Assessing Hospital Adaptive Resource Allocation Strategies in Responding to Mass Casualty Incidents

Abstract

Background

Hospitals are expected to operate at a high performance level even under exceptional conditions of peak demand and resource disruptions. This understanding is not mature yet and there are wide areas of possible improvement. In particular, the fast mobilization and reconfiguration of resources frequently result into the severe disruption of elective activities, worsening the quality of care. This becomes particularly evident during the ongoing Covid-19 pandemic. More resilient resource allocation strategies, i.e. which adapt to the dynamics of the prevailing circumstance, are needed to maximise the effectiveness of health care delivery.

Objective

In this study a simulation approach was adopted to assess and compare different hospital's adaptive resource allocation strategies in responding to a Mass Casualty Incident (MCI).

Methods

A specific set of performance metrics was developed to take into consideration multiple objectives and priorities and holistically assess the effectiveness of health care delivery when coping with a MCI event. Discrete Event Simulation (DES) and System Dynamics (SD) were used to model the key hospital processes and the MCI plan.

Results

In the daytime scenario, during the recovery phase of the emergency, a gradual disengagement of resources from the Emergency Department (ED) to restart ordinary activities in Operating Rooms and Wards, returned the best performance. In the night scenario, the absorption capacity of the ED was evaluated by identifying the current bottleneck and assessment of the benefit of different resource mobilization strategies.

Conclusions

The present study offers a robust approach, effective strategies and new insights to design more resilient plans to cope with MCIs. It becomes particularly relevant when considering the risk of indirect damage of emergencies, where all the available resources are shifted from the care of the ordinary to the "disaster" patients, like during the ongoing Covid-19 pandemic. Future research is

needed to widen the scope of the analysis and take into consideration additional resilience capacities such as operational coordination mechanisms among multiple hospitals in the same geographic area.

Keywords: Mass casualty (MCI); Resource allocation strategies; resilience; simulation; case study.

1. Introduction

Hospitals are vital assets for society, playing a crucial role in delivering high quality health care securing reliable emergency medical services. In case of disasters, the number of patients to be rapidly treated increases significantly and the disruption of healthcare ordinary services would result into more severe consequences for the population.[1] During disasters, in particular pandemics, there is an evident increased risk of indirect damage due to the shift of resources from the care of ordinary to disaster patients. The literature is already full of reports of acute as well as chronic diseases been neglected because the health systems facing a disaster. [2-4] Such reports are already appearing also in regard to the ongoing Covid-19 pandemic. [5-6]

In recent years, the concept of system resilience has been widely adopted to enhance the coping capacity against traditional and emerging threats to society. [7,13] A broad definition of resilience integrates all different capacities, notably "the intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances, so that it can sustain required operations under both expected and unexpected conditions".[14]

The concept of resilience is also recalled in several recent studies on continuity of medical services under pressures or shocks of any type, even though many of them just touch a few aspects of the problem.[15-24] A wider and comprehensive view on building resilience capacities in the healthcare sector emerged during the 2005 World Conference on Disaster Reduction,[25] when the model of 'safe and resilient hospitals" was promoted. Over the years since, there has been work conducted in the field of healthcare resilience directed towards the development of a consistent body of knowledge.[26-28] However, the research mainly focused on structural or functional hospital performance,[29-31] on organisational aspects, such as staff attendance in disasters,[32] on risks assessment,[33] disaster management,[34] or capacity improvement,[35] and only technical reports tried to offer a common framework for evaluating hospital resilience, starting from the "safe and resilient hospitals" model.[25]

Indeed, improving hospital emergency management procedures to respond and adapt to emergency conditions and rapidly escalate operations in the Emergency Department (ED) is not enough.[36,37] When a hospital organisation has to cope with a crisis, elective and urgent care activities are normally halted, since most of the available resources are redirected to the suddenly emergent needs.[38-40] The process of recovering to normal routine operations and the re-planning of halted activities takes time, which results into a worsening of the quality of care delivered to a wide spectrum of hospitalised and outpatients, even in critical conditions.[38-41]

This is why during the recent Covid-19 pandemic some Health Systems, like for instance the one of Lombardy Region, concretely modified the existing organization of the networks for the treatment of time-dependent clinical and surgical emergencies (STEMI, stroke, major traumas, neurological, cardiac and vascular surgical emergencies) and of the urgent oncological conditions, ultimately to avoid this indirect damage. [42-44]

According to some authors, instilling hospital resilience with a Business Continuity Management (BCM) perspective[45,46] is expected to improve hospital performance and quality of the healthcare system at large, as highlighted in seminal studies.[47-51] However, a comprehensive view of BCM practical integration is still lacking, since building hospital resilience means finding more effective ways of orchestrating the available resources to concurrently secure the best possible response to the surge of medical emergency service demand and minimising the disruption of critical and elective care delivery.

The aim of this study is to advance the knowledge and practice on hospital resilience, by identifying potential resource trade-offs in emergency situations and assessing different resource allocation strategies, oriented to preserve the continuity of ordinary and urgent medical services while securing responsiveness to the demand surge of emergency medical service. To this end, a simulation approach was adopted to study hospital's core healthcare delivery processes under routine and emergency conditions. The main objective was to compare different resource allocation strategies to respond to a Mass Casualty Incident (MCI), taking into consideration emergency, critical and elective care delivery processes. A specific set of performance metrics was developed to take into consideration multiple objectives and priorities. The study was conducted taking Ospedale San Raffaele (OSR), a large Italian hospital located in the Milan metropolitan area, as the empirical case.

2. Background

In the healthcare domain, an MCI is defined as "a sudden and unexpected event that generates a number of patients that exceeds the response capacity of the local health system".[52] The definition explicitly refers to both the number of patients involved, and the amount of available resources, and ultimately, "it is not related to any specific number of critically ill or injured individuals, or to any specific level of resources, but to the balance between resources and need".[53]

In the present study, the effectiveness of different resource allocation strategies in response to an MCI are investigated in the context of PEMAF (Piano di Emergenza per il Massiccio Afflusso di Feriti, according to the current Italian nomenclature) implementation in OSR hospital as a study case. The PEMAF is a setting of organizational and procedural provisions that allows a hospital to cope with an MCI, maintaining a standard of treatment of patients comparable to the one granted to the single patient.[52]

OSR is a private for profit hospital included in the Lombardy Region Health System. Because of the Region health policy, [54] OSR can accept private patients (paying the health care themselves or being covered by insurance companies) but also patients covered by the national health insurance. It is the biggest Italian health complex: 1200 beds general hospital (including almost all the specialties), medical research centre and university. The Emergency Department (ED) counts for around 200 visits per day (73.000 yearly). The admission rate from the ED to the inpatient wards is around 15% (11.000 per year). The rate of bed occupation is close to 90% for the surgical wards, 75% for the medical ones. OSR was selected for this study because it was previously involved in researches in the topic of hospital preparedness and management of MCI,[55] in particular related to the EU funded project THREATS (Terrorist attacks on Hospitals: Risk and Emergency Assessment, Tools and Systems. HOME/2013/CIPS/AG/4000005056)[56] and has developed a robust experience in this field.

In normal operating conditions trauma team's resources are devoted to the ordinary activities of the ED, which determines a condition of trade-off of the ED resources since they are devoted to different patients according to priority logic. This setting is suddenly changed with the recognition of an MCI, through the activation of PEMAF, to maximize the ED delivery capacity and properly treat the most critical patients. This requires the interruption of all the ordinary activities of the hospital: medical staff, spaces and devices normally allocated to the usual demand of patients are immediately shifted to the demand of the "disaster patients". [57] Therefore, a second trade-off emerges, between the ordinary activities of the entire hospital and those specifically required for managing the MCI, which is designed to assure the maximum possible responsiveness to emergency, without paying enough attention to the disruption induced on a wide spectrum of other hospital services. Consequently, the recovery to normal hospital service performance for taking care of the majority of patients - e.g. time waiting for services and the completion time of diagnostic protocols - may require weeks.

3. Hospital's response strategy to a MCI: current practice and possible alternatives

According with the SICUT guidelines,[52] PEMAF is commonly activated in two steps following a different procedure under daytime and night/holiday scenarios. During normal operating hours, in case of MCI alarm, a pre-defined portion of hospital staff, beyond the ED staff, is rapidly alerted and relocated to the ED. If the number of incoming patients significantly exceeds the available resources, specific hospital medical staff receives the signal to move to the ED and elective services and procedures are interrupted.

The activation procedure of the PEMAF is radically different during night or holiday times, when the specialized trauma resources (general surgeons, anaesthesiologists and Operating Room – OR - nurses), are at home on call and should be called in to create 4 different trauma teams in less than 30 minutes. If the number of incoming patients increases, a second level of activation is triggered which involves "all the available" staff, pre-selected to form a list of voluntary personnel (courtesy list). Besides the activation of additional resources, the PEMAF establishes procedural modifications at both ED level and in other hospital wards. (Figure 1)

Figure 1 Reconfiguration of processes at OSR Hospital during a MCI.

The PEMAF clearly states that its activation requires the interruption of all the ordinary activities. This means that all the scheduled surgeries are postponed to a date to be rescheduled, as well as outpatient activities and hospitalizations, at least in the daytime scenario. This does not apply during the night or holiday MCI when the abovementioned activities are absent.

3.1 Alternative resource allocation strategies for a daytime scenario

Regarding the daytime scenario, the investigation of the coordination between emergency and elective medical service delivery is of particular interest. The study considered the possibility to develop alternatives to the strategy stated in the PEMAF (also referred as the "As-is" strategy), i.e. activating and deactivating the reconfiguration of resources in one single step. The logic guiding such approach is that of guaranteeing the maximum service delivery capacity to the ED for a matter of prudence. It is in fact considered unacceptable to put the conditions of urgent patients at risk to guarantee ordinary non-emergencies procedures. On the other hand, the disservice induced to ordinary patients is the drawback of this strategy. When considering ordinary patients, in particular those scheduled for a surgery, the heterogeneity of the procedures and of treatments cannot be neglected. There are cases in which a delay represents a very significant issue, beyond the revenue loss for the hospital. The limitations of the "As-is" PEMAF strategy has been clearly confirmed by the revision of the management of a real event: the Pioltello train derailment[58]. The Pioltello incident has been also used as reference to set the scenario for the simulations campaign of this study.

Figure 2 shows the current strategy suggested by the PEMAF.

Figure 2 – Time profile of resource reallocation in case of MCI: a) PEMAF strategy (Baseline); b) Steps On-off strategy; c) Steps Off strategy

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Two alternative resource allocation strategies were explored and compared against the current one: they are named "Steps On-Off" and "Steps Off". The logic applied by researchers in designing these alternatives is grounded on the resilience principle of dynamic adaptation to changing demand or operating conditions. In particular, the aim was to determine whether a more gradual release of additional resources to the ED and restoration of normal operating conditions may limit the disruption of ordinary activities without worsening the capacity of the ED to promptly and fully respond to the MCI. A belt shaped arrival rate of MCI patients is the underlying assumption (Figure 2).

According to the "Steps On-Off" strategy, ordinary activities (in particular ORs activity and admissions to wards) are gradually interrupted, in more than one step. Consequently, resources, in particular medical staff, are switched from ordinary to MCI activities in a gradual manner. In the recovery phase, as long as the amount of patients arriving in the ED decreases over time, ordinary activities are resumed gradually as well.

According to the "Steps Off" strategy, ordinary activities (in particular ORs activity and admissions to wards) are suddenly interrupted, similarly to the current PEMAF strategy. In the recovery phase, ordinary activities are resumed gradually, similarly to the "Steps On-Off" strategy. The underlining logic is that the maximum amount of available resources is allocated to the ED as soon as possible, in order to respond to the sudden inflow of patients.

3.2 Alternative resource allocation strategies for the night/holiday scenario

The night/holiday scenario is the most critical one because of the limited available resources to sustain the hospital trauma capacity, either already on shift or that can be mobilized in few minutes; the OSR's PEMAF is mainly built considering this worst case scenario.

In the present study, a detailed analysis was carried out on the maximum capacity for high priority disaster patients (red and yellow codes) the ED is able to accept without reducing the level of care to non-disaster patients, with the available resources once the plan is activated. The aim is identifying the most critical resources and the best option for increasing the ED capacity. More specifically, taking the current PEMAF as a reference, alternative combinations of resources were analysed and compared by the researchers. In particular, an increase of one or two units of the following critical resources was considered: shock rooms; anaesthesiologists; general surgeons; entire trauma team; nurse and porter.

4. Study Methodology

4.1 Modelling approach and method

Model boundaries were set around the core processes related to the treatment of critical patients (red code), since they absorb the highest amount of resources. Starting from activities, procedures and resources involved in the ED, the focus was expanded modularly to those hospital areas that interact with the ED and generate synergies or trade-offs. The ED, the ORs as well as the critical wards were all set within the scope of the analysis.

Table 1 accounts for the main process parameters and the resources allocated to the ED and ORs respectively under normal operating conditions.

Table 1 – Main operational parameters and resources allocated to the Emergency Department (ED) and Operating Rooms (ORs).

The Operating block, includes 28 ORs, where general and specialized surgeries are performed. Elective surgical interventions begin at 8:00 a.m. and ends at 8:00 p.m., without any interruption. Among the 28 ORs, there is also 1 OR specifically dedicated to emergencies (24/7 logic). Each OR was modelled including the induction room (pre-surgery) and the recovery room (post-surgery), since it was considered as the appropriate level of detail for the aim of the study.

Other medical wards were modelled as a unique "black box", where hospitalized patients, outpatients in day hospital, or those who entered the hospital through the ED, spend a certain period of time and then are discharged. Incoming patients are: patients from ORs; patients from ICU; red code patients from the shock room; yellow and green code patients from the MCI and ordinary patients. The overall balance between the hourly inflow and outflow determines the level of saturation of wards beds that are subdivided into non-surgical and surgical.

Information regarding OSR activities was collected through a series of in-field visits and meetings with the Medical Officer Responsible for the PEMAF. A flowchart representing the main processes of each unit was the main output in this phase. Other sources of information were exploited as well, such as the database of patients treated in ED in the last two years (2017-2018) as generated by the ED information system. The availability of resources under different scenarios were estimated by taking into consideration the predefined shifts of the personnel and the information contained in the hospital PEMAF.

Discrete Event Simulation (DES)[59] technique was selected to model the ED and the ORs, to secure the full time tracking of each single patient. Other wards were modelled via System Dynamics[60] to represent the required balance between admitted patients and resources (beds and personnel). The two models were implemented into a unique integrated simulation model within AnyLogic® suite. The data presented in this study are completely anonymous. OSR Ethical Committee authorized the publication of the study's data on 10.06.2020.

4.2 Performance measurement of different resource allocation strategies

When it comes to quantitative studies on Emergency Medical Service Management, quality of care and time-related performance metrics are typically used. Chow et al.[61] proposes two different indicators for measuring quality of care in the ED: Adverse Non-Admit events and Adverse Hospital events; the first one is the number of patients who will suffer an adverse impact due to the inability to access hospital treatments in time, while the second refers to the number of patients who will suffer an adverse event while inside the hospital. Several studies refer to the "backlog" of patients, such as in Hirsh,[62] Manley & Hardy,[63] Yu Wang et al.[64] Measuring the proportion of patients who voluntarily leave the ED because of the delay in receiving a medical evaluation (the so-called "walkouts") is proposed by the General Accounting Office (GAO),[65] in a report published in 2003. Time-based performance metrics reported in literature are mainly of two types: the number of patients treated per time unit (e.g. Alsubaie et al,[66],; Lubyansky,[67]), and the patient's waiting time. Bayram & Zuabi[68] proposed the Injury to Hospital Interval (IHI) indicator, which is the time interval from the occurrence of the injury event to the completion of care to critical patients.

Patient waiting time is largely used in resilience studies to measure ED ability to provide emergency care to all the injured during a MCI (e.g. Cimellaro et al.,[69]; Cimellaro et al.[70]). Coherently, in the present study the patient waiting time parameter was selected as the key performance indicator. To account for different patients' critical conditions, importance weights of waiting times in different phases of the care path were assigned via experts' judgement elicitation using the AHP method,[71] a robust and widely used multi-criteria assessment method based on pairwise comparisons. In this way, priorities for waiting time minimization were set, as reported in Table 2.

Table 2 – Relative importance of waiting times for different patient categories during a MCI.

The importance of red code patients' waiting time before being admitted to shock room was considered incomparable to any other waiting condition. As it will be illustrated in the next paragraph, those patients who are not admitted in shock room in a sufficiently short time have been considered as "Patient-at-risk" and counted through a specific performance parameter (PAR). Normalized weights of the remaining 6 categories were used to create the "Weighted Waiting Time Index - WTI" indicator. WTI is computed as the weighted average of the waiting time of the last patient in queue for each patient class, that is:

$$WTI = \left(\sum_{i=1}^{n}(w_i * WT_i)\right)_t \quad \forall t \tag{1}$$

where: i = patient class, i.e. green, yellow and red code.

t = minute of the simulation run;

WT_i = waiting time of the last patient in queue of class i-th;

w_i = relative importance (priority) of patient i-th (Table 4).

Consequently, the WTI is expected to give a representation of the overall hospital performance dynamics along the simulation timespan: the lower WTI the better the ED performance. Grounding on WTI, two resilience indicators were developed:

- HR_k = Hospital resilience under different resource allocation strategies (k) or the baseline

$$HR_k = \int_{First\ MCI\ patient}^{Return\ to\ normal\ operations} WTI(t)dt \tag{2}$$

  which provides a quantification of the hospital's overall performance: the lower the value of HR_k the better the performance, provided the lower the peak of waiting time or the shorter the time to normal operations, or both.

- HRI_k = Hospital Resilience Improvement under different resource allocation strategies (k) against the baseline

$$HRI_k = \frac{HR_{Baseline}}{HR_k} \tag{3}$$

The higher HRI_k the better the considered response strategy in comparison to the baseline (i.e. the current PEMAF resource allocation strategy in the present study).

Moreover, the number of red code patients at risk (PAR) was assumed as an additional indicator to assess the performance of different alternative strategies. This parameter refers to the situations in which critical patients have to wait before accessing the shock room; it represents a very significant risk for a red patient leading to a catastrophic adverse event. In the simulation, these types of events are represented by red code patients (agents) leaving the queue before entering the shock room (through a cut-off exit time) after the time threshold of 15 minutes set by the Medical Officer Responsible for the PEMAF. PAR is a variable counting the number of cut-off events that occur in the simulation run. This index was evaluated against the expected number of PAR under normal operating conditions, assessed by a specific simulation campaign.

Considering the peculiar hospital's operational setting under the night scenario, performance was evaluated by means of three indexes:

- Red code patients at risk (PAR);
- Patients assigned to an incomplete team, so resulting in a lower level of care (LLoC); it refers to the possibility of reducing the standard quality of care, in terms of staff assigned to a single patient, to face a sudden increase of incoming patients at the ED, which is above the available resources;
- Maximum waiting time of red code patients to be admitted in the shock room (MaxWT).

4.3 Characteristics of the simulated MCI

The MCI assumed for all the simulation campaigns was conceived as a sudden onset external to OSR MCI, characterized by peak demand soon after the alarm but limited in time.

In order to consider a severe MCI, a sequence of patients was generated stochastically departing from the dynamics of a real event, a rail derailment incident that directly involved OSR on January 25, 2008.[58] On that date, a five-car train, with about 300 passengers aboard, derailed in the eastern suburbs of Milan resulting in a total of 133 patients managed by the EMS. In accordance with START triage (the triage routinely used by EMS in Lombardy in the case of an MCI), 3 patients (2,25%) were dead at the time of access to scene by medics (black code), 5 (3,75%) were red (highest priority for evacuation), 9 (6,76%) yellow (intermediate priority) and 116 (87,24%) were green (low priority).

Out of 133 patients, 78 (58,64%) were hospitalized. OSR represented the Trauma Center nearest to the scene of incident and received the most severe patients.

It was further assumed that no green code patients, more than the ordinary ones, arrive to the hospital from the scene of the event (either through EMS or self-presented). This hypothesis corresponds to a MCI that is properly managed by EMS as incident Type 2 according with Lennquist's definition.[53]

The generated sequence was recorded and replicated deterministically in every simulation, so as to simulate always the same event, which comprised 18 red code patients and 27 yellow code patients entering the ED in approximately 6 hours triggering time of the event were set when simulating the daytime (Tuesday, 17th September at 11:00 a.m.) and at night (Wednesday, 18th September at 02:00 a.m.) scenarios.

4.4 Calibration and validation

Two different methods were applied to validate the simulation model against the available data and the experience of the Medical Officer Responsible for the PEMAF.

For what concerns the green and yellow code ordinary patients' waiting times in the ED, a comparison of simulated data with real historical data under normal operating conditions was performed, using data recorded in the ED database in the period June 2017- June 2018 (total number of records: 70,012).

In table 3 the simulated demand profile is reported and compared to the real profile extracted from the OSR ED database. According to historical data, the simulated demand falls in the 0.75 percentile of registered peak demand and according to OSR PEMAF Medical Officer's experience it represents almost the upper bound of the total number of patients acceptable in the ED per week based on its current normal capacity. --

Table 3 also reports the comparison between simulated and real waiting time distributions of green and yellow code patients. Again, OSR PEMAF Medical Officer considered the simulated data satisfactory and adequate to capture and assess the real behaviour of the ED.

Table 3 – Simulated vs. real case demand parameters for a generic week at OSR ED: average number of patients by type; average waiting times of green and yellow code patients

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A focus group of experienced doctors and nurses from different OSR Departments (ED, OR, Wards) was involved in the validation of the simulation data generated by the remaining part of the hospital model, i.e. OR procedures and hospitalization in wards, under the guidance OSR Medical Officer Responsible for the PEMAF. Finally, the same focus group decided on the most effective way of implementing the alternative resource allocation strategies in the context of the simulated MCI, under the daytime scenario, provided that the available resource are those reported in the PEMAF for all the cases.

5. Results

5.1 Baseline scenario

Under stable normal operating conditions, OSR performance results into an average WTI of 32.11 min (95% confidence interval = ± 4.7 min). Only 1 patient at risk (PAR) was recorded in the baseline night scenario in 9 simulations, therefore baseline PAR is 0.11 on average.

5.2 Daytime scenario

Table 4 summarises the results of the first simulation campaign. For each one of the three response strategies, the HRI_k and PAR indexes were computed. HRI_k equal or close to 1 means that Hospital's performance loss is limited during a MCI and that the corresponding strategy proves to be effective. At the same time, PAR should remain as low as possible and close to the baseline.

Table 4 – Results of the Daytime scenario simulation – Values of the three different resource allocation strategies are reported in lines.

The graph reported in Figure 3 compares the WTI trends of the three alternative strategies.

Figure 4 depicts the time variability of the average WTI standard deviation of the "As-is" and the "Steps Off" strategies respectively.

Figure 3 – Results of the Daytime Scenario simulation: average hourly WTI of different resource allocation strategies vs. the baseline.

Figure 4 – Results of the Daytime Scenario simulation - Average WTI Standard Deviation of: a) "As-is" strategy; b) "Steps off" strategy

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5.3 Night scenario

Overall, nine different resource configurations were generated and ten simulations were run for each. An additional time-based analysis was performed to compare the PEMAF configuration against the best alternative resource configuration, i.e. adding one anaesthesiologist and one general surgeon (Avg. PAR = 3.90 patients; Avg MaxWT = 28.10 min; Avg LLOC = 3.00 patients). The aim was to better evaluate the capability of the ED to dynamically respond to the MCI over time. The temporal development of the MCI was analysed looking at the occurrence of situations in which red code patients are exposed to risk (number of red code PAR) or treated at a level of care lower than the standard (number of LLoC patients), as reported in Figure 5 – Results of the Night Scenario simulation - Temporal development of performance indexes: a) "As-is" strategy; b) improved strategy (additional resources: 1 Anaesthesiologist, 1 General surgeon).

Figure 5 – Results of the Night Scenario simulation - Temporal development of performance indexes: a) "As-is" strategy; b) improved strategy (additional resources: 1 Anaesthesiologist, 1 General surgeon).

5.4 Analysis of results

Daytime and night/holiday scenarios are radically different in terms of resource configuration and possible hospital's resource mobilisation in case of a MCI is declared, which cannot be generalised across scenarios; they have been investigated accordingly and now will be discussed separately.

As for the daytime scenario, when it comes with the waiting time performance (WTI), the proposed alternative resource allocation strategies ("Steps On-Off" and Steps Off") perform better than the current PEMAF "As-is" strategy. Indeed, the HRI value of "As-is" scenario is the lowest, whereas "Steps On-Off" returns the highest HRI value. However, its PAR (1.7 on average) is unacceptable because it is much higher than the threshold (0.11 on average). It can be argued that the "Steps Off" strategy is the best compromise, granting a relatively better HRI (0.66 > 0.60 on average) and the same PAR value (0.11 on average) of the "As-is" strategy. In other words, a gradual release of resources to the ED from ordinary activities, at the early stages of a MCI, is not able to grant an adequate priority and quick treatment to red code patients (higher PAR), even though it returns the lowest WTI. On the contrary, the "Steps Off" strategy shows some marginal improvement when shifting resources gradually back from the urgent to the ordinary activities. Particularly relevant is the possibility to reallocate some ORs to the most urgent and already scheduled elective surgical interventions. The possibility of limiting the disruption of pre-existing waiting lists for elective surgeries and of limiting time delays before hospitalization of non-critical patients, without worsening the capability of the system to absorb the demand pick induced by the emergency is coherent with the general criteria of PEMAF and the common healthcare management policies.[34, 31,37]

As for the night/holiday scenario, our simulation campaign returned a clear indication on the most critical resources and improving the operational capacity of the ED to properly treat red code patients. Adding one anesthesiologist and one general surgeon to the current configuration of a night shift ("As-is" strategy) is sufficient to significantly reduce the number of patients at risk (PAR), from 8.20 to 3.90, as well as the number of patients treated at a lower level of care than the standard (LLoC), from 5.40 to 3.00. Adding one entire trauma team would grant similar results (PAR = 3.50; LLoC = 3.20) but at a much higher cost.

A more aggregate assessment of the absorption capacity of the ED, and of the shock rooms in particular, can be achieved by looking at the time delay between the first arrival of a red code patient linked to the MCI and the first PAR within the ED, which represents a degraded care delivery condition. Under the "As-is" strategy the ED is able to absorb the demand pick with limited decrease in performance (few LLOC patients) for about one hour (first 4-5 red code patients), whereas under the "Improved strategy" the time delay expands up to one hour and half (first 6-7 red code patients). According to OSR experts the second one is perfectly compatible with the time needed to activate the PEMAF and then mobilize additional staff during a night shift.

6. Discussion

The ongoing COVID-19 pandemic pressure on hospitals is showing how responding to a medical emergency inevitably results into a worsening of the quality of care delivered to a wide spectrum of hospitalised and outpatients.[5-6, 38-40] This phenomenon is well echoed in the literature addressing hospitals' response to an MCI. [2, 4, 28, 41]

However, the growing discourse around hospital resilience,[25-28] has so far focused on the preparedness and response capacities to cope with the sudden surge of the number of incoming critical patients in the ED. In the present study a novel view was taken, trying to address at the same time the persisting needs of the other hospitalised patients, thus extending the investigation of a resilient response to a wider spectrum of hospital's healthcare delivery processes.

To this end, while extant literature limited the investigation of hospital resilience to structural or functional performances,[29-31] to organisational aspects - such as staff attendance in disasters[32] or disaster management procedures[34] – in this study specific attention was devoted to assessing the effectiveness of adaptive resource allocation strategies. The obtained results contribute to moving forward the development of hospital resilience against a MCI through a better mobilisation of resources able to preserve as much as possible less critical and elective activities.

The study considered the possibility to develop alternatives to the strategy stated in the PEMAF (also referred as the "As-is" strategy), i.e. in one single step. The logic guiding such approach is that of guaranteeing the sudden mobilisation of all the available resources for a matter of prudence. It is in fact considered unacceptable to put the conditions of urgent patients at risk while continuing ordinary non-emergencies procedures. On the other hand, when considering ordinary patients, in particular those scheduled for a surgery, the heterogeneity of the procedures and of treatments cannot be neglected. There are cases in which a delay represents a very significant issue, beyond the revenue loss for the hospital.

The single step strategy of activating and deactivating the reconfiguration of resources stated in the PEMAF (As-is strategy), guarantees the maximum service delivery capacity for the "disaster" patients, while the disservice induced to ordinary "non-disaster" patients represents its drawback. This becomes extremely evident when considering among the ordinary patients whom suffering for time-dependent diseases (trauma, stroke, acute myocardial infarction).

Along this line, the proved effectiveness of a dynamic resource allocation approach, able to better fit the intrinsic dynamism of an incident, may help in closing the existing knowledge and practical gaps when it comes to leveraging on BCM principles and practices[47-51] for enhancing hospital resilience in response to a crisis. Indeed, thanks to a more effective use of resource a wider spectrum of care processes can be supported even during the crisis and shorter but realistic recovery time objectives can be set as well. Beyond the practical value of the returned results, the present study also offers a possible methodological approach, based on Discrete Event Simulation and System Dynamics, for selecting and validating resource allocation strategies in advance, i.e. in the preparedness phase.

Also the economic implications of the achieved results are worth to be mentioned and advisable for further more specific investigation. Indeed, the proposed dynamic recourse allocation strategy for the day-time scenario is iso-resource when compared to the current strategy implemented in the PEMAF. Thus, the proposed alternative strategy is not only more effective but also more efficient, since it grants better care and higher revenues from elective procedures with the same level of operating costs. Similarly, the suggested improvement for the night-time scenario, i.e. adding one more trauma team, requires a relatively small amount of additional economic resources if compared to the revenue loss reduction granted by the continuity of elective care delivery. Future studies could address the economic benefits of dynamic response strategies in a quantitative way and enlarging the scope to a metropolitan or regional health system, where a cost-effective allocation of resources is even more challenging.

However, the dynamics of the hospital's performance during a MCI shows a common pattern; two waves of performance loss are observable, under any resource allocation strategy, that degrades the quality of care compared to normal operating conditions. The first wave translates the increasing saturation of resources at the ED that is later mitigated by the allocation of additional resources. Whereas, the second wave of performance loss is mainly due to the interruption of elective activities in the ORs and other wards and is always worse than the first. This dynamic clearly shows that there is a time delay before the hospital system enters a status of performance instability generated by the MCI demand. Interestingly, the time frame of this dynamic is invariant to different internal resources reconfigurations transients; thus, it is of more structural nature, depending on the healthcare process configuration and on the overall amount of available resources at hospital level. It can be concluded that further improvements could be only achieved by orchestrating resources between different hospitals in the area where the MCI occurred[72]. Further investigations are advisable to verify to what extent the adaptive resource allocation logics tested in the present study are still valid for orchestrating resources within a network of hospitals.

7. Conclusions

In the present study a simulation-based approach was adopted to select, validate and improve hospital's resource allocation strategies to MCIs. The study aimed at identifying strategies able to minimise the disruption of hospital elective activities while safeguarding the priority access to care for critical patients.

This seems to be a very relevant topic in today scenario represented by the Covid-19 pandemic. Although not qualifiable as a MCI, this is without doubt one of the worst disaster since the World War II, where the Health Systems of almost all around the world are facing the challenge to deal with the incredible pressure represented by the Sars-Cov2 patients but as well with the risk of indirect damage and the imperative to avoid to neglect ordinary acute and chronic conditions while shifting resources to the "disaster" patients.

The study originally contributes to the advancement of research on resilience and BCM in healthcare. It proposes a set of metrics to account for different objectives and priorities in the management of a MCI, along with a multi-method simulation approach enabling a suitable modelling of all the relevant hospital departments and functions.

The study provides relevant insights for practitioners as well. Simulation campaigns confirmed the general suitability of the current hospital approach towards the reconfiguration of resources to cope with an MCI (the PEMAF plan), which is primarily intended to guarantee the maximum care delivery capacity of the ED in the early stages of the event. On the other hand, it was demonstrated that a gradual reallocation of resources to ordinary activities in OR and wards minimises the disservice to elective surgical patients without any significant impact on red code patients. This alternative strategy proved to enable better hospital resilience both in terms of reduced waiting time (WTI) and patients-at-risk (PAR). In the night scenario case, when resource constraints are tougher, an efficient resource allocation and configuration strategy was identified that grants the minimum time delay needed for the mobilisation (call on duty) of additional professional resources.

Considering the different phases and waves of the ongoing Covid-19 pandemic and the need for the hospitals to be very flexible in resources allocation, a clear message of this study is that the anticipation of the needs should always be respected to avoid being unprepared when the surge in demand will arrive, but at the same time it is necessary to develop strategies alternative to the on-off one to re-allocate resources to the "non-disaster patients" as soon as possible.

The capacity to maintain an adequate level of treatment for the "non-disaster patients", at least for those with emergent conditions (time-dependent and urgent oncological diseases) during the pick of disaster patients, can only be addressed on a systemic point of view: the strategy implemented by the Lombardy Region[42], to modify the organization of the existing networks (STEMI, stroke, trauma and oncological) identifying few hubs and leaving the most of spoke resources available for the Sars-Cov2 patients, seems to guarantee some good results.[43-44]

The present study has some limitations. Firstly, it involved only one hospital; for the sake of generalisation of results, it is desirable to test the proposed strategies over a wider set of hospital's characteristics and MCI response plans. Secondly, the validation process of simulation data was conducted involving some experienced doctors and nurses from different OSR Departments and largely relied on the experience of the Medical Officer Responsible for the PEMAF; different and more robust validation protocols could be proposed in the future.

It has to be noticed also that modelling the resources to be mobilized in case of PEMAF activation only the specialized trauma staff has been considered: this makes a lot of sense considering how in case of a MCI this is the most significant limiting factor to actual as well as surge capacity.[55]

Despite this it cannot be silenced that other bottlenecks should be considered: even remaining in the staff domain we have to mention the support personnel (porters); the flow of patients from the ED gate to the final destination cannot of course exist without staff who care the transport. But we could as well mention many other well-known bottlenecks under the “stuff” domain, like ventilators, surgical sets, blood…

Future research should be directed towards network level analysis and simulation, along with the testing of alternative response strategies against MCI of different nature, with different time patterns and demand profiles.

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Figures

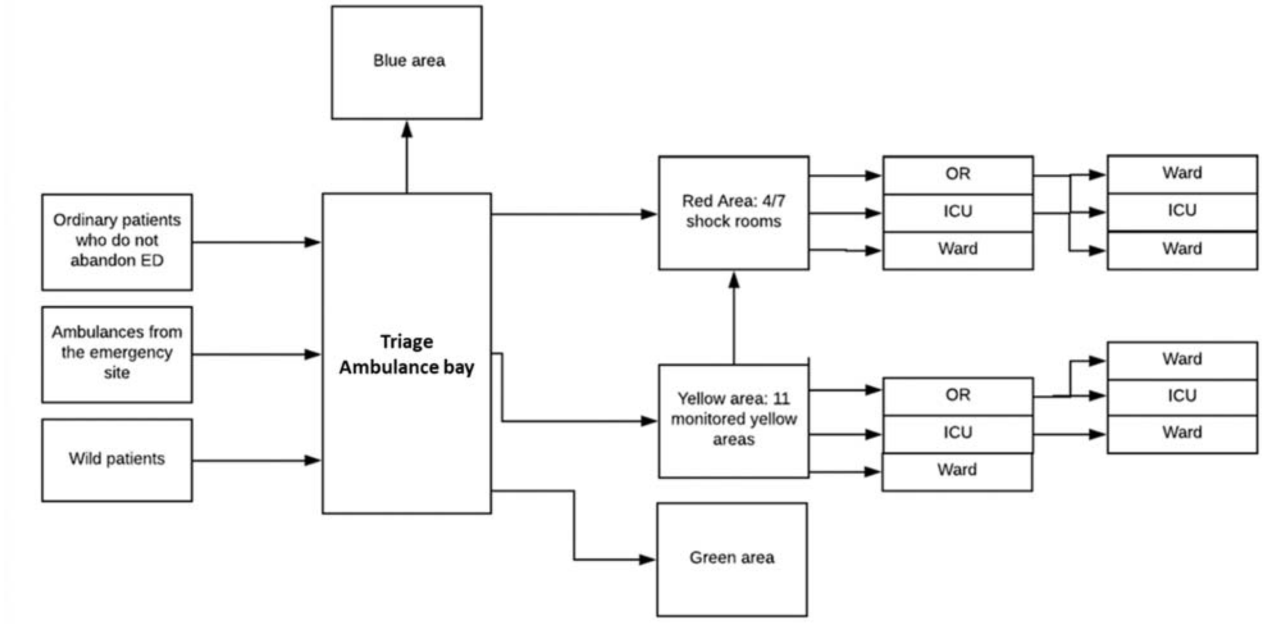

Figure 3 Reconfiguration of processes at OSR Hospital during a MCI.

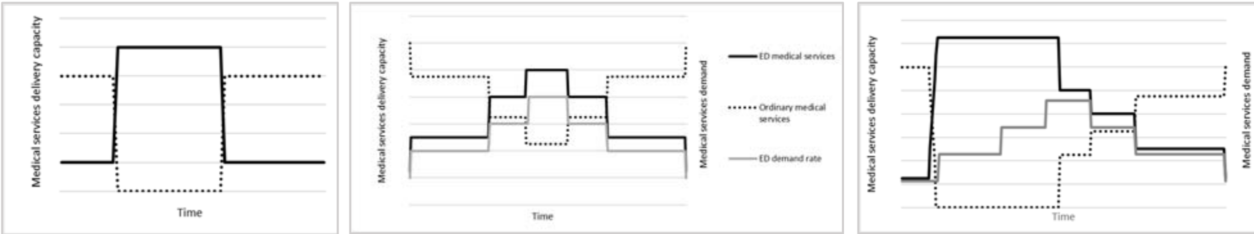

Figure 4 – Time profile of resource reallocation in case of MCI: a) PEMAF strategy (Baseline); b) Steps On-off strategy; c) Steps Off strategy

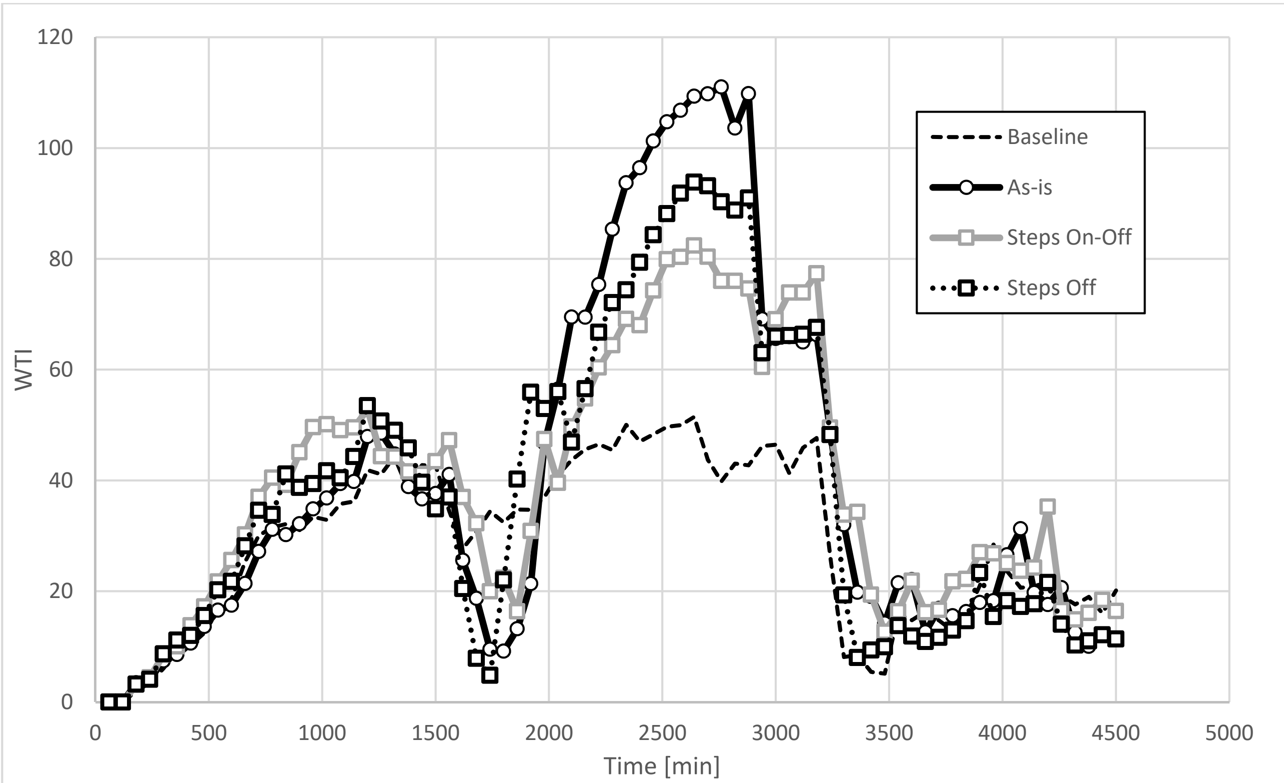

Figure 5 – Results of the Daytime Scenario simulation: average hourly WTI of different resource allocation strategies vs the baseline.

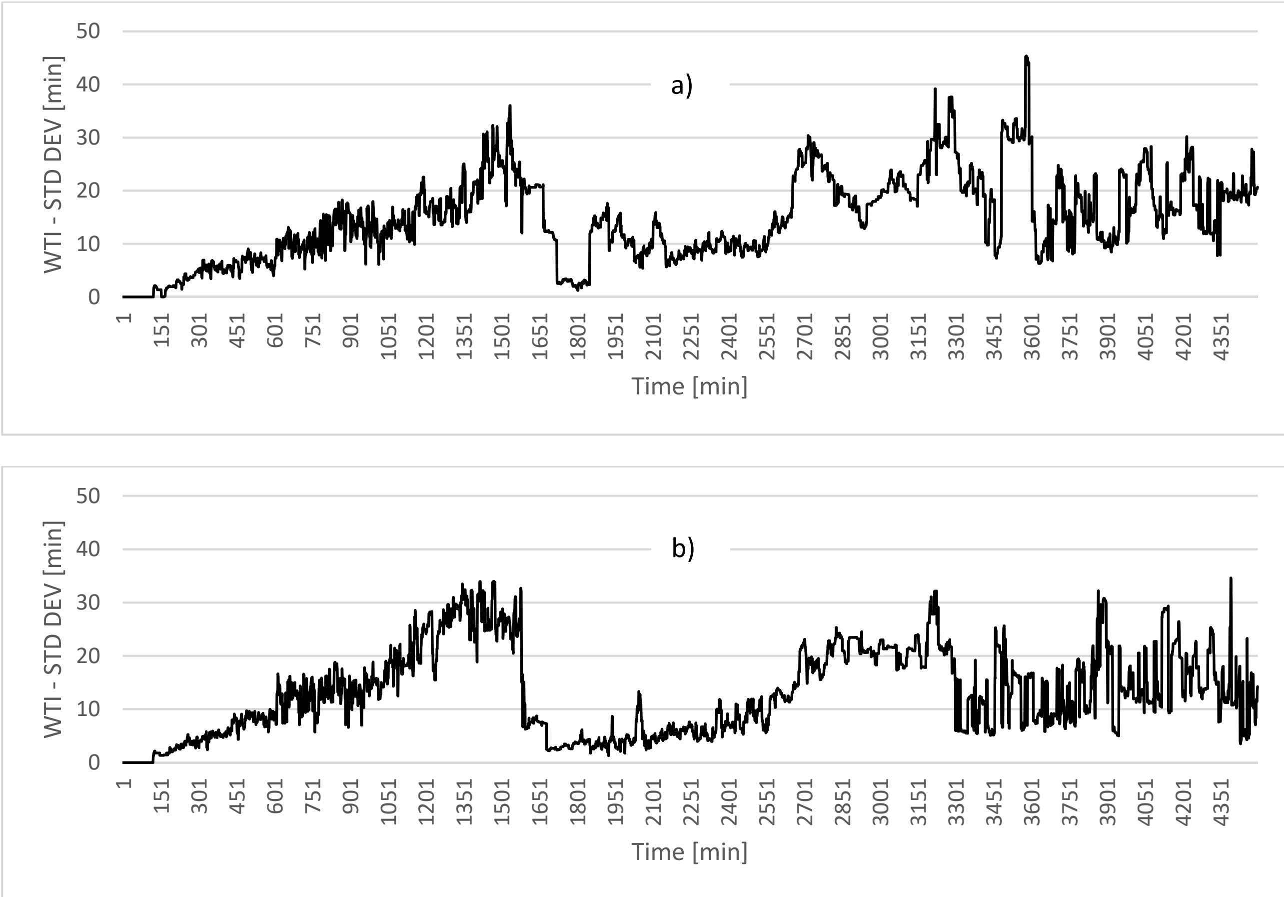

Figure 6 –Results of the Daytime Scenario simulation - Average WTI Standard Deviation of: a) "As-is" strategy; b) "Steps off" strategy

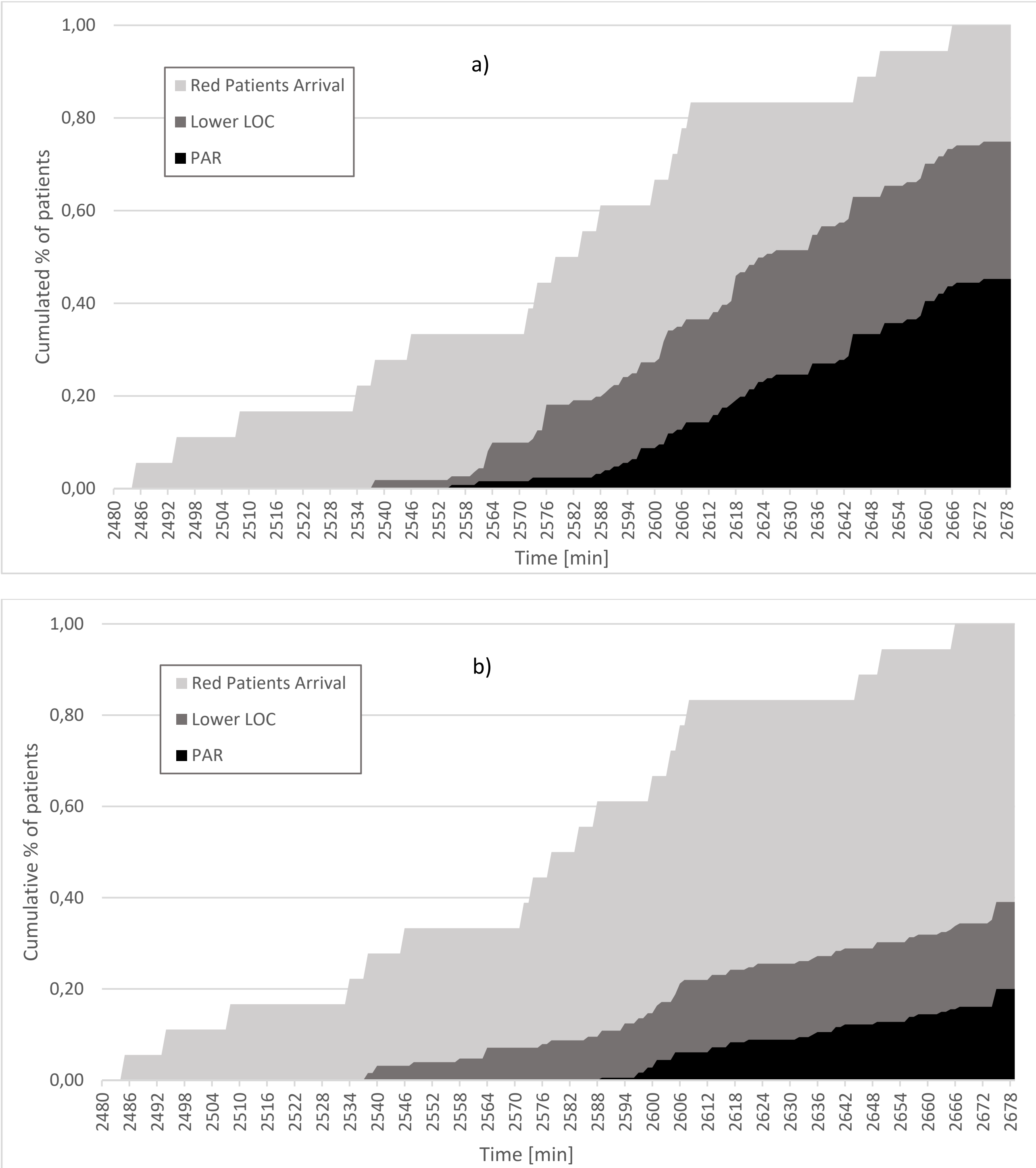

Figure 7 – Results of the Night Scenario simulation - Temporal development of performance indexes: a) "As-is" strategy; b) improved strategy (additional resources: 1 Anaesthesiologist, 1 General surgeon).

Tables

Table 2 – Main operational parameters and resources allocated to the Emergency Department (ED) and Operating Rooms (ORs).

Area		**Dedicated resources**	**Process parameters**
Emergency Department	Shock room	1 trauma team per surgical patient, composed of: 1 general surgeon, 1 anaesthetist, 2 nurses, 1 auxiliary operator; 1 trauma team per non-surgical patient, composed of: 1 internist physician, 1 anaesthetist, 2 nurses, 1 auxiliary operator; 1 instrumented room and one bed.	• Length of stay of a surgical patient: 60 min; • Length of stay of a non-surgical patient: from 60 min to 6 hours
	Medical area	• Monitored spaces; • Internist physicians (when the patient is just monitored the physician can treat multiple patients concurrently, so the ratio patient/physician is >1).	• Treatment: from 30 minutes (visited and discharged) to 24 hours (maximum period of observation in the ED).
Operating Rooms	Elective ORs	1 Ordinary general Surgeon; 1 Ordinary anaesthetist; 1 Operating room team of nurses; 1 specialist surgeon; 1 auxiliary operator; 1 OR for elective patients.	• Surgery duration modelled as a triangular probability density function (pdf) with parameters: 30, 60, 240 mins.
	Urgent OR	1 ED general surgeon; 1 ED anaesthetist; 1 Operating room team of nurses; 1 specialist surgeon; 1 auxiliary operator; 1 OR for urgencies.	• Surgery duration modelled as a triangular probability density function (pdf) with parameters: 30, 60, 240 mins.

Table 2 – Relative importance of waiting times for different patient categories during a MCI.

Class of patient	**Priority**	**Normalised Weight**
Red code patients waiting time before being admitted to shock room;	1	Incomparable
Red code patients waiting time before being admitted to OR;	2	0.555
Elective patients waiting time before being admitted to OR.	3	0.153
Yellow code patients waiting time before being admitted to ED rooms;	4	0.132
Yellow code patients waiting time before being admitted to OR;	5	0.088
Green code patients waiting time before being admitted to ED rooms;	6	0.036

General patients waiting time before being admitted to wards;	7	0.036

Table 3 – Simulated vs real case demand parameters for the OSR ED: average number of patients by type; average waiting times of green and yellow code patients

Parameter	Simulation [#/week]	Historical data [#/week]	MPE (%)
Total number of patients treated in the ED (average)	1400	1459	-4.04%
Number of Green code patients (average)	1000	1110	-9.91%
Number of Yellow code patients (average)	350	296	18.24%
Number of Red code patients (average)	50	53	-5.66%

Parameter	Green code patients			Yellow code patients		
	Simulation (average)	Real (2018-06-17)	MPE (%)	Simulation (average)	Real (2018-06-17)	MPE (%)
#pat WT < 60	55%	53%	3.7%	35%	46%	-23.9%
#pat WT < 120	65%	71%	-8.4%	51%	65%	-21.5%
Max WT [min]	761	837	-9.0%	420	369	13.8%

Table 4 – Results of the Daytime scenario simulation – Values of the three different resource allocation strategies are reported in lines.

Response strategies	HRI	PAR [pt/sim]
"As-Is"	0.60	0.11
"Steps On-Off"	0.72	1.7
"Steps Off"	0.66	0.11