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(Article begins on next page)

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In: Nicosia G., Pardalos P., Giuffrida G., Umeton R. (eds) Machine Learning, Optimization, and Big Data. MOD 2017. Lecture Notes in Computer Science, vol 10710. Springer, Cham. Available online 21 December 2017.

DOI: 10.1007/978-3-319-72926-8_46

Evaluating the dispatching policies for a regional network of emergency departments exploiting health care big data

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Abstract. The Emergency Department (ED) is responsible to provide medical and surgical care to patients arriving at the hospital in need of immediate care. At the regional level, the EDs system can be seen as a network of EDs cooperating to maximise the outputs (number of patients served, average waiting time, ...) and outcomes in terms of the provided care quality. In this paper we discuss how quantitative analysis based on health care big data can provide a tool to evaluate the dispatching policies for the network of emergency departments operating in Piedmont, Italy: the basic idea is to exploit clusters of EDs in such a way to fairly distribute the workload. Further, we discuss how big data can enable a novel methodological approach to the health system analysis.

Keywords: emergency care pathway, health systems, big data.

1 Introduction

The Emergency Department (ED) is responsible to provide medical and surgical care to patients arriving at the hospital in need of immediate care. At the regional level, the ED system can be seen as a network of EDs cooperating to maximise the outputs (number of patients served, average waiting time, ...) and outcomes in terms of the provided care quality. Many EDs, especially those serving a large amount of people, complain about the large number of non-urgent patients usually transported by the Emergency Medical Service (EMS) ambulances. Further, EMSs usually do (or can) not take into account the ED workload level when assigning and transporting a patient to an ED. When a peak of emergency demand arises, EDs suffer from increasing overcrowding [9]. The systematic review reported in [8] describes the causes, effects and solutions to the ED overcrowding. The causes described are non-urgent visits of patients, influenza seasons, hospital closures, ambulance diversion, inadequate staffing, delay in diagnostics and hospital bed shortages. As described before, ED overcrowding leads to delayed patient care. This results in an increased risk of mortality, patients who left without being seen (LWBS) and also financial losses. Both academic literature [2] and the ED managers argue that the efficiency and the equity of the ED system can depend on the interplay between the EMS and the ED network.

The development of models for the analysis of a health system as a whole is one of the main challenges in the health care management field. The basic idea is to have a tool capable to validate management policies at health system level modelling the patient flow through the care pathway. As a matter of fact, the current trend in the analysis of health care systems is to shift the attention from single departments to the entire health care chain in such a way to increase patient's safety and satisfaction, and to optimise the use of the resources.

In order to apply such an approach to the analysis of a regional ED network, one of the main difficulties is the collection of all the information regarding the transportation of the patients from the emergency scene to the ED. Nevertheless this problem can be now overcome exploiting the immense amounts of data generated by health care systems. Health Care Big Data (HCBD) are a key enabling technology to support detailed health system analysis: exploiting the HCBD, one can replicate the behaviour of the health system modelling how each single patient flows within her/his care pathway.

In this paper we discuss how quantitative analysis based on the HCBD can provide a tool to evaluate dispatching policies for a regional network of emergency departments: the basic idea is to exploit clusters of EDs in such a way to fairly distribute the workload. We present a simulation model based on the case study of the Piedmont in Italy, and powered by the knowledge provided by the analysis of regional HCBD.

The paper is organised as follows. In Section 2, we introduce the general concept of clinical pathway and its application to the emergency care. Further, we discuss how big data can enable a novel methodological approach to the health system analysis. In Section 3, we first discuss the case study under consideration and then we report how we implemented the simulation model. In Section 4, we report a quantitative analysis of the results obtained running the simulation model. Conclusions and future works are discussed in Section 5.

2 Clinical Pathways and Health System analysis

The current development of the health care systems is aimed to recognise the central role of the patient as opposed to the one of the health care providers. In this context, Clinical Pathways (CPs) shift the attention from a single health benefit to the health care chain that is involved in the illness episode treatment. A CP can be conceived as an algorithm based on a flow chart that details all decisions, treatments, and reports related to a patient with a given pathology, with a logic based on sequential stages [7]. A CP is therefore "the path" that a patient suffering from a disease traverses in the National Health System. For this reason, they can be considered an operational tool in the clinical treatment of diseases, from a patient-focused point of view [11]. Many papers show that, appropriately implemented, CPs have the potential to increase patient outcome, to reduce patient length of stay and to limit variability in care, thereby yielding cost savings [6, 13]. On the contrary [1], limited attention has been dedicated to study how CP can optimise the use of resources (see, e.g., [4, 10]).

The development of models for the analysis of a health system as a whole is one of the main challenges in the Health Care Management field [12]. The basic idea is to have a tool capable to validate management policies at health system level modelling the patient flow through the corresponding CP. Literature indicates that System Dynamics (SD) seems to be the most appropriate methodology. A first attempt has been made by Wolstenholme during his collaboration with the NHS. In [16], he applies SD to the development of national policy guidelines for the U.K. health service. The tested policies include the use of "intermediate care" facilities aimed at preventing patients needing hospital treatment. Intermediate care, and the consequent reductions in the overall length of stay of all patients in community care, is demonstrated here to have a much deeper effect on total patient wait times than more obvious solutions, such as increasing acute hospital bed capacity. More generally, as discussed in [17], the key message is that affordable and sustainable downstream capacity additions in patient pathways can be identified, which both alleviate upstream problems and reduce the effort for their management.

A SD model has been used as a central part of a whole-system review of emergency and on-demand health care in Nottingham, as reported in [5]: due to a growing emergency care demands, the hospital systems were unlikely to achieve some government performance and quality targets. Such a model discovered a range of undesirable outcomes associated with the growing demand and, at the same time, suggested policies capable to mitigate such impacts. In [15], the authors were interested in determining whether SD can be an appropriate methodology to model the patient flow in a hospital, and to analyse it from a strategic planning perspective. The SD model were developed in collaboration with the General Campus at The Ottawa Hospital with particular attention to the delays experienced by patients in the ED. The authors reported about the modelling techniques, validation and scenarios tested, accompanied by their comments regarding the appropriateness of SD for such a strategic analysis.

From a modelling point of view, SD is a simulation methodology whose main elements are stocks and flows: a stock is any entity that accumulates or depletes over time; a flow is the rate of change of a stock. For instance, in health care a stock can represent the waiting list for a surgery, that is a number of people requiring a surgery, while a flow can be the rate of a new insertion in the list. One of the main limitation of using SD for health system analysis is that patients are indistinguishable from each other within stocks and flows. On the contrary, health care services are generally characterised by a large variety of different patients suffering from the same diseases and flowing in the same care pathway.

From the above remarks, Discrete Event Simulation (DES) seems the more appropriate methodology to model such a large variety of patients flowing in their corresponding pathway because of DES has the capability of representing each single patient (or entity) within one of more pathways. Further, DES can easily enable the application of optimisation algorithms to take the best (or the most rational) decision regarding a single or a group of entities modelling a single or a group of patients.

It is worth noting that such a modelling approach requires a lot of detailed data, that is all the data needed to replicate the behaviour of each single patient flowing in its corresponding pathway. Moreover, in terms of health system analysis, such a model requires the availability of all the data for all patients flowing in all pathways of the same type in the health system under consideration. A defining characteristic of today's data-rich society is the collection, storage, processing and analysis of immense amounts of data. This characteristic is cross-sectoral and applies also to health care.

Therefore, we argue that the HCBD can power a detailed health system analysis using DES methodology: exploiting the HCBD, one can replicate the behaviour of the health system modelling how each single patient flows within her/his care pathway. The novelty of the paper is therefore the use of the DES methodology for the health system analysis exploiting the Big Data in order to better represent the variety of the patients accessing the health system.

3 A DES model powered by the HCBD

In this section we report about the development of a Discrete Event Simulation (DES) model powered by the Health Care Big Data (HCBD) for the analysis of the dispatching policies for a regional Emergency Department (ED) network. First we present the specific case study (Sect. 3.1) and then we discuss our two-phase DES model (Sect. 3.2).

3.1 The ED network operating in Piedmont region

Piedmont (Italian: Piemonte) is one of the 20 regions of Italy. It has an area of 25,402 square kilometres and a population of about 4.6 million. The capital of Piedmont is Turin. Piedmont is organised in 7 provinces. The province of Cuneo is the largest one while the province of Turin is the most populated one: actually, about 2.3 million of inhabitants are living in, and 1.4 million are living in the area of Turin. Figure 1 reports the number of inhabitants living in Piedmont and in the province of Turin, divided in different age classes.

According to the 2015's report of the "Programma Nazionale Esiti" by the Ministry of Health, the waiting time for a urgent and a non-urgent code could exceed respectively 60 minutes and 450 minutes, in the worst case. In other similar Italian regions, such waiting times are about 20% lower. We remark that in Italy, the Regions are in charge of providing the health services in accordance with the minimal level decided at the national level by the Ministry of Health. This comparative analysis demonstrates the need of investigating the reasons of such differences and, eventually, to individuate some possible improvements.

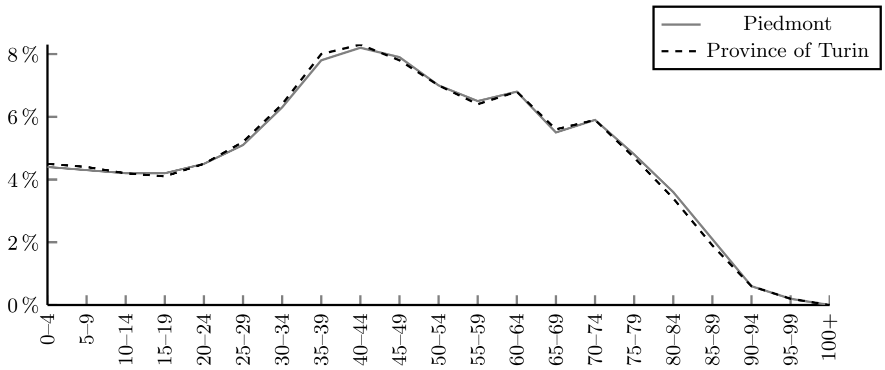

Fig. 1. Population of Piedmont and province of Turin: age distribution (ISTAT 2011).

From more than 10 years, the Piedmont region is collecting data about the regional health system, and released a regional law to unify the flows of data gathered from all the health care providers operating in Piedmont, that is, local health agencies, hospitals, and all the private structures in agreement. Such a regional law guarantees the quality of the data collected in accordance with the national standards: all the information must respect a standard format and their consistency is checked for financial reasons since health providers are reimbursed w.r.t. the number and the type of treatments.

Concerning the access to the network of EDs, the HCBD contains all the information regarding the access: encrypted patient ID, patient registered residence, times (arrival, discharge, ...), urgency code, ED, treatment(s), etc.. Each year they collect all the information regarding about $1,800,000$ accesses to the regional network of EDs: for instance, in 2013, there were $1,768,800$ accesses; among them, the 90.53% were non-urgent. The network is composed of 49 EDs, mostly – about 20 – located in the province of Turin. The EMS usually transports patients to the closest ED, apart some particular – limited in number – cases.

3.2 A two-phase DES model

We propose a quantitative model for the analysis of the network of EDs operating in Piedmont. The proposed model is organised in two phases, and it operates on a time horizon of one month. The first phase is devoted to data analysis concerning the time horizon taken into account in order to determine the appropriate value of the parameters of the DES model, which is the main part of the second phase. As a matter of fact, the emergency demand depends on the day of the week and the time of day [14]. Further, a not accurate forecasting can lead to managerial solutions that worsen the EMS performance, and by consequence the quality of the access to the ED, even if more resources are used, as discussed in [3].

Dynamic estimation of the parameters. In order to have a proper representation of the main parameters of the network of EDs, the first phase of our quantitative model concerns the analysis of the big data relative to the time horizon considered in the running experiments. Parameters and their corresponding distributions are empirically computed over adequate time intervals in such a way to fit the model on a given and fixed time horizon, and to replicate both the patients flow and their management by the EDs.

The main parameters dynamically evaluated are the emergency demands and their urgency code, the capacity and the service time of each ED, and how the patients are distributed to EDs with respect to their geographic origin. The general evaluation procedure consists in scrolling the data concerning each access in chronological order to keep track of the information needed to estimate the considered parameters and their corresponding empirical distribution, as we describe in the following.

Emergency demands. The emergency demand consists in the number of accesses to the whole regional ED network. Such a distribution is computed counting the average number of accesses in each time interval of 30 minutes over each day of the time horizon considered.

Urgency distribution. The urgency distribution measures the percentage of patients having a urgent or a non urgent code with respect to the origin of the patients.

Service time of each ED. The service time of each ED is estimated using the information regarding the time on which the patient has been take over by the ED, and the time on which the patient has been discharged. The service time has been estimated by the code of urgency.

Capacity of each ED. An ED usually has a formal capacity defined a priori. On the contrary, the real practice showed that the real capacity could be different. Further, we should take into account variations in the staffing. From these considerations, we estimate the capacity of the ED by counting the maximum number of patients that are in the ED at the same time. We compute such a value for each interval of three hours in a day, for each day in the time horizon. The capacity of each interval of three hours is finally set to the value corresponding to the 90-percentile of all the values measured in the same interval and in the same day of the week.

Patient geographical distribution. From the data of the patients, we estimate the number of the patients coming from a city identified by its postal code. We also estimate the number of patients that accessed an ED from a given city.

Although the percentage of patients transported by the EMS could be evaluated dynamically, our preliminary analysis showed that such a parameter currently ranges in $[13.3\%, 14.2\%]$. Therefore, we decided to set this parameter in such a way to study the interplay between the EMS and the ED network varying such a percentage in Section 4.

Figure 2 reports an example of the distribution of the daily arrival of the patients derived from the about $150,000$ accesses to the ED network in July

2001. Note that the figure reports ticks of 1 hour (instead of 30 minutes) only to improve its readability.

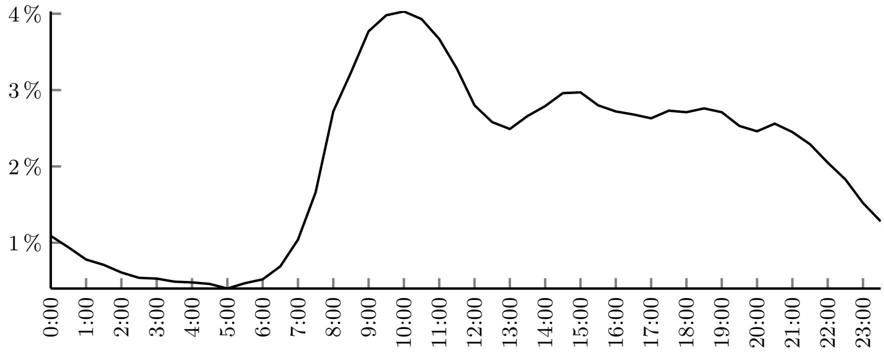

Fig. 2. Distribution of the patient arrivals during the day (July 2011).

The DES model. We propose a DES model to represent the pathway of the patient entering in the ED network. Our DES model is based on a straightforward representation of the flowchart depicted in Figure 3.

An emergency request of a patient is generated in accordance with the geographical distribution of the patients and the arrival distribution. At the moment of its generation, an ED is associated to the patient pursuant to the distribution of the patients accessing each ED, which usually corresponds to the closest one. Such an emergency request can be served or not by an EMS ambulance. When the request is not served by the EMS, we assume that the patient reaches – in some way – the ED previously associated. On the contrary, the transportation of the patient is in charge of the EMS. In our model, the ambulance transports the patient to the associated ED only if the urgency code is high (red or yellow in the Italian system), otherwise the EMS can decide where to transport the patient in accordance with some policies (dispatching decision for non urgent patients). After arriving at the ED, the patient will wait for the treatment, which usually lasts for a time distributed following the service time distribution dynamically estimated. When the patient will be discharged, he/she will exit from the model.

The considered dispatching policies are two. The first one, say P_0, dispatches a non urgent patient to the ED associated to the patient at the moment of its generation, without any change. The second one, say P_1, dispatches a non urgent patient following a service state policy, that is, at the moment t, the patient is dispatched to the ED h having minimal ratio r_h^t

$$r_h^t = \frac{w_h^t + s_h^t}{c_h}\,, \tag{1}$$

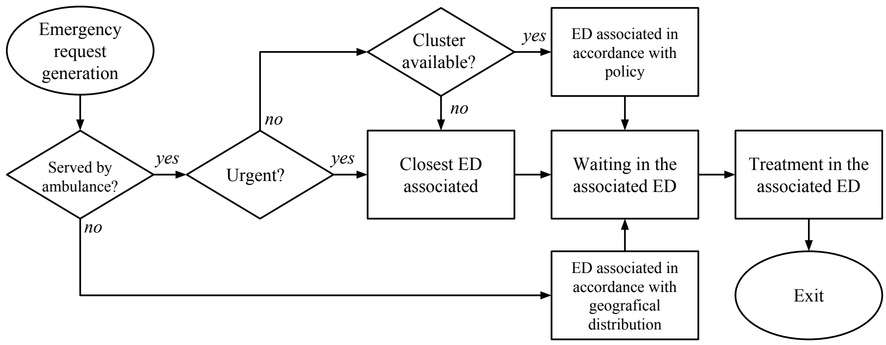

Fig. 3. The flowchart representing the emergency pathway.

in which the values w_h^t and s_h^t are respectively the number of patients waiting and receiving health care, and c_h is the estimated capacity of the ED. This policy is suggested by the fact that Piedmont region is building an ICT infrastructure to share the real-time information regarding the workload of the EDs.

The policy P_1 does not consider all the ED network but only those belonging to a cluster of EDs. A cluster of EDs is a subset of all the EDs operating in Piedmont that can be reached in no more than 30 minutes from a given origin. We identified 5 different clusters in Piedmont, denoted by C_i, $i = 1, \dots 5$. The largest one C_1, composed of 20 EDs, is located in the Turin area. The clusters C_2 (province of Alessandria) and C_3 (province of Cuneo) are composed of 7 and 6 EDs, respectively. Finally, two smaller clusters, composed of 2 EDs each, are located in the area of "Valli di Lanzo" (C_4) and in the area of Alba and Bra (C_5).

The proposed DES model is quite flexible: as a matter of fact, the ED network operating during the time horizon considered can be obtained by simply activating the dispatching policy P_0. Note that this also provide a tool to evaluate the ED network as a whole system, instead of having simpler measures as those reported in the "Programma Nazionale Esiti".

Implementation details. The dynamic estimation of the parameters has been implemented in Python 2.7. A script evaluates data concerning the time horizon of interest from the input data-set and generates an Excel file with the the parameters of the distributions described above.

Apart from the emergency demand, that has been evaluated at the regional level calculating, as mentioned before, the average number of accesses in each time interval of 30 minutes over each day of the time horizon considered, the rest of parameters takes also into account the origin of the patients and/or the related EDs. Urgency code distribution has been estimated by distinguishing for each ED four different codes (from 1 to 4). The accessing distribution has been estimated considering both the distribution of provenance of patients and the distribution of accesses of the EDs, mitigating in this way the possibility of not considering patients collected from an ED in a different location from their city of provenance. Finally the service time distribution has been estimated considering both the ED and the gravity of patients.

The DES model has been implemented using AnyLogic 7.2. At simulation start-up it takes in input the file before generated and uses it to initialise the parameters. Custom distributions have been used for the parameters above described, while specific objects (`Service` and `ResourcePool`, `Schedule` and `Agent`) have been used for the definition of the EDs, their capacities (varying pursuant to the hour of the day) and for the patients. When a patient is generated it is assigned to him a provenance, the destination hospital (pursuant to the selected policy), an urgency code and the expected service time. The routing of patients has been implemented using two matrices, associating each patient provenance to one (in case of policy P_0) or more (policy P_1) possible EDs of destination.

4 Quantitative Analysis

In this section we report the quantitative analysis performed to test our two-phase DES model.

In our analysis, we considered four different months in 2011. Table 1 provides more details about the input of our model. For each month considered, the table reports the total number of accesses considered and their classification with respect to the urgency code (1 represents the more urgent code while 4 the less one) and their origin with respect to the property of belonging or not to a cluster.

We would remark that the total number of accesses considers only those accesses for which at least one between the origin of the patient or the ED of destination is correctly reported in the data. Finally, the last column of the table reports the percentage of the accesses to an ED belonging to one of the five clusters. This means that the majority of the patients can be served by an ED belonging to a cluster. Further, the cluster C_1, composed of 20 EDs over 49, treats more than the 50% of the accesses.

Table 1. Description of the data considered in our quantitative analysis.

	total	requests by urgency			requests by clusters					
	accesses	3–4	2	1	C_1	C_2	C_3	C_4	C_5	
Jan	126,698	107,773	17,688	1,237	69,773	11,480	12,467	3,701	4,201	80.21%
Feb	116,961	99,806	16,074	1,081	64,876	9,819	11,548	3,379	4,008	80.05%
Jun	132,654	113,734	17,562	1,358	70,292	11,672	12,632	3,568	4,451	77.36%
Jul	123,758	106,404	15,970	1,384	62,505	11,027	12,836	3,507	4,196	76.01%

Our quantitative analysis consists in using the two-phase DES model to solve the four instances arising from the four months in Table 1. For each instance, a test consists in solving the instance by varying the percentage of patients transported by the EMS, denoted by p_E, in the interval $[7\%, 27\%]$ with a step of 5%. The rationale is to study the interplay between the EMS and the ED network, as discussed in Section 3.2 and suggested in [2]. Finally, the results for each solution are the average values among those obtained by running the two-phase DES model 100 times, each time starting from a different initial conditions in such a way to have independent and identically distributed repetitions.

Table 2. P_1 vs. P_0: waiting time reduction Δ_w in minutes.

		p_E	7%	12%	17%	22%	27%	**avg.** Δ_w
Jan	all		15.51	25.91	34.70	42.16	50.79	33.82
	EMS		17.75	21.63	24.73	27.74	34.37	25.24
	no EMS		15.43	26.67	37.01	46.62	57.39	36.62
Feb	all		6.81	13.10	19.75	26.29	31.87	19.56
	EMS		-4.31	1.62	6.68	11.33	15.70	6.21
	no EMS		7.67	14.70	22.48	30.60	37.99	22.69
Jun	all		19.70	39.12	64.51	75.73	80.82	55.98
	EMS		5.78	19.88	45.51	58.88	66.45	39.30
	no EMS		20.81	41.85	68.54	80.63	86.28	59.62
Jul	all		8.27	13.19	17.64	21.15	24.23	16.90
	EMS		-3.86	-2.62	0.22	3.89	7.55	1.04
	no EMS		9.20	15.35	21.20	26.03	30.43	20.44
avg. Δ_w	all		12.57	22.83	34.15	41.33	46.93	
	EMS		3.84	10.13	19.28	25.46	31.02	
	no EMS		13.28	24.64	37.31	45.97	53.02	

Table 2 shows the results of our quantitative analysis reporting the waiting time reduction Δ_w considering the whole network of EDs. Such values are computed as follows: for a given dispatching policy $i = 0, 1$, we compute the average waiting time w_{ij} for each ED $j = 1, \ldots, 49$, and then we set W_{P_i} equals to the average of all the values w_{ij}; finally, $\Delta_w = W_{P_1} - W_{P_0}$. Note that P_1 is better than P_0 when $\Delta_w > 0$.

The results prove a general improvements of the waiting times, which improves further as soon as the percentage of the patients transported by the EMS increases. It is worth noting that the different results for each different instances depend on the different composition of the emergency demand reported in Table 1 (see, e.g., the last column reporting the percentage of the accesses to an ED belonging to a cluster).

Table 3 shows the results of our quantitative analysis reporting the waiting time reduction considering the cluster C_1, that is the bigger one in terms of both the number of EDs and the number of accesses. Although the general improvement is inferior than those for the whole network, such results confirm the comments done for the whole network.

Table 3. P_1 vs. P_0, cluster C_1: waiting time reduction Δ_w in minutes.

		p_E	7%	12%	17%	22%	27%	**avg.** Δ_w
	all		11.88	19.75	22.96	24.24	27.55	21.28
Jan	EMS		30.81	29.65	24.95	22.54	24.52	26.49
	no EMS		2.63	7.74	9.03	9.02	12.11	8.10
	all		-3.15	-1.11	1.66	4.57	6.64	1.72
Feb	EMS		6.41	5.40	5.06	5.86	7.27	6.00
	no EMS		-9.57	-9.80	-8.32	-6.37	-4.85	-7.78
	all		2.19	14.53	36.13	46.32	51.54	30.14
Jun	EMS		9.89	15.69	29.30	36.75	42.02	26.73
	no EMS		-2.19	9.17	31.60	42.18	47.85	25.72
	all		8.43	11.60	11.96	10.58	8.86	10.29
Jul	EMS		-0.76	6.17	9.52	9.87	9.47	6.85
	no EMS		12.59	16.96	18.11	17.17	15.89	16.14
	all		4.84	11.19	18.18	21.43	23.65	
avg. Δ_w	EMS		11.59	14.23	17.21	18.75	20.82	
	no EMS		0.87	6.02	12.60	15.50	17.75	

5 Conclusions and future developments

We presented a two-phase DES model to evaluate the dispatching policies for the regional network of emergency departments powered by the knowledge provided by the analysis of regional health care big data. The model has been tested on the case study of the Piedmont in Italy showing that there is room to improve its efficiency. Further, we observed that such an improvement is more significant as soon as the percentage of the patients transported by the EMS increases. This remark has an evident managerial implication that would not have been possible without an analysis of the entire ED network.

More generally, the results showed the effectiveness of the proposed approach in terms of the capability of modelling a whole health care system through a discrete event simulation approach, which exploits the availability of the health care big data. As discussed in [16, 17], there could be a significant difference between the formal description of the health system and the its real functioning. To overcome this modelling problem, our idea is to retrieve a picture of the system from the big data through the dynamic estimation of the parameters, which allow to fit the model on a given time horizon replicating both the patients flow and their management.

Future developments will be follow two main research lines. The first one is to improve the current model adding a more detailed representation of the transportation network and predictive dispatching policies. The second one is to validate such a methodological approach on a more complex health care network, such as those of the hospitals with their specialties.

Acknowledgments. The authors acknowledge the Regione Piemonte for providing the access to its health care big data repository. The first and the third authors acknowledge support from the *Fondazione CRT* under the grant "Big data supporting Emergency Care imprOveMEnt" (BECOME).

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