also experienced some changes presented in Figures 10 and 11. Response time at districts such as Binh Tan, Binh Chanh, Hoc Mon, areas that were heavily infected by the outbreak, has decreased significantly, with the average response time of 2 hours. However, because of the changes in ambulance distribution across districts, it is inevitable that some areas may have experienced an increase in response time due to the decrease in the number of ambulances distributed in such areas since these locations were less affected by the pandemic. Nonetheless, the average response time for this improved AS is around 1.5 hour, while in the initial model, this value was approximately 4 hours. The similar trend in request waiting time at ambulance bases provided at Figure 11, with the maximum value is approximately 1 hour, the ambulances waiting time before dispatching to pick patients seems balanced well out across 22 bases. This is because the distribution of ambulance has been revised based on the severity of the areas.

6 Conclusion and Recommendation

6.1 Conclusion

Through this model, distribution of ambulance in each area is considered as one of the most important conditions help increase the number of people can be saved. In summary, the AS model for COVID-19 has successfully demonstrate the actual situation happened during the pandemic, where the number of response time drastically changed among areas, deficient performance in ambulance utilization where there was a big gap in the number of ambulances used among 22 districts. This was all because an ineffective plan to distribute ambulances to 22 bases across the city. AS modeling is one of the effective approaches supports making decisions more effectively, especially when it comes to people lives.

6.2 Recommendation

In order to improve AS in the future, consider having ambulances patrol around assigned areas such as districts and wards in the city when an epidemic occurs is said to reduce response time, this idea is inspired by giving Police cars patrol crime-prone areas, this approach will help police forces respond more promptly when there is an incident, whether it is in criminal matters or emergency. Further studies should focus on additional factors, or questions:

(1) Scheduling ambulance for patrol; (2) number of ambulances should patrol; this consideration helps to

allocate resources more efficiently in case the request occurs in an area closer to the ambulance base; (3) the ambulance's path. Unlike police cars on patrol, which will often focus on crime-prone areas based on historical data, EMS needs to cover a larger area when patrolling during the pandemic since there is an absolute uncertainty that the risk of infection happens in many areas in any district all at once. Therefore, ambulances will usually cover a larger area than police cars when patrolling. And (4) the cost of transportation, medical supplies for treatment, and human resources to operate EMS system are among the main costs that need to be considered to increase the efficiency of the model.

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