A Simulation Optimization for Location and Allocation of Emergency Medical Service

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Abstract—Emergency medical services are an essential element in the modern healthcare system. Health care services are the most important because they play an important role in saving people's lives and reducing rates of mortality and morbidity. Especially during the covid-19 pandemic and the new normal era makes this problem very interesting to discuss. For this reason, this study tries to overcome the problem location and allocation of Emergency Medical Services (EMS) by using a combination of metaheuristics and simulation. The approach taken to overcome these challenges is developing Symbiotic Organisms Search algorithm and then use the simulation method to validation the result. The transition of the ambulance system from a centralized to decentralized system by using the Modification of Symbiotic Organisms Searrch (Mod-SOS) algorithm, found that to shorten the response time to 9 minutes, need to combine the 5 core bases with about 12 potential bases. From the simulation scenarios tested, the total number of ambulances involved in the proposed system is 16 units. So it can be concluded that involving several potential bases can produce a short response time.

Keywords—ambulance location and allocation, emergency medical services, simulation optimization, symbiotic organisms search

1 Introduction

Emergency Medical Services (EMS) are an essential element in the modern healthcare system [1]. Health services play a very important role because it is related to saving people's lives and has a great opportunity to reduce mortality and morbidity [2]. Emergency medical services are a very sensitive and complicated matter [3]. The importance and sensitivity of decision-making in the field of Emergency Medical Services (EMS) has been extensively studied by researchers from operations research, EMS planning, and healthcare practitioners regarding the many problems that have arisen in the management of EMS systems since the 1960s [4]. The ability of EMS to save lives is highly dependent on the time it takes for an ambulance to arrive at an emergency scene after the emergency call they receive [5]. [6] Stating that time is very important in emergency situations and therefore it is important for vehicles to be at all centralized times so that they can ensure, see which coverage area is adequate to send an ambulance and the fastest response time.

The main goal that became the core problem of EMS was to save the life of emergency patients. The potential for improving EMS system performance is directly related to reduced response times [7]. The goal of EMS is to reduce mortality, disability, and suffering. EMS decision makers tackle the difficult task of finding ambulances to promptly and optimally serve emergency medical calls [8]. Especially for patients with urgent needs, response time determines mortality. One of the key factors in EMS performance is the speed at which emergency vehicles can respond to incidents [9]. Proper analysis in predicting handling, will result in an increase in service quality [10].

In emergency medical services, response time is the time interval between the arrival of the emergency call and the arrival of the medical team at the location of the call. This is of major concern as this delay may cause the difference between life and death for the patient, depending on the seriousness of the medical condition. Many previous researchers have conducted research on the minimization of the response time of EMS. Various approaches have been taken and can be grouped into 3 major approaches including determining the optimal location of the ambulance, determining the optimal number that must be alerted at each ambulance base and determining how the scenario will be sent from the ambulance.

Several studies that most initiated to overcome this problem were [11] which stated that switching the EMS system from centralized to decentralized reduced response time very significantly. Then this study also tries to involve consolidation between several small bases so as to form a wider cover area such as the future work suggested by [9]. Especially during the covid-19 pandemic and the new normal era makes this problem very interesting to discuss [12]. For this reason, this study tries to overcome the problem of location and EMS allocation by using a combination of metaheuristics and simulation technique because calculations with the optimal approach are very complex. In the metaheuristic method, the location of the facility serves as a determination of the origin of the departing ambulance and other stations serving as the destination and determining the extent of the coverage area for each base. In this study, it is assumed that it is not necessarily a special ambulance belonging to a facility that must move from the origin and deliver it back to the facility. While the simulation approach serves as a determinant of the number of ambulances that must be allocated.

2 Literature review

The importance problem of determining location of a facility has actually begun to be discussed around 1909 but is still limited to the object of the warehouse. It was not until the 1960's that the issue of determining the exact location for an ambulance began to be discussed. EMS planner must determine the best location for the ambulance they want and it must be delivered in a timely and efficient manner, this is known as the ambulance location problem. Decisions on ambulance location strategies can be used to increase the expected coverage area. Problem of ambulance location refers to the assignment of a small number of ambulances to maximize coverage, given that the system has a fixed number of potential locations and demand zones that are considered closed when the ambulance is within a predetermined time. [13] conducted a study to find the optimal location of the ambulance to reach patients in need with the shortest possible time and dispatching problems. Previous research has taken many approaches to this problem such as [14]–[16] but mostly done in a centralized system. This system has the characteristic that each ambulance fleet is required to be at the base location belonging to a certain health facility and perform pre-hospital actions (starting from picking up patients to delivering patients to the health facility unit). The weakness of such a system is that it requires a long response time.

Schmid [17] conducted a study to find the optimal location of the ambulance to reach patients in need with the shortest possible time and dispatching problems. The method proposed to solve this problem is stochastic dynamic programming. The results obtained are a decrease in the average time of 12.89% with a note that they have to relocate their current ambulance base. Still in the same year [18] apply Linear upper-bound unavailability set covering models to overcome the problem of determining the optimal location of the ambulance with the case study used is the EMS problem in Iran. The model calculates the area of demand that can be fulfilled maximally by ambulance. With the proposed model, it shows a decrease in response time and the number of needs for ambulances by dividing into several locations.

Zhen et al. [19] also conducted research on relocation and redeployment strategies. The challenge in making decisions in estimating the amount to be allocated is the ever-changing demand at each different location. The approach taken to overcome these challenges is to use the simulation method with the aim of removing obstacles from stochastic demand. The results obtained are in the form of a strategy for placing ambulance units and their scheduling based on demand forecasting and real-time dependent. Then this study also tries to involve consolidation between several small bases as disclosed [20], the advantage of consolidation is to form a wider cover area so that it can reduce response time.

3 Proposed methodology

The method that will be developed in this research is Symbiotic Organisms Search (SOS) which was first introduced by [21]. Symbiotic Organism Search Algorithm is a metaheuristic method inspired by the interactions seen among organisms in the universe. The natural trait possessed by organisms is that they cannot live alone so that one organism is very dependent on other organisms to maintain its survival. This dependency-based relationship is known as symbiosis. There are several forms of symbiosis, namely mutualism symbiosis, commensalism symbiosis and parasitism symbiosis. The SOS algorithm is capable of being superior to other algorithms (this algorithm is compared with several other metaheuristic methods such as Genetic Algorithm, Differential Evolution, Bee Algorithm, Particle Swarm Optimization and Particle Bee Algorithm using 26 Benchmark functions).

Several previous studies on SOS, have shown that SOS has good accuracy and convergent speed [22]. However, the obstacle faced in the application of the basic SOS algorithm to solve combinatorial problems is that in the parasitic phase the SOS algorithm requires to create a parasitic organism using the dimensions of the objective function to be searched (continuous function), while the location and allocation problems do not have the dimensions of the objective function to Therefore, it is necessary to have another suitable mechanism to replace the mechanism in the parasitic phase. To make this SOS algorithm able to overcome the problem of location and allocation of ambulances, we propose a hybrid approach simulation optimization by combining SOS with a local Nearest Neighborhood (NN) search mechanism. Although, the weakness of NN is that the search can get stuck in a certain region of the search-space (if there is no change in the adjacent solution) but NN is able to guide the search steps towards the optimal solution very fast [23].

3.1 Local search

In this phase, a set of bases and potential bases involved will be calculated to calculate the proximity between each base and the resulting demand. The local search function (NN) will guide the initial search of several bases that have the potential to pick up patients. Furthermore, some of these potential bases will be selected to be candidates in the Mutualism Phase of the SOS algorithm. For the calculating the distance between each base we use euclideance formula (1) and (2) for generate initial of ecosystem.

$$dist(p,q) = \sqrt{[(p_i - p_j)^2 + (q_i - q_j)^2]} \tag{1}$$

$$Ecosystem = rand \times ((ub - lb) + lb)) \tag{2}$$

Where *(p,q)* is the coordinate longitude and latitude of each base then, the upper bound and lower bound of the searching area are *ub* dan *lb.*

3.2 Mutualism phase

This SOS phase mimics the mutualistic relationship between organisms in nature. SOS describes X_i as a matched organism, in this case is base of ambulance, with an ecosystem member. Another organism or base X_j is then randomly selected from the ecosystem to interact with X_i. Both bases engage in a mutualistic relationship with the aim of increasing the mutual benefit of survival in the ecosystem. The new candidate solutions for X_i and X_j are calculated based on the mutualistic symbiosis between organisms X_i and X_j, which is modeled in equations [3] and [4] below:

$$Xinew = Xi + rand\,(0,1) * (Xbest - Mutual\_Vector * BF1) \tag{3}$$

$$Xjnew = Xj + rand(0,1) * (Xbest - MutualVector * BF2) \tag{4}$$

$$\text{Mutual Vector} = \frac{\text{Xi+Xj}}{2} \tag{5}$$

The proposed model of decentralized, call command center as the decision maker in the system, calculates the distance between the patient and each base that will be assisted by the location of public health centers available in various areas so that they are more spread out in the hope of speeding up response time. Then after the ambulance delivers the patient to the health facility, the ambulance is positioned as new stock from the facility or can return to the initial base. The stage of local search aims to see the alternative or potential ambulances that can be sent to patient on the smallest travel time. Then the distance will be calculated by assuming an average speed of 50 km/h.

- **Step 1**. Generate random point coordinates as request.
- **Step 2**. The closest distance between the demand point and each available health unit will be calculated in this step. Then the distance will be divided by the ambulance speed (assumed average speed is 50 km/h). The purpose is to see the response time.
- **Step 3**. The facilities are capable of fulfilling the request will be sorted by the specified time limit parameters.
- **Step 4**. With the local search (NN) selected facilities that have the potential as fleet delivery facilities.
- **Step 5**. Through the mechanism of mutualism phase in SOS, the potential facility will be selected for ambulance delivery considering the availability of ambulances and the minimum of response time.

By using $\propto$ of 5%, the value for $t_{(0,025;4)}$ of 2.7764, and the value of $Z_{\propto/2}$ of 1.96, then the value of half width (6) and minimum number of replications (7) can be calculated as follows:

$$hw = t_{(\propto/2; n-1)} \frac{s}{\sqrt{n}} \tag{6}$$

$$hw = 2{,}7764 \frac{0{,}081907}{\sqrt{5}} = 0{,}1017$$

So the minimum number of replications required is:

$$n' = \left[\frac{Z_{\propto/2}\, s}{hw}\right]^2 \tag{7}$$

$$n' = \left[\frac{1{,}96\ (0{,}081907)}{0{,}1017}\right]^2 = 2{,}491828923 \approx 3 \text{ times}$$

In this decentralized model, there are agents who play a role in the process of handling medical emergency conditions, including callers, command center teams as dispatchers, hospitals, main bases and potential bases. The caller is a condition of demand for emergency needs, which is in fact not only related to EMS services, but also such as firefighters, police, etc. For this reason, in this system the command center team is tasked with separating the types of incoming requests from callers. This research focuses on requests for EMS so that all requests related to EMS will be forwarded to the dispatcher. The dispatcher is in charge of determining which base ambulance will be sent with consideration of the short distance and in available condition. Number of facilities used in the centralized system is 5 and for decentralized system is 26 ambulances spread across the region from the city of Surabaya, Indonesia. Existing model has limited coverage locations and the number of available fleets, if the nearest ambulance is not available then the request will be added to the queue list. While in the proposed model, number of ambulance base locations will increase with involvement of potential health facilities so as to expand the coverage area and increase the number of available ambulance fleets. Then after the ambulance delivers the patient to the health facility, the ambulance is positioned as new stock from the facility or can return to the initial base. For a clearer view of the current system see Figure 1 and the interaction between agents in the decentralized sistem can be seen in Figure 2. The variables and parameters that will be used in the experiment can be seen in Table 1.

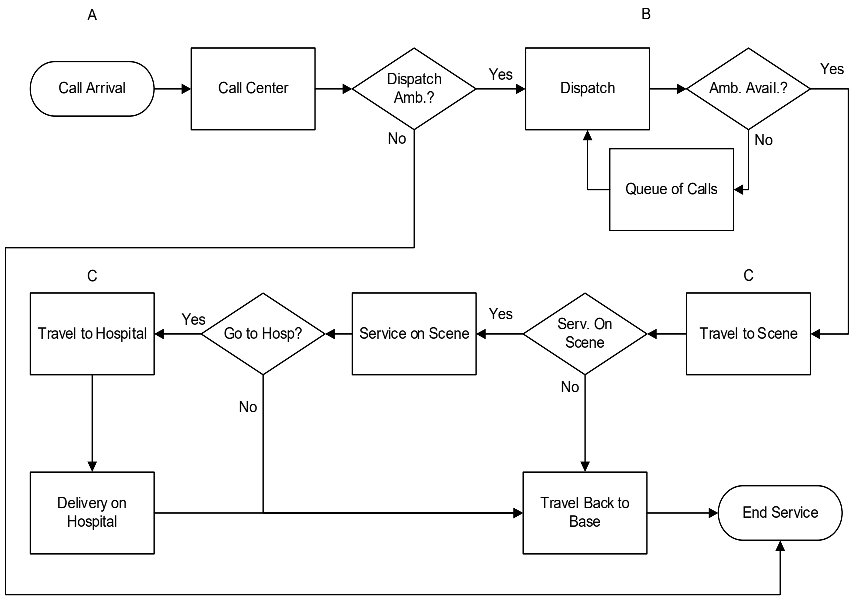

Fig. 1. Existing system of EMS

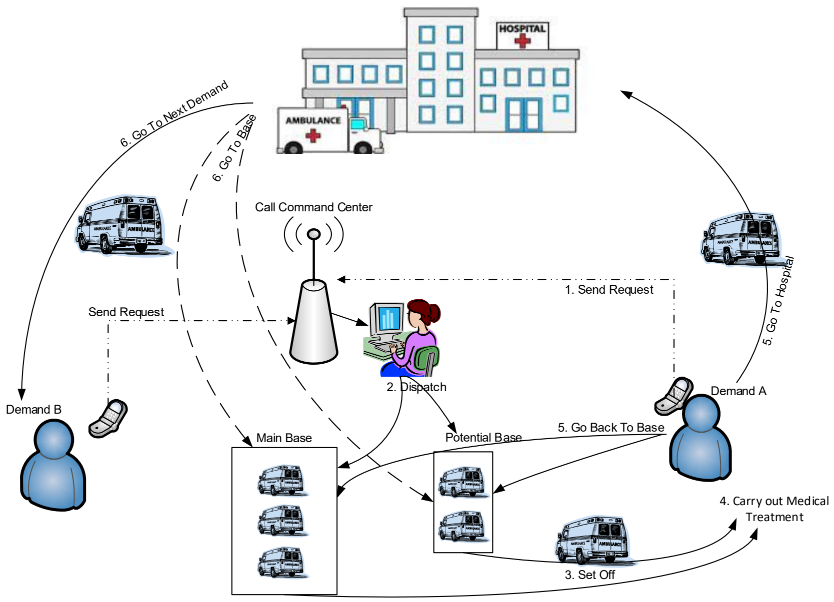

Fig. 2. The interaction between agents in the decentralized system of EMS

Table 1. Variables and parameters

Variables	Description
Potential base	Number of all potential healthcare facilities
Random demand	Longitude and latitude in one area as random demand
Ambulance speed	Average speed of ambulance
Benefit factor	Availiability of ambulance
Travel time	Travel time by the average speed
Maximum eval	Number of iteration
Demand	Number demand of ambulance in time
Time limit	Threshold of ambulance time to pick up demand

4 Experiment and results

This research was conducted in the city of Surabaya, Indonesia. The Government of Surabaya has several potential bases that can be involved in the decentralization system. In building the discrete event simulation model of EMS, it is divided into 3 parts, starting from the demand generation process, the process of determining the dispatch rules from the ambulance for pickup and the patient handling process. In the first stage, the demand generation process uses historical data to see how the distribution pattern of demand is, both the time between arrivals, the location of the demand and the type of demand. In addition, the position of the ambulance post is also raised which is available as an ambulance supply. Existing conditions, the City of Surabaya has a call center known as Call Command Center 112. Callers who have an emergency will call 112 then explain their personal data, address and type of need. Call Command Center acts as a dispatcher who will forward information to all existing base. The total number of base currently available are 5 that spread from Central, East, West, North and South. After the information is submitted to the nearest base from the caller, the team will immediately be assigned to the location according to the type of request. After the ambulance is at the patient's location, there are 2 alternative processes the process of handling patients at the location and the process of handling further patients. After the process is complete, the ambulance will return to their respective base.

Calls for ambulances have a certain distribution in some areas, arrival rates may vary and are time dependent. Furthermore, the call data that has been recorded in the system will be analyzed to see the type of distribution of the geographical coordinates of the caller's location. The position of the ambulance base and hospital will also be translated in the form of geographic coordinates. The first stage begins by compiling an input model for the system which includes generating demand, location of command posts and health facilities. At the generate demand stage, a demand analysis is carried out which aims to see the distribution of the time between call arrivals, the location of the demand coordinates and the type of request. In addition, at this stage, the location of the ambulance post and health facilities was also carried out. To minimize the response time until approach the standard response time of 8,8 minutes, the model is developed by adding some potential bases, see Table 2.

The scenario that will be used in this research is to test any potential bases that can provide services to all existing requests. Then the scenario of the number of requests that appear in the time interval will also be tested starting from the emergence of 1 request to the extreme condition of 15 requests in the time interval. Another scenario is to test response time limits, the goal is that the system can meet international response time standards. Experiments for each parameter were carried out to see how the impact and amount of potential base involved in a decentralized system would be. Testing is done by varying the size of the ambulance time limit (maximum coverage) to the destination and the number of requests from demand. The proposed algorithm can be seen in pseudocode, the algorithm written in MATLAB code on Intel(R) Core(TM) i3 processor 2.27 GHz see Figure 3. The results of running the algorithm see in Table 3.

Table 2. Potential bases

No	Potential Base	Coordinate	
1	PB-KR	-7.321882	112.770713
2	PB-KDG	-7.225995	112.773592
3	PB-KJR	-7.232475	112.754415
4	PB-RGH	-7.238551	112.767876
5	PB-TRJ	-7.240576	112.756036
6	PB-PCKG	-7.240576	112.762196
7	PB-MJO	-7.265317	112.771434

8	PB-KLPS	-7.279636	112.778363
9	PB-KPT	-7.288513	112.801748
10	PB-MA	-7.316576	112.793953
11	PB-MNR	-7.296776	112.764255
12	PB-JGR	-7.305243	112.757758
13	PB-SWN	-7.335739	112.737564
14	PB-KD	-7.258444	112.736790
15	PB-SL	-7.258730	112.727841
16	PB-SM	-7.257871	112.711096
17	PB-DK	-7.278491	112.711962
18	PB-PS	-7.286079	112.755556
19	PB-NR	-7.292957	112.748781
20	PB-SS	-7.306945	112.755696
21	PB-WNKR	-7.302729	112.730916
22	PB-TGL	-7.321586	112.761768

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  Pseudocode Mod-SOS to Emergency Medical Service
  Input: Number of demand, Total of facility, speed of
ambulance, Time limit
  Output: Facility Numb. and Response Time
  Process:
          Generate set of random demand;
          Calculate initial distance and travel time;
          Threshold Time ≤ Time limit;
               Generate neighbor set
               Local search;
           Set Max time, Random Demand;
           for i = 1 to i < total time limit
           Calculate mutual phase:
           Conditions:
           if ambulance (i) available then
           if x(i) ≤ Max time; Average time = x(i)
           Demand = index x(i)
  End
```

Fig. 3. Pseudocode of Mod-SOS

Table 3. Result of Mod-SOS under different parameter

Numb. of demand	Time limit	Max. Iteration	Potential Base	Std. Dev
1	15	10	10, 5, 11, 6, 19, 7, 16, 8, 13	0,625
		100	11, 5,10,6, 19, 7, 15,8, 14, 15,13,16	0,3125
		1000	10, 5, 11, 6, 15, 13, 7, 18, 8, 12	0,4375
	10	10	12, 5, 11, 6, 14, 7, 10	0,5625
		100	13, 5, 11, 6, 16, 14, 8, 12, 14, 8, 12, 7	0,25
		1000	15,5,13,7,11,10,6,9,12	0,4375
	8.8	10	15, 5, 13, 12, 11, 19, 7, 14	0,5
		100	17, 6, 15, 16, 14, 5, 13	0,5625
		1000	16, 6, 15, 13,18, 5	0,625

In this experiment, a comparison will also be made between the centralized ambulance system and decentralized system. A centralized ambulance system where the locations of ambulances are only in a few core areas while the decentralized system has ambulance positions spread out. Each parameter repeats 3 times running to see the performance of the algorithm. Table 4 contain information on the results of running algorithms with various parameters that were tested on a centralized and decentralized system. Ambulance requests with a decentralized system are faster than a centralized system. The result is when the timeout parameter is set to the international standard response time, the average of response time decreases but the number of non-covered requests increases. Thus confirming the statement of (9) that decentralization will decreases response time but will increase investment and operational costs.

Table 4. Response time with time limit and number of demand parameters

		Numb. of Demand					
		3		***5***		***10***	
		C	***D***	***C***	***D***	***C***	***D***
Average of response time (minutes)	Max. Covering 15 min	19.3	4.3	18.6	5.9	15.5	7.1
	Max. Covering 10 min	18.6	5.2	12.5	4.9	21.6	6.5
	Max. Covering 8.8 min	14.6	6.1	13.2	4.2	18.6	6.7

C = Centralized System, D = Decentralized System

Based on Table 5, the centralized system shows that there are several requests that cannot be fulfilled because the location of the requests is not in the coverage area. There are value exchanges where to satisfy all demands, a decentralized scenario or a combination of several potential bases is the best choice. As a consequence, the system must add new locations (involving potential bases) as many as 18 stations and if still use the centralized model, the system must add 10 - 13 ambulances. But, the limitation of this study is that it still needs development to take into account the costs that arise due to the implementation of the decentralized system. For further research, it would be more interesting if it involves calculating the costs that will arise as a result of implementing a decentralized system as well as how policies related to the coordination of each base involved.

Table 5. Result of Mod-SOS centralized vs decentralized system of EMS

	Centralized	Decentralized
Total Demand in Time	15	15
Average response Time (minutes)	19.3	5.2
Amount of ambulance can cover demand (unit)	1	4
Demand out of treshold time	7	0
Demand can not serve, ambulance out of stock	2	0
Potential Bases Involved	-	16, 6, 2, 3, 21, 18, 13, 8, 11, 7, 4, 15, 5, 10, 9, 1, 12, 19

In this study, it is proposed to change the centralized system to a decentralized and also tries to involve consolidation between several small bases as disclosed [20]. The advantage of consolidation is to form a wider cover area so that it can reduce response time. The approach taken to overcome these challenges is to use the simulation optimization method with the aim of removing obstacles from stochastic demand. The existing model has the principle that each base must cover the demand in its own area. while the closest distance coverage model is that the request will be fulfilled by the base that has the shortest distance. This is what causes many differences in the results of the fulfillment of requests on each basis which can be seen in Table 6. On the other hand, this model has a large impact on reducing the response time to an international standard response time of 8.8 minutes. When the timeout parameter is decreased to the international standard response time.

Table 6. Comparison between historical data with the model

Base	Historical Data	Output of Closest Distance Model
Center	86	196
East	126	82
West	47	49
North	46	58
South	142	62
Total	447	447

Figure 4. shows that the existing conditions at each base are still not optimal in meeting demand quickly. The ones that need the most concentration of additional fleets are on the west and south bases of Figures 4 (c) and (e). the west base must have at least 4 consolidated bases or ambulances involved, while the south base must have at least 6 consolidated bases or ambulances involved in that base. This is due to the high demand for ambulances in these two areas.

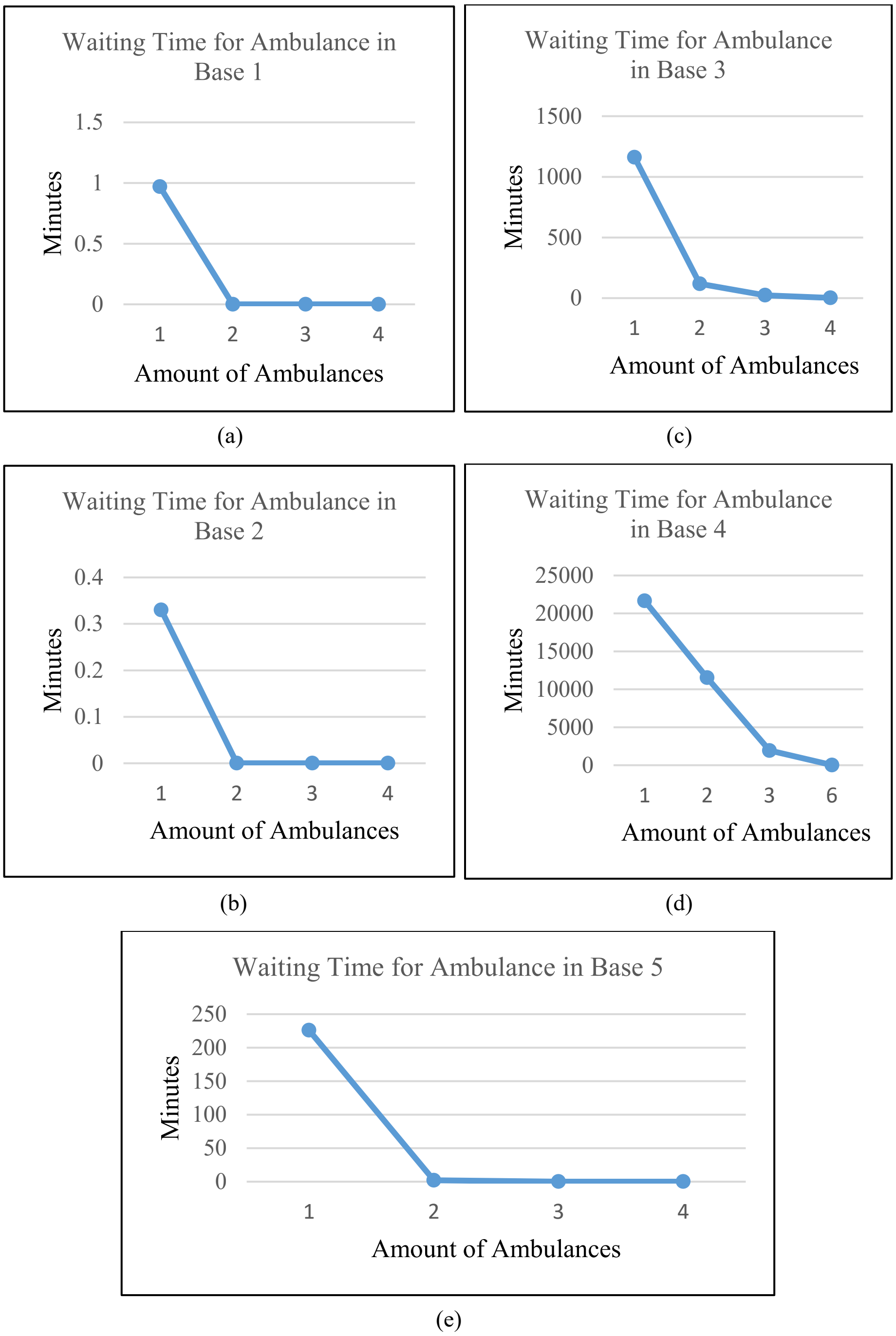

Fig. 4. Comparison of waiting time based on the numb. bases involved

5 Conclusion

This paper discusses determining how many bases and ambulances should be allocated to deal with the request of ambulance. From the experiment tested, to achieve a small response time or meet the international standards 8,8 minutes, then a decentralized system is very appropriate to be applied with an increase in efficiency of about 7.6%. Formation that can meet the problem of location and allocation, the result is 2 units of ambulances will be applied at the central base, 2 units of east base, 4 units of west base, 6 units of south base and 2 units of north base so that the total number of ambulances involved in the proposed system is 16 units.

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