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A Framework and Decision Rules for Emergency Medical Service Scheduling DSS

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Abstract: This paper proposes a framework of decision support system (DSS) for emergency medical service scheduling. The scheduling decision rules embedded in the DSS consider the criteria on the average response time and the percentage of the medical service requests that are responded within fifteen minute, which is usually ignored in traditional scheduling policies. The challenge in designing the DSS lies in the stochastic and dynamic nature of request arrivals, fulfillment processes, and complex traffic conditions as well as the time-dependent spatial patterns of some parameters complicate the decisions in the problem. To illustrate the proposed DSS's usage in practice, a simulator is developed for performing some numerical experiments to validate the effectiveness and the efficiency of the proposed DSS.

Keywords: Decision support systems; Emergency medical service; Ambulance scheduling.

1 Introduction

Emergency transportation on ambulances and other specialized vehicles is important for rescuing people when their health is in risk of irreparable damage. Rising costs of medical equipments, increasing call volumes, and worsening traffic conditions in metropolis make emergency medical service control centers face increasing pressure so as to meet performance targets. The service control centers are supposed to schedule ambulances from their bases (waiting locations) so that medical service requesters can be reached in a time efficient manner. In usual practice, the emergency medical transportation is scheduled by some criteria and protocols provided by regulatory authorities. The emergency medical service requests have different priorities from each other. Every priority level requires an ambulance to arrive at the patient's location within a particular response time. For the requests with high priorities, ambulances usually should arrive at the patients' location within fifteen minutes, which is a golden time and during which the patients should be timely transported to a proper healthcare center where appropriate medical team can give the patients sophisticated medical treatments. The widely used ambulance scheduling policy is to dispatch the closest ambulance to a requester's location. However, this intuitive scheduling policy cannot guarantee a high percentage of the requests that can be responded within fifteen minutes. In reality, the criterion on the percentage of fifteen minute response is more important than the criterion on the average response time. How to design a good decision support system (DSS) for emergency medical service scheduling so as to ensure a high percentage of fifteen minute response is critical for the emergency medical service control centers in metropolises. Moreover, the scheduling decisions are in a dynamic environment where the spatial distribution of potential requesters is changing along the time, and the spatial patterns of traffic situations in the metropolises are also different in peak hours and off-peak hours. The ambulance travelling and serving processes are also in a stochastic environment where the travel time for a certain journey may contain randomness; the service time at the request calls' scenes and hospitals is also uncertain. The above mentioned dynamic and stochastic nature of the request arrivals and ambulance fulfillment processes as well as the environments complicates the ambulance scheduling decision. Therefore, this paper makes an explorative study on designing a DSS for scheduling ambulances efficiently.

The remainder of this paper is organized as follows. Section 2 is the literature review. Section 3 gives a

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framework of the proposed DSS. The core of the DSS, i.e., the embedded decision rule, is elaborated in Section 4. Some numerical experiments are performed in Section 5 for a further investigation on the proposed DSS. Closing remarks and conclusions are outlined in the last section.

2 Related works

The early studies on the resource optimization of the emergency medical service are mainly related with the minimal covering model [1], which tries to minimize the number of ambulances necessary so as to cover all demand point, and the maximal covering model [2], which tries to maximize the total demand coverage given a feet of fixed size. In the recent years, some scholars concentrate on the dispatching policies. For example, Centrality policy [3], which evolved from the nearest neighbor (NN) policy, is proposed in an effort to reduce the response time in demanding emergency situations. The auction mechanism [4] based on trust is designed for dispatching ambulances for emergency patient transportation. Besides the above studies on ambulance dispatching, some scholars focus on the ambulance redeployment. One stream of the studies on the redeployment models is to apply integer programming methods when an ambulance dispatching decision needs to be made [5,6,7,8,9]. Another stream of the studies is based on applying integer programming methods in a spare time. Dispatchers manage to dispatch so as to keep the ambulance configuration close to the one suggested by the lookup table, which contains the number of available ambulances and the place the ambulances should be dispatched [10]. Besides the studies by using the integer programming, some studies employ the approximate dynamic programming (ADP), which is a useful approach to optimize the ambulance dispatching. Berman [11,12,13] represents the first papers that provide a dynamic programming approach for the ambulance redeployment problem, and this approach was revisited recently by Zhang et al. [14]. ADP is also used to solve resource allocation problems [15,16,17] and large-scale fleet management [18,19]. However, these papers follow an exact dynamic programming formulation, and as is often the case, this formulation is tractable only in oversimplified versions of the problem with few vehicles and small transportation networks. Salmero'n and Apte [20] develop a two-stage stochastic optimization model to guide the allocation of budget to acquire and position relief assets. Maxwell [21,22] design some optimize algorithm by using the ADP approach in order to make ambulance redeployment decisions in a dynamic setting under uncertainty.

When compared with the above mentioned studies, this paper provides some advantages. In contrast to some DSSs that only consider the average response time, ours captures both the criteria on the average response time and the percentage of the medical service requests that are responded within fifteen minute. We seize the random evolution of the system over time, and the stochastic nature of request arrivals, fulfillment processes, and complex traffic conditions as well as the time-dependent spatial patterns of some parameters to establish some formulae with a set of proper parameters which are based on the historical data of the request arrivals during a certain time period. Some experiments are also performed to validate the effectiveness and the efficiency of DSS.

3 Framework of the decision support system

This section proposes a design of decision support system (DSS) for emergency medical service scheduling. The system receives requests that may come from any location at any time in a city. Then the system must make a decision timely. Thus the system is a type of real-time DSS. The framework of the DSS contains five core modules. Six databases are also embedded in the DSS so as to support the decision processes of modules. The details on these modules are elaborated in the following subsections.

3.1 Request receiver module

The request receiver module is to receive service requests from patients through call centers, and transfer the requests into a structured form so that the requests can be handled by other modules. A request for medical service is a five-item tuple, which is denoted as follows:

Request: $\langle LO, TM, HP, AT, AN \rangle$

LO: the location of the service requester.

TM: the request on the response time. It means an ambulance should arrive at the patient's location (i.e., LO) within a response time (i.e., TM). If TM = 0, it means the highest priority; an ambulance should arrive at LO as soon as possible.

HP: the set of hospitals which are suitable for the patient. If HP = NULL, it means there is no special requirements on hospital.

AT: the ambulance type. There are two types of ambulance: type-A is an advanced vital support vehicle (SVA), type-B is a basic vital support vehicle (SVB). If AT = A, it means an SVA is needed. If AT = B, it means any type of ambulances are acceptable for the patient.

AN: the number of ambulances that are needed by the service requester. For some accidents, there are a number of casualties that need more than one ambulance.

Another function of the request receiver module is the maintenance on a **historical database of requests**. Based on the historical data, the distribution of the request frequencies in regions can be obtained so as to support some decision processes in other modules.

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3.2 Instruction sender module

The instruction sender model is to send instructions to ambulances. The instructions are the results of the decision process embedded in the DSS; they are also structured information. An instruction's structure is also a five-item tuple, which is denoted as follows:

Instruction: $\langle AI, LA, TA, LH, TH \rangle$

AI: the index of the ambulance that receive the instruction.

LA: the location of the accident, where the ambulance should arrive first.

TA: the target time (or the estimated time), before which the ambulance should arrive at LA.

LH: the location of the hospital, where the ambulance should carry the patient to.

TH: the target time (or the estimated time), before which the ambulance should arrive at LH.

An instruction for an ambulance reflects the routes for the ambulance: 'its current location' $\rightarrow$ 'LA' $\rightarrow$ 'LH' $\rightarrow$ 'its base location'. During the route from LH to its base, the ambulance may be assigned with another task, and go to the next LA directly. So we need not to include the target time of arriving at its base in the instruction.

3.3 Travel time analysis module

The city map module maintains the basic information on the roads in the city. Given a route's source and destination, time, and date, the module can output an estimated time for an ambulance traveling through the route. The module connects two databases: (1) **city map database**, from which the route length between two locations can be obtained; (2) **historical database of trips**, from which the estimated traveling speeds in some roads during some periods can be obtained. Based on the data from the above two sources, the module can estimate the travel time for an ambulance traveling between two locations. The traffic information among roads is obtained from a sensor network that is usually contained in a city's traffic infrastructure project. The real-time traffic status in all the roads of the city can be captured dynamically through the sensor network.

3.4 Ambulance management module

The ambulance management module is to acquire and manage the real-time data on every ambulance's status, location, and undertaking task. The status of an ambulance could be: idle at its base, traveling to an accident location, stay at an accident location, transporting a patient to a hospital, travelling to its base, and etc. The module also maintains two databases: (1) **trajectory database**, which records all the travelling routes of an ambulance; (2) **performance database**, which records every ambulance's performance during fulfilling their assigned tasks. For example, the estimated time and actual time for an ambulance arriving at a certain location reflect the ambulance's performance, which may be influenced by the ambulance driver's experiences.

3.5 Decision making module

The decision making module is a core part for the DSS. The decision process embedded in this module is triggered by a request that is delivered from the 'request receiver module'. The output of the decision making module is the instructions that are delivered to ambulances through the 'instruction sender module'. For the decision process between the above inputs and outputs, some support information is obtained from the 'travel time analysis module' and 'ambulance management module'. For a received request, which ambulance should be assigned with the task, which hospital should the ambulance transport the patient to, are the decisions that should be made by the module in a short time. For making these decisions, some rules are needed, and should be maintained in a database that is connected with the decision making module. The database could be named by **decision rule base**, which is elaborated in the next section.

4 Decision rules embedded in the DSS

The decision rules are the core for designing and implementing the DSS. The decision rules can work when a request (i.e.,$\langle$ LO, TM, HP, AT, AN$\rangle$) is received. The output of the rules is the assignment of an ambulance to the request. The main ideas of the rules are: if the request is very urgent, i.e., TM = 0, the ambulance that can arrive at the location of the patient (i.e., LO) in the shortest time should be assigned with the task. If the request is not very urgent, i.e., TM $>$ 0, there may be several ambulances that can arrive at LO within the time window [0, TM]. When choosing an ambulance from these candidates, we have three criteria: (1) the earlier it can return to its base, the higher priority it is chosen; (2) the more available ambulances are idle in its base, the higher priority it is chosen; (3) the less requests may emerge in the neighborhood of its base, the higher priority it is chosen. The details on the decision rules are shown in Table.1.

In the decision rules, α and β are two important parameters, the setting of which has influence on the performance of the rules. There is no optimal setting on the α and β parameters for all the situations. When applying the above decision rules in reality, the DSS should determine a proper setting on the α and β parameters according to the historical data of the request arrivals during a certain time period.

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Table 1: Decision rules embedded in the DSS

```
Input: a request ⟨LO, TM, HP, AT, AN⟩
Output: an ambulance u* is assigned to fulfill the request

Define a set U = all the ambulances whose status is 'idle at its base' or ' travelling to its base'.
IF AT = A, THEN
  U ← set {u ∈ U;and u.type = A}.
END IF
For all the ambulances u ∈ U, acquire their current locations, i.e.,u.location.
Obtain T_e(u.location, LO) by 'travel time analysis module'.
   // T_e is the estimated travel time between u.location and LO.
Obtain T(u) on the basis on T_e by 'Ambulance management module'.
   // T(u) is the estimated time for ambulance travelling from u.location to LO.
   // T(u) = T_e ± △_u, △_u is estimated according to u's past performances.
IF TM = 0, THEN
   u* = argmin_{u∈U} T(u)
ELSE
   U ← set { u ∈ U;and T(u)≤ TM }.
   IF U = ∅ THEN
      u* = argmin_{u∈U} T(u)
   ELSE
      IF HP = NULL, THEN
         HP ← the hospital that is nearest to LO  END IF
      END IF
      For ∀ u ∈ U, obtain T'(u) and T"(u).
         // T'(u) is the estimated time for ambulance travelling from LO to HP.
         // T"(u) is the estimated time for ambulance travelling from HP to its base.
      For ∀ u ∈ U, calculate C_1(u) = T(u)+T'(u)+T"(u).
         // C_1(u) is the first criterion, which is the smaller, the better
      For ∀ u ∈ U, obtain C_2(u), i.e., the number of available ambulances in 's base now.
         // C_2(u) is the second criterion, which is the larger, the better.
      For ∀ u ∈ U, obtain C_3(u), i.e., the average rate for a request emerging in the
         neighborhood of u's base.
         // C_3(u) is the third criterion, which is the smaller, the better.
         // The region is a circle area with its center at u's base and radius equal to a certain value.
      u* = argmin_{u∈U} {C_1(u) - α × C_2(u) + β × C_3(u) })
         //α and β are parameters for the weighted sum of the three criteria.
   END IF
END IF
```

5 Numerical experiments

Some numerical experiments are performed to investigate the performance of the proposed DSS and the decision rules contained in the system. A simulator is built for performing the comparative experiments. The simulator generates a number of requests by following the Poisson distribution. Then the simulator locates the generated requests in specific locations according to the distribution of requests densities among different areas in a city. Here the simulator uses Shanghai city as the example in the experiments. Shanghai is the largest city by population in China. Shanghai has a population of over 23 million and a land area of about 6340 square kilometers. In such a megalopolis, the medical service call center usually receives a request and set off an ambulance every 1.2 minute on average. Facing so many arriving medical service requests, a good DSS on ambulance scheduling is very necessary for reducing the average response time. For patients, the first few hours are the best time (golden hours) for giving them some proper treatments. Thus the average response time for all the requests reflects the service level of a city's medical service response DSS. In addition, the percentage of the requests that are responded in fifteen minutes is also used as a criterion in the experiments.

The experiments are based on some comparisons with two other scheduling strategies, which are introduced as follows.

Strategy 1: For the urgent requests (i.e., TM = 0) and the non-urgent requests (i.e., TM $>$ 0), the ambulance that can arrive at the LO is dispatched.

Strategy 2: For the urgent requests (i.e., TM = 0), the ambulance that can arrive at the LO in the shortest time is dispatched. For the non-urgent requests (i.e., TM $>$ 0), the ambulance that can take patients at the LO and take them to the LH in the shortest time is dispatched.

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Three series of comparative experiments are conducted by changing the number of requests, ambulances, and ambulance bases. These experiments can help to investigate the influence of the parameters on the outperformance of the proposed DSS by comparing with some traditional methods. The comparative experimental results are listed in the following tables.

The results in Table.2 show that the average time ($\overline{T}$) increases and the percentage of requests that are responded in fifteen minutes (P_{15m}) decreases with the number of requests growing for all the scheduling strategies. For the comparison between the proposed DSS and the two other strategies, Table.1 indicates that the proposed DSS's $\overline{T}$ is longer than the two strategies, but it outperforms with respect to the criterion on P_{15m}. In addition the outperformance degree of the proposed DSS on the criterion P_{15m} becomes more and more evident with the number of requests growing. In reality, the criterion on P_{15m} is more important than the criterion on $\overline{T}$. Thus the proposed DSS is more suitable for realistic environments than the two intuitive strategies.

For the demo example in the experiments, i.e., Shanghai, the city has 1200 requests every day on average. According to the results in Table.2, it indicates that the proposed DSS can ensure 80% of all the requests can be responded within fifteen minutes on average.

Similar as the above experiments, the comparison under different numbers of ambulances is performed and the results are shown in Table.3.

The results in Table.3 show that the $\overline{T}$ decreases and the P_{15m} increases with the number of ambulances growing for all the scheduling strategies. For the comparison between the proposed DSS and the two other strategies, Table.1 indicates that the proposed DSS's performance is worse than the two other strategies on the criteria of both the $\overline{T}$ and the P_{15m} when the number of ambulances is not sufficient. When the number of ambulances exceeds 78, the proposed DSS's P_{15m} becomes larger than the two other strategies. Another finding from the results in Table.3 is that there exists a certain upper limit on P_{15m} for the Strategy 1 and the Strategy 2 when increasing the number of ambulances. For example, Strategy 2's P_{15m} cannot surpass the limit '76%' when adding more ambulances. However, the proposed DSS's P_{15m} can reach a level of '85%' easily by adding more ambulances. This phenomenon shows that the proposed DSS has a good scalability to support the expansion of the ambulance fleets so as to increase the performance of the request responding.

6 Conclusions

This paper designs a framework of DSS for emergency medical service scheduling. Some decision rules are proposed so that the medical service requesters can be reached in a time efficient manner. Some experiments are also performed to validate the effectiveness and efficiency of the DSS.

By comparing with the literature on the related topics, the contributions of this paper are mainly as follows. Most related studies on DSSs for emergency medical scheduling only concentrate on the average response time. However, this intuitive scheduling policy cannot guarantee a high percentage of the requests that can be responded within fifteen minutes. In reality, the criterion on the percentage of fifteen minute response is more important than the criterion on the average response time. Moreover, the DSS in this paper also considers a dynamic environment where the spatial distribution of potential requesters is changing along the time, and the spatial patterns of traffic situations in the metropolises are also different in peak hours and off-peak hours. The ambulance travelling and serving processes are also in a stochastic environment where the travel time for a certain journey may contain randomness; the service time at the request calls' scenes and hospitals is also uncertain. The above mentioned dynamic and stochastic nature of the request arrivals and ambulance fulfillment processes as well as the environments makes this study is different from the existing studies in the related areas.

There are also limitations in this study. There are some parameters contained in the decision rules. How to optimize them is an interesting issue for the further investigations. For example, the initial deployment of ambulances is an important decision problem in this area. In addition, the emergency medical services include various types of resources. This paper mainly considers the ambulances. The scheduling problems on some medical equipments, medical service teams, and etc. can also be studied in the future.

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Table 2: Comparison between the DSS and other methods under different numbers of requests

Number of requests per day	Strategy 1 $\overline{T}$	Strategy 1 P_{15m}	Strategy 2 $\overline{T}$	Strategy 2 P_{15m}	Proposed DSS $\overline{T}$	Proposed DSS P_{15m}
700	10.9	84.7%	13.7	88.7%	14.5	91.1%
800	11.8	80.9%	14.3	85.4%	15.2	88.2%
900	11.8	79.9%	15.0	85.3%	16.5	88.0%
1000	12.6	76.4%	15.4	83.0%	17.2	86.6%
1100	13.2	72.8%	16.8	80.4%	18.5	84.5%
1200	14.6	70.3%	17.3	75.6%	18.8	80.7%
1300	15.6	65.2%	18.7	72.6%	19.0	75.6%
1400	15.9	64.6%	19.5	66.1%	20.2	70.7%
1500	17.4	56.3%	20.2	57.5%	20.6	62.3%
1600	16.1	50.3%	21.8	52.9%	22.4	58.9%

Notes:$\overline{T}$ denotes the average response time; P_{15m} denotes the percentage of requests that are responded in fifteen minutes.

Table 3: Comparison between the DSS and other methods under different numbers of ambulances

Number of ambulances	Strategy 1 $\overline{T}$	Strategy 1 P_{15m}	Strategy 2 $\overline{T}$	Strategy 2 P_{15m}	Proposed DSS $\overline{T}$	Proposed DSS P_{15m}
74	16.4	63.4%	17.7	74.0%	22.4	70.4%
75	15.6	67.2%	17.6	74.6%	22.0	72.9%
76	15.2	66.9%	17.5	77.1%	21.4	76.0%
77	15.1	68.8%	17.6	75.8%	21.1	74.2%
78	14.8	69.6%	17.4	76.0%	20.8	76.9%
79	14.6	70.4%	17.4	76.1%	20.5	77.6%
80	14.6	70.3%	17.3	75.6%	18.8	80.7%
81	14.3	71.1%	17.3	76.0%	19.0	81.3%
82	13.7	71.5%	17.3	76.0%	18.7	82.1%
83	13.7	71.7%	17.3	76.0%	18.9	83.6%
84	13.5	72.5%	17.3	76.0%	17.8	85.8%
85	13.4	72.7%	17.3	76.0%	17.8	85.8%

Notes: $\overline{T}$ denotes the average response time; P_{15m} denotes the percentage of requests that are responded in fifteen minutes.

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