Simulation of Emergency Medical Services Delivery Performance Based on Real Map

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***Abstract*— Performance of Emergency Medical Services (EMS) delivery is normally measured via ambulance response time. Quick ambulance response can effectively reduce the disability, morbidity and mortality of the emergency patients. Ambulance dispatch policy and ambulance location model both have a significant impact on the ambulance response time. In this paper, we present a prototype of simulation framework to study the performance of local EMS delivery in terms of a simulation model that consists of both ambulance dispatch policy and ambulance location model. Several real-life dispatch policies are simulated in a real map to evaluate the efficiency of local EMS delivery in Johor Bahru. By using a suitable dispatch policy, the results show an improvement in average response time for higher priority call. The total calls covered are also found to increase significantly with the application of Maximal Covering Location Problem (MCLP), especially at a bigger fleet size.**

Keyword- Ambulance dispatch policy, Emergency Medical Services (EMS), Geographical Information System (GIS), Simulation

I. INTRODUCTION

Emergency Medical Services (EMS) delivery performance is commonly measured based on the efficiency of its ambulance services [1]. In any emergency cases especially that involve a life-threatening situation, response time is vital. Pell *et al.* [2] and Vukmir [3] report a positive relationship between faster ambulance response time and survival of prehospital cardiac arrest patient. Meanwhile, Sánchez-Mangas *et al*. [4] suggest that mortality rate of road traffic accidents can be reduced to one third with a 10-minute reduction of response time. Furthermore, the performance of one-tier EMS system in urban areas is studied by Blackwell and Kaufman [5]. In the finding, response time less than five minutes would have an improved survival rate compared with higher response time.

In general, ambulance response time and coverage percentage are used together as a standard preset in Key Performance Indicator (KPI) for EMS delivery [6]. Every country has a different KPI for its EMS delivery. In Western Australia, the required ambulance response time for emergency call is within 15 minutes, and at least 90% of total received calls must be covered [6]. In contrast, The United States Emergency Medical Services Act states that 95% of the received emergency calls should be served within 10 minutes and 30 minutes in urban and rural areas respectively [7].

Simulation has been used by many researchers to study the performance of EMS delivery [1], [8]-[10]. It has been a good alternative in the EMS study because of the flexibility, time saving and low-cost yet it can provide a comprehensive decision support tool for operational planning analysis. In addition, it also can be used as a data visualization tool for descriptive information display [10], [11]. In our previous simulation work [1], a variance of MCLP is studied by using a grid system on a hypothetical region. Lim *et al.* [1] have proposed the use of real map with actual road network and local geodata to evaluate the near real world performance of EMS delivery.

II. PREVIOUS WORKS

Su and Shih [12] use an object-oriented simulation tool (eM-Plant software) to study and evaluate the performance of EMS system in Taipei. In addition to the existing two-tier rescue model, they have proposed four solutions to improve the performance of EMS system targeting at reducing both service time and operational cost. Basically, a two-tier EMS model provides a service that consists of Basic Life Support (BLS) and Advanced Life Support (ALS). The solutions strategically combine 36 EMS subgroups (BLS) with a network of 23 hospitals (ALS) to create a collective two-tier rescue model. In addition, probably the most significant result of the study is the performance of two-tier rescue model is found to be 10 times better compared to the one-tier rescue model.

In another work by Aringhieri *et al*. [11], a static ambulance location model to optimize EMS performance in the city of Milan is proposed. The proposed model is tested using an agent-based simulation via AnyLogic software. Lower-Priority Calls Coverage (LPCC) is introduced as a new optimization model. It is an extension of static Location Set Covering Model (LSCM) after considering the percentage of low priority calls coverage and some real-life issues such as ambulance availability. In general, the model targets mainly at reducing the number of required ambulances to cover all demands and locating the ambulances at strategic places. Similar to other static models, LPCC ignores the dynamic natures of time-dependent traffic congestion and ambulance demand. However, deterministic static model is always helpful at the planning stage to determine a lower bound on the number of ambulances required to ensure full coverage [13]. For example, it requires 17 and 25 ambulances to cover all areas in the city of Milan for a whole day with full ambulance capacity and half ambulance capacity respectively. Ambulance capacity is the number of tasks that can be assigned to an ambulance in a given time interval [11].

In the research of [14], a discrete-event simulation (Arena software) is used in conjunction with an optimization procedure for EMS delivery performance analyses in the city of Belo Horizonte, Brazil. The optimization model proposed is a static ambulance location model. The model seeks optimal locations for BLS and ALS emplacements in agreement with the lowest operational cost. An optimizer is used to find the solutions based on the proposed model while the simulator is used to evaluate the performance of each solution. From the obtained simulation results (i.e., the response times, waiting times and queue sizes), two thorough analyses are produced. The first analysis is to evaluate the EMS performance with increasing demand of the service. Meanwhile, the second analysis is to find the required number of ambulances at each base to achieve response times within the predefined thresholds. These analyses can enhance the performance of EMS delivery by providing an alternative solution that promises a better performance. For example, 20 BLS and eight ALS are required to achieve response times less than 18 minutes and less than 15 minutes for BLS and ALS services respectively. More importantly, the study shows that the discrete-event simulation can be used as a good analysis tool in studying the EMS delivery performance.

III. METHODOLOGY

A. Study Area

Johor Bahru (JB) is the capital city of Johor and it is located at the southern Peninsular Malaysia. Majlis Bandaraya Johor Bahru (MBJB) and Majlis Perbandaran Johor Bahru Tengah (MPJBT) are two of four administrative bodies that have been given the responsibilities for the developments of the city. The total area covered by both administrative districts is about 558.5 km^2 and the population is estimated to be around 1,012,529 in 2010 [15]. It is one of the most populous urban areas in Malaysia. Its road network represents a sizeable graph that consists of 32,317 vertices and 27,784 edges as extracted from OpenStreetMap data. Fig. 1 shows the boundary of the study area and its road network. Currently, there are three hospitals that have been managed by Ministry of Health (MOH) in MBJB and MPJBT administrative districts. Meanwhile, no distribution of ambulances exists since all the ambulances are based at the hospitals. Brotcorne *et al*. [13] suggest parking lots as the potential ambulance location site for ambulance deployment. Therefore, several petrol stations that have facilities like grocery store, public parking lots and toilets are identified to be used as a possible ambulance location site for solving the ambulance location model (see Fig. 2).

B. Simulation Model

The simulation model used in this study is based on an object-oriented programming and a discrete-event simulation technique. In general, EMS delivery can be modeled into sequential queue events, and every event is waiting for its execution time. The waiting time can be a random value or a predefined assumption value. When a call center receives an emergency call, a dispatcher is responsible to send an appropriate ambulance according to the call priority. In the simulation, ambulance response time is the time interval measured from receiving the emergency call to the arrival of the ambulance at call scene. The main components of the simulation model are further discussed in this section.

1) EMS Dispatcher: Basically, EMS dispatcher is like a central of dispatching that consists of ambulances assignment method, calls queuing method and add-on dispatch policy which in overall determine the output of EMS dispatching process. The three dispatch policy components can be manipulated to obtain a new ambulance dispatch policy and, to achieve a specific performance [1]. At the point of receiving the emergency call, the implemented calls queuing method determines if the call should be served immediately. A waiting list is used to queue the incoming calls. If the call can be served immediately, it is the function of the ambulances assignment method to find the best ambulance to be assigned with the call. If there is no ambulance available at that time, the call will be registered back onto the waiting list. The add-on dispatch policy is used to alter the process. For example, it can release the ambulance that currently serving a low priority call to serve the higher priority call. The released call will then be listed back onto the waiting list based on the calls queuing method applied. Each

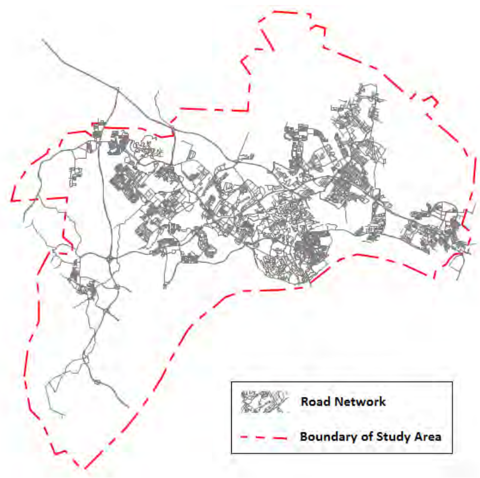


Fig. 1. Boundary of the study area and the road network.

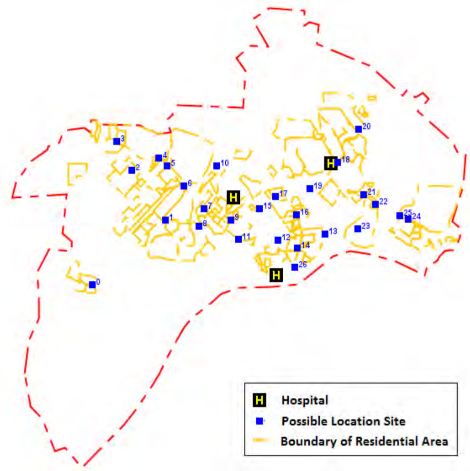


Fig. 2. Location of hospitals and the identified possible ambulance location sites in the study area.

policy has a different result on the performance of the EMS delivery. In this paper, several real-life dispatch policies are simulated in a real map of the study area by using local geographical information.

2) Ambulance Deployment: Initially, all ambulances are to be positioned at strategic locations namely ambulance bases. The ambulance bases are predetermined by solving the implemented ambulance location model (e.g., MCLP). Each ambulance base has its own perimeter that defined its coverage area. The perimeter is determined by using a Quick Hull algorithm [16]. The algorithm used the shortest path tree created by the Dijkstra algorithm to form a convex hull that includes all the locations in the shortest path tree. The coverage area of the ambulance is the area where the ambulance can travel from its base to any location in that area within a predefined time threshold. Commonly, the ambulance response times from the KPI are used to set the perimeter of the ambulance base. The implemented ambulance deployment is based on the coverage model. The main objective of this model is to maximize the total demand covered by the ambulances [17]. A set of demand points in the study area is required prior to solving the ambulance deployment. A model based on dot density map approach is used to integrate the demands into the study area. It is assumed that the demands are distributed uniformly over the residential area. The unpopulated places such as water bodies are excluded from the model to increase the accuracy of the demand distribution. More details on the model can be found in [18]. Based on the ambulance coverage area and the demand distribution, the combination of the ambulance bases that maximize the total demands covered for a given number of ambulances in any particular area can be found.

C. Simulation of Dispatch Policies

Several combinations of real-life dispatch policy components are simulated in the real map to study the performance of local EMS delivery. The current local EMS delivery in the study area has all its ambulances based at the hospitals. Therefore, at first, the simulation of dispatch policies is run without implementing any of the ambulance location models such as to replicate the current system. All ambulances are located at the hospitals. The ambulance response times are recorded to analyse the current system performance. Next, the ambulance location model is introduced in the simulation. In this regard, the ambulances are located at selected petrol stations to increase the coverage of the EMS delivery. A covering model is used by implementing the extended version of MCLP that is firstly proposed by Lim *et al*. [1]. In contrast to the original MCLP [19], Lim *et al*. introduces a new constraint so that the percentage of total coverage achieved by the model must be greater or equal to a certain preset standard that normally stated in the KPI of local EMS delivery. For example, in U.K, category-A and category-B calls should be covered at least 75% and 95% of the total calls respectively [20].

First-in-first-out dispatch, priority (simplified) dispatch, closest (tiered) dispatch and reroute-enabled dispatch; all are combined interchangeably to establish four different EMS dispatch policies. First-in-first-out and priority dispatches are used mainly for sorting the incoming calls. The Code-1 call has the highest priority followed by Code-2 call and Code-3 call i.e., the lowest priority. Two-tier closest dispatch is used as the ambulance assignment method where the fastest and available BLS and ALS unit is dispatched accordingly. Meanwhile, reroute-enabled dispatch is the add-on component of the dispatch policy that enables any assigned ambulance to be released from the current call so that it can be assigned to other higher priority calls on the waiting list. The released call is then listed back on the queue based on the applied calls queuing method. Further information on the implemented dispatch policies and other real-life dispatch policy components can be found in [1]. Table I summarizes the four policies and its dispatch components that being used in the simulations.

IV. RESULT

As mentioned before, two sets of simulations are being run to analyse the performance of the current system, and the new system where the ambulance location model is introduced. The first set of simulation used the hospitals as the ambulance bases whereas the second set used the selected petrol stations obtained from the ambulance location model as the ambulance bases. All simulations are run using a real map of the study area.

A. Results of Simulation Using the Hospitals as Ambulance Bases

Three hospitals are used as ambulance bases in the simulations for the current system. More than one ambulance with possible combinations of BLS and ALS units can be located at the hospitals. The number of ALS and BLS units used is based on a 0.5 utilization rate. The utilization rate is the ratio between the numbers of ALS to BLS units. In total, 12 simulations are run with three different ambulance configurations and four different dispatch policies. In addition, each simulation is fed with 60 unique calls that are randomly generated and consist of 20 calls for each call's priority. As a result, a total of 720 different calls are generated for the whole simulation. For every simulation, the average ambulance response time for each call's priority is calculated. Table II shows the average response times obtained in the simulations for every call's priority.

At the smallest fleet size (three ambulances), the impact of the implemented dispatch policies on the average response times is more significant, mainly for policies B, C and D. For policy A, the obtained average response time for each priority does not vary too much (93.80, 104.90 and 89.04 minutes). Policy B is the extension of policy A by introducing the reroute-enabled dispatch. As a result, the average response time of the higher priority call (Code-1 call) is much shorter compared to the lower priority calls (Code-2 and -3). Moreover, both policies C and D which applied the priority dispatch have successfully reduced the average response time for Code-2 call while maintaining a shorter average response time for Code-1 call.

However, the response for Code-3 call is inadequate, but this is acceptable considering the limited number of

TABLE I
Dispatch Policies Used in the Simulation

Policy	Components of Dispatch Policy		
	Calls Queuing Method	Ambulance Assignment Method	Add-on Dispatch Policy
Policy A	First-in-first-out dispatch	Closest (tiered) dispatch	None
Policy B	First-in-first-out dispatch	Closest (tiered) dispatch	Reroute-enabled dispatch
Policy C	Priority (simplified) dispatch	Closest (tiered) dispatch	None
Policy D	Priority (simplified) dispatch	Closest (tiered) dispatch	Reroute-enabled dispatch

TABLE II
Simulation Results for Using Hospitals as Ambulance Bases

Policy	Number of Ambulances								
	ALS		BLS	ALS		BLS	ALS		BLS
	1		2	2		4	3		6
	Average Response Time Based on Call's Priority (min)								
	Code-1	Code-2	Code-3	Code-1	Code-2	Code-3	Code-1	Code-2	Code-3
Policy A	93.80	104.90	89.04	9.31	13.16	10.07	8.19	6.18	8.03
Policy B	11.58	162.73	249.82	10.44	21.66	43.08	7.75	6.12	9.64
Policy C	14.29	36.61	175.88	8.72	10.95	12.25	6.11	7.12	7.94
Policy D	15.07	49.85	539.29	8.40	10.24	10.27	6.87	9.27	7.47

ambulances available and the main objective of policies B, C and D is to increase the performance of the higher priority call. By increasing the number of the ambulances to six and nine, the overall average response times have significantly reduced particularly for Code-2 and -3 calls. Although the impact of the dispatch policies seemed to decrease with the higher number of ambulances, policies B, C and D can still manage to reduce the response time of higher priority call. Since all the ambulances are stationed at the hospitals, the coverage is low. Consequently, the total calls covered for all the simulations (three, six and nine ambulances) are lower than 50% of total calls (see Fig. 3).

B. Results of Simulation Using Ambulance Location Model

MCLP is only applied on the BLS units to cover all three priorities of calls. ALS units are located at the hospitals due to the limited resources and they are reserved for Code-1 calls assignment only. The ALS/BLS utilization rate used is the same as before i.e., at 0.5. For MCLP, the percentage of total coverage required must be greater than 90%. Therefore, an 8-minute time threshold is sufficient as preset coverage standard for two and four BLS units where the percentages of total coverage achieved are 95.45% and 99.91% respectively. However, with six BLS units and an 8-minute time threshold, it would produce a total coverage of more than 100%. Therefore, for the six BLS case, a 6-minute time threshold is used instead, where the percentage of total coverage achieved is 96.47% (see Table III). An example of graphical representation for MCLP result is shown in Fig. 4. Table IV shows the results for 12 simulations with different policies, number of ambulances and priorities of incoming calls.

In general, the obtained performance for each dispatch policy is almost the same as the first simulations (hospitals as ambulance bases) where the average response times varied depending on the policies used. However, the overall average response times for six and nine ambulances have significantly reduced from a range lower than 50 minutes to a range lower than 20 minutes (see Fig. 5). Since MCLP is only targeted to increase the coverage of the BLS units that are mainly responsible to answer the lower priority calls, most of the average response times obtained for Code-2 and -3 calls have been reduced. Furthermore, the total calls covered are slightly increased for most of the cases compared to the first simulations (see Fig. 3).

V. DISCUSSION

TABLE III
Results for MCLP (BLS only)

Result	Number of BLS units		
	2	4	6
	Preset Coverage Standard		
	8 minutes	8 minutes	6 minutes
Selected Ambulance Locations (Optimal Locations)	7, 21	0, 2, 15, 21	2, 7, 15, 18, 23, 24
Total Coverage Percentage (%)	95.45	99.91	96.47

TABLE IV
Simulation Results for Using Ambulance Location Model (BLS only)

Policy	Number of Ambulances								
	ALS	BLS		ALS	BLS		ALS	BLS	
	1	2		2	4		3	6	
	Average Response Time Based on Call Priority (min)								
	Code-1	Code-2	Code-3	Code-1	Code-2	Code-3	Code-1	Code-2	Code-3
Policy A	88.15	85.09	84.39	9.64	8.61	7.39	8.05	3.99	4.67
Policy B	15.41	190.78	269.87	8.68	6.54	9.83	6.80	4.42	6.64
Policy C	22.20	44.73	307.17	11.39	11.09	10.42	6.47	7.07	5.84
Policy D	15.43	14.59	89.81	8.31	13.15	23.75	7.79	5.42	4.66

Tables II and IV show that by increasing the number of ambulances from six to nine there is no significant improvement in terms of overall performance for each of the call's priorities except for only a small decrease in the average response time. Therefore, six ambulances would be a better option compared to nine ambulances as it can save on the resources, and yet provides comparable performance. In addition, the performance of higher priority call is improved by using the established dispatch policies (B, C and D) even though at the smaller fleet size (i.e., three ambulances), but at the expense of longer response times for lower priority calls.

The ambulance utilization rate also has an impact on the average response time. A good utilization rate is where the value is close to the preset utilization rate, i.e., 0.5. When the obtained utilization rate is closer to the preset value, the average response time obtained is also shorter as shown in Fig. 5. In addition, a bigger fleet size can improve utilization rate. This is because most of the ambulances are able to complete their first priority task (e.g., ALS units for Code-1 call and BLS units for Code-2 and -3 calls) and thus avoid a reroute process. Besides, a lower utilization rate can cause a longer average response time for lower priority calls, especially for Code-3 calls. For example, from Fig. 5(a), the simulation of dispatch policy D with three ambulances (D-3) has a 0.2 utilization rate and we can see from Table II that the average response time for Code-3 call is much longer compared to Code-1 and -2 calls.

The components of dispatch policy certainly affect the average response time, especially at a small fleet size [1]. Sorting the incoming emergency calls based on first-in-first-out and without reroute-enabled (e.g., policy A) can lead to higher utilization rate. However, it lacks in higher priority call optimization since all calls are treated equally. Therefore, policy A is a better option for a system where the emergency call has the same priority level or does not involve in a triage process. Priority dispatch is introduced as an alternative for calls queuing method that can be used to improve the average response time for higher priority calls, and thus it is more suitable for triage system. The drawback is when at a small fleet size, the average response time for lower priority call is significantly increased. Therefore, it is important that the triage process is performed as accurate as possible.

Numerous studies have shown that a two-tier rescue model can further enhance the performance of EMS

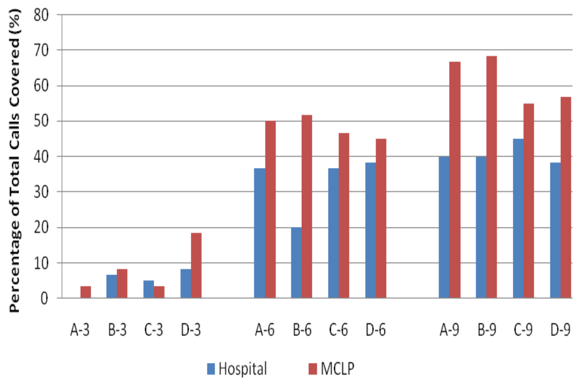


Fig. 3. Percentages of total calls covered for the first simulations (hospitals as ambulance bases) and the second simulations (MCLP).

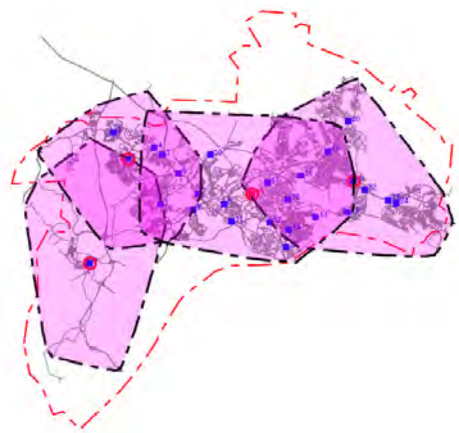
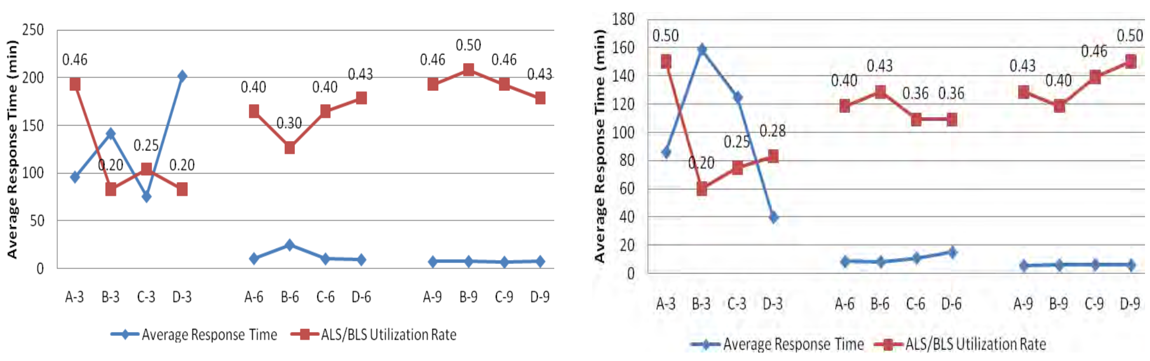


Fig. 4. Graphical representations for MCLP result at a fleet size of four ambulances and an 8-minute time threshold.



(a) (b)

Fig. 5. The relationship between the average response time and the ALS/BLS utilization rate for first simulations (a) and second simulations (b).

delivery [11], [21]. Consequently, the closest (tiered) dispatch is used in the simulations as the ambulance assignment method where a Code-1 call is served by the closest ALS unit and Code-2 and -3 calls are served by the closest BLS unit. However, some of the Code-1 calls might be served by BLS unit to further shorten the response time of the higher priority calls. Different study can have a different type of two-tier EMS model in terms of assigning the ALS and BLS units. For example, one of the two-tier models established by Braun *et al.* [22] required ALS units to answer all calls but the transfer of the patient to the hospital will be handled by BLS units. In this study, our two-tier model is mainly established to optimize the performance of the higher priority call.

Another factor that can certainly contribute to the improvement of the average response time is high ambulance coverage. Increasing the number of total calls covered can shorten the average response time indirectly. By locating the ambulances at the hospitals, the ambulance coverage is limited by the locations of the hospitals. Emergency calls from remote areas surely would have a longer response time. MCLP is introduced to overcome this problem by searching for the optimal locations based on the ambulance demand. As a result, the ambulances are distributed strategically within the service area, and hence are able to serve the emergency call with a quick response. Fig. 3 shows that most of the total calls covered in the second simulations (MCLP) are more than in the first simulations (hospitals as ambulance bases). However, the percentages of total calls covered from the second simulations are lower than the calculated values as shown in Table III, where all coverage should be more than 90%. The reason for this is because the implemented MCLP is a static deterministic model that completely ignores the busyness of the ambulances during the service time. When the ambulances are deployed, the total coverage has decreased below the calculated value due to the reducing number of available ambulances. To overcome this, a probabilistic model can be used to take into consideration the effect of ambulance busyness.

VI. CONCLUSION

Larger fleet size can indeed reduce the ambulance response time. However, the drawbacks are higher operational cost and lower efficiency of ambulance utilization [23]. The simulation results show that the combination of dispatch policies and ambulance location model can be a good alternative to improve the performance of EMS delivery in terms of reducing the average response time. Moreover, the simulations are run using actual map, road network and demand to obtain near real world results [1]. However, the ambulance location model used in the simulations is a static model which does not consider time-varying travel time and demand. Therefore, it is highly recommended to consider the application of dynamic model for ambulance deployment in the future work in order to achieve better insight on the performance of local EMS delivery.

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