Decentralization of Medical Emergency Service to Minimize Response Time

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Abstract

Medical Emergency Service (MES) is an important element in modern healthcare system. MES becomes important issue because it plays an important role in saving lives and reducing mortality and mordibility. The ability of MES to save lives depends on the time it takes for an ambulance to arrive on the scene after an emergency call received. This research will focus on changing the MES system from initially centralized to decentralized by considering the determination of the allocation and redeployment of ambulance. We propose the Nearest Neighbourhood – Symbiotic Organisms Search algorithm (NN-SOS) to overcome the problems. This study is expected to be able to solve the problems in the limitation of the number of ambulance required and the minimization of response time. From this study, it can be concluded that a decentralized ambulance system is needed. The comparison of the response time generated from the two systems is a centralized system with the best time limit having an average response time of 10-13 minutes while the decentralized system is better which is 3-6 minutes.

Keyword : Ambulance allocation and redeployment, Decentralized, Medical Emergency Service, Response time

1. Introduction

In medical emergency services, the response time is the interval between the arrival of the emergency call and the arrival of the medical team at the location of the call. This is a major concern because this delay may cause a difference between the patient's life and death, depending on the seriousness of his medical condition. MES managers must take operational and tactical decisions in this system to evaluate trade-offs between providing appropriate patient care (service level) and reducing costs associated with medical resources and capacity (ambulances, stations, specialties and equipment) (de Souza et al ., 2015).

The performance of pre-hospital medical (MES) emergency services depends on existing transportation infrastructure and medical resources (limited and important). The ambulance response time is generally considered an important factor for the survival of MES patients. Especially for patients with urgent needs, the response time determines the mortality rate (Chen et al., 2016). One key factor in MES performance is the speed at which emergency vehicles can respond to incidents (McCormarck & Coates 2015). The main objective of MES is to save the lives of emergency patients. The potential to improve MES system performance is directly related to the reduction in response time. The goal of MES is to reduce mortality, disability and suffering. MES decision makers handle the difficult task of finding ambulances to immediately and optimally serve medical emergency calls (Maleki et al., 2014).

Many previous researchers have conducted research on minimizing the response time of MES. Various approaches have been carried out and can be grouped into 3 major approaches including determining the optimal location of the ambulance, determining the optimal number that must be alerted in each base ambulance and determining the delivery scenario of the ambulance (Umam et al. 2018).

The ambulance location problem refers to the assignment of a small number of ambulances to maximize their coverage, considering that the system has a number of potential locations and demand zones that are considered constant when the ambulance is within a predetermined time (Brotcorne et al., 2003). Schmid (2012) has conducted research to find the optimal location of ambulance to reach patients in need with the shortest possible time and dispatching problems. The method initiated to solve this problem is stochastic dynamic programming. The results obtained in the form of a decrease in the average time of 12.89% with a note that they must relocate their existing ambulance base. In the same year, Shariat-Mohaymani et al. (2012) applied a linear upper-bound unavailability of set covering models to overcome the problem of determining the optimal location of ambulances with the case studies used were MES problems in Iran. The model calculates the area of demand that can be fulfilled optimally by an ambulance. With the model initiated, it shows a decrease in response time and the number of needs for an ambulance by dividing it into several locations. Sariyer et al. (2016) and Nickel et al. (2016) conducted a study to determine the best location of an ambulance by looking at the trend of previous demand data. So that location selection is determined based on the distribution of data from these requests. Whereas Van-Barneveld et al. (2016) adopted a configuration approach that allows ambulances to trade-off each other so that the response time will be smaller.

Billhardt et al. (2014) stated that there are two main problems faced by managers of MES, namely the problem of allocation and redeployment. The allocation problem is the determination of how much to spend to fulfill the demand, while the problem of redeployment is choosing an available ambulance and having the closest distance to the request. Scenario models are initiated in the form of coordination between ambulances by combining dynamic allocation models and dynamic redeployment. The results obtained were minimizing travel time and increasing the level of fulfillment of requests. Zhen et al. (2014) also conducted research on relocation and redeployment strategies. The study stated that the challenge in determining decisions in estimating the amount to be allocated is the constantly changing demand in each of the different locations. An approach is taken to overcome these challenges, namely by using simulation methods with the aim of eliminating barriers from stochastic requests. The results obtained are in the form of an ambulance unit placement strategy and scheduling on the basis of demand forecasting and real-time dependent.

Some of the most recent determinations regarding the determination of the location of an ambulance are as done by Takeda et al. (2007) who analyzed the differences in the location determination system centralize and decentralized using a hypercube queue model. The results found in the form of decentralize system scenarios can improve the performance of the ambulance and reduce the average response time, on the other hand the operational and investment costs are also getting bigger. In Indonesia, the overall management of the MES at each hospital (both government hospitals and private hospitals) is carried out independently by these hospitals (centralize). The impact that occurs when implementing centralization is a fairly long response time and the limited number of ambulances that will be allocated to meet the overall demand. In this paper, we propose a decentralized system to minimize response time. Hybrid Variable Neighborhood Search and Symbiotic Organisms Search (VNS-SOS) were conducted to solve the location and problem of ambulance allocation because Umam and Santosa (2018) stated that the VNS-SOS algorithm was able to overcome NP-Hard problems with more convergence, divergence and computational time better than the original SOS and PSO algorithm.

2. Methodology

Alba (2005) states that the basic idea of VNS is a better environmental change. VNS starts from the method set to reach the local minimum, then investigates randomly and simultanly, so that the environment is closer to the solution. Every time, one or more points in the current environment are as initial solutions for local declines. A jumping point from the current solution is used as a new reference with the condition that found the better solution. VNS is not like Simulated Annealing or Taboo Search method. Although simplicity is more specific.

Table 1. Presents data on health facilities in Surabaya. Indexes number 1 to 22 are potential locations that are current government assets (decentralized). While index numbers 23 to 26 are currently ambulance resource locations (centralized)

Table 1. MES Fasilities in Surabaya

Health Facilities Index	Coordinate	
1	-7.321882	112.770713
2	-7.225995	112.773592
3	-7.232475	112.754415
4	-7.238551	112.767876
5	-7.240576	112.756036
6	-7.240576	112.762196
7	-7.265317	112.771434
8	-7.279636	112.778363
9	-7.288513	112.801748
10	-7.316576	112.793953
11	-7.296776	112.764255
12	-7.305243	112.757758
13	-7.335739	112.737564
14	-7.258444	112.736790
15	-7.258730	112.727841
16	-7.257871	112.711096
17	-7.278491	112.711962
18	-7.286079	112.755556
19	-7.292957	112.748781
20	-7.306945	112.755696
21	-7.302729	112.730916
22	-7.321586	112.761768
23	-7.267395	112.758611
24	-7.316137	112.751469
25	-7.245913	112.757886
26	-7.270864	112.747956

Step 1. Generate random demand

Table 2. Generate Random Demand

Random demand	Coordinate	
Demand 1	-7.283746	112.797894
Demand 2	-7.265568	112.718114
Demand 3	-7.296477	112.736469

Step 2. Calculate the closest distance between the demand point and each health unit available.

The VNS stage aims to see alternative ambulances that can be sent to staff based on the smallest travel time. Then the distance will be divided by the assumed average speed of 50 km / h to see how big the response time is. In Table 3, column A contains information on the distance between demand and each health facility. Column B is a normal response time between health units assuming an average ambulance speed of 50km / hour and with conditions there are no obstacles along the way. Column C is the fastest sequence of response times with a maximum threshold parameter of 20 minutes.

Table 3. Normal Response Time Calculation

Facilities	Demand 1			Demand 2			Demand 3		
	A	B	C	A	B	C	A	B	C
1	46.831	56.197		77.058	92.469		42.639	51.166	
2	62.656	75.187		68.146	81.774		79.661	95.592	
3	67.225	80.669		49.121	58.945		66.470	79.764	
4	54.256	65.107		56.623	67.947		65.892	79.070	
5	60.131	72.157		45.417	54.500		59.227	71.071	
6	56.018	67.221		50.674	60.808		61.537	73.844	
7	32.245	38.694		53.321	63.984		46.835	56.201	
8	19.959	23.951		61.870	74.243		45.152	54.182	
9	6.130	**7.356**	1	86.724	104.069		65.763	78.915	
10	33.066	39.679		91.397	109.676		60.896	73.075	
11	36.074	43.289		55.704	66.844		27.788	33.345	
12	45.530	54.637		56.087	67.304		23.023	27.627	
13	79.643	95.571		72.817	87.380		39.277	47.132	
14	66.135	79.362		19.989	23.986		38.034	45.641	
15	74.386	89.263		11.890	**14.268**	2	38.721	46.464	
16	90.573	108.687		10.416	**12.499**	1	46.198	55.437	
17	86.093	103.311		14.313	**17.175**	3	30.399	36.478	
18	42.402	50.883		42.692	51.230		21.736	26.082	
19	49.969	59.963		41.117	49.340		12.805	**15.366**	2
20	48.155	57.786		55.897	67.076		21.892	26.270	
21	69.616	83.539		39.304	47.165		8.362	**10.034**	1
22	52.316	62.779		71.019	85.222		35.644	42.772	
23	42.550	51.060		40.538	48.645		36.552	43.862	
24	56.608	67.930		60.579	72.694		24.729	29.674	
25	55.063	66.076		44.364	53.236		54.913	65.895	
26	51.573	61.887		30.308	36.369		28.071	33.685	

Table 4. Comparison between Centralized and Decentralized Unit Response Times

Demand	Centralized		Decentralized	
Demand 1	Facility 26	51.060	Facility 9	7.356
Demand 2	Facility 26	36.369	Facility 16	12.499
			Facility 15	14.268
			Facility 17	17.175
Demand 3	Facility 24	29.674	Facility 21	10.034
			Facility 19	15.366

From table 5, it can be seen that the response time ratio between the centralized and decentralized systems is very large. With a maximum time limit of 20 minutes from the three demands, the central system is not able to handle it in a timely manner. While the decentralized system is better because it can meet the 20 minute threshold with a choice of several units available. Note that the international standard MES response time based on previous studies is 8.8 minutes (Takeda et al., 2007). after going through the stage of determining the nearest neighbor from random demand, the next stage is the Symbiotic Organisms Search.

The Symbiotic Organisms Search algorithm is one of the newest metaheuristic methods inspired by the interaction behavior seen among organisms in the universe. There are several forms of symbiosis, namely symbiosis of mutualism, commensalism symbiosis, and symbiosis of parasitism. In general, the algorithmic stages of Symbiotic Organisms Search (SOS) are as follows. (Cheng and Prayogo, 2014)

1. INITIALIZE

$$Ecosystem = rand \times ((UB - LB) + LB) \tag{1}$$

Where:

Rand = random number [0 1]
UB = upper limit value
LB = value of the lower limit

2. REPEAT
   - Mutualism phase
   - Phase of commensalism
   - Parasitism phase
3. UNTIL (do it until the termination criteria are met)

- Mutualism Phase

This SOS phase mimics mutualistic relationships between organisms in nature. SOS describes Xi is an organism compatible with members of the ecosystem. Other organisms, Xj Then randomly selected from the ecosystem to interact with Xi. Both organisms engage in mutualistic relationships with the goal of improving survival together with benefits in the ecosystem. New candidate solutions for Xi and Xj are calculated based on the mutualistic symbiosis between the organisms Xi and Xj, which are modeled on equations (2) and (3) follows:

$$Xinew = Xi + rand\,(0,1) * (Xbest - Mutual\_Vector * BF1) \tag{2}$$

$$Xjnew = Xj + rand\,(0,1) * (Xbest - Mutual\_Vector * BF2) \tag{3}$$

$$\text{Mutual Vector} = \frac{\text{Xi+Xj}}{2} \tag{4}$$

- Commensalism Phase

Similar to the phase of mutualism, an organism Xj is randomly selected from the ecosystem to interact with Xi. In this case, the Xi organism tries to get advantage of interaction. However, organism Xj alone does not profit or suffer relationship. New candidate solutions from Xi are calculated according to the symbiosis between organisms commensal Xi and Xj, which are modeled in Eq. (2). Following the rules, Xi organism updated only if the new fitnessss are better than the previous interaction fitness.

- Parasitism Phase

In SOS, the Xi organism is given a role similar to anopheles mosquito through the creation of an artificial parasite called " Parasite Vector ". Parasite Vector is made in space search by duplicating the Xi organism, then modify selected at random dimensions using random numbers. Organism Xj is randomly selected from the ecosystem and serves as the host for vector parasites. Parasite Vector tries to replacing Xj in the ecosystem. Both organisms are then evaluated to measure their fitness value. If Parasite Vector has a better fitness value, it will kill the organism Xj and assume its position in the ecosystem. If the fitness value of Xj is better, Xj will have immunity from parasites and Parasite Vector will no longer can live in the ecosystem.

In the Symbiotic Organisms Search stage the level of congestion and the probability of the availability of ambulances will be taken into account at each health facility. at the Symbiotic Organisms Search stage, it will consider the parameters of the time limit, the level of congestion and the probability of the availability of ambulances at each health facility. the result of this stage is the selection of health facilities that will send ambulances to patients.

Table 5. The Mechanism for Calculating the Total Response Time

Demand	Decentralized		Xi or xj	Random jam	Duration of congestion	Mutual vector	Total Response Time
Demand 1	Facility 9	5,108	Xi	0,2	1,4712	3,22485	**7,878**
	Facility 8	16,632	Xj	0,25	4,9785		26,007
Demand 2	Facility 16	8,680	Xi	0,5	6,2496	8,397	**10,451**
	Facility 15	9,908	Cxi	0,3	4,2768	6,42375	19,557
	Facility 17	11,927	Xj	0,25	4,2939		13,144
	Facility14	16,657					
Demand 3	Facility 21	6,968	Xi	0,5	4,9956	5,7639	**12,983**
	Facility 19	10,671	Xj	0,1	1,5366		18,211
	Facility 18	18,112					
	Facility 20	18,243					

3. Result and Discussion

Tests on research are carried out by varying the size of the ambulance time limit (maximum covering) to the destination and the number of requests from demand. The results obtained are shown in Table 2, 3, 4 and Table 5. The algorithm written in MATLAB code and limit of iteration of each is 15 on Intel(R) Core(TM) i3 processor 2.27GHz.

Table 6. List variables

Variables	Description
Total of facility	number of all health facilities that have ambulances in one area
Random range	longitude and latitude in one area that will be used for random ranges
Average speed	average speed in the ambulance
BF weight	ambulance is available or not
Time	distance traveled is divided by the average speed
Max iteration	iteration limit in one process
Demand	number of ambulance requests
Limit time	ambulance time limit to demand
Total of demand	the number of requests to order an ambulance

We use an average of ambulance speed is 50 km/h, assuming there nothing distruction when heading to the destination. The number of facilities used in centralized system is 4 and for decentralized system is 22 with the assumption that each facility has one ambulance.

Step 1. Generate several random coordinate points as demand.

Step 2. Calculate the closest distance between the demand point and each available health unit. Then the distance will be divided by the assumed average speed of 50 km / h to see how big the response time is.

Step 3. Sort out which facilities are able to cover demand according to the specified timeout parameters.
Step 4. With the VNS mechanism selected facilities that have the potential as facilities to send the fleet are selected.
Step 5. Through the Mutualism stage in SOS, which facilities will be selected for sending ambulances with consideration of the small response time and the availability of ambulances.

These steps will be illustrated in Fig. 1.

Pseudocode SOS-VNS to Minimize Response Time

```
Input : Total of facility, Total of demand, Random range, Average speed, Time limit
Output : Average time, Demand
Process :
Begin
    Generate ecosystem;
    Calculate initial distance; (using Euclidean distance equation)
    Calculate Time;
    Threshold Time less than Time limit;
    Generate neighbour set
        Local search;
        Set Max time, Demand;
        for i=1 to i<total threshold of facility
            Calculate:
                x(i) = x' + rand[0 1] × (x' − mutual vector ∗ BF(1));
                x(i + 1) = x' + rand[0 1] × (x' − mutual vector ∗ BF(2));
            Conditions:
                if x(i)=~0 then
                        if x(i) less than Max time then
                            Average time = x(i)
                            Demand = index x(i)
                            break;
                        end;
                else
                        continue;
                end
        end
End
```

Figure 1. The Pseudocode of SOS-VNS algorithm

Tests on research are carried out by varying the size of the ambulance time limit (maximum covering) to the destination and the number of requests from demand. The results obtained are shown in Table 7, 8, 9 and Table 10.

Table 7. Result Time Limit = 20 minutes

Time limit = 20 minutes	System Ambulance					
	Centralized	Decentralized	Centralized	Decentralized	Centralized	Decentralized
Total of demand	5		10		15	
Average of Response time (minutes)	12	11	13	12	14	12
Average ambulance can cover (unit)	1	5	1	3	2	2
Demand that does not enter the threshold	1	0	2	0	2	0
Demand is not served because of the limited number of ambulances	3	0	1	0	2	0

Table 8. Result Time Limit = 15 minutes

Time limit = 15 minutes	System Ambulance					
	Centralized	Decentralized	Centralized	Decentralized	Centralized	Decentralized
Total of demand	5		10		15	
Average of Response time (minutes)	10	8	12	9	13	9
Average ambulance can cover (unit)	1	5	1	3	2	2
Demand that does not enter the threshold	1	0	1	0	1	0
Demand is not served because of the limited number of ambulances	2	0	1	0	1	0

Table 9. Result Time Limit = 10 minutes

Time limit = 10 minutes	System Ambulance					
	Centralized	Decentralized	Centralized	Decentralized	Centralized	Decentralized
Total of demand	5		10		15	
Average of Response time (minutes)	7	5	8	5	9	7
Average ambulance can cover (unit)	1	4	1	4	2	3
Demand that does not enter the threshold	3	0	4	0	6	0
Demand is not served because of the limited number of ambulances	3	0	6	0	10	0

Table 10. Result Time Limit = 8,8 minutes

Time limit = 8,8 minutes	System Ambulance					
	Centralized	Decentralized	Centralized	Decentralized	Centralized	Decentralized
Total of demand	5		10		15	
Average of Response time (minutes)	6	3	7	4	8	6
Average ambulance can cover (unit)	1	4	1	3	3	1
Demand that does not enter the threshold	4	0	5	0	7	0
Demand is not served because of the limited number of ambulances	3	0	6	0	10	0

Based on Table 7, 8, 9 and Table 10, ambulance ordering with a decentralized system is faster than a centralized system. If an ambulance at any health facility can be used by a patient who does not distinguish between public or private health facility problems, then the patient will have many opportunities to obtain services from an ambulance. Table 10. serve the result when the parameter of time limit decrease into international standards of response time. The average of response time is decrease but the number of un-covered demands is increase. the lack of fleet for this scenario is the same as the 10-minute time limit scenario which is 3 until 10 fleet of ambulances.

Based on parameter demand, ambulance ordering with a 5, 10 and 15 demands the system shows that there some demands can not served because the demands in out of covering area. There is a trade-off where if the goal is to meet all demands, the 15-minute deadline scenario is the best option in centralized system but with response time considerations that still exceed international response time standards. On the contrary if the goal is to meet international standards from the response time then the scenario that can be chosen is the 8.8 minute timeout scenario. With the consequence the system must add new locations as much as 4 - 7 stations and add 3 - 10 ambulance fleets. Thus confirming the statement from Takeda et al. (2007) decentralization will minimize response time but will increase investment and operational costs.

From several scenarios have been carried out, a maximum time limit of 15 minutes can overcome almost all requests in centralized system. Experiments use parameters of the number of requests 5, 10 and 15 patients and time limit 20 minutes, 15 minutes, 10 minutes until 8,8 minutes. Afterwards, the average demand is not within the coverage area is only 1 patient. From the perspective of the amount to be allocated, the systems must add 1 fleet to fulfill the overall demand. So the average response time is approximately 13 minutes. Otherwise, to minimize response time can use the 8,8 minutes maximum covering time scenario and the response time becomes 6 - 8 minutes. The consequence is the existing system (centralized) need 11-12 stations and 15 unit ambulances to allocated to cover max 15 demands.

4. Conclusion

From this study, it can be concluded that a decentralized ambulance system is needed. This is because it facilitates the request to get an ambulance. We cannot expect emergency conditions so that at least we can do prevention by using such solutions. To choose the best time limit that will be set as the standard of each system judging by how fast the response time is generated and how much the system is able to meet the demand. The best time limit for ambulances can serve patients on a centralized system, which is 15 minutes with an average speed of 50 minutes assuming nothing when heading to the destination, while the best time limit for a decentralized system is 8.8 minutes. The comparison of the response time generated from the two systems is a centralized system with the best time limit having an average response time of 10-13 minutes while the decentralized system is better which is 3-6 minutes.

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