Decision Support System for Hospital Selection in Emergency Medical Services: A Discrete Event Simulation Approach

D. Tedesco, G. Feletti, P. Trucco

***Abstract*—**The present study aims to develop a Decision Support System (DSS) to support operational decisions in Emergency Medical Service (EMS) systems regarding the assignment of medical emergency requests to Emergency Departments (ED). This problem is called "hospital selection" and concerns the definition of policies for the selection of the ED to which patients who require further treatment are transported by ambulance. The employed research methodology consists of a first phase of review of the technical-scientific literature concerning DSSs to support the EMS management and, in particular, the hospital selection decision. From the literature analysis, it emerged that current studies mainly focused on the EMS phases related to the ambulance service and consider a process that ends when the ambulance is available after completing a mission. Therefore, all the ED-related issues are excluded and considered as part of a separate process. Indeed, the most studied hospital selection policy turned out to be proximity, thus allowing to minimize the travelling time and to free-up the ambulance in the shortest possible time. The purpose of the present study consists in developing an optimization model for assigning medical emergency requests to the EDs also considering the expected time performance in the subsequent phases of the process, such as the case mix, the expected service throughput times, and the operational capacity of different EDs in hospitals. To this end, a Discrete Event Simulation (DES) model was created to compare different hospital selection policies. The model was implemented with the AnyLogic software and finally validated on a realistic case. The hospital selection policy that returned the best results was the minimization of the Time To Provider (TTP), considered as the time from the beginning of the ambulance journey to the ED at the beginning of the clinical evaluation by the doctor. Finally, two approaches were further compared: a static approach, based on a retrospective estimation of the TTP, and a dynamic approach, focused on a predictive estimation of the TTP which is determined with a constantly updated Winters forecasting model. Findings reveal that considering the minimization of TTP is the best hospital selection policy. It allows to significantly reducing service throughput times in the ED with a negligible increase in travel time. Furthermore, an immediate view of the saturation state of the ED is produced and the case mix present in the ED structures (i.e., the different triage codes) is considered, as different severity codes correspond to different service throughput times. Besides, the use of a predictive approach is certainly more reliable in terms on TTP estimation, than a retrospective approach. These considerations can support decision-makers in introducing different hospital selection policies to enhance EMSs performance.

***Keywords*—**Emergency medical services, hospital selection, discrete event simulation, forecast model.

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I. Introduction

EMS systems are a fundamental component of a society's essential services since they provide initial care to critical patients, trying to ensure timely and effective treatment in line with their acute needs. In this context, information systems to support decisions are essential for analyzing the large volume of data and making the best choices. EMS decisions are classified into strategic decisions (i.e., long-term), tactical decisions (medium-term), and operational decisions (short-term or real-time). Among the operational decisions, the assignment of medical emergency requests to ED, also called "hospital selection" decision, is fundamental and requires constantly updated and near real-time information. To this end, it is essential to rely on a dynamic operational model, able to guarantee real time information sharing between the ambulance operations center and the ED. In absence of an integrated platform, indeed, the pre- and post-ED phases are managed independently, with significant losses in efficiency (i.e. use of scarce resources) and in quality of patient's care (i.e. treatment speed).

The aim of the present study is to develop a DSS for the assignment of medical emergency requests to ED and thus to optimize the management of patients throughout the entire EMS process (from the ambulance transportation to the medical treatment in the ED, up to the disposition order and the final departure from the ED). In particular, the proposed optimization model grounds on information related to the expected length of stay in the ED and the capacity of the departments. This perspective, which covers the entire service delivery process to patients, differs from the prior EMS studies, which instead consider the ambulance service and the ED care as two independent processes and optimization problems. In order to understand and compare the expected performance improvement granted by the proposed DSS, a simulation model was developed to test different hospital selection policies and consequently identify the best one in terms of time performance and capacity balance.

The paper is organized as follows: after having described the methodology adopted for this research, a critical review about the decisional models currently used in the EMS domain is presented, as well as the forecasting methods used to estimate the arrival of patients in an ED. The subsequent paragraphs will be focused on the description of the simulation model, presenting the difference between the static and dynamic approaches, and specifying the input parameters introduced to develop the model. After having reported the results obtained by testing different hospital selection policies, the paper ends with the main conclusions and possible future developments.

II. Research Methodology

The research methodology adopted in this study was organized into the following steps:

1. Literature review to gather information about:
   a. DSS currently used in EMS management and in hospital selection decisions in particular;
   b. Forecasting models currently used in EMS domain to predict ED arrivals and consequently the expected length of stay;
2. Identification of opportunities for improving hospital selection decisions, based on the gaps emerged from literature review;
3. Development and use of a DES model for testing alternative hospital selection policies:
   a. DES model development in AnyLogic;
   b. Identification of different hospital selection policies to be tested;
   c. Implementation of the different policies in AnyLogic;
   d. Test and validation of the model on a real case;
4. Analysis of the results to compare the effect of different hospital selection policies on system's performances.

III. Literature Review

A. Decisional Models in EMS Domain

The literature review about DSS models used in EMS domain was performed on Scopus through the following search formula: *(dispatch* OR despatch*) AND ("Hospital Emergency Department" OR "Emergency Medical Service") AND (planning OR "decision support" OR simulation OR model* OR optim*)*. To refine the results, some filters were applied to subject area (*Engineering, Mathematics, Computer Science, Decision Science*), document type (*Article, Conference Paper*) and language (*English*).

It emerged that the decisional models supporting EMS systems can be distinguished according to application context and decision type [1]-[4]. The application context can be characterized by a *medium-low workload* in case of standard ordinary situations where an ambulance is generally associated to a single patient, or by a *high workload* in case of mass casualty incidents (e.g., earthquakes, terrorist attacks) where it is necessary to associate more ambulances to a single emergency location. On the other side, EMS decisions are divided in *strategical* long-term decisions, as the subdivision of the reference territory in districts and the location of ambulance bases, *tactical* medium-term decisions, as the number of ambulances needed in each base to respond to emergency calls, and finally *operational* short-term decisions, usually real-time, that are related to the movements of ambulances within the reference territory.

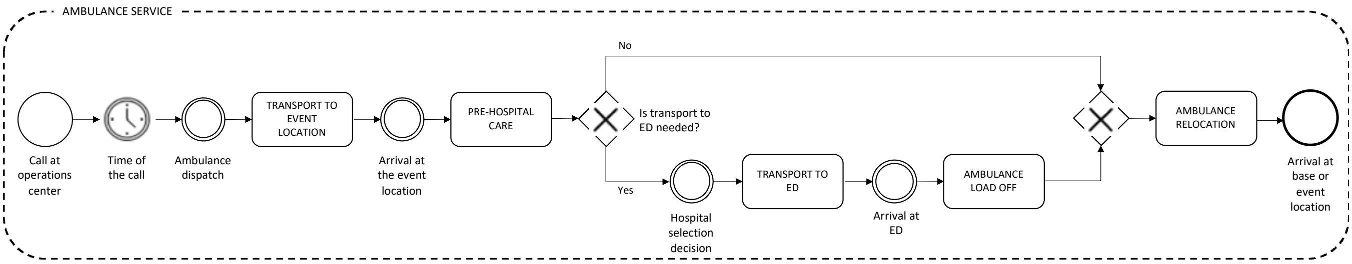

Fig. 1 Ambulance service process

This study specifically focused on a standard context characterized by a medium-low workload and entails operational decisions. The literature evidences found in this domain consider a process (Fig. 1) which starts with the call received at the operations center, followed by ambulance dispatching to the emergency location, the provision of pre-hospital care, the transportation to an ED, if needed, and the final relocation of the ambulance on the territory. Consequently, the operational decisions supported by literature are related to:

- Ambulance dispatch after the emergency call, whose scope is to reduce the time to reach the patient at the emergency location;
- Hospital selection, if necessary, whose scope is to assign the patient to the most proper ED;
- Ambulance relocation on the territory, after the current mission is finished.

Table I shows the different analytical methods used to support the three operational decisions. It is possible to observe that the ambulance dispatch is the most investigated decision, since it is considered in 91% of the analyzed papers, and usually it is supported by DES. Hospital selection, instead, is the less investigated problem. It resulted that the decision can be based on different criteria (i.e., proximity, traffic, capacity, structure specialization, patient's wish, time series estimation, ED crowding); however, in most cases, the patient is assigned to the nearest hospital in order to minimize the travel distance and release the ambulance in the shortest possible time [5]. Although it is recognized that the proximity criterion does not allow to obtain a balanced workload among the different EDs, just a few studies take into account the availability/saturation of resources or the expected length of stay as a method for hospital selection. Therefore, literature is mainly focused on an ambulance-driven logic, according to which the hospital selection is not based on the entire healthcare process, but just on the ambulance transport phase. The methods used to support hospital selection are mainly DES and complex Integer Programming Model (IPM) or Integer Linear Programming Model (ILPM) solved through heuristic algorithms. Finally, the ambulance relocation aims at guaranteeing effective EMS performances by redirecting an ambulance to the nearest base, to a predefined one, to a new emergency event or to the base that enables to achieve the highest level of coverage of the territory.

TABLE I
ANALYTICAL METHODS TO SUPPORT EMS OPERATIONAL DECISIONS

EMS Operational Decisions	Methods	References
Ambulance dispatch	Markov Process	[6]-[10]
	Stochastic optimization model	[11]
	DES	[3], [9], [12]-[26]
	Hypercube model	[27]
	Genetic algorithm	[28]
	IPM and ILPM with heuristic algorithms	[1], [27]-[33]
	Agent-based simulation	[8]
Hospital selection	Markov Process	[9]
	DES	[3], [9], [14], [15], [17], [21]-[23], [25]
	IPM and ILPM with heuristic algorithms	[4], [32]
Ambulance relocation	Markov Process	[9]
	Stochastic optimization model	[11], [34]
	DES	[3], [9], [13], [14], [17], [22], [23], [25]
	Hypercube model	[27], [35]
	Genetic algorithm	[35]
	IPM and ILPM with heuristic algorithms	[1], [27], [33]

B. Forecasting Models in the EMS Domain

A further literature analysis was then performed to gather information about the forecasting models that can be used to predict the expected length of stay in ED phases. Indeed, forecasting the future patient flow in EDs is fundamental to correctly estimate the impact of hospital selection decisions. The search formulas used on Scopus were the following:

- *((demand OR "arrival rate" OR "hourly rate") AND ("Hospital Emergency Department" OR "Emergency Medical Service") AND (forecast* OR predict*))*
- *((demand OR arrival*) AND ("Hospital Emergency Department" OR "Emergency Medical Service") AND (forecast*).*

It resulted that existing literature about demand forecasting in EMS domain is based on three macro-areas: time series, regression, and data mining [36].

With time series methods, the patient arrival is forecasted investigating past data and determining the process at their basis. The main models are:

- Autoregressive Integrated Moving Average (ARIMA): It considers three parameters (p, d, q) where p is the number of autoregressive terms, d is the degree of differencing and q is the order of the moving average. Other variants of this model are Autoregressive Moving Average (ARMA), Seasonal ARIMA (SARIMA), Multivariate Seasonal ARIMA (MSARIMA), multivariate Vector ARIMA (VARMA) and Box-Jenkins ARIMA [2], [37]-[46].
- Exponential smoothing or Winters' model: It is based on a weighted moving average and considers both trend and seasonality phenomena [37]-[39], [41], [43].

Regression methods aim to estimate a potential relationship between the dependent variable (demand for EMS) and a series of independent variables (e.g. age, income, pollution, climate, time of the day, resource availability). The main models are:

- Linear: The dependent and the independent variables are linked by a linear relationship [2], [41], [45].
- Logistic: It can be binomial (or binary) when the output of the dependent variable can assume just two values, or ordinary (or multinomial) when the output of the dependent variable can assume three or more values [41].
- Poisson: It assumes that the events of a time period are independent from the events of another time period [38].

Data mining methods are able to simultaneously represent time and place of the EMS requests. The main models are:

- Graphs-based methods: They are machine learning algorithms that solve computational processes in specific areas by using interconnected elements [38]-[42], [47]-[49].
- Support Vector Machine (SVM): It is a machine learning technique that can be used for regressive analysis and classification problems [2], [47].
- Decision trees: They are non-parametric machine learning algorithms that can be applied to regressive analysis and classification problems [49].
- Kernel models: They are used to recognize patterns and classify the demand calculating its probability of belonging to a specific class [38], [42], [50].
- Bayesian networks: They assume that each variable is independent from the others and they are used to calculate the probability of a certain class given a certain variable [38].

While time series and regression models are the most studied and the most diffused ones, the importance of data mining models has grown in the last years. Indeed, they are more complex models that require a high computational effort; therefore they produce benefits just if applied to a particular temporal and spatial granularity.

Although waiting times in ED are recognized as one of the most important factors that enhance patients' satisfaction and thus the overall healthcare quality, it emerged that the current studies are not specifically focused on the prediction of the expected length of stay in the different phases of ED process. Indeed, the majority of forecasting models in EMS domain are intended to predict the number of patients' arrivals in the near future with the aim of anticipating potential overcrowding situations and acting to prevent them. However, making operational decisions considering throughput times instead of patients' flows could benefit the overall EMS system: it enables to implicitly consider the resource availability of an ED since, given the number of patients, a higher number of resources implies a lower throughput time. Therefore, by forecasting the time spent by patients in ED's phases, it is possible both to reduce overcrowding situations and to guarantee a quicker access to medical care.

IV. Simulation Model

The model developed to support hospital selection decisions is based on a DES. The process it intends to simulate starts with the patient's need to be transported to an ED, after the first intervention at the event site has already taken place. Subsequently, the ED to which the patient will be transported is selected from those present in the network (respecting a defined assignment criterion). Alternatively, a patient can present autonomously to one of the EDs in the network. At this point, the patient's process in ED begins. It is composed of triage, clinical evaluation, disposition (e.g., discharge, observation, admission, and transfer to another facility), and departure from the ED, following the path established by the disposition. This process is summarized in Fig. 2.

A. Model Architecture

To implement the process in the DES model, two main modules have been realized (Fig. 3). The hospital selection module supports the assignment of medical emergency requests to EDs. The assignment policy focuses on the entire EMS and considers, in addition to ambulance transportation, also information relating to the EDs of the network. To establish the optimal assignment policy, several criteria were applied:

1. *Travel Time (TT) minimization* (base case): It assigns patients to the closest ED in meters with respect to the place of the event for which the travel time is shorter (since the travel time is calculated as distance/speed).
2. *Time To Provider (TTP) minimization*: It assigns patients to the ED with the lowest time from the start of the ambulance journey to the start of the clinical evaluation.
3. *Net Patient Throughput time (NPT) minimization*: It assigns patients to the ED with the lowest time from the start of the ambulance journey to the disposition of the clinical evaluation.
4. *Gross Patient Throughput time (GPT) minimization*: It assigns patients to the ED with the lowest time from the start of the ambulance journey to the departure from the ED.

Each of the criteria represents an objective function (OF) of the assignment problem and refers to minimizing the time of a specific part of the ED process (Fig. 4). The service throughput time is the decision variable taken into consideration since, besides being a highly relevant indicator in EMS processes, it also implicitly provides fundamental information, such as the saturation state of the ED resources and the case mix present in the facilities, as different severity codes correspond to different service throughput times.

Consequently, the development of a second module related to the ED process was necessary to provide the information regarding the length of stay in the EDs. The aim of the ED process module, indeed, is to simulate the ED process, considering both self-introduced patients and patients arriving by ambulance as established by the previous module. Each stage of the process is simulated with a specific service time and capacity; in particular:

1. The *Welcome and Triage* activity follows a normal distribution with infinite capacity, as it is assumed that every patient who enters the ED is immediately admitted.
2. The *Clinical Evaluation* activity follows an exponential distribution different for each triage code and has a limited capacity. This stage represents the bottleneck of the process.
3. The *Waiting for departure from ED* timer event follows an exponential distribution different for each triage code and has an infinite capacity, as it is assumed that no more resources are needed for this phase.

To allow the development of a simple model, the following simplifications and hypotheses have been made:

- The EMS demand is stochastic and randomly located on the territory.
- The demand is generated through an hourly rate that varies according to the time slots of the day, but which is constant for all days of the week.
- It is assumed that all requests for ambulance transport already have a vehicle assigned.

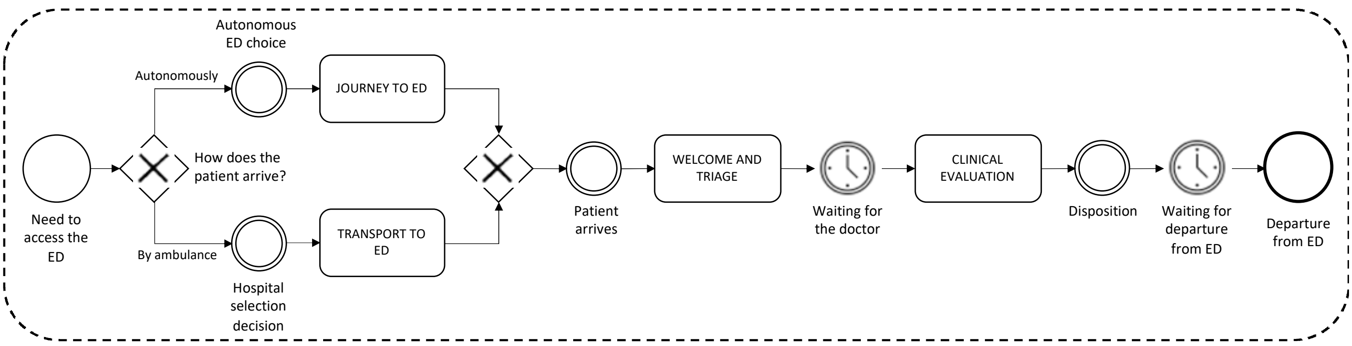

Fig. 2 EMS process considered

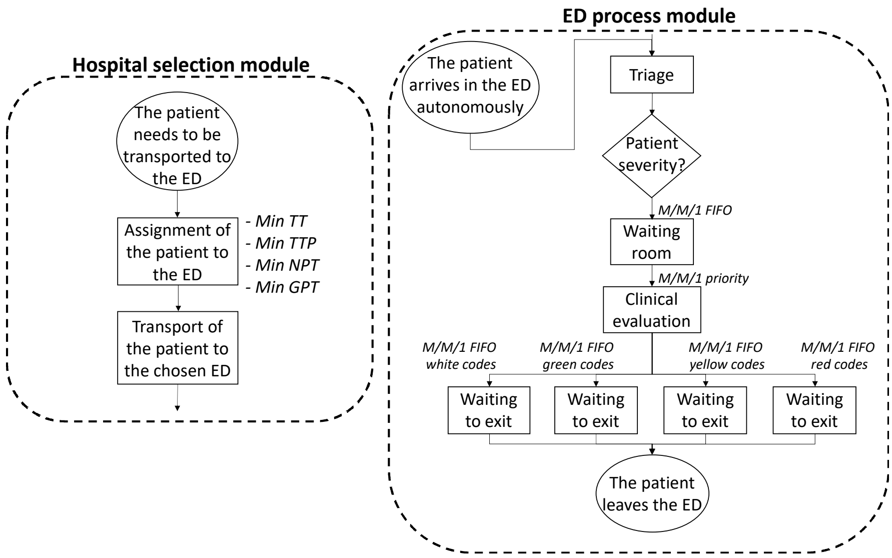

Fig. 3 Flowchart and modularization of the DES model

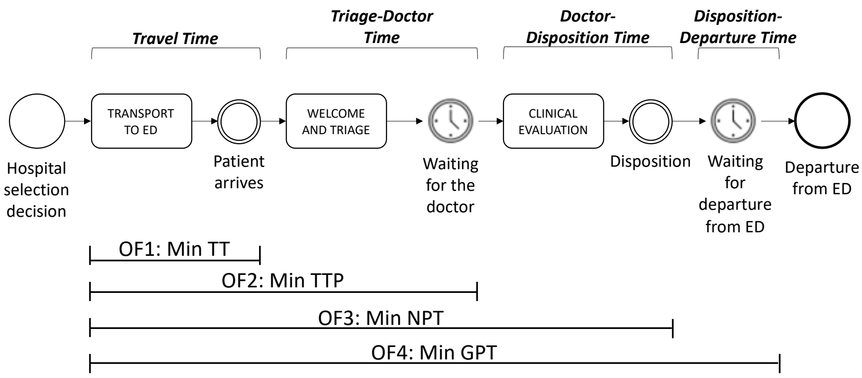

Fig. 4 Objective functions of the assignment problem

- The availability of ambulances is not considered. It is assumed that the ambulance is already at the place of the request and the problem of its repositioning is not considered.
- Ambulances move at a speed of 60 km/h following the paths identified in the GIS map.
- The EMS demand is classified according to two categories: by generic problem (77% of patients) or by trauma (23% of patients).
- The EDs in the network can be of a general type (i.e., they welcome patients regardless of their type of problem) or trauma (i.e., they only receive patients with a trauma problem).
- Patients are assigned to EDs respecting the constraints related to their problem and the type of ED facility.
- It is assumed that patients do not leave the ED before the end of the process.
- The resources elasticity of the ED facilities is not considered: The capacity in the clinical evaluation phase is fixed.
- The service throughput times of each ED patient depend on his triage code.

The next step in building the simulation model is to evaluate the most suitable data to feed the OFs. Indeed, while the expected travel time can be easily calculated in the simulation model by considering the distance between the event location and the hospital, the expected service throughput times of the ED phases must be predicted. To this end, the research proceeded by applying at first, a static approach based on retrospective data and then a dynamic approach based on predictive estimates, as explained in the next paragraphs.

B. Static Approach

The proposed static approach intends to investigate the past recorded times of patients in a certain ED in order to have an estimation of the future behavior of that ED. In this regard, several considerations were made to identify the best time window to extract data. By considering the most recent ones (i.e. the time interval metrics of the last recorded patient), it is possible to build a reactive model, able to detect real-time critical situations that can arise in EDs and consequently adapt the hospital selection decisions. However, this method cannot be easily applied in a real context, since recorded data need to be processed and thus are not immediately usable. For this reason, four reference time windows were introduced (Fig. 5):

- Case 1: the OF considers the average recorded time of one time slot, from t_{-2} to t_{-1}

- Case 2: the OF considers the average recorded time of one time slot, from t_{-3} to t_{-2}
- Case 3: the OF considers the average recorded time of two time slots, from t_{-3} to t_{-1}
- Case 4: the OF considers the average recorded time of two time slots, from t_{-4} to t_{-2}

The four time windows will be tested and compared with the aim of identifying the one that guarantees the best performances of the EMS system in terms of hospital selection problem.

C. Dynamic Approach

Unlike the static model which considered the data of the previous time windows, the purpose of the dynamic simulation is to assign patients to ED on the basis of the expected times in the next hour. This approach, therefore, based on the analysis of the past time series, also considers the future evolution of the saturation state of the ED. The assignment is based on predictive estimates that are updated every hour, based on historical data from the previous 24 hours (Fig. 6). The most appropriate method for predicting the throughput times resulted to be the Winters' model, as it is a statistical analysis and regression tool of time series that takes into account both trends and seasonality.

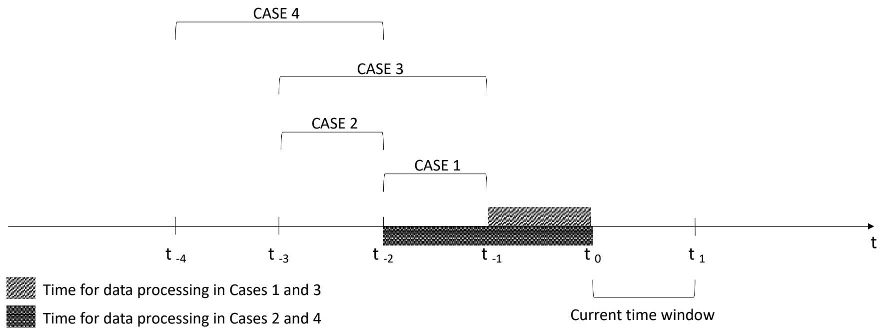

Fig. 5 Reference time windows in the static approach

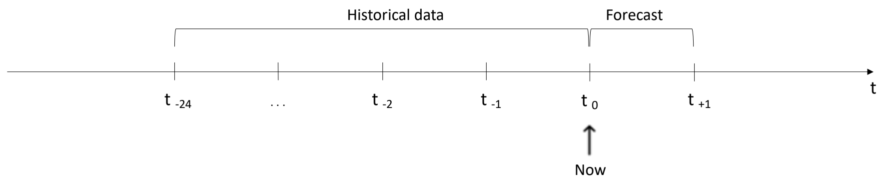

Fig. 6 Dynamic assignment logic

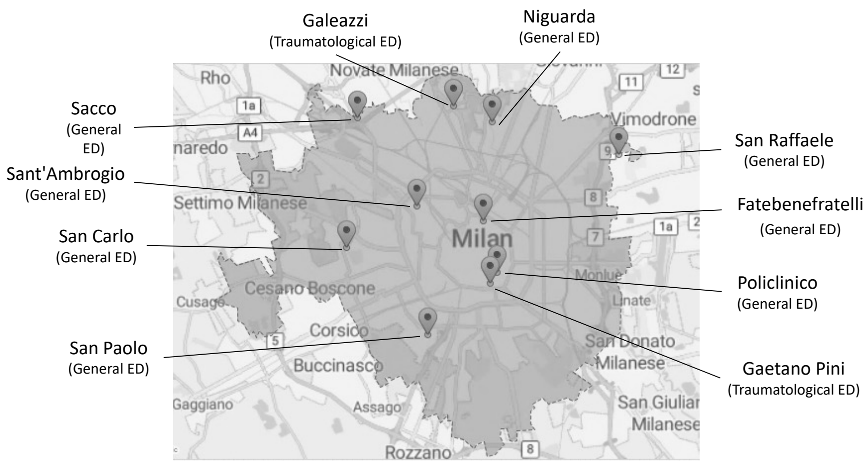

Fig. 7 Experiment area and localization of the EDs

D. Input Parameters

The case-study considers the city of Milan, Italy, as the area of the simulation model. Ten EDs are equally distributed throughout the area, as presented in Fig. 7. Requests for ambulance transport are randomly located on this territory and are generated following different stochastic hourly rates for the various time slots of the day. The algorithm developed in the simulation aims to assign these patients to one of the EDs considered, based on the assignment policy taken into consideration. Each ED has different input parameters. In particular, EDs differ in the number of patients presented autonomously, clinical evaluation service times, capacity, and waiting times for departure. The different characteristics determine different service throughput times for each ED, and this makes possible to apply the proposed objective functions.

V. Results and Discussion

The DES model was developed using the simulation software AnyLogic 8 University. Experiments were performed using data from the EMS of Milan area (Italy). Computational results of the different assignment policies as well as the results of the static and dynamic approaches are presented in this section. Finally, the overall results are discussed.

Fig. 8 shows the overall average times obtained with each of the objective functions. It is evident that the OF2, OF3 and OF4 significantly improve the results compared to the OF1. The OF2 allows to obtain shorter times for each of the time Key Performance Indicators (KPIs) considered, except for travel time. In particular, compared to the base case, it allows reducing the total time of the EMS process (called GPT) from 7.28 hours to 6.08 hours (about 20% improvement). Analyzing the number of patients in ED obtained from each experiment (Fig. 9), it emerges that the variability (intended as the oscillation between the maximum and minimum number of patients in ED) is better with the OF1, intermediate with the OF2 and worse with the OF3 and OF4. Furthermore, overcrowding situations (intended as exceeding the threshold of available beds) are minimized by applying OF2. These results are summarized in Table II, which shows the best, the medium, and the worst case for each dimension of comparison. Overall, the assignment policy returning the best overall performance is the OF2 (*TTP minimization*).

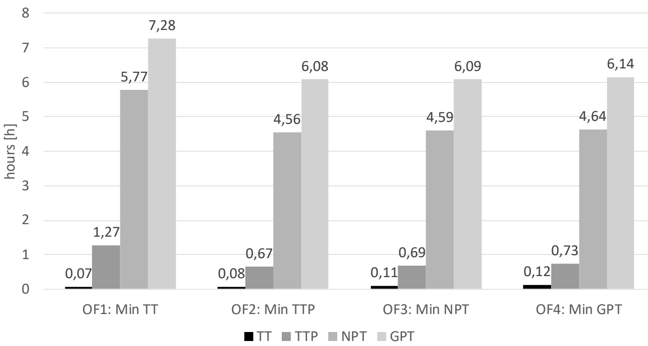

Fig. 8 Average times obtained by the different assignment policies

	OF1: MIN TV			OF2: MIN TTP			OF3: MIN NPT			OF4: MIN GPT			
ED	min	avg	max	min	avg	max	min	avg	max	min	avg	max	theshold
Sacco	11	24	35	9	20	29	7	18	29	7	18	28	34
San Carlo	13	27	38	12	24	34	9	21	30	9	20	29	57
San Paolo	21	45	63	16	35	53	13	32	50	13	33	51	54
Sant'Ambrogio	5	10	14	6	10	16	8	13	19	8	13	19	11
Galeazzi	2	5	7	2	5	8	3	5	8	3	6	9	17
Niguarda	9	26	39	9	27	41	9	27	40	9	28	43	41
Fatebenefratelli	5	17	25	7	21	32	8	23	34	8	24	35	40
Policlinico	30	43	51	18	30	40	15	27	37	14	27	37	58
Gaetano Pini	3	9	14	4	10	15	5	12	17	4	10	15	13
San Raffaele	32	45	58	21	37	51	20	36	51	20	36	50	65
TOTAL	**133**	**250**	**345**	**103**	**221**	**317**	**96**	**215**	**314**	**96**	**216**	**315**	
VARIABILITY		**211**			**214**			**219**			**219**		

Fig. 9 Patients in ED obtained by the different assignment policies

TABLE II
Results of the Comparison of the Assignment Policies

Case	Time	Variability	Overcrowding
OF1	Worst	Best	Worst
OF2	Best	Medium	Best
OF3	Medium	Worst	Medium
OF4	Medium	Worst	Medium

After having identified that the OF2 (*TTP minimization*) is the optimal one, the study proceeded by applying that OF with the static approach using the four reference time windows. Table III summarizes the results. In particular, it emerges that Case 1 is the best in minimizing times, since it considers a more recent time slot to extract data of the patients. Case 4, instead, is the worst since it refers to less recent time slots. Concerning the variability of the number of patients in ED, it results that Case 3 allows obtaining the best performance, while the situations of overcrowding are minimized using Cases 1 and 3. In addition, considering the applicability of the model in a real context, Cases 2 and 4 are easier to be implemented since they leave two time slots for data processing. Finally, the last dimension of comparison is the estimation accuracy, i.e. the difference between the service throughput times estimated with the retrospective method for a specific time slot and the ones effectively obtained in that time slot. It resulted that Case 1 and 3 allows building a reactive model with a high estimation accuracy, while Case 4 is the worst since it considers less recent data that do not fit the reality with a high level of precision. These results are also shown in Fig. 10, where the average absolute errors in the estimation of the service throughput times of the static approach (four cases) and of the dynamic approach are compared.

TABLE III
Results of the Comparison of the Four Cases of the Static Approach

Case	Time	Variability	Overcrowding	Applicability	Estimation accuracy
Case 1	Best	Worst	Best	Low	High
Case 2	Medium	Medium	Medium	High	Medium
Case 3	Medium	Best	Best	Low	High
Case 4	Worst	Worst	Worst	High	Low

Starting from the considerations in Table III, it results that, although Case 2 is never the best one, it allows obtaining a good balance among the different dimensions considered for the comparison. Indeed, the difference with respect to Case 1 in terms of time is minimal, as well as the difference with respect to Case 3 in terms of variability and overcrowding. The estimation accuracy reaches intermediate levels, meaning that the model is able to detect unexpected changes in the service throughput time in an acceptable way. Moreover, Case 2 is better than Cases 1 and 3 as it guarantees a higher level of applicability in a real context.

The last step consists in comparing the best alternative of the static approach (i.e. Case 2) with the dynamic approach. Regarding the times, there is a 2% improvement in travel time and 5% in TTP, while the throughput times of the subsequent ED phases remain almost constant. On the other hand, the variability and overcrowding worsen slightly. Results are summarized in Table IV.

TABLE IV
RESULTS OF THE COMPARISON OF THE STATIC AND DYNAMIC APPROACHES

Approach	Time	Variability	Overcrowding	Applicability	Estimation accuracy
Static	Medium	Best	Best	High	Medium
Dynamic	Best	Medium	Medium	Medium	High

From analyses in Table IV, it emerges that the dynamic model, tough it is based on a more accurate estimation (Fig. 10), brings slight benefits in patient-hosx"pital assignment choices, allowing a quicker first access to treatment. However, there is slight worsening of ED crowding. Considering that quicker access to care in emergency situations can be vital for the patient, an improvement in TTP is a major achievement to pursue. Nevertheless, it should be noted that the application of the dynamic model requires data to be updated in near real-time. Therefore, if this information was available, it is advisable to use the dynamic approach given its ability to optimize times and high estimation accuracy. On the other hand, if more time is required for recording and processing the data, Case 2 is an excellent alternative.

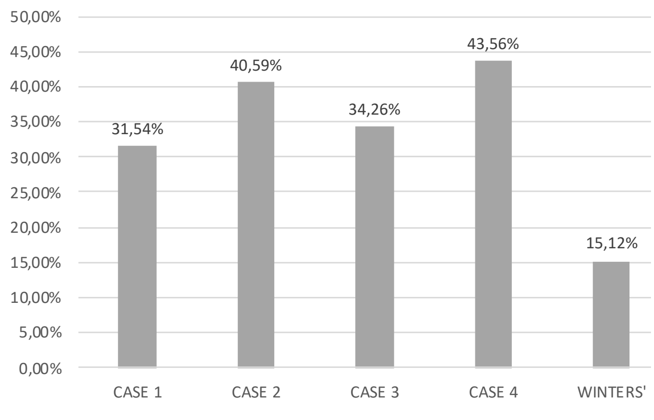

Fig. 10 Average absolute error in the estimation of the service throughout times

The results of the present study made it clear that, when dealing with the hospital selection problem in EMS orchestration, it is reductive to consider just the ambulance travel time without having visibility on the subsequent phases of the process. The minimization of the travel time enables to reach the ED in the shortest possible time but does not guarantee immediate treatment to the patient. Indeed, by applying the OF1 (min TT), the length of stay in ED and the situations of overcrowding are greater than applying the other OFs policies. When the service throughput times are considered, instead, it is possible to assign patients to less saturated EDs, which leads to higher performance of the entire EMS system, since patients' waiting times can be reduced and EDs' overcrowding situations can be limited. In particular, the results obtained from the simulation show that the optimal hospital selection policy is the one that minimizes the TTP (OF2), thus allowing patients to start the clinical evaluation in the shortest possible time. A quicker access to medical treatments has an impact also on the subsequent phases of ED process, indeed the OF2 enables to reduce also the time to the disposition (NPT) and the time to the final departure (GPT). Concerning the time window to extract data for the TTP calculation, the simulation shows that the optimal case is the one that considers the average recorded time from t_0-3 to t_0-2 given the current time slot t_0. Indeed, Case 2 enables to obtain intermediate performances in time minimization, variability, overcrowding and estimation accuracy, as well as a high level of applicability. Finally, a dynamic approach based on predictive estimates is more accurate and the overall benefits on the EMS performance translate into an optimization of treatment access times. However, this approach requires updated data in near real-time and therefore has a slightly reduced applicability.

VI. CONCLUSIONS

In this paper, several assignment policies to support the hospital selection decision in EMS management have been presented and analyzed. A DES model was developed using AnyLogic simulation software in order to test different assignment criteria. In particular, the standard and most widely used policy of assigning patients to the nearest ED was used as a base case. It was compared with three other policies (TTP, NPT and GPT minimization) which, instead of focusing only on the ambulance service, also consider the length of stay and, consequently, the saturation status of the EDs.

The hospital selection policy that returned the best results is the minimization of the TTP, considered as the time from the beginning of the ambulance travel to the assigned ED to the beginning of the clinical evaluation of the patient by the doctor. Besides, different time windows to extract data for the TTP calculation were further compared. The best compromise between performance, accuracy and applicability turned out to be the time window from t_0-3 to t_0-2. Besides, the use of a dynamic approach for the TTP calculation is more accurate and further improves service times than a static approach but entails a more difficult application. These considerations can support decision-makers in introducing different hospital selection policies to enhance EMS performance.

In the future, the study could be further expanded by introducing functionalities to extend the adoption of the DSS in specific operating contexts, such as mass casualty incidents that determine a sudden pick of workload on the EMS systems.

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