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MODELING REQUIREMENTS FOR AN EMERGENCY MEDICAL SERVICE SYSTEM DESIGN EVALUATOR

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ABSTRACT

Emergency Medical Service (EMS) consists of a chain of processes that encompass the on-scene management, patient transport, and care provision at an ED. Much research has been conducted in order to improve EMS design, and simulations are commonly used to evaluate EMS design. In many cases, a specific component of an EMS system is selected to model aspects relevant to the analysis, while the other EMS components are treated as model inputs and assumptions. This could lead to a fragmentary assessment because it does not capture the complexity of real EMS operations. Ideally, EMS designs should be evaluated by a model that represents the entire chain of EMS operations. In this paper, a wide spectrum of operation design problems of EMS systems and simulation models used in previous studies are examined. Then, a set of modeling requirements are defined and a model framework is proposed for EMS system design evaluator.

1 INTRODUCTION

The Emergency Medical Service (EMS) system is a major element of the healthcare delivery system: it is responsible for providing patient care and transport for the duration prior to the provision of definitive care. The quality of care provided during the pre-hospital phase is significant in patients' health outcomes. The quality of the EMS consists of two primary components: timeliness in its response and quality in the out-of-hospital clinical intervention. While the design of an EMS system for clinical quality resides in the domain of emergency medicine, there are many engineering design issues when addressing the timeliness aspect of the EMS system design.

The EMS process is triggered by a service request from a patient and ends with the delivery of the patient to the point of definitive care. Taking a simplified view of a single instance of the EMS process, it can be depicted as a series of events as shown in Figure 1. The patient transportation phases depicted in the figure are based on the EMS interval model presented by Spaite et al. (1995). Once an EMS request is received, one or more EMS vehicles are dispatched to the scene. Upon arrival, the EMS crew administers the necessary and feasible first responses. Then, it takes the patient to a point of definitive care, which is typically an emergency department (ED) in a hospital. After handing the patient over to the hospital, the EMS vehicle returns to its base to wait for the next service request.

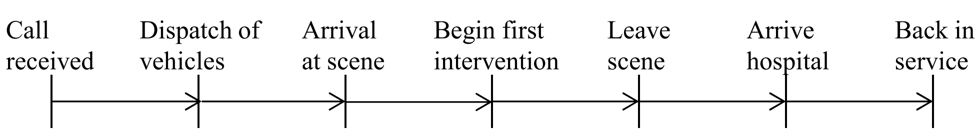

Figure 1: An example of an EMS process

The goals of EMS system design research are to plan the EMS's underlying logistics system and to design operational policies and protocols that support seamless execution of the service process. An example of an EMS logistics system design is determining the locations of the EMS vehicles that maximize service coverage. Optimizing the dispatch decisions for incoming service requests is an example of an operational policy design problem.

In much EMS system design research, some form of computer simulation is used as a means to evaluate the performance of the EMS system. Design alternatives have been proposed using various means, and the proposed solution's effectiveness is assessed using a simulation model. The simulation models enable virtual experiments to test the design solutions prior to real world implementation. This is particularly relevant and useful for EMS design because experiments in real EMS environments are generally restricted due to health and safety issues for patients.

These simulation models are typically developed in the specific context of the problem being addressed, which tends to focus on a specific component or phase of the EMS process. In such individual simulation models, the other components are often considered by simplifying assumptions or are external to the model scope. For example, in a simulation that evaluates ambulance location solutions, congestion at nearby emergency departments may not be modeled and it is always assumed that an ambulance is allowed to take a patient to the nearest ED. While this certainly simplifies the model building and enables the experiments focus on the specific aspect of the EMS system, it may lead to some problems.

A critical problem of such simplifications is the possibility of missing important interactions among the components of the overall EMS process. When an ambulance arrives at the nearest ED and finds it unable to accept the patient due to overcrowding, the ambulance must either wait for a bed at the ED or travel to another ED. This increases the ambulance's service time from what was assumed based only on the distance measure. Another problem is that, in many cases, changes in the system states, which are often caused by decisions made earlier in the process, may not be appropriately captured. As ambulance operations involve sequential decision-making processes, the decisions in previous stages have impacts on the decisions and operations for the next steps. For example, if a dispatcher orders redeployment for a returning ambulance to move to another site, the dispatch decision for the next request can be changed from what it would have been without the redeployment. Thus, a simplified EMS simulation model could lead to fragmentary performance assessment of an EMS system design solution. A stronger approach is to build a model that represents the entire chain of EMS operations in order to properly capture interactions among the various components and decisions throughout the process.

In this paper, a generic model framework for an EMS system design evaluator is developed. The primary goal is to provide a set of modeling requirements and guidelines for developing an EMS simulation model. First, the existing literature is reviewed in order to identify the commonly studied problems in EMS system design and also to understand the simulation models used in those studies. This provides a basis for defining the ranges of problems to scope the model framework. Next, a generic process model is developed for EMS system operations by integrating various features from numerous simulation models. Lastly, the key modeling issues are described related to each element in the general process model.

2 DESIGN PROBLEMS FOR EMS SYSTEMS

In this section, a summary of the literature on EMS system design is presented. In a broad sense, some prior research considers the planning issues of EMS systems, e.g. determining locations for ambulances; other research focuses on the problem of EMS system operations such as designing a dispatch policy where the optimal decisions on assigning an ambulance to an incoming service request are examined. In this paper, the first type of problem is referred to as a strategic planning problem and the second type as a tactical operation problem.

2.1 EMS System Planning Problems

A significant topic of strategic planning problems for EMS systems is the location problem for EMS ambulances, which has a long history of investigation since the early 1970s (Toregas et al. 1971, Church and ReVelle 1974). A wide range of models for EMS location problems has been developed. A relatively simple, deterministic model assumes that ambulances are always available to respond to emergency calls. However, the probabilistic models relax this assumption and incorporate the probabilistic availability of vehicles in an effort to represent more realistic ambulance operations. Many variations of these models exist as a result of the needs of specific problem circumstances, including the two-tiered ambulance model and double standard model, for example. Owen and Daskin (1998), Brotcorne, Larporte, and Semet (2003), and ReVelle and Eiselt (2005) have provided a comprehensive review of such studies. The primary goal of these problems is to determine the optimal number of and locations for ambulances in order to satisfy the relevant performance targets.

The optimal segmentation of a demand area (i.e. defining dispatch priority for a demand region) for EMS vehicles is another example of an EMS system planning problem. For example, Mendonca and Morabito (2001) and Iannoni, Morabito, and Saydam (2008) developed a model to locate appropriate segments of demand areas. Assigning the zones of primary responsibility is a key determinant for workload balance among ambulances and, therefore, affects the performance of the entire EMS system.

Planning an EMS system also includes designing a workforce shift schedule. In their study of the Edmonton EMS system, Ingolfsson, Erkut, and Budge (2003) proposed a single start station system where all ambulances begin and end their shift at the same location. Compared with a multiple start system, the single start station system can reduce the downtime for shift changes by pooling the spare ambulances in one location.

2.2 EMS System Operation Problems

Figure 2 presents the various types of decisions made during the major events in an EMS system for a patient transport process. Managing the EMS system operation involves sequential decision-making, and the EMS system operation problems primarily relate to making decisions during the process of the EMS operation.

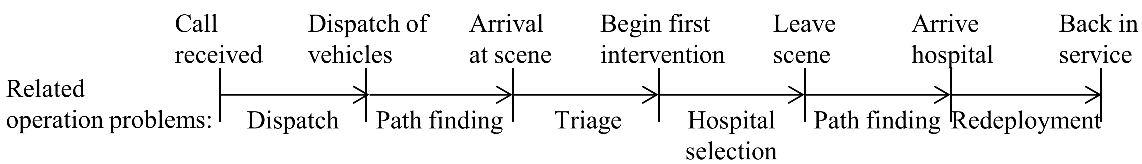

Figure 2: EMS system operation decisions at each phase of the patient transportation process

Ambulance dispatch policy design is among the most actively studied topics in EMS system operations. Dispatch refers to the assignment of an ambulance to incoming emergency calls. While it is a common practice to dispatch the closest ambulance to the scene, it is possible that different dispatch schemes can improve system performance. For example, one may give a higher dispatch priority to an ambulance with the longest idle time even if it is not the closest. The dispatch policy is an important factor in EMS system performance, and various dispatch policy designs have been discussed in Lim, Mamat, and Braunl (2011).

Triage decisions in a mass casualty event determine the transport priority for patients. Transporting patients to an appropriate hospital in a priority order other than the “first-come, first-served” basis can yield a better outcome. A transport priority may be determined based solely on the severity of a patient’s clinical condition or on more complicated schemes as well. Inoue, Yanagisawa, and Kamae (2006) proposed a subgroup sorting method that could determine the transport priority for patients and demonstrated that triage decision-making by subgroups improves the survivability outcome. Mills, Argon, and Ziya (2011) developed a triage scheme (Resource-Based START) in which mapping between the severity level and transport priority changed after a threshold time. The motivation of this scheme was that after a certain period, the survival probability of lower severity patients deteriorates faster than patients with higher severity. Related to the triage decisions, a decision may be made not to transport a patient at all; this is called a non-conveyance decision (Snooks et al. 2004). While there is practical difficulty in exercising a non-conveyance decision, it can improve the ambulance operations by limiting the ambulance tasks to the true demands.

The next decision to be made is regarding which hospital a patient will be transported to for emergency care. While the nearest emergency department with available beds is a reasonable decision in most situations, the current congestion level at the candidate EDs should be considered when determining the destination. This is particularly relevant to a mass casualty event where the availability and capability of nearby EDs should be appropriately distributed to a large number of patients requiring different levels of services, but at the same time. Jotshi, Gong, and Batta (2009) suggested a method of determining the destination ED for patients from a mass casualty event, by considering the candidate EDs' available capacities, waiting times, and distances from the incident scene.

Once a destination ED is selected, the sub-problem of finding the optimal path from the scene to the destination should be considered. For example, Haghani, Tian, and Hu (2004) developed a simulation model where the path with the shortest time was determined for an individual origin-destination pair at a certain time of day. While the path finding itself is not a significant problem in the context of the EMS operation, it is a sub-problem that can be used as a part of another problem such as the dispatch problem.

Upon completing a transport task, an ambulance may return to a base other than where it originally departed from in order to optimally respond to the dynamically changing coverage of the fleet of ambulances. A returning ambulance moves to a temporarily uncovered area where all ambulances in the area are busy. This practice is referred to as dynamic ambulance relocation. In a dynamic ambulance relocation system, when an ambulance is dispatched, thereby leaving an area uncovered, the remaining ambulances are relocated to achieve optimal coverage with the reduced ambulance units. Mathematical models for ambulance relocation have been proposed by Gendreau, Laporte, and Semet (2001), Gendreau, Laporte, and Semet (2006), and Maxwell et al. (2010).

3 SIMULATION APPROACHES FOR EMS SYSTEM DESIGN

This section reviews the applications of simulations to EMS system designs. Specifically, the simulation models are discussed in terms of the type of problems they address and the phase of EMS process each model investigates.

Many of the simulation models developed for EMS design aim to evaluate EMS system configurations, and most have focused on ambulance locations (Savas 1969, Fujiwara, Makjamroen, and Gupta 1987, Iskander 1989, Goldberg et al. 1990, Repede and Bernardo 1994, Yang, Hamedi, and Haghani 2004, Silva and Pinto 2010). The first such application of simulation modeling is found in Savas (1969). A simulation model was constructed to analyze the effectiveness of alternative system configurations of the redistribution of ambulances and addition of more vehicles. In Iskander (1989), a simulation model evaluated the ambulance locations, but their model considered other components including the reduced time in dispatch, time spent at the scene, variations in emergency call arrival rates, and non-conveyance scenarios. A similar simulation model can be found in Goldberg et al. (1990). Most of these models simplified the dispatch decision component as a simple, nearest ambulance dispatching operation and a first-come, first-served queuing policy. In a few models, alternative dispatch rules were considered. For example, Repede and Bernardo (1994) considered the least likelihood of receiving calls in a zone of primary responsibility in the dispatch decision. Yang, Hamedi, and Haghani (2004) modeled the dispatch decision for ambulances currently in the outside-depot state. The simulation model developed by Silva and Pinto (2010) also considered ambulances that are assigned to patients as candidate units for dispatch to incoming service requests.

Simulation models are particularly useful for predicting the performance of new system configurations. Ingolfsson, Erkut, and Budge (2003) modeled a single start station system to evaluate its effectiveness in reducing the downtime for shift change. The operations for the ambulance shift are represented in the model. Their model includes a dispatching decision model in which the destination hospitals are determined using a probabilistic distribution extracted from historical data. Su and Shih (2003) designed a two-tiered system that provides advanced pre-hospital care. In their simulation model, the advanced life support (ALS) units are dispatched according to a predetermined dispatch priority and then the dispatched ALS units determine the destination hospital. Gunes and Szechtman (2005) developed a simulation model for a helicopter EMS system with a simple dispatching policy to assign the nearest helicopter to a patient.

Some other models have been incorporated operational decision components with richer details, many of which address dispatch decisions. Lubicz and Mielczarek (1987) developed a simulation model that includes the modeling of dispatch operations and non-conveyance operations. Furthermore, ambulance preemption using a higher priority call and priority queuing policy to assign an ambulance were implemented in the model. The simulation model presented in Zaki, Cheng, and Parker (1997) allows the evaluation of the inter-zone dispatch policy and priority-based dispatching policy. Andersson and Varbrand (2007) used simulation experiments to test the proposed algorithms that dispatch and relocate ambulances in order to improve the preparedness of the EMS system. Lim, Mamat, and Braunl (2011) also used simulation experiments to compare performances among various dispatch policies for EMS systems. Haghani, Tian, and Hu (2004) used a simulation model to analyze the dynamic assignment policy where the shortest path algorithm was included with time varying traffic information. Relocation or redeployment is another operational decision problem, and Gendreau, Laporte, and Semet (2001), Gendreau, Laporte, and Semet (2006), and Maxwell et al. (2010) have built a simulation model for redeployment in order to assess the performance of the solutions they developed in an analytic model.

Table 1 summarizes the simulation models reviewed in this section; it shows the operational decision components included in each model. The dispatch component is included in all models because the dispatch of an ambulance is a basic feature of EMS simulations. However, there are varying degrees of detail and sophistication in the dispatch decision model: some use a simple nearest, first-come, first-served rule, while in others, the dispatch components are modeled with a variety of dispatch policies. Redeployment or relocation is also represented in many models; including redeployment decisions requires system state changes by non-active ambulance vehicles, which potentially complicates implementation. For example, allowing an ambulance to respond to a call while it is on its way to a new deployment location requires tracking of ambulance positions. The triage and hospital selection components are part of the dispatch decision in a broader sense, but they have modeling and input requirements unique to their decision-making process. Both of these are particularly relevant to a mass casualty response when the demands for EMS surge in a concentrated fashion in both time and space. However, determining a path for the ambulance trip is usually not considered in EMS simulation models. This is mostly because in typical problems studied using a simulation model, such resolution is not required or can be computed externally. In most cases, the time for an ambulance trip is considered using the simple shortest travel distance and driving speed.

4 MODELING FRAMEWORK FOR EMS SYSTEM DESIGN EVALUATOR

The reviews in Section 3 suggest that the simulation models presented in EMS system design research have often focused on a specific component or phase in the EMS process. That is, the models have had a model scope decision according to the individual modeler and can be well justified as with any other modeling for simulation studies. However, there appears to be an advantage in designing a more generic simulation model that encompasses the entire spectrum of the EMS operation process and the decision-making associated with the entire process. First, there is a possibility that some key interactions among the EMS components and decisions are overlooked, which potentially leads to a fragmented assessment of the system performance. Considering that the ultimate goal of EMS system research is to create an impact by implementation, it is important to assess the expected performance of the proposed solutions in an environment as close to the real world environment as possible. In doing so, a key factor is to represent the entire chain of EMS processes. There is also an issue of reusability. The simulation models developed for individual studies are generally not applicable for other studies due to the different modeling scopes. However, an EMS simulation model that represents the entire EMS operation process can facilitate individual modeling building efforts.

Table 1: Operational features and logics included in reviewed simulation models

Decision / Reference	Dispatch	Path finding	Triage	Hospital selection	Redeployment
Savas (1969)	● Nearest			○	
Fitzsimmons (1971)	● Preemption		●	●	●
Fuziwara, Makjamroen, and Gupta (1987)	● Nearest				
Lubicz and Mielczarek (1987)	● Preemption			●	●
Iskander (1989)	● Nearest		●		●
Goldberg et al. (1990)	● Shortest travel time				●
Repede and Bernardo (1994)	● Least likelihood			●	
Zaki, Cheng, and Parker (1997)	● Inter-zone dispatch				●
Ingolfsson, Erkut, and Budge (2003)	● Nearest		●	●	●
Su and Shih (2003)	● Nearest			●	
Haghani, Tian and Hu (2004)	● Dynamic assignment	●			●
Yang, Hamedi, and Haghani (2004)	● Dynamic assignment				
Gunes and Szechtman (2005)	● Nearest				
Andersson and Varbrand (2007)	● Preparedness				
Silva and Pinto (2010)	● Earliest arrival time		●	●	
Lim, Mamat, and Braunl (2011)	● Policy review				●

● Modeled
○ Addressed but not modeled

An EMS system simulation model must satisfy a number of fundamental requirements. First, it should be able to capture the possible interactions among the EMS components and decisions. Each component in the EMS operation process should be represented with sufficient detail for the problem at hand and should be integrated so that their interactions can be modeled appropriately. Second, it should allow analysts to evaluate the solutions for various types of EMS system design problems. In order to achieve this, the model must provide a means to incorporate design solutions into the model. This may not be straightforward because there are different types of solutions to consider ranging from what can be represented as location data, queuing policy, or logic and algorithm for decision-making based on system states. Lastly, it is desirable for the model to have flexibility for a modeler to incorporate modifications to meet the requirements specific to their problem.

A conceptual framework for an EMS system simulation model is presented in Figure 3. It consists of three modules: modeling of the input data, the EMS process flow, and decision-making. The EMS process flow module, shown in the middle row, is the central part of the simulation model: it describes the EMS process following a patient's transaction through the process. The input data module includes the EMS demand modeling, EMS system configuration, and time interval generation, which are shown in the top row of Figure 3. The EMS system configurations initialize the setting for the target EMS system in the simulation model. The EMS demand modeling and time interval generation manage the various attributes for service requests and processing times for each process step that are used in the process flow module. The decision-making module controls the decision-making process at various points in the EMS process by providing a set of rules or logics.

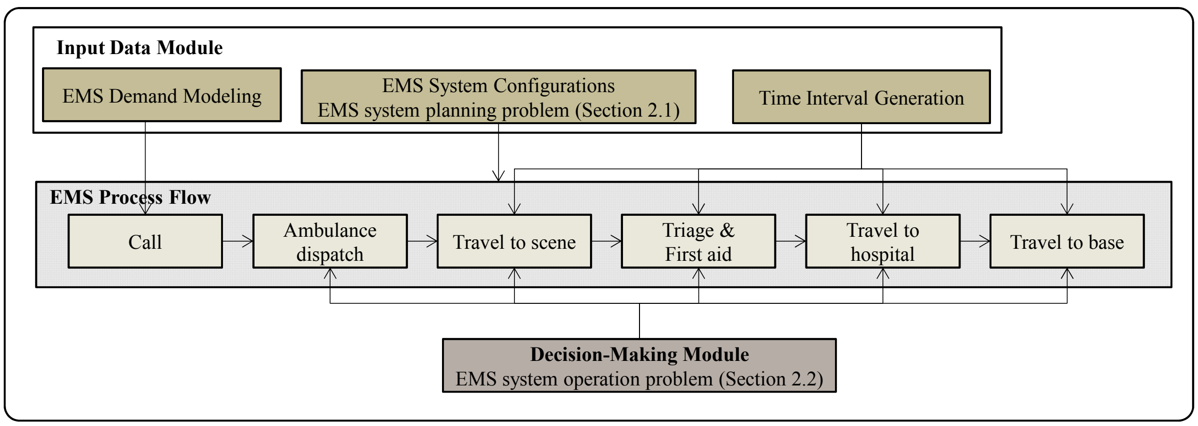

Figure 3: A framework for EMS system design evaluator

4.1 Input Data Modeling Module

The input data modeling module consists of three components: the EMS demand modeling, EMS system configurations, and time interval generation. The EMS demand modeling generates the attributes of the incoming EMS requests. The typical attributes of EMS requests include arrival time, severity (priority), and location of the incident. The attributes can be obtained from historical data in a format of raw samples or probabilistic distribution. The forecasting technique is an alternative to generating attributes of the EMS request from historical data. Channouf et al. (2007) and Matteson et al. (2011) developed forecasting techniques that effectively capture the features of the EMS request arrival process. The EMS demand modeling may also be extended to include a function that can construct a virtual set of EMS request data from a hypothetical scenario such as a mass casualty event or wide-area disaster event.

The EMS system configurations are required in order to define the initial settings of the simulation experiments. The number of ambulances and their locations are examples of the information managed in the configurations. Alternative configurations can be obtained from EMS system planning problems through optimization or heuristics, and input to the EMS system configurations.

The last part of the input data modeling is to generate the time intervals for various processing times; travel time, time spent at the scene, and time spent at the hospital are examples of time intervals. The travel time is key information for the simulation because it typically occupies the largest portion of the active ambulance operations and thus is an important determinant of the EMS system performance. Decision-making such as ambulance dispatch and hospital selection is primarily based on the expected travel time. There are numerous studies that propose a means to predict the travel time of an ambulance, and a brief review is provided here.

Early studies in EMS simulation used simply approximated travel times. Fitzsimmons (1971, 1973) used a rectangular distance based on the orthogonal arrangement of streets between two points as the travel distance. Lubicz and Mielczarek (1987) obtained the travel distance using the actual road network and average driving speed. In some cases, the linear distance was used and the travel time was adjusted with a coefficient to compensate the nonlinearity of the travel distance (Iskander 1989). Some models have adopted a slightly more refined version. The *square root law* was proposed in order to approximate a fire engine travel time in an attempt to consider acceleration and cruising speed separately (Kolesar, Wakler, and Hausner 1975). Fuziwara, Makjamroen, and Gupta (1987) also used a piecewise function to generate the travel time for an EMS simulation model, as follows:

$$T(D)=\begin{cases} c\sqrt{D} & if\ D \le d \\ a+bD & otherwise \end{cases},$$

where *T(D)* is the expected travel time, *D* is the travel distance, and *d* is the distance required to achieve cruising speed. The parameters *a, b, c,* and *d* were empirically estimated in the study. Ingolfsson, Erkut, and Budge (2003) adopted a similar scheme to generate travel times for ambulances. Goldberg et al. (1990) applied a travel time generation method that considers different road types and travel speeds on the road types. They divided the road network into four categories (freeways, major roads, non-major roads, and local roads), and the path between two points was divided into segments of the four road categories. Then, the travel time was calculated using a linear regression function with the four road category factors. Henderson and Mason (2005) considered time-varying travel time. They used actual road traffic data to find a representative value for morning peak travel time (8 AM), midday travel time (12 PM), and evening peak travel time (5 PM). Then, the travel times during other hours of the day were estimated using weighted combinations of the three values. While these models provide a deterministic travel time, a probability distribution is also often used to generate travel time. Repede and Bernardo (1994), Zaki, Cheng, and Parker (1997), Christie and Levary (1998), Su and Shih (2003), and Haghani, Tian, and Hu (2004) used probability distributions in their simulation models in order to generate travel times that reflect the target region's travel time pattern. Budge, Ingolfsson, and Zerom (2010) proposed a travel-time distribution model that incorporates a dependence between the distance and median travel time.

While the schemes discussed above are sufficient in most cases, there are some applications where more substantial models may be required. For example, in a disaster scenario, the data or model developed for a nominal condition will not apply. There may be a loss of road infrastructure, unexpected heavy traffic, local congestion at the disaster scene, and so on. For this, integrating a traffic simulation into the model may be considered as long as the increased complexity is manageable.

4.2 EMS Process Flow Module

The EMS process flow module defines the basic process flow for the simulation. Driven by the requirements from the EMS system design problems identified in Section 2, a generic process flow for EMS operation is presented in Figure 4. The process flow is designed to allow representation of the identified design problems in the EMS system. The backbone of the process flow is the process of patient transport, which dictates how patients are transported through a number of sub-processes and decisions throughout the main process. Delays associated with supporting the operations, such as maintenance or redeployment of ambulance units, are also included because the ambulance availability is affected by these events.

Figure 4 is a generic representation of an EMS process, which can be easily modified to reflect the specific attributes of the target EMS system. For example, for an EMS system with an ambulance relocation policy, the waiting ambulances move to another station located in a temporally uncovered area; this type of operation can be incorporated by modifying the maintenance operation flow. Some other features may need more significant modification in order for them to be incorporated into the model.

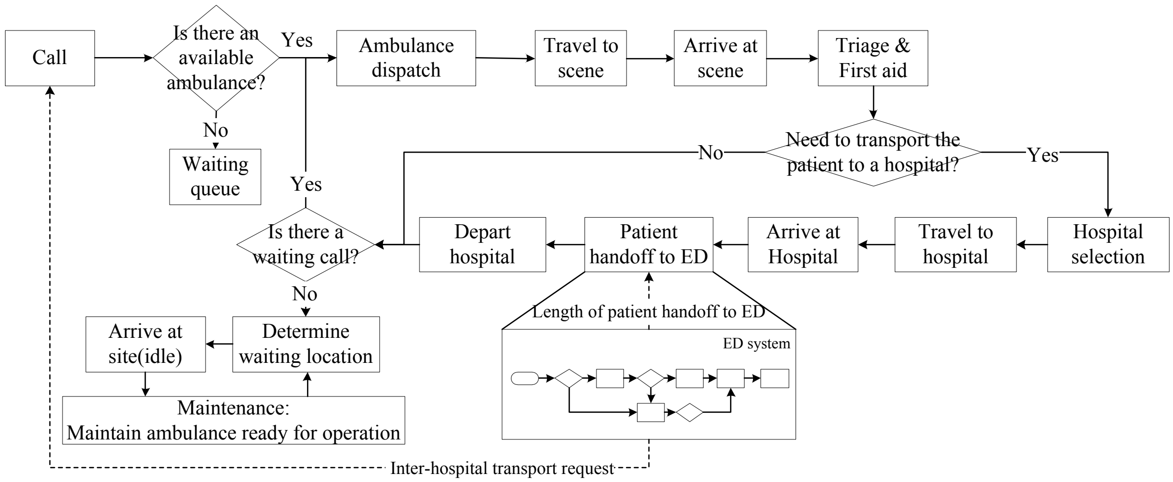

Figure 4: A generic process flow for EMS operations

4.3 Decision-Making Module

The decision-making module provides rules or logics for making operational decisions in the EMS flow process. The four major decisions identified in Section 2.2 are dispatch, triage, destination hospital selection, and redeployment. These decisions control the details of the EMS operation during the process flow. The operational decisions can be developed external to the simulation model and a set of rules, protocols, or priorities may be simply provided for the model. In other cases, a decision-making model may be designed using real-time (simulation time) information for the EMS system state. This would require interoperation or integration of the decision-making module and the main EMS process flow model.

A common criterion for decision-making in the EMS system design is the response time, i.e. the time period between the receipt of an EMS request and an ambulance's arrival at the scene. The response time is accepted as a key performance measure of an EMS system. A possible weakness of using the response time is that it is an indirect measure of the true system performance, and there are some studies that address this issue. For example, McLay and Mayorga (2010) discuss appropriate threshold response times that maximize the survival rate of cardiac arrest patients. Erkut, Ingolfsson, and Erdogan (2008) provide a review for estimating the survival rate of cardiac arrest patients. The Resource-Based START, which is the triage scheme proposed by Mills, Argon, and Ziya (2011), is based on survivability as a performance measure.

5 SUMMARY

In this paper, various system design problems that were studied in prior EMS research were reviewed. Simulation has been frequently used in these studies to evaluate the proposed designs for the problems. In most cases, the simulation models have been developed with a specific focus on their target problems. While defining the model scope according to the problem being studied is reasonable, there appears to be an advantage of implementing a more generic EMS system simulation model. An EMS system simulation model that encompasses the entire spectrum of the EMS operation process and decisions involved will enable the capture of possible interactions between the system components and operational decisions. Also, it will allow researchers to more easily evaluate their design solutions under various assumptions and conditions for other process components. As a first step toward a generic EMS system simulation model, a conceptual framework for an EMS system simulation model was presented in this paper. The modeling considerations and practices are discussed in three parts of the framework: the input data modeling, EMS process flow, and decision-making.

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