A smart health grid solution for demand management of Emergency Departments

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Abstract

Overcrowding is a very challenging problem that Emergency Departments (EDs) face every day. Many scholars dealt with it focusing on a single ED and few works analyse the problem in a network perspective. In this paper, we reinforce the idea that managing EDs as a network can be an appropriate solution for mitigating overcrowding. Based on energy smart grid concept, we propose an optimization model of demand side management for reducing the waiting time of the ED network. In order to show the potential of model, its application to a 3 EDS network located in Naples (Italy) is presented.

Keywords: Network, Demand Forecasting, Overcrowding

Introduction

Emergency Department (ED) overcrowding is a situation in which available resources are not enough for the requested emergency services. Reducing overcrowding is a worldwide challenge as it affects the quality of care in terms of delays in diagnosis, delays in treatment, poor patient outcomes, decrease in access to care (Derlet, 2002; McCarthy et al. 2009; Pines and Yealy 2009).

ED performance indicators are waiting time and length of stay. These are affected by patient arrivals whose increase may compromise the timeliness of the service, putting patients in serious condition at risk (Horwitz et al., 2010; Asplin et al 2003).

Patient's flow in ED can be articulated in two sequential phases: 1) evaluation and treatment: 2) admission to hospital. In evaluation and treatment phase, the triage procedure assigns to patient a priority code, based on the urgency of receiving the first treatment. After the evaluation and treatment, the patient can be discharged or admitted to hospital.

Patient's waiting time depends on different variables and it is due to supply–demand mismatch (Horwitz et al., 2010, Xu et al., 2013). Asplin et al. (2003) proposed a conceptual model of ED overcrowding partitioning it into 3 interdependent components: input, throughput, and output. Input factors are related to the demand for ED services, throughput factors are related to the ED processes of evaluation and treatment, and output factors are related to admission to hospital.

In this paper we focus on the first component of overcrowding conceptual model that is the demand for ED services. We model the flow of patient arrivals to all EDs in a territorial area in order to redistribute it among the EDs. The redistribution of patients' flow can reduce ED patient input and relieve overcrowding (Scheulen and Kelen, 2001).

We propose an optimization model based on Demand Side Management (DSM), assuming that the EDs are nodes of a network and a centralized aggregator manages the patient's flow. The optimization model manages efficiently the patient's flow, minimizing the overall waiting time, sum of the travel and waiting time for the treatment.

According to Kao et al. (2015) and Deo and Gurvich (2013), the paper reinforces the idea that EDs' network, managed by a centralized coordination, can be the solution to the problem.

Literature on ED overcrowding

The overcrowding issue has been analysed from different perspectives leading to identify several caused and different solutions.

Many scholars put in evidence the overcrowding depends on unavailability of inpatient beds, that contributed to significant delays and congestion difficulties (Kyriacou et al.1999; Arkun et al. 2010; Espinosa et al., 2002). Other causes concern the considerable number of low-acuity patients and the day of the week (Siddharthan, 1996; Arkun et al., 2010).

In order to solve the overcrowding, organizational and process redesign solutions are proposed. Possible solutions are improving the support from other centres or general practitioners, nurses or doctors (Pines, 2009), expanding nursing roles or health service delivery (Elder et al., 2015), enforcing a toll on non-emergency users of the ED, so as to deter their usage (Siddharthan, 1996), implementing a fast-track facility for coping with the low-acuity patients (Fernandes and Christenson, 1995; Rodi et al., 2006), increasing numbers and coverage hours of physicians and nurses (Duguay and Chetouane, 2007).

In a review on causes, effects and solutions related to overcrowding phenomena, Hoot et al. (2008) grouped the solutions of crowding in three clusters: a) increased resources; b) demand management; c) operations research.

In demand management group, many scholars have analysed the impact of ambulance diversion on overcrowding. Ambulance diversion can be a solution for balancing the capacity and demand in a network, patients are rerouting from overcrowded EDs to less crowded ones (Scheulen and Kelen, 2001; Burt et al., 2006). However, empirical evidences show that ambulance diversion has no beneficial impact on waiting times at EDs (Mihal and Moilanen, 2005; Kowalczyk, 2008).

Deo and Gurvich (2011) suggest that "operational benefits of ambulance diversion presuppose centralized coordination that can match excess capacity and excess demand. Diversion decisions are often made by ED administrators with the object of mitigating overcrowding at their own location while keeping the number of diverted patient at reasonable levels. Kao et al. (2015) confirm that ambulance diversion does not provide beneficial from a regional point of view. The patients can be properly diverted to the EDs less crowded only if the flow is managed by a centralized regional coordinator.

In summary, we can conclude that solutions are mainly addressed to analyse resource and demands of a single ED not connected to other ones. Ambulance diversion can be considered as a network solution, but it is necessary to pass from a decentralized strategy to centralized one. Few works deal with the ambulance diversion issue from a centralized managing perspective applied a queueing theory, but they do not keep in account the travel time, that is a relevant variable for selection of ED in diverting ambulance (Deo and Gurvich, 2011).

ED health smart grid as network solution to overcrowding

The proposed conceptual model is based on the following assumptions.

Firstly, the EDs of a given territorial areas are the nodes of a network and the patient arrivals (ambulance and walking-in) can be directed to any ED of the network.

Secondly, the decision-maker of system is a centralized actor.

Thirdly, the decision is made considering the forecast of patient arrivals of each EDs, the priority code of the patient and the total time (travel and waiting time for the treatment).

Lastly, the optimization model directs the flow of the patients in such way as to minimize the overall waiting time of the network.

We tackle the redistribution of the patients' flow that everyday arrive to the EDs at the same way of the residential load in a smart grid. In energy smart grid, demand side energy consumption pattern can be modified to foster better efficiency through a desired electric load profile (Behrangrad, 2015; Siano, 2014) for a predefined control period. Traditional DSM measures are mainly used to smooth the utility load profile, exploiting characteristics of some controllable loads. Generally, controllable loads can be classified into curtailable and shiftable loads (Schwaegerl et al. 2011, Wang et al. 2010). The first category refers to loads that can be reduced or switched off during specific time periods; the second one refers to loads that can be postponed to a later time
In an analogous way, a centralized actor manages the shiftable load (patient arrivals) among EDs acting as a smart grid that we label health smart grid. The DSM model can be applied for reducing the peaks load in the emergency department.

The centralized actor is an aggregator optimization load demand integrated with the forecasting problem of each ED. ED forecasting identifies and quantifies an expected load demand, and ED optimizes its internal scheduling. Knowing both the expected load of each ED and the total load of the system, the aggregator can plan the optimal strategy for the following day respect to day of demand forecasting. This is a short-term load management problem (Behrangrad, 2015; Boivin, 1995; Kinhekar, 2014; Mohsenian-Rad et al. 2010; Paulus and Borggrefe, 2011; Siano, 2014; Wang et al., 2010; Strbac, 2008): the input data are the forecasting data whereas the output is the choice of the best facilities to divert ambulance. As in energy smart grid, the model can work only if there is a collaboration among different EDs belong to the same smart grid. This collaboration is guaranteed as the decision-maker is not the single ED (as in the case of classical ambulance diversion solution) but a centralized actor aimed at minimizing the waiting time of the total network and not of a single ED.

The mathematical model

We apply the model of DMS, used usually to manage an electric smart grid, to reduce the peaks load in the emergency department, flattening the patient load among EDs.

The assumptions are the followings:

- patients are classified in four priority codes (white, green, yellow, red). The white and green codes imply low urgency to be admitted to the treatment area whereas yellow and red code are assigned to patients with a high priority. Each j_{th} code is characterized by an own lead time that is affected by a set of parameters (travel time, waiting time, treatment time). These parameters are influenced by the priority code;
- each patient's waiting time to be admitted to the treatment area is the sum of the travel time S_j, need to reach the ED, and the waiting time T_j of in the ED;
- each ED present the same number of patients;
- each area coverages the same population density;
- patients do not have preference with respect to EDs.

Considering the j_{th} code, the hourly patients $D_{SH_{t,j}}$ is expressed as:

$$D_{SH_{t,j}} = N_j \cdot d_{SH_{t,j}} \quad (1)$$

where N_j is the total amount of patients present in the network and available to be shifted; $d_{SH_{t,j}}$ is the shiftable amount of a single patient belongs to $j_{th,}$ assumed to be the same for all the codes. Finally, the profile of shiftable loads is added to the profile of fixed loads.

Let us define a suitable shifting model to be implemented into the general load management model. The relation between the loads before and after shifting can be represented through a binary variables $u_{t,j}$.

The condition $u_{t,j}$= 1 identifies the initial interval t where the j_{th} shiftable load starts to be supplied for the next S_j hours with *j* belongs to interval [0;24]. S_j represents the number of hours that each patient is available to wait for access to the treatment area.

Considering that the profile of the j_{th} shiftable load starts only once time, only a binary variable can be equal to one. We have that:

$$\sum_{t=1}^{T_j - S_j + 1} u_{t,j} = 1 \ \ (j \in \Omega_{D_{SH}}) \qquad (2)$$

Let us consider that $D_{SH_{t,j}}$ is the shiftable load of the j_{th} code at *th* hour, $d_{SH_{t,j}}$ is the shiftable load of the j*th* single patient at *th* hour, $P_{DSHt,j}$ is the shifted load of the j_{th} shiftable load at *th* hour.

The links between shiftable and shifted loads are:

$$P_{D_{SH_{t,j}}} = \sum_{s=1}^{t} D_{SH_{(t-k+1,j)}} \cdot u_{k,j} \ \ (j \in \Omega_{D_{SH}}; t = 1, \dots, T_j - S_j + 1) \qquad (3)$$

with $k = t_j - S_j + 1$

Moreover, only the first (T_j -S_j +1) binary variables can be defined because each $u_{t,j}$ variable is associated with the next (S_j +1) variables $P_{D_{SH_{t,j}}}$.

The value of $u_{t,j}$ depends on the objective function to be optimized

The objective function is to minimize the overall time, subjected to a set of constraints:

$$Min! \sum_{t=1}^{24} \sum_{j \in \Omega_G} (\alpha_{tr,j} T_{tr} + \alpha_{wa_{t,j}} T_{wa})] \qquad (4)$$

In (4), the weights $\alpha_{tr,j}$ and α_{wa} are linked by the priority codes. T_{tr} and T_{wa} represent, travel time and waiting time, respectively. The functions are assumed to be linear. $\alpha_{tr,j}$ and α_{wa} assume value in the interval [0,1], depending on the priority code. For example, red code has a greater priority therefore we set $\alpha_{tr,j}$ = 1 and α_{wa} = 0

Equality constraints are the balance constraints:

$$\sum_{j \in \Omega_G} P_{Gt,j} = \sum_{j \in \Omega_{DF}} P_{DFt,j} + \sum_{j \in \Omega_{SH}} P_{DSHt,j} \ \ (t = 1, \dots, 24) \qquad (5)$$

where Ω_{SH} is the set of shiftable loads; Ω_{DF} is the set of fixed loads and Ω_G is the set of the patients arrive at ED.

The constraints that express the links between shiftable and shifted load, are equations (2) and (3).

The Case Study

The proposed model is tested on a smart grid characterized by ED of 3 Hospitals located in Naples, namely for privacy concern H1, H2, and H3. The EDs' load and priority code distribution are the followings:

-H1 has a load of 29821 patients in ED, subdivided in 5127 white code (17%), 22826 green code (76,9%), 1829 yellow code (6%) and 39 red code (0,1%);

- H2 has a load of 24408 patients in ED, subdivided in 208 white code (0,9%), 17727 green code (72,6%), 6270 yellow code (25,7%) and 203 red code (0,8%);

- H3 has a total load 21866 patients in ED, subdivided in 128 white code (1%), 15588 green code (71%), 5792 yellow code (26%) and 358 red code (2%).

It is assumed that each ED have the same capacity in terms of resources available in the EDs.

In tab. 1, tab. 2, and tab. 3 load profile description, for each ED, are shown. The fixed load is composed by the red and yellow codes that are in the ED at time t; the shiftable load is the load that is possible to be posticipated, composed by white and green codes.

Table 1 – H1 ED's load description

Hour	$\sum_{j\in\Omega_{De}} P'_{De_{t,j}}$	$\sum_{j\in\Omega_{DF}} P_{DF_{t,j}}$	$P_{DSHt,j}$	$D_{SH_{t,1}}$ **(white code)**	$D_{SH_{t,2}}$ **(green code)**
1	780	49	731	134	597
2	780	49	731	134	597
3	800	50	750	138	612
4	800	50	750	138	612
5	800	50	750	138	612
6	850	53	797	146	651
7	830	52	778	143	635
8	900	56	844	155	689
9	1000	63	937	172	765
10	1000	63	937	172	765
11	1200	75	1125	206	919
12	1300	81	1219	224	995
13	950	60	890	163	727
14	800	50	750	138	612
15	800	50	750	138	612
16	1000	63	937	172	765
17	1243	78	1165	214	951
18	1500	94	1406	258	1148
19	1600	100	1500	275	1225
20	1750	110	1641	301	1340
21	1870	117	1753	322	1431
22	2329	146	2183	400	1783
23	2650	166	2484	456	2028
24	2300	144	2155	395	1760
TOT	29832	1869	27963	5129	22834

Table 2 – H2 ED's load description

Hour	$\sum_{j\in\Omega_{De}} P'_{De_{t,j}}$	$\sum_{j\in\Omega_{DF}} P_{DF_{t,j}}$	$P_{DSHt,j}$	$D_{SH_{t,1}}$ **(white code)**	$D_{SH_{t,2}}$ **(green code)**
1	500	133	367	4	363
2	500	133	367	4	363
3	600	159	441	5	436
4	600	159	441	5	436
5	650	172	478	6	472
6	680	180	500	6	494
7	730	194	536	6	530
8	750	199	551	6	545
9	750	199	551	6	545
10	800	212	588	7	581
11	800	212	588	7	581
12	900	239	661	8	654
13	970	257	713	8	704
14	1000	265	735	9	726
15	1100	292	808	9	799
16	1150	305	845	10	835
17	1200	318	882	10	872
18	1300	345	955	11	944
19	1400	371	1029	12	1017
20	1450	385	1065	12	1053

21	1550	411	1139	13	1126
22	1700	451	1249	14	1235
23	1800	477	1323	15	1307
24	1528	405	1123	13	1110
TOT	24408	6473	17935	208	17727

Table 3 – H3 ED's load description

Hour	$\sum_{j\in\Omega_{De}} P'_{De_{t,j}}$	$\sum_{j\in\Omega_{DF}} P_{DF_{t,j}}$	$P_{DSHt,j}$	$D_{SH_{t,1}}$ **(white code)**	$D_{SH_{t,2}}$ **(green code)**
1	400	113	287	2	285
2	450	127	324	3	321
3	500	141	359	3	356
4	500	141	359	3	356
5	550	155	395	3	392
6	600	169	432	4	428
7	650	183	467	4	463
8	650	183	467	4	463
9	700	197	503	4	499
10	750	211	539	4	535
11	800	225	575	5	570
12	900	253	647	5	642
13	800	225	575	5	570
14	650	183	467	4	463
15	700	197	503	4	499
16	750	211	539	4	535
17	800	225	575	5	570
18	900	253	647	5	642
19	1000	281	719	6	713
20	1200	338	862	7	855
21	1500	422	1078	9	1069
22	1714	482	1232	10	1222
23	2000	563	1438	12	1426
24	2400	675	1725	14	1711
TOT	21864	6149	15715	128	15587

Based on the load descriptions, we plotted the EDs' load profile in the pre and post-shift state. Fig.1 shows the total load for the EDs, composed by fixed load (red and yellow codes) and shiftable loads (white and green codes) in the pre- and post-shift state..

In the figure 1, the axis of the abscissas represents the daily hours while the axis of the ordinates the patients present in ED. We can notice that the post-shift load can be also higher than pre-shift load in some hours.

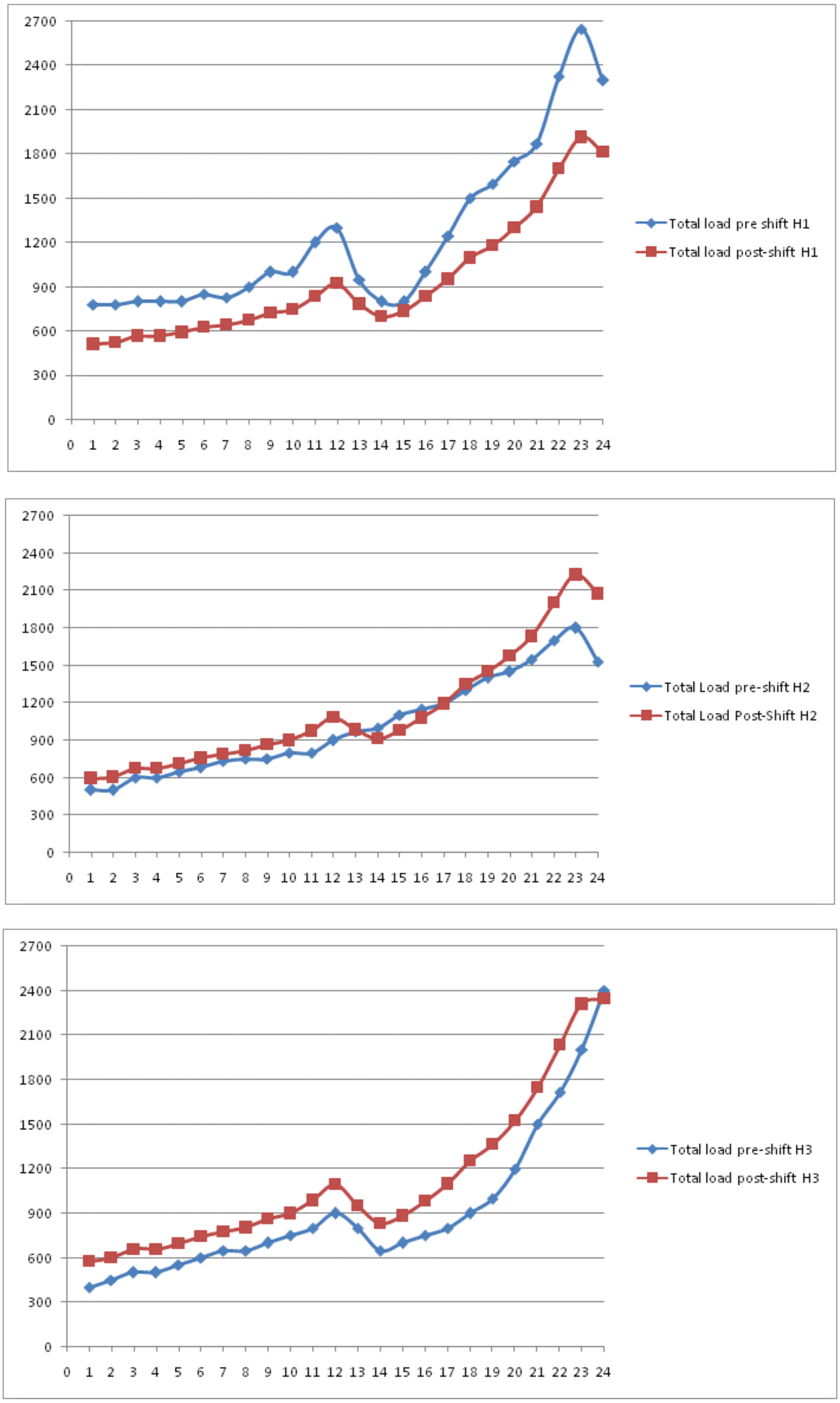

Figure 1 – Total Load pre and post shift for each ED

After the implementation of the model, all shiftable loads move from an ED to another one in each daily hour in order to obtain the lowest sum of travel and waiting time, namely total time. This is coherent with the model whose aim is to identify the optimal solution for the whole system and not for a single ED.

In order to quantify the variability of the load, we have computed the flattening indices, showed in table 4.

Table 4 – Flattening Indices

Index	H1		H2		H3	
	Pre-shift	Post-shift	Pre-shift	Post-shift	Pre-shift	Post-shift
Peak	2650	1914	1800	2225	2400	2343
Peak Variation		**-38,50%**		**23,7%**		-2,43%
Peak to valley	1870	1403	1300	1630	2000	1768
SQRT		1699		888		1082

The flattening indices are the followings:

- *Peak Evaluation* is the highest value of load in pre and post shift in the 24 hours;
- *Peak Variation* is the variation between the peak in pre and post shift;
- *Peak to Valley* is the difference between highest value (pick) and lowest value of the load in pre and post shift.

We notice that a significant peak variation is in H1 and H2. The model allows to redistribute the flow of patients above all between H1 and H2. The Peak to valley indicate that the peak among the three EDs has been smoothed.

This model allows to improve the efficiency of the system even if the efficiency of a single ED sometimes is worst. This confirms the idea that a centralized approach to network management improve the ED performances.

Conclusion

The ED overcrowding problem has been treated as a classical problem of load management considering the EDs as part of a health smart grid. The health smart grid is a network managed by a centralized actor whose aim is to distribute the patients, with different priority codes, to EDs. The optimization model is based on DSM, considered as an integral part of the optimal short-term management problem. In such problem, the variable is the allocation of shiftable loads to EDs. In the current version of the model, shiftable load concerns the green and white codes.

The health smart grid model works well in reducing the overcrowding under the following conditions:

- there is the presence of a difference between the maximum and minimum load;
- there is a notable percentage of shifted load from high load to low load;
- the flexibility to differentiate the load in different typology of codes
- the availability of the load to wait for the treatment.

We applied the model to a health smart grid composed by 3 EDs.

Even if it is not possible to prevent the access of a patient to ED, the model takes in account a capacity constraint of ED imposing α_{wa} equal to 1 to all patients, green and white, exceeding the capacity.

The results highlight that shaving the peaks is the more appropriate solution to overcrowding. We notice that the peak variation is high for some H1 and H2. In particular, H1 will be a negative variation of the peak whereas H2 a positive variation of the peak. In H2, there could be possible organizational problems connected to an higher request of nurses and physicians. This aspect will be investigated in the future developments.

Furthermore, the variation of the peak reveals also a preference of the patients towards H1 rather than H2. In the model, we have assumed that the patients are indifferent respect to ED. Future development of the model will be addressed to introduce a behavioral variable to keep in account the preferences of the patient.

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