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Simulation of covering location models for emergency vehicles management: A comparison study

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Abstract

The efficiency of the emergency management services EMS consists in responding as quickly as possible to the arriving emergency calls. This objective may be attained by insuring a good preparedness of the population, i.e a good coverage of the geographical zones under control. Since a well covered zone means the availability of close vehicles to assist any arriving calls from this zone, reducing the response time to emergencies pass through choosing the best positions to the available vehicles. In this work, we aim to compare the performance of different coverage models for locating emergency vehicles on the long run using simulation. The comparison takes into account both response time to emergency calls and the preparedness of the zones. The obtained results show that using a binary weighted coverage measure gives better quality solutions for both response time and coverage.

Index Terms

decision support system, simulation, optimization, crisis response management, linear programming.

I. INTRODUCTION

The crisis response management is a very crucial domain that deals with saving human lives and minimizing damages. In such kind of systems, the response time is a critical factor in making decisions that generates the difference between survival or death. In the last decades, several models and methods have been proposed to deal with the challenges that face the EMS and more particularly the management of resources for the covering issue. The main objective of covering in the context of emergencies is to find suitable locations for the emergency facilities to maximize the preparedness of some geographical region to future emergency calls and consequently reduce the response time. Because of the uncertain service requests, the system status is likely to change unpredictably during a day and the dynamic redeployment is an interesting alternative to regain a good level of service. Among the works that studied the dynamic aspect in the facility location, the model proposed by Gendreau et al.,[1] that maximizes the proportion of calls covered by at least two vehicles within a distance threshold. In the model of Rajagopalan et al. The objective is to minimize the number of vehicles to be located to cover each demand zone with a certain probability over several time periods and that was solved with a tabu search algorithm[2]. The TIMEXCLP (Time-dependent Maximum Expected Coverage Location Model) has been developed by Repede and Bernardo, it is derived from the MEXCLP model , and was incorporated into a decision support system developed for EMS in Louisville, Kentucky. It allows the number of vehicles at a site to vary at different hours of a day as demand evolved[3]. Extended literature on the dynamic and stochastic models can be found in [4] and [5]

Simulation is typically used when experimentation with the real system is too expensive, too dangerous, or not possible [6]. The EMS systems are highly complex systems that give rise to numerous challenges and cannot be solved in reality. Therefore, simulation offers a natural framework within which to address these challenges and help us to gain knowledge about improvement of the system. In[7] the authors used a simulation model to the management of emergency vehicle fleet. They emphasized the integration and exchange of information across public safety and transportation agencies, and coordinated the activities of three public safety services, namely fire protection agencies, police and paramedic services. In [8] the authors established an optimization model based on the simulation of evacuation route that can simulate the evacuation traffic flow and proposed a heuristic algorithm for the optimization of the model. Simulation was also used in [9] where several policies for districting/dispatching where proposed and provided as inputs to a simulation model that compares the performances of different policies.

In this paper we are concerned with relocation strategies to manage the emergency vehicles when provisional events create temporary decreases in ambulances availability. For this purpose, a discrete event simulation (DES) model is developed to study and compare the performances and the impact of the relocation strategies under various scenarios based on the response time to emergencies and the coverage rates of the zones. In the remaining of this paper we will present the relocation and simulation models in section 2. In section 3, the experimental results are presented and the paper is concluded in section 4.

II. MODELS AND SIMULATION

When vehicles are dispatched to calls some points become uncovered , this issue is ignored in the static models. It is crucial to match ambulance availability with the emergency demand; this approach involves the repositioning of ambulances in real time so as to maintain zone coverage when the number of available ambulances decreases. In the three compared models, we consider a geographical area partitioned into zones which regroup the emergency demands situated within them. The location of each one is represented by its geographical centroid, and the corresponding demand (weight) is the sum of the expected demand in the zone; all service requests within a zone are covered if the zone is covered. In general, a zone is said to be covered by a vehicle station if the distance between them is within a predefined distance ”r” (radius). The objective is to find the most suitable locations (stations) of the emergency vehicles to provide the best coverage for all the area. The linear programs of the three studied models are described as follows:

Decision variables:

$$X_{vj} = \begin{cases} 1 \text{ if a vehicle v is assigned to station j} \\ 0 \text{ otherwise} \end{cases}$$

$$yz = \begin{cases} 1 \text{ if a zone z is covered} \\ 0 \text{ otherwise} \end{cases}$$

A. First model

Maximizes the total weighted demand covered within a maximum predefined distance.

$$\text{Maximize} \quad \sum_{z \in Z} w_z y_z$$

$$\text{Subject to} \quad \sum_{v \in V} \sum_{j \in Sz} x_{vj} \geq y_z \quad (\forall_{z \in} Z) \qquad (1)$$

$$\sum_{j \in Sz} x_{vj} = 1 \quad (\forall_{z \in} Z) \qquad (2)$$

$$\sum_{v \in V} x_{vj} \leq \max_j \quad \forall j \qquad (3)$$

$$x_{vj}, y_z \in \{0, 1\} \; (\forall j \in S, \; z \in Z) \; ; \qquad (4)$$

Where W_z represents the weight of the zone, and S_z is the set of stations that are within the target response time. In constraint (1) , a zone is considered covered if there is an ambulance located at any station that is within the target response time. constraint (2) requires that , at a given instant of time , each vehicle is assigned to only one station, Constraint (3) states that a station cannot contain more than a fixed number of vehicles. Constraint (4) indicates the binary nature of decision variables.

B. Second model

This model minimizes the total sum of distances between demand points and the location of the vehicles.

$$\text{Minimize} \quad \sum_{z \in Z} \sum_{v \in V} \sum_{j \in S} x_{vj} d_{zj}$$

$$\text{Subject to} \quad \sum_{j \in S} x_{vj} = 1, \; \forall v \; ; \qquad (5)$$

$$\sum_{v \in V} x_{vj} \leq \max_j \; \forall j \qquad (6)$$

$$X_{vj} \in \{0, 1\} \qquad (7)$$

Constraint (5) requires that each vehicle is assigned to only one site , Constraint (6) determines the maximum number of vehicles that a station can contain .

C. Third model

The third model is similar to the second one but takes into account the weight of the zones.

Minimize $\sum_{z \in Z} w_z \sum_{v \in V} \sum_{j \in S} x_{vj} d_{zj}$

Subject to $\sum_{j \in S} x_{vj} = 1\ , \ \forall\, v\ ;$ (8)

$\sum_{v \in V} x_{vj} \leq max_j \ \forall\, j$ (9)

$x_{vj} \ \in \{\, 0\, ,1\, \}$ (10)

In order a discrete-event simulator (DES) [1 :isions involved in vehicle relocation. In DES , the model is discrete: the simulated clock always jumps from one event time to the most imminent event time , instead of advancing continuously. It advances according to the next scheduled event. Each event occurs at a particular instant in time and marks a change of state in the system (e.g.,dispatching , relocating vehicles). The simulation begins considering all vehicles simultaneously idle. We organized the simulation model according to the following specification :

- Call inter-arrival time: corresponds to the time between two successive calls. we generate the arrivals of calls by simulating a Poisson process with arrival rate $\lambda(t); t \geq 0$ [11].
- Call locations : specifying the exact location of each call may require considerable effort calculation due to the large number of calls received by emergency systems. Thus, the method commonly used in the literature is to aggregate the calls based on their proximity to the zones.
- Call service time according to a first-come, first-served policy since there is no priority scheduling or differentiation of calls, and a log-normale distribution with mean of 20 minutes.
- Possibility of evacuation to hospital uses a uniform distribution with probabilities equal to 1/2.
- The idle vehicle with the shortest expected travel time to the calls zone location is dispatched and the rest of idle vehicles are relocated according to the different strategies which we considered in the previous section.

III. EXPERIMENTAL RESULTS

To solve the linear formulations, we have used lp solve, a free linear programming solver based on the revised simplex method and the Branch-and-bound method for the integers. The simulator is written in java programming language. The LP models have been coded in lp solve 5.5.2.0 java distribution and embedded into the simulator. Tests were conducted on a Windows environment with an Intel(R)Core(TM) i3-3220 CPU ,3.30GHz and 4GB of RAM. For tests, several synthetic instances were generated, each one contains a set of zones, stations, hospitals, and the total number of available ambulances. The locations of the zones, stations and the hospitals are given by their coordinates which can be used to determine the Euclidean distance between two locations. An example of a generated instance is depicted in Figure1. The value of the covering standard (r) was determined for each instance separately. Figure2 shows the parameters of each instance.

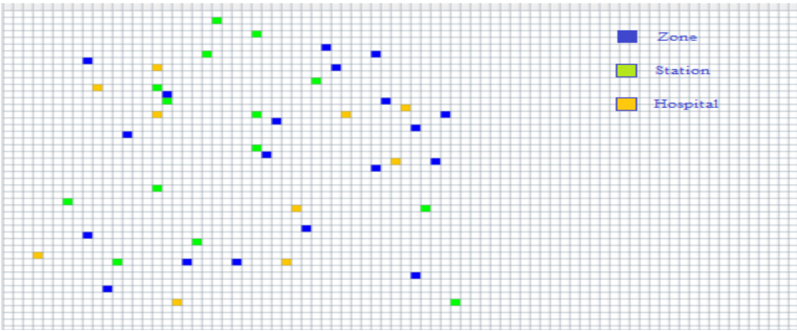

Fig. 1: A generated instance

	# veh	# zon	# stat	# hosp	r
Inst1	36	10	6	5	12
Inst2	70	19	14	10	14
Inst3	32	49	16	15	18
Inst4	36	40	18	15	23
Inst5	60	100	30	15	39
Inst6	177	40	30	16	19
Inst7	135	100	27	15	19
Inst8	100	76	50	30	32
Inst9	100	100	50	15	28
Inst10	50	150	50	28	16

Figure2: Instances description

To evaluate the efficiency of our models we have run a number of experiments. In each experiment, we run the simulation for a time period of 72 hours, each simulation was repeated 10 times to get an averaged result. We changed some of the simulation model parameters to investigate the impact of such variations on the performance of the system.

A. Response Time

In this part we test the effects of the different inter arrival times on the models performance. Response time is the time interval measured from receiving the emergency call to the arrival of the ambulance at the call scene. The models were solved and simulated for several values of arrival time lambda , the results presented here concern the tests with respectively : 6 calls/h , 10 calls/h , 20 call/h , 30 call/h, the results are presented in table I.

The obtained results show that the average response times varied depending on the policies used and the demand size. As expected , when calls appear more frequently with lower inter arrival time, the maximum waiting time increases, however, the overall average response times for the first model were the most optimal compared to the second and the third models. The third model performs slightly better than the second one. As shown in figures 2,3 and 4, in most cases the proportion of calls that have been responded within 10 mns is higher using the first model; and model3 performs better than model2. The only case where model2 outperforms the two others was in instance10 when arrival rate is low.

B. Coverage

Another factor that can certainly contribute to the improvement of the solution quality is the coverage rate , we have calculated the proportion of the number of covered zones after each relocation plan. The results depicted in Table II show that for all the instances, the first model ensures the highest coverage rates compared to the two other models. The difference between model2 and model3 is inconsiderable since for some instances model2 performs better than model3 and for others model3 is better.

C. Computation time

This part contains some results on the average computational times for different sized problems using our linear models. The number of zones, stations and the number of ambulances affect the size of the integer program, lp solve is slow on the large data set .

Figure 6 shows the relation between time to solve the model and the instance size, for the three models: problems solved by the maximization weighted zones coverage model take more time as compared to the distances minimization models, the difference increases as the size of the instance gets bigger. It seems that the first model is more sensitive to the size of problem. Computational time increases much rapidly as compared to the other models. When looking at the solution quality, maximizing the area coverage is an interesting approach to reduce response time and maximize the expected demand coverage, the first model performs better nearly for all cases, but , if we consider the case where the number of ambulances is really small compared to the size of the area , the third model may perform better , as is shown in figure 4. The results of the second and third models , allow us to highlight the influence of the distribution of demand call around the area on the model performance, considering the weight of the zones is very important to reduce response time.

IV. CONCLUSION

In this work we compared three distinct integer relocation models for the management of emergency vehicles. The models were described to dynamically find the best location for the emergency vehicles, based on status of ambulances and stations and the population distribution through the region in the time of the relocation. Simulation was a good option that makes it possible to deal with the dynamic aspect of this kind of systems

The obtained results have shown that using a binary (0/1) coverage measure with considering the weighted

zones is the best choice when looking to a relocation strategy that minimizes the response time and improving the covering rates compared to a measure that minimizes the sum of the distances between the emergency vehicles and the zones. the drawback of such strategy is its required computation time for large sized instances. As an improvement of this work, we may think to applying an approached solving method for the model. Also, other realistic parameters like the calls priority as well as diversion and rerouting strategies may be considered in future works.

	λ / Response time	6		10		20		30	
		MAX	AVG	MAX	AVG	MAX	AVG	MAX	AVG
Instance 1	Model1	7,97	4,18	7,97	4,41	7,97	4,4	7,97	4,3
	Model2	8,82	4,31	10,53	4,59	14,64	4,55	22,72	4,92
	Model3	7,97	4,32	9,57	4,4	30,35	4,77	41,14	5,04
Instance 2	Model1	10,44	3,79	10,44	3,78	10,44	3,88	10,44	4,05
	Model2	10,16	3,88	10,44	3,74	10,44	4,02	10,44	4,1
	Model3	9,88	3,78	10,09	3,77	10,44	3,8	10,44	3,81
Instance 3	Model1	12,83	6,52	13,21	6,8	47,6	7,98	131,94	12,02
	Model2	400,02	11,38	1097,04	18,23	1051,09	60,66	4589,67	381,55
	Model3	824,33	26,05	971,76	46,45	1048,89	23,57	3535,35	153,09
Instance 4	Model1	16,22	6,48	16,38	6,35	25	6,94	44,71	8,86
	Model2	23,51	6,27	56,95	7,13	1725	28,12	2236	62,88
	Model3	26,28	6,22	42,95	6,98	508,17	15,96	3767,12	101,89
Instance 5	Model1	28,67	11,07	36,85	11,74	140,33	14,64	92.6	17,45
	Model2	292,08	14,85	2771	59,44	4192,63	79,17	4390	150,75
	Model3	167,06	12,86	341,15	14,72	4227,98	273,58	4525,98	341,07
Instance 6	Model1	14,23	5,58	14,23	5,31	14,23	5,1	14.23	5,4
	Model2	14,48	5,16	23,26	5,36	60	5,54	40,01	5,84
	Model3	14,48	5,35	14,48	5,32	58	5,33	14,48	5,48
Instance 7	Model1	13,95	4,73	13,95	4,52	13,95	4,68	13,95	4,73
	Model2	13,95	4,96	28,35	4,89	410	6,43	1223	14,46
	Model3	22,35	4,9	25,97	4,85	15,1	4,88	15,4	4,89
Instance 8	Model1	22,83	7,89	23,83	7,9	23,85	8,37	24,48	9,02
	Model2	72,67	9,95	63,49	9,8	59,98	10,19	75,24	10,55
	Model3	23,83	8,22	23,83	9,02	61	9,61	80,3	10,82
Instance 9	Model1	20,4	6,89	20,4	7,06	20,4	6,85	20,4	7,46
	Model2	20,57	7,7	53,96	8,12	130,28	10,69	2244	101,51
	Model3	20,4	7,17	28,82	7,6	1631	19,54	463	11,5
Instance 10	Model1	12,02	6,04	12,09	5,95	4130	123,29	4130	123,92
	Model2	605	14,96	3328	57,24	4309	213	4130	277,02
	Model3	824	13,78	1374	33,50	4041	153,89	3810	272,12

TABLE II: The effect of increasing demand on the response time (min)

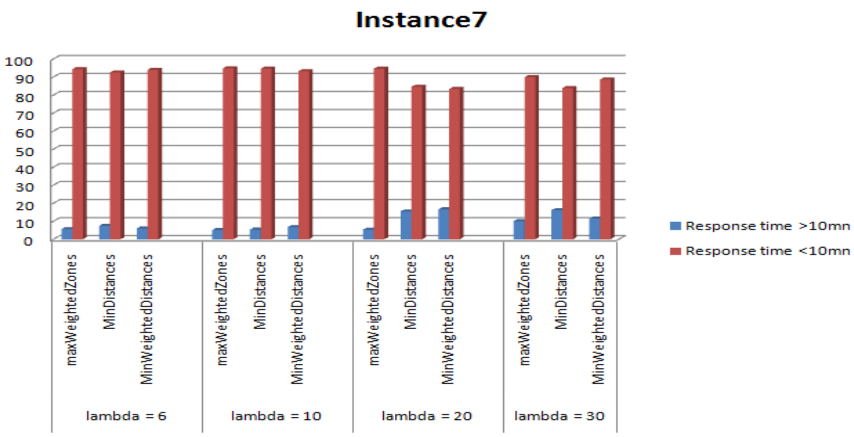

Fig. 3: Instance7

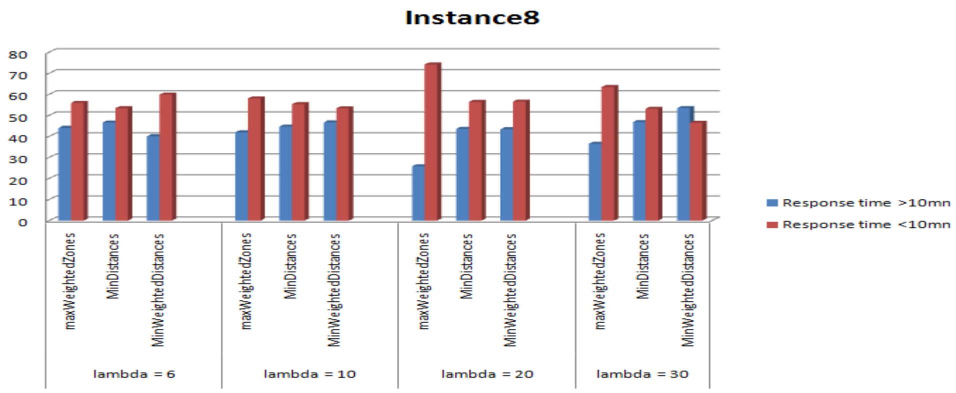

Fig. 4: Instance8

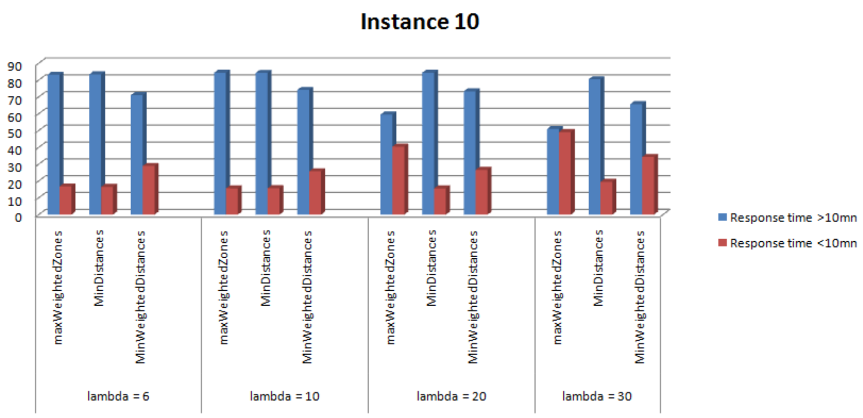

Fig. 5: Instance10

	Lambda	**6**	10	20	30
Instanse 1	Mode1 1	100	100	100	100
	Mode1 2	98,6	97,96	96,15	94,57
	Mode1 3	99,95	99,31	96,95	94,57
Instance 2	Mode1 1	100	100	100	100
	Mode1 2	100	100	100	100
	Mode1 3	100	100	100	100
Instance 3	Mode1 1	100	99,86	93,42	68,06
	Mode1 2	89,99	82,19	67,77	60,47
	Mode1 3	83,95	77,84	64,03	54,31
Instance 4	Mode1 1	100	100	99,62	91,46
	Mode1 2	99,45	97,70	90,92	75,18
	Mode1 3	99,39	96,96	83,84	72,82
Instance 5	Mode1 1	99,99	99,63	96,69	85,89
	Mode1 2	94,56	93,72	81,16	65,65
	Mode1 3	93,74	88,06	77,34	67,49
Instance 6	Mode1 1	100	100	100	100
	Mode1 2	100	99,86	97,81	97,94
	Mode1 3	100	100	100	100
Instance 7	Mode1 1	100	100	100	100
	Mode1 2	99,93	99,42	97,89	97,28
	Mode1 3	99,64	99,61	99,57	99,44
Instance 8	Mode1 1	100	100	100	100
	Mode1 2	96,50	95,53	95,01	94,23
	Mode1 3	99,98	99,32	95,88	94,93
Instance 9	Mode1 1	100	100	100	100
	Mode1 2	99,88	99,18	92,42	85,18
	Mode1 3	99,91	98,03	91,27	90,40
Instance 10	Mode1 1	99,86	99,01	80,45	62,43
	Mode1 2	89,56	79,27	69,36	60,18
	Mode1 3	89,67	85,24	70,40	63,69

TABLE II: Computational results for zone coverage proportion (%)

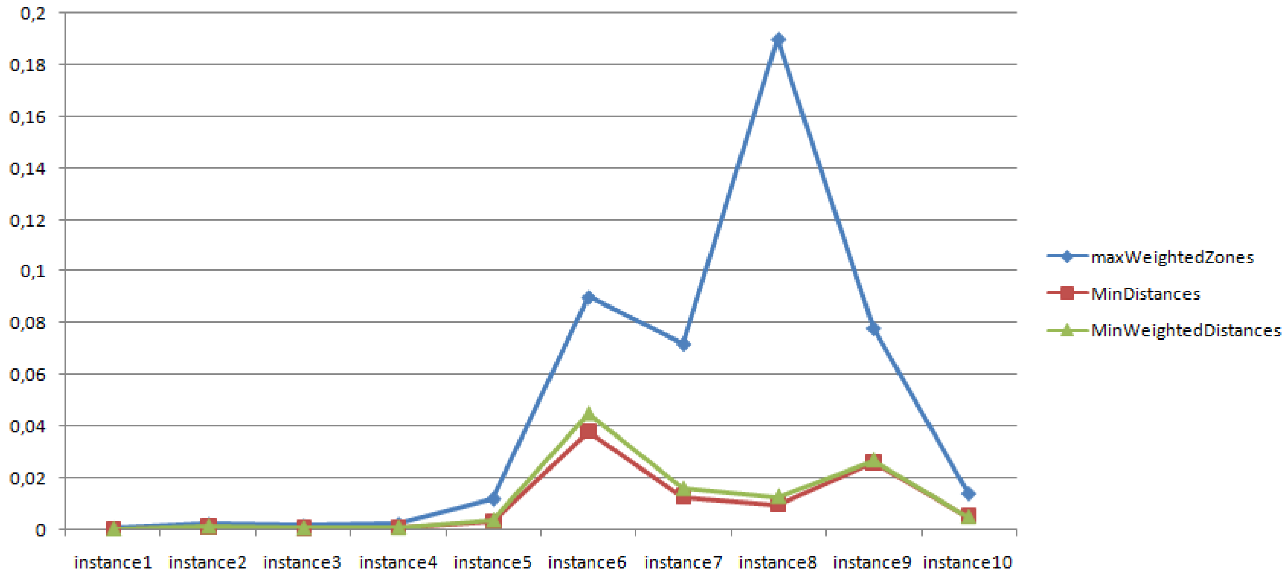

Fig. 6: Average model computation time

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