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# COVID-19 Bed Management Using a Two-Step Process Mining and Discrete-Event Simulation Approach

Jules Le Lay, Vincent Augusto, Edgar Alfonso-Lizarazo, Malek Masmoudi, Baptiste Gramont, Xiaolan Xie, *Fellow, IEEE*, Bienvenu Bongue, and Thomas Celarier

**Abstract**—The sudden admission of many patients with similar needs caused by the COVID-19 (SARS-CoV-2) pandemic forced health care centers to temporarily transform units to respond to the crisis. This process greatly impacted the daily activities of the hospitals. In this paper, we propose a two-step approach based on process mining and discrete-event simulation for sizing a recovery unit dedicated to COVID-19 patients inside a hospital. A decision aid framework is proposed to help hospital managers make crucial decisions, such as hospitalization cancellation and resource sizing, taking into account all units of the hospital. Three sources of patients are considered: (i) planned admissions, (ii) emergent admissions representing day-to-day activities, and (iii) COVID-19 admissions. Hospitalization pathways have been modeled using process mining based on synthetic medico-administrative data, and a generic model of bed transfers between units is proposed as a basis to evaluate the impact of those moves using discrete-event simulation. A practical case study in collaboration with a local hospital is presented to assess the robustness of the approach.

Note to Practitioners: **Abstract**—In this paper we develop and test a new decision-aid tool dedicated to bed management, taking into account exceptional hospitalization pathways such as COVID-19 patients. The tool enables the creation of a dedicated COVID-19 intensive care unit with specific management rules that are fine-tuned by considering the characteristics of the pandemic. Health practitioners can automatically use medico-administrative data extracted from the information system of the hospital to feed the model. Two execution modes are proposed: (i) fine-tuning of the staffed beds assignment policies through a design of experiment and (ii) simulation of user-defined scenarios. A practical case study in collaboration with a local hospital is presented. The results show that our model was able to find the strategy to minimize the number of transfers and the number of cancellations while maximizing the number of COVID-19 patients taken into care was to transfer beds to the COVID-19 ICU in batches of 12 and to cancel appointed patients using ICU when the department hit a 90% occupation rate.

**Index Terms**—Discrete Event Simulation, Healthcare Applications, Process Mining.

Jules Le Lay, Vincent Augusto and Xiaolan Xie are with Mines Saint-Etienne, Univ Clermont Auvergne, INP Clermont Auvergne, CNRS, UMR 6158 LIMOS, Centre CIS, F - 42023 Saint-Etienne France

Edgar Alfonso-Lizarazo is with Université Jean Monnet Saint-Étienne, LASPI, F-42023 Saint-Étienne, France

Malek Masmoudi is with University of Sharjah, College of Engineering, United Arab Emirates

Bienvenu Bongue is with Université Jean Monnet, Chaire de santé des aînés, Centre Technique d'Appui et de Formation des centres d'Examens de Santé (CETAF) Saint-Étienne, 42000 France

Thomas Celarier and Baptiste Gramont are with University hospital, University Jacques Lisfranc, Department of Clinical Gerontology, Saint-Étienne, 42000, France

## I. INTRODUCTION

**B**ED management is a crucial matter in health care centers, and the occupancy ratio of medical units (MU) is an important indicator of performance for hospital managers. Keeping a small number of unoccupied beds is costly but necessary to address emergency admissions and patient surges. Resource sharing, through the creation of new MUs for example, makes sense to take into care patients with special requirements that do not fit in acute care and very specialized units, such as patients with multimorbidity.

During spring and autumn 2020, SARS-CoV-2 (coronavirus disease 2019, abbreviated as COVID-19) caused a massive increase in recovery unit requirement, compelling hospital managers to open new beds and convert others. To avoid the contamination of patients and staff in health care centers, dedicated units were created and isolated from the rest of the facility. Simultaneously, to provide additional staff and beds for this new COVID-19 pathway, other MUs had to cancel their scheduled admissions. Operational research and industrial engineering techniques, such as discrete-event simulation (DES), are useful to size such new organizations and test response strategies and their impact on the whole facility via a systemic approach.

To apply a systemic approach for MU sizing, we need to accurately model both COVID-19 and non-COVID-19 patients' hospitalization pathways. Process mining (PM) techniques can be used to analyze existing pathways based on available medico-administrative data in a health care center and to summarize the results into a graph. Such representation can be used to generate patient pathways for the simulation model.

The objective of this work is to provide a decision-aid tool for hospital managers and practitioners to help answer the following questions, taking into account the sudden surge of COVID-19 patients:

- How many and which planned patient hospitalizations should be canceled?
- How many resources from which MUs should be transferred to dedicated COVID-19 units ?

The scientific contribution of this article is threefold:

- 1) A new methodology using PM to learn from hospitalization pathway data and generate new patient matching with the population of interest is proposed. It automatically generates patient replicas from cohorts using medico-administrative data available in the hospital.

- 2) A generic hospitalization meta-model allowing the simulation of sequences of care within a hospital is designed.
- 3) A MU sizing approach combining patients' hospitalization pathways generated using our PM approach (1) and our hospitalization meta-model (2) is developed. DES is used to run test scenarios and manage the COVID-19 units.

The remainder of this article is organized as follows. Section II presents insightful related works and provides the positioning of this paper against the literature. Section IV presents the PM approach used to generate patients that will be used within DES. Section V details the modelling of the COVID-19 epidemics. Section VI describes the application of our method to the University Hospital of Saint-Étienne (France) before analyzing the results. Section VII concludes this paper and presents further research opportunities.

## II. RELATED WORK

### A. Healthcare Simulation and discrete-event simulation

As explained in [1], DES is a stochastic method of simulation in which individual entities pass through a network of queues and activities, and it is traditionally used at an operational level [2]. DES has been extensively covered in the literature, as [3] identifies DES as the second most commonly used simulation technique in health care systems and in a wide variety of scenarios. In a systematic review on DES articles published between 1997 and 2017, [4] identifies 4 main areas of use for DES: health and care systems operation, disease progression modeling, screening modeling and health behavior modeling. However, 65% of the 211 studies focus on system operations, which enforces the idea that DES is mainly used for tactical-level decision making. This category groups papers covering problems such as staff or patient scheduling, capacity management and evaluation of operational changes. A good example of operation modeling can be found in [5], where 3 case studies illustrate the use of DES as a financial evaluation tool or a decision tool for capacity planning. Similarly, [6] studies the impact of integrating HIV patients and general consultation in one department on waiting times and sets into relief the causes of the observed increase in patient waiting times.

DES studies in healthcare mainly focuses on the ED [4]. Indeed [7] identified 254 papers published on this subject between 2000 and 2018, with a strong increase in the last 10 years reviewed. The main investigation area found was the improvement of performance. Recently [8] used DES to evaluate the impact of organizational changes (like the addition of resources and caregivers) on performance metrics in the emergency department (ED)s of two Toronto hospitals. A generalizable DES framework for ED was presented by [9], and implemented on an Australian ED. However, some facility-specific processes must be explicitly represented in the model.

After ED, [4] notes that a high interest is taken in intensive care units (ICUs). Recently, [10] models an ICU department subject to planned and unplanned admissions. The DES model captures the patient flow in the ICU and assesses the capacities

needed to handle patients in the different specialties of the MU. Departments like ICUs are deeply connected to other units, and the solution for improving the patient flow can be found in the patient's pathway management. [11] test the effect of different control policies on the performance of an ICU department. The assessed policies are applied to the ED, MU and intermediate care units. For instance, postponing planned surgeries is one of the policies evaluated and considered as a viable option for the short-term handling of the pandemic.

Global models are rarely designed but are becoming more common [4]. "Whole hospital" DES models tend to study the main areas of the hospital, namely, emergency, medicine and surgery, with different levels of detail. Based on previous experience and an extensive literature review, [12] establish a 4-level classification of models, from generic to specific:

- 1) Broad 'generic principle' model, e.g., a generalized theoretical queuing model;
- 2) Generic framework that can be developed into a toolkit;
- 3) Setting-specific generic model, where specificity is ensured by a change in the input data;
- 4) Setting-specific model, i.e., not necessarily transportable to another provider of the same service.

[13] aims to provide a "macro level overview of the hospital system", where the main variable studied is the occupancy of the emergency, medicine and surgery MUs. Two additional units are modeled: the extended emergency care unit (designed for monitoring patients from the ED before being discharged), and the acute medical unit, an assessment unit for general medical and acute care elderly patients. The model is validated for daily operations and is intended to act as a decision aid tool for implementing organizational changes. However, this model does not take into account sudden increases in arrivals that can create crowding in the hospital. [14] design a model to evaluate such situations, called surges. The model focuses on the emergency, medicine and surgery units and is designed to test the impact of different policies on a set of variables describing the hospital's state. It designed in collaboration with health care centers but is sufficiently generic to be applied in other facilities, provided access to the required data. Since most hospitals share the same concerns of optimizing the use of available resources and managing patient pathways while running near capacity, generic models allow developers to save time by tailoring these pre-existing models to their needs.

The ongoing COVID-19 pandemic has caused a massive influx of patients in hospitals, most requiring prolonged hospitalizations in ICUs, thereby creating new challenges for hospital managers. In this context, [15] identify several areas where simulation modeling could support decision makers during the pandemic. Eleven decisions that could be assisted by simulation tools have been identified and mapped in terms of their area of impact and appropriate techniques. For operational management in the ICU, [16] propose an adaptation of their model to handle COVID and non-COVID patients in the ICU. In particular, they study the impact of capacity and arrival rates on the throughput of service to improve patient flow management. [17] developed in the early stages of the epidemics a DES model for decision-support on short-

term planning of beds in Navarre, Spain, a work that was extended in [18]. It calculates stochastically the number of beds necessary to face the patients influx in hospitalization and ICU beds. It does not take into account the operational decisions needed to make the beds available, but gives decision makers information on the likely hospital attendance on the short term.

Other studies combine epidemiological models with DES to study the COVID-19 epidemics and response scenarios. [19] and [20] both used variation of the SIR (Susceptible - Infected - Recovered) model to forecast the number of COVID patients to care for. [19] represented geographic areas as a red of nodes, each running a locally-tuned SEIR (Susceptible - Exposed - Infected - Recovered) model. [20] used a more advanced SEAIRD model (Susceptible - Exposed - Asymptomatic - Infected - Recovered - Death) in combination with multi-agent simulation to measure the effects of lockdown policies. Reinforcement learning is then used to determine the best lockdown resource allocation policy to adopt. The present article focuses mainly on challenges 6 and 8 identified in [15], i.e., hospital capacity and resource management, and aims to optimize the organization of a regional hospital, using DES as a decision tool.

### B. Process Mining for Trace Generation

PM is a relatively recent technique in business process management that has become popular in the past 15 years [21]. It combines data science and business process techniques to analyze operational processes from event data. The literature often divides PM into 3 main areas: process discovery, conformance checking and process business enhancement [22]. Processes in health care are complex, and decisions taken during a patient's stay depend strongly on the current state of the health care system and the patient's characteristics. Thus, PM can be seen as an opportunity to clearly identify processes using a comprehensible technique and to understand the global behavior of patients and underlying patterns. Overall, process discovery is dominant in the health care literature [23], [24]. As noted in [23], there is an opportunity to use PM techniques with multiple MUs or facilities, as it is most frequently applied for discovering health care processes in a single unit. This approach may be especially useful to identify macroscopic pathways and recurrent relations between services. Simulation is the most commonly used technique for process enhancement according to [23]. In particular, DES has been successfully used with PM on several occasions. In [25], event logs are transformed into DES models. From the study of the clinical pathway, [26] implement the resulting net of the PM approach in a hybrid agent-based and DES simulation model. The net is translated into an agent state-chart, and a simple DES model is then used for medical decisions in each state.

In this paper, we use PM to learn from historical hospitalization pathways data using a discovered graph to generate new patients matching the population of interest, taking into account macroscopic pathways and relations among departments.

## III. PROBLEM SETTING

A health care center is a complex system where patients, health practitioners, and administrative personnel interact frequently and use a great variety of supplies, such as medications, equipment or numeric devices to access patients' electronic files. Our objective is to provide practitioners a decision-aid tool to assess the effect of organizational changes on bed requirements in the hospital. Thus, we focus on a macroscopic model of the care processes of the hospital.

### A. Hospital Description

Since we focus on macroscopic care processes, we disregard the treatment of patients themselves, such as the administration of drugs, the nurse care episodes, and appointments with doctors. Thus, the hospital is a set of entities (MUs) that deliver care to patients.

A MU  $\mu$  is a medical entity dedicated to the care of patients with certain conditions. Each unit  $\mu$  is characterized by its identifier in the database  $id$ , its capacity  $c$  measured as the number of beds available, its type  $a$  regarding the present problem (see section V-C), and the length of stay distribution  $D$  in this unit. We formally define this agent as follows:  $\mu = (id, c, a, D)$ . Finally,  $H$  is the set of all MUs of the hospital,  $H = \{\mu_i | i \in 1..N\}$ , where  $N \in \mathbb{N}$  is the number of units in the hospital.

### B. Patient Description

A patient is an entity receiving care in the studied hospital, defined by the ordered sequence of stays in individual units. Let  $\pi = \{\mu_{i_j} | i \in \llbracket 1; N \rrbracket, j \in \llbracket 1; J \rrbracket\}$  be the pathway of a patient with  $J \in \mathbb{N}$  stays, where  $i$  is the unit index and  $j$  is the relative position of the stay in unit  $\mu_i$  in pathway  $\pi$ . The population of all patients is denoted as  $\Pi$  and is further divided into two subsets,  $\Pi_{em}$  and  $\Pi_p$ , corresponding to (i) patients admitted to the hospital after an ED visit and (ii) patients directly admitted into MUs. This distinction is made to take into account the difference in management of care between an emergency admission, which cannot be anticipated by the hospital, and planned stays, which are known before the admission of the patient.

### C. Hospitalization Pathway

Fig. 1 describes our generic hospitalization pathway using a Petri (or place/transition) net. It is a bipartite graph representing places (nodes of the net) and transitions (links between the places). Planned admissions are modeled using source transition  $t_p$ , while emergent admissions are modeled using source transition  $t_e$ . Place  $p_1$  models the stay in the ED, and place  $p_2$  models the stay in any unit  $\mu$  of the hospital. Transition  $t_{ED}$  shows the transfers from ED to other units, while planned patients transit directly to  $p_2$ . At this point, depending on the trace of the patient, the patient loops through a sequence of MUs (transitions  $t_1, \dots, t_{N_e}$ ) until the discharge (transition  $t_d$ ), still represented by place  $p_2$ .

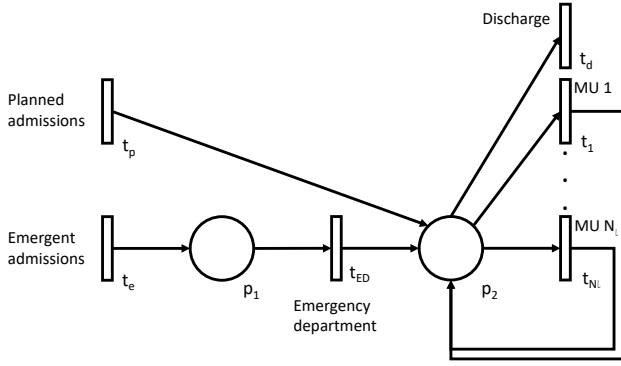


Fig. 1: Generic hospitalization pathway Petri net

#### D. COVID-19 units and COVID-19 patient pathway

In the present study, we aim to assess the effect of the admission of COVID-19 patients in the ICU on the care routine in the hospital. COVID-19 patients can be hospitalized in a dedicated ICU (named COVID-19 ICU), short stay unit (COVID-19 short stay), or in both unit in any possible order. The admission in each unit as well as the transfer probabilities between these units are calculated using the ScanCovid open data [27] provided by the ATIH (Agency for Information on Hospital Care). We also estimate the distribution of length of stay using the same ScanCovid open data.

#### E. Summary

In this section, we defined a generic hospitalization pathway using a formal Petri net model, which can be altered with one or more exceptional hospitalization pathway, such as the COVID-19 patient pathway.

### IV. PATIENT HOSPITALIZATION PATHWAY GENERATION USING PROCESS MINING

The methods and tools proposed in this article are intended to be used with commonly available medico-administrative data in a hospital. This section describes the method we propose to automatically turn a medico-administrative database into data that can be used to populate our model.

To use PM techniques, we first need to format the data information of all patients as event logs. The following section details this formatting and the further transformation into a graph. We also propose the trace generation process used in the simulation.

#### A. Process Mining

*Definition 1 (Event):* An event  $e = (l, \theta)$  is a couple of a label  $l$ , representing an activity, and the time of the event  $\theta$ , called a timestamp. Let  $N_\ell \in \mathbb{N}$  be the number of possible labels.

In this study, an event models a stay in a MU, the label giving the name of the unit and the timestamp corresponding to the date of admission to the unit.

*Definition 2 (Trace):* A trace  $\sigma = \langle e_1, e_2, \dots, e_{n_t} \rangle$ ,  $n_t \in \mathbb{N}$  is a chronological sequence of events linked by a unique identifier.

A trace represents the inpatient's sequence of stays in individual units that occurred between his or her admission and discharge.

*Definition 3:* An event log  $L = \{\sigma_1, \dots, \sigma_{|L|}\}$  is the set of all traces corresponding to the input data of the study, i.e., all included hospital stays.

We use the fuzzy miner algorithm from [28] to build a graphical representation of the process from the data stored in  $L$ . This graphical representation can be described as an oriented graph  $G = (V, C)$ , with  $V$  being the set of nodes in the graph and  $C$  being the set of oriented arcs. In addition, we impose that (i)  $G$  should have only one source node and only one sink node, (ii)  $G$  should be acyclic, and (iii)  $V$  contains as many nodes as event labels from  $L$ .

*Definition 4 (Frequency):* The frequency  $f(n_1, n_2)$  associated with an arc is the number of observations in  $L$  of transitions between MU  $\mu_1$  and  $\mu_2$  represented by nodes  $n_1$  and  $n_2$ .

*Definition 5 (Hospitalization process map):* A hospitalization process map  $\mathcal{H} = (V, C, P)$  is an oriented acyclic graph with

- $V$  the set of nodes,  $|V| = N_\ell + 2$ ,
- $C$  the set of oriented arcs,
- $P : V \times V \rightarrow \mathbb{Z}$  the function returning the probability to transit from one node to another,  $P(n_1, n_2) = f(n_1, n_2) / \sum_{k \in |V| \setminus \{n_1\}} f(n_1, k)$ .

A node of set  $V$  corresponds to a MU of the studied hospital, the label of our event. In addition, there are two particular nodes: the *source* node  $n_{source}$ , which is the fictitious origin point of all traces, and the *sink* node  $n_{sink}$ , which is common to all discharged patients. Thus, we have  $|V| = N_\ell + 2$ .

An oriented arc  $(n_1, n_2) \in V \times V$  represents possible transfers of patients between MUs  $n_1$  and  $n_2$ . From the data stored in log  $L$ , we are able to calculate the frequency  $f(n_1, n_2)$  of each transfer and the probability for a patient in MU  $n_1 \in V \setminus \{n_{sink}\}$  to be transferred to MU  $n_2 \in V \setminus \{n_{source}\}$ .

*Example 1 (Event log and associated hospitalization process map):*

Fig. 2 is an example of the conversion of a simple event log into a hospitalization process map. This example uses an event log describing the cases of 2 patients in a process with 3 activities.

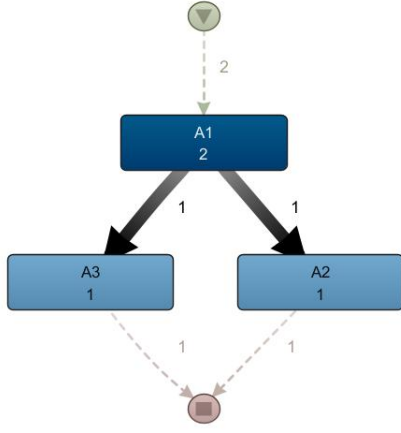
#### B. Trace Generation

Our hospitalization process map from *Definition 5* obtained using the PM algorithm is used during the simulation to generate patients similar to the modeled cohort (e.g., scheduled, planned, or COVID-19 patient hospitalization pathways). We use an automatic procedure detailed in Algorithm 1 to determine the patient's pathway  $\sigma = (n_1, n_2, \dots, n_{sink})$  using a hospitalization process map as input.

In Algorithm 1, we build an empty trace  $\sigma$  from the generated patient. For the first step of the stay, i.e., the admission of the patient to a MU, we build an ensemble  $\chi_0$  that contains all MUs directly following  $n_{source}$  in  $\mathcal{H}$  and their associated probabilities (see line 2). To complete the trace, we recursively

Fig. 2: Simple Event Log and Associated PM Graph Generated with Disco Software

Case ID	Timestamp	Activity
Patient 1	01/01/2021	A1
Patient 1	05/01/2021	A3
Patient 2	03/01/2021	A1
Patient 2	05/01/2021	A2



**Algorithm 1** Trace generation

- 1:  $\sigma \leftarrow \emptyset$  {Initialize  $\sigma$ }
- 2:  $\chi_0 \leftarrow \{e_{candidate} = (e_i, P(n_{source}, e)) | e \in V, P(n_{source}, e) \neq 0\}$  {Build  $\chi_0$ }
- 3: Select  $n_1$  among elements  $e_{candidate}$  in  $\chi_0$  following probabilities  $P$  {Select the first element of  $\sigma$ }
- 4:  $\sigma \leftarrow \{n_1\}$  {Assign to  $\sigma$ }
- 5: **while**  $n_{i+1} \neq n_{sink}$  **do**
- 6:  $i \leftarrow card(\sigma)$
- 7: Build  $\chi_i = \{e_{candidate} = (e_i, P(n_i, e)) | e \in V, P(n_i, e) \neq 0\}$  {Set of potential transfers}
- 8: Select  $n_{i+1}$  among elements  $e_{candidate}$  in  $\chi_i$  following probabilities  $P$  {Select the next stay in the trace}
- 9:  $\sigma \leftarrow \{n_1, n_2, \dots, n_{i+1}\}$  {Assign to  $\sigma$ }
- 10: **end while** {Repeat until discharge of patient}
- 11: Assign  $\sigma$  to the patient's trace  $\pi$

build the set of candidate stays  $\chi_i$  using the last element (stay in a MU) of the trace  $\sigma$  and select a new stay following the transition probabilities. The algorithm stops when the selected candidate element corresponds to the sink, i.e., when the patient is discharged.

*C. Summary*

In this section, we provided an automatic procedure to generate virtual patients similar to a cohort defined through an event log. For a real case application, the procedure described in table I could be applied by practitioners for all cohorts of patients of interest.

Step	Instructions
1	Extract medico-administrative data following inclusion criteria defined by health practitioners (e.g., all adults admitted to the hospital through the ED).
2	Execute a PM algorithm (such as fuzzy miner), adapted to the needs of the particular study, to obtain a hospitalization process map.
3	Execute Algorithm 1 to generate a virtual patient similar to the set of patients of the cohort of interest.

TABLE I: Procedure to apply the PM framework in a simulation study.

The following variables are necessary to execute this procedure:

- anonymous patient identifier,
- MU sequence to which the patient has been admitted,
- date of admission in each MU.

Our patient hospitalization pathway generation approach is different from a frequentist analysis, as filtering performed on the data modifies the transitions probabilities. In addition, the use of our approach allows the standardization of the patient generation process and simplifies its application to other healthcare centers. Using a different PM algorithm allows to capture different aspects of the pathway (the temporality of the sequence for instance). Finally, the output of our approach can be directly injected into the simulation module.

In our case-study, described in Section VI, we generate virtual patients to simulate the day-to-day activities that are disrupted by COVID-19 crisis. We extended this method in [29]. We generated 33% of the traces from the original dataset, using fuzzy miner, a 95% filter, 150 generated variants and no more than 2 occurrences of the same activity, resulting in a satisfying representation of the original dataset, as 21 variants represented more than 90% of the traces.

In the following section, we define the generic hospitalization model used for DES.

V. COVID-19 CAPACITY MANAGEMENT

The present article demonstrates how our simulation model can be used as a decision-aid tool to elaborate a response to the COVID-19 epidemics. This section is divided in four parts that describe covid patient admissions, the potential healthcare center's response, the experiment plan for fine tuning response policies, and the section's conclusion.

A. COVID-19 arrival patterns

First we focused on the accurate modeling of COVID patients. In this paper, we vary the COVID-19 patients generation pattern to test how it affects the system and the response strategy. Two admission strategies were tested. Since the ScanCovid data provide admission rates for the whole region, we scaled down the numbers to match the studied hospital's population pool. We modeled the first wave of COVID-19, that occurred in 2020 and the waves 2, 3 and the time interval between the two successive waves, which is characterized by a moderate admission rate. These arrival patterns model two interesting situations for healthcare professionals: a first scenario with a massive arrival of patients in a short timespan,

with similar initial and final situations without COVID patient admissions and a second scenario with two waves of admission separated by a constant and intermediate admission rate period.

**B. COVID-19 management rules**

As explained in III-D the hospital response to the arrival of COVID patients is the creation of a dedicated aisle, composed of two units: the COVID ICU and short-stay units. To allow care in this COVID-19 dedicated aisle, the hospital can activate two drivers: transfer beds from other units and convert them into ICU or short-stay beds, or cancel planned patients before their arrival at the hospital. The first driver allows COVID patients’ care, while the second reduces care activity in the units affected by bed transfers.

For this purpose, we divide MUs into four distinct types:

- $T_1$  : units that cannot be affected by COVID-19 episodes.
- $T_2$  : units in which planned patients can be canceled to make staff available.
- $T_3$  : units in which beds can be converted to COVID-19 ICU care.
- $T_4$  : units in which beds can be converted to COVID-19 short-stay care.

There are 4  $T_3$  units: the ICU and the 3 different surgery units.  $T_4$  units are all the hospitalization units with sufficient baseline capacity to maintain an activity on usual patients after COVID-19 requisitions.

1) *Resource reassignment*: The total number of beds that can be transferred from each  $T_3$  and  $T_4$  unit is defined upstream. We calculate the daily incoming and outgoing flow of COVID patients and decide whether the COVID services need more beds or if some beds can be redirected to their original MUs. The number of beds transferred from each MU is determined during the simulation depending on the number of available beds in each MU, the maximum number of transferable beds and the arrival and discharge of COVID patients. This process is further described in table II.

We consider that the transfer of beds and associated staff from  $T_3$  and  $T_4$  units takes 24 hours, which represents the work needed to prepare the beds and organize the staff’s work schedules. Available beds are set aside immediately for transfer, the rest are transferred when a patient is discharged from the unit. If the COVID service is full, the patients wait in a queue and are discharged if not admitted in the first 48 hours. We consider that the hospital decides the transfer of batches of beds instead of individual beds.

2) *Planned hospitalization cancellation*: The direct consequence of dedicating beds to the treatment of COVID-19 patients is the decrease in the number of beds available for the care of other patients. Indeed, we have seen during this pandemic that most hospitals had to delay planned hospitalizations in conventional MUs and make more staff available for COVID-19 units. We have modeled this by enabling stays cancellation before their admission to the MU. These cancellations only concern scheduled patients, as we can not predict and cancel emergency patients. We define two cancellation policies: (1) “By ICU”: the patient’s stay is canceled if the patient is admitted in a  $T_2$  unit and has a stay in

TABLE II: Necessary conditions to trigger the transfer of beds to or from the COVID-19 ICU.

Daily evolution <sup>a</sup>	COVID ICU Capacity	Occupation Rate	Action
$\geq 2$	0 $\neq 0$	- $\geq 95\%$	Add beds Add beds
$-1 \leq . \leq 1$ <sup>b</sup>	$\neq 0$ $\neq 0$	= 100% $\leq 75\%$	Add beds Remove beds
$\leq -2$	$\neq 0$ $\neq 0$	=100% $\leq 80\%$	Add beds Remove beds

<sup>a</sup> Daily evolution is calculated as the difference between the number of arrivals and the number of discharges over 24 hours.

<sup>b</sup> Beds are transferred if and only if the COVID situation stagnated for 3 consecutive days to stabilize the situation.

the ICU in his pathway, and the ICU occupation rate exceeds a percentage (that is an experiment plan parameter), or (2) “By Block”: the first stay of the patient is in a  $T_3$  unit, and the ICU occupation rate exceeds a percentage. These 2 solutions are tested in our experiment plan described in Section V-C.

For policy (1) the program looks at the whole generated trace of the patient and cancels his stay if the conditions are met. For policy (2) the program looks at the first hospitalization step only. These policies aim to cancel only scheduled patients with a high risk of using the ICU facility, for instance patients hospitalized in a service before a surgery.

**C. COVID-19 policy tuning**

As explained in V-B, to increase the capacity of ICU and short-stay COVID-19 units, the hospital rely on two drivers: using resources from other units and cancelling appointed patients. We intend to use the simulation model to test these policy parameters. We formalize here the elements of this experiment.

1) *Objectives*: Our experiment plan aims at finding which combination of values for the decision variables performs best when considering the following objectives:

- $O_1$  Maximize the number of COVID-19 patients admission.
- $O_2$  Minimize the impact on day-to-day activities by closing as few beds as possible in MUs.
- $O_3$  Minimize the number of time windows dedicated to bed transfer that the hospital has to set up.

Objectives  $O_1$  and  $O_2$  ensure that the COVID situation is handled while reducing its impact on the day-to-day activities of the hospital. Objective  $O_3$  reflects the fact that transfers are costly and arduous to implement, as they involve the administrative and medical staff, as well as the supply chain of the hospital to provide the additional furniture.

In the simulation we keep track of the following performance indicators to evaluate how these three objectives are reached:

- 1) the number of rejected COVID-19 patients,
- 2) the number of elective hospitalizations canceled during the course of the simulation
- 3) the numbers of ICU and short-stay transfer windows.

These indicators are summed and normalized to establish a score  $s$ , between 0 and 1, that reflects the relative performance of the response scenario.

2) *Input variable*: The input variable defining the problem to solve is the COVID patient arrival pattern as defined in V-A.

3) *Response variables*: The drivers identified above are represented in the simulation as a set of variables, that altogether define the response of the healthcare center. The first is the bed transfer batch size. As explained in subsection V-B1, we transfer beds from  $T_3$  and  $T_4$  units in batches. We chose for this variable the possible following values: 4, 6, 8, 10 or 12. This value is chosen independently for ICU and short-stay transfers. The second and third response variables define the cancellation policy. One is the policy choice as detailed in Section V-B2. The other is the occupation rate of the ICU beyond which we cancel patients. This value is therefore referred as the 'cancellation cutoff point'. 4 possible values are defined: 80%, 85%, 90% and 95%. They allow to either keep more beds available for potential transfer, or dedicate more beds to the care of usual patients.

Covid Arrival pattern	ICU Bed Batch size	Short-stay Bed Batch size	Cancel-lation policy	Cancel-lation cut-off point	Nb of experi-ments
Wave 1, Waves 2 & 3	4, 6, 8, 10, 12	4, 6, 8, 10, 12	By ICU, By Block	80%, 85%, 90%, 95%	400

TABLE III: Summary of explored valued for input and response variables, and total of resulting experiments.

#### D. Summary

In this section, we detailed the settings of the COVID epidemics as well as the possible response of the healthcare center as used in the simulation. We formulated the main elements of the problem: the objective through the normalized score  $s$ , the input of the COVID arrival pattern, the mechanism behind the bed transfers and behind the cancellation of planned patients.

## VI. CASE STUDY: COVID-19 CARE UNITS OF THE SAINT-ÉTIENNE HOSPITAL

### A. Background

Saint-Étienne’s University Hospital (CHUSE) is a university hospital of 60 MUs at the head of a large health care network named the Loire Hospital Group (GHT, *Groupement Hospitalier de Territoire* in French). CHUSE has 1,802 beds in total. In 2020, CHUSE admitted 93,905 patients for hospitalization and 78,400 patients were seen in its ED.

Regarding COVID-19 activity, CHUSE hosted 2,161 COVID-19-related stays, including 285 stays in ICUs. At the peak of the crisis in November 2020, 365 beds (resp., 46 beds) were dedicated to COVID-19 patients in MUs (resp., in ICUs).

### B. Data

1) *Patient Data*: The patient data we used for the present study were generated specifically for the purpose of this study by mimicking adult patient pathways. It comprise a case mix of rather simple pathways for each MU (direct admissions with no transfers or emergency admissions with a transfer to

one unit) and complex stays (initial stay in a unit, transfer to surgery and ICU, or random transfers between units). The data use the format of the medico-administrative hospitalization database (PMSI, *Programme de Médicalisation des Systèmes d’Information* in French), to be easily applicable for other studies. We generated the hospitalization process map from this synthetic database and used it to populate our model with “regular patients”.

Medico-administrative databases hold rich and useful information about health care pathways at an individual level: visited units, received medical exams and treatments, length of stay in each unit etc. In addition, historical data are readily available for longitudinal analysis of care trajectories.

Accessing this data for all patient and linking it to the pathway is technically complex. To address this situation, we hypothesized that the pathway of each patient was representative of his or her personal situation.

Thus, the sequence of individual stays in the units and their stay information is all the information required to model the patients admitted. We generated the following elements for each synthetic inpatient:

- anonymous patient identifier,
- MU sequence to which the patient has been admitted,
- date of admission in each MU,
- length of stay at each MU of the sequence,
- admission modalities and origin of the patient.

Only adult patients were modeled: outpatients (e.g., patients coming to the hospital for chemotherapy or dialysis) and ambulatory visits were generally not considered, as we considered ambulatory units outside the scope of this study, unless a second stay was generated, to mimic the detection of critic situation by ambulatory units staff.

2) *Medical Units Data*: The partner hospital provided us with a detailed list of the MUs. Ideally, we would use the exact staff and setting of all those units; however, those figures are constantly evolving. The capacities  $c$  were defined using the last reliable number of beds opened in each unit at the beginning of the project. This was during the last consolidation of numbers in December 2018. The length of stay distribution  $D$  and types  $a$  of each MU were defined by our medical experts.

### C. Model implementation

The PM approach was implemented using Disco® software, while the Petri net hospitalization models were implemented using AnyLogic® simulation software.

Patients and MUs are implemented as agents. Each step of the pathway is implemented using a delay block for which the delay time is determined by a triangular distribution. We keep track of the occupancy of each unit with the corresponding variable when patients enter the process block. If a MU is full, patients wait in a queue. In the case of a transfer from one MU to another, the patient remains in his or her current unit until a bed is available in the destination MU.  $[T_2]$  and  $[T_4]$  are noted on the simulation model using boolean parameters, while  $[T_3]$  are directly identified and used in the bed transfer functions.



Urgent patients all go through the ED before following the hospitalization pathway. This ED stay is represented by a delay block with a delay time determined by a triangular distribution between 0 and 6 hours with a mode of 3 hours. These patients are then redirected to the main part of the hospital to complete their stay.

Elective patients are directly routed toward the hospital's MU after the trace's assignment.

For both categories of patients, we estimated the mean number of arrivals for each day of the week with hospital professionals. Those figures are uploaded to the model's database in the form of two schedule objects that are used to set the arrival rates for the two sources of patients.

#### D. Experimental design

As explained in III-D, we implemented 2 different arrival patterns based on the history of the COVID-19 epidemics. The first pattern is based on the initial wave of COVID-19, that occurred in April and May 2020. We limit the wave to 104 days between the first admissions and the end of the wave (close to zero arrival rate). The second pattern mimics the waves 2 and 3, that were separated by several week with a high and almost constant admission rate at the hospital. It consists in 2 epidemics spikes with a high arrival rate between them. This second pattern is 320 days long. The simulation's length is set to 550 days to allow simulation warm-up, experiment and return to initial situation. The hospital is initially empty. The first 90 days are used as a warm-up period, at the end of which we start to measure hospital status indicators, such as the mean occupancy rate in the MUs and indicators about the pandemic: length of stay in the MUs, number of non-admitted patients, etc. The data was accessed for the entire AURA region and scaled to the population pool of Saint-Étienne. Due to confidentiality concerns, we accessed the weekly number of admissions only.

Fig. 3 displays the number of COVID-19 patients cared for in the dedicated units, the capacity of the COVID units and the changes of capacity in the impacted non-COVID units for the wave 1 scenario as described in Section VI-E.

The efficiency of the COVID-19 response scenario is measured through the following figures that corresponds to objectives described in III-D: (i) the number of COVID-19 patients that could not be admitted, (ii) the number of elective hospitalizations that were canceled and (iii) the mean occupation ratio in the hospital. The global performance of the scenario was assessed by normalizing these 3 values to make them comparable, summing them and dividing the result by 3 to obtain a score between 0 and 1. We aim at minimizing the obtained score. Indeed, our goal is to take into care as many COVID patients as possible, while canceling as few conventional hospitalizations as possible, and having as few bed transfer windows as possible to relieve staff.

The input and response variables are described in V-C. The 400 experiments were assessed using the simulation model, with a 100 replications to achieve a 95%-confidence interval.

#### E. Results

1) *Generation of Patients Using Process Mining*: We generated process maps to generate patients in the non-COVID department of the hospital, both for the elective and emergency admissions processes. The simplified process map that was generated using the synthetic data for emergency admissions is shown in Fig. 4a, and that for elective admissions is shown in Fig. 4b.

The emergency patient process map was generated using only the 90% most frequent cases to filter the most unusual cases. This particular value was chosen to exclude unique and non-representative interactions between units and only keep in the process map links made by more than one patient. This choice was driven by the relatively high proportion of unique hospitalization pathways in the dataset. We display the 30% MUs and the 50% most frequent paths between MUs for readability purposes. For the same reasons, the elective process map displays only the 30% most frequent MUs.

The elective patient process map is dominated by a direct path: patients are admitted into their scheduled unit and are discharged. Cardiac surgery is also a well represented unit. This result was expected as our synthetic population was composed of mainly one-unit stays and elective surgery pathways. The urgent patient population requires a wider variety of MUs. Our synthetic population was targeted to consume ICU and surgery resources in priority, while other pathways were similar to elective patient pathways with an additional step for post-emergency treatment.

Full maps were exported in XML format, and we applied algorithm 1 to generate 100,000 patients from each map.

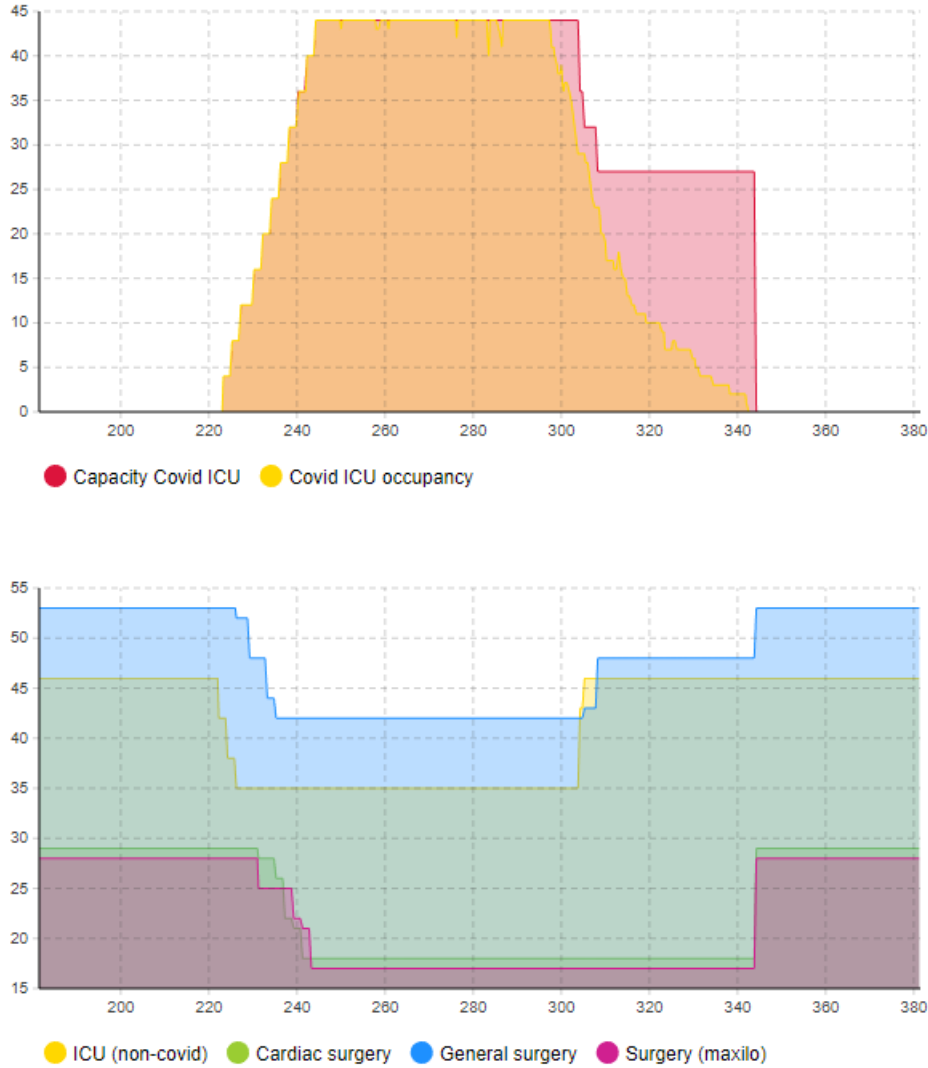
2) *Sizing Experiments*: Via simulation, we ran all the scenarios induced by the variation of parameters described in Section V-C. Notably, the number of COVID-19 patients rejected is higher than the number of elective patients that must be canceled. This can be explained by the relatively low occupancy rate of the ICU (from 60 to 70 %), which allows us to transfer beds without affecting the unit's ability to host elective patients.

Table IV displays the response scenario that is best suited to each situation when considering the trade-off between the number of elective stays canceled and the number of rejected COVID-19 patients.

When taking a closer look at the results, we can observe that the 'By Block' policy is almost always less effective than the 'By ICU' policy, mainly because it logically results in more cancellation of elective stays. The best performing 'By Block' strategy for wave 1 scenario, 12 and 6 beds batches for ICU and MCO transfers respectively, and a 0.95 cutoff point for patient cancellation, has a score of 0.508, while the 'By ICU' cancellation strategy with the same parameters has a score of 0.468.

To conclude, the simulation model is intended to be used by practitioners as a decision-aid tool. Depending on the characteristics of the pandemic (COVID-19 arrival rate, time frame, etc.) and of the hospital, the tool provides meaningful insights to help practitioners make the best decisions regarding cancellation policy and the quantity of resources to transfer to COVID-19 units.

Fig. 3: Occupation and capacity of the COVID ICU when using wave 1 arrival pattern.



### VII. CONCLUSIONS AND PERSPECTIVES

The present research describes the development of a macroscopic simulation model of a health care center for the study of patient pathways. Automated generation of pathways from a graph proved to be a viable option for the simulation studies and presents some advantages. First, using PM to generate an agent’s pathway in the simulation increases the variety of pathways included in the model, as simulation studies often use a small number of pathways, usually the most prevalent pathways, while our approach allows modelers to take into account less frequent interactions. In addition, using PM could simplify the development of such models. When implementing the simulation in a new facility, applying a standardized PM approach allows to fuel the model with a formatted and comparable input. The impact of the different parameters used for PM on the simulation must be investigated further to determine the best settings of the simulation.

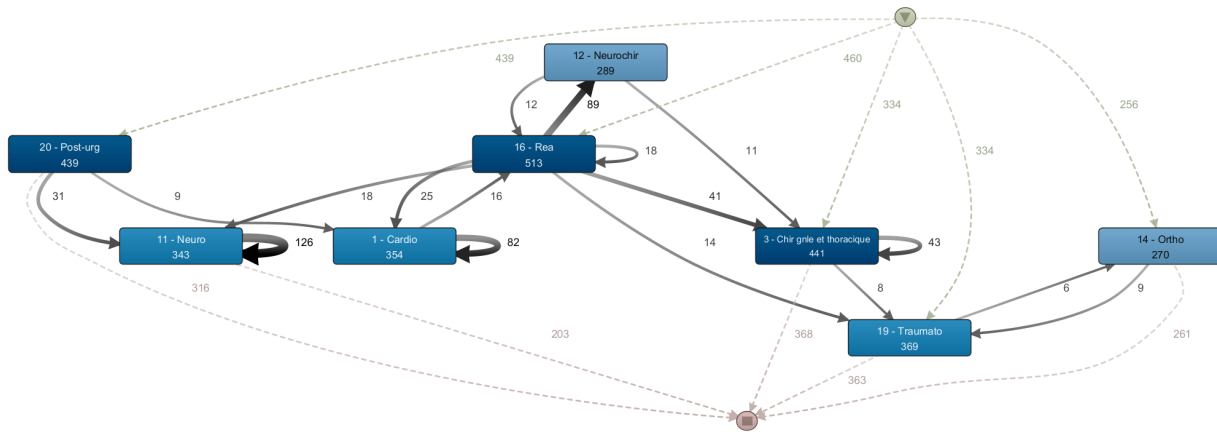
The application of the model when considering organizational changes is also interesting. For the example of the management of the pandemic, this model could be used to help

the hospital decide whether opening a new MU in the next weeks would be beneficial. For instance, simple admission projections, like temporal series or polynomial functions based on epidemiological data, could easily be implemented and a close study using the model would provide the modeler insights into how the resource allocation to the COVID-19 dedicated units will help absorb the sudden admission of COVID-19 patients.

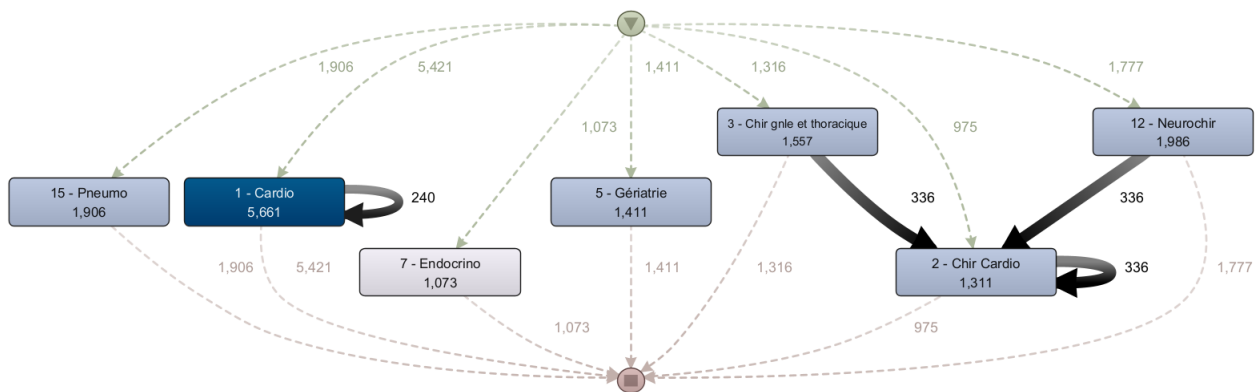
When using the present model, one should note that the results described in Section VI-E are not to be seen as gold standards when confronted with this type of situation. Each set up should be carefully studied and implemented in the simulation before being applied. We recommend using this model by first implementing actual predictions about the epidemic before proceeding in a two-step process: (i) create an experiment with a possible response and (ii) adjust the implemented response according to the results and the available resources. This model should be updated on a regular basis using the latest epidemiological data and observations from the field.

Fig. 4: Simplified Process Map Representing our Synthetic Data, Generated Using Disco® .

(a) Simplified Process Map of Emergency Patients.



(b) Simplified Process Map of Elective Patients.



The present article aims to demonstrate the potential of the model when representing organizational problems. The experiments were designed to do so, and some of the simplifying assumptions are quite strong and not fully representative of the situation in the hospital.

For instance, we did not take into account some patients and MUs based on use, and we decided for the graph generation to take into account patients such that the result would account for 90% of the pathway variability. These assumptions, made to simplify the graph, may have hidden some marginal interactions between MUs that could affect the hospital. In addition, we chose a simple and widely used PM algorithm. Using more specific algorithms should give better results and better represent the sequence of stays inside the patient journey, particularly regarding loops or recurrent sequences of stays. The two cancellation policies are absolute scenarios, and decision makers in the field will want to modify them. The 'By ICU' policy assumes that we know in advance the entire pathway of the patient, which is unrealistic. However, this simplifying policy models the fact that healthcare professional

will cancel interventions that could result in the consumption of ICU resources, as it was done at the peak of the pandemic. Using different ruling based on the pathway, or advanced machine learning technique could be useful.

In addition, we considered the beds in MUs to be equivalent, so that a bed from a surgery unit could be transformed into an ICU bed providing minor changes. We included these changes in the form of a one-day delay before the transfer. However, for many reasons, such as staff ability and availability of specific resources, this assumption is not operationally realistic. For use in real conditions, facility-specific adjustments might be necessary. Specifically, we recommend using an ability matrix to define the staff that needs to be re-assigned to the new unit to calculate the additional beds that must be closed.

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TABLE IV: Estimated best response scenarios to answer the two situations.

COVID Arrival pattern	Bed batch sizes <sup>a</sup>	Cancellation policy	Cancellation cutoff point	Score
Wave 1	12 - 4	By ICU	0.95	0,429
Wave 1	12 - 8	By ICU	0.95	0,431
Wave 1	12 - 8	By ICU	0.90	0,433
Wave 1	12 - 12	By ICU	0.95	0,433
Wave 1	12 - 8	By ICU	0.95	0,434
Wave 1	12 - 4	By Block	0.95	0,466
Wave 1	12 - 12	By Block	0.95	0,469
Wave 1	12 - 6	By Block	0.95	0,469
Wave 1	12 - 10	By Block	0.95	0,470
Wave 1	12 - 8	By Block	0.95	0,471
Waves 2 & 3	12 - 10	By ICU	0.95	0,481
Waves 2 & 3	12 - 6	By ICU	0.95	0,483
Waves 2 & 3	12 - 6	By ICU	0.90	0,486
Waves 2 & 3	12 - 4	By ICU	0.95	0,486
Waves 2 & 3	12 - 12	By ICU	0.95	0,486
Waves 2 & 3	12 - 6	By Block	0.95	0,541
Waves 2 & 3	12 - 4	By Block	0.95	0,542
Waves 2 & 3	12 - 12	By Block	0.95	0,545
Waves 2 & 3	12 - 8	By Block	0.95	0,545
Waves 2 & 3	12 - 10	By Block	0.95	0,547

<sup>a</sup> (ICU bed transfer batch size - MCO bed transfer batch size)

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**Jules Le Lay** holds a Ph.D in industrial engineering from the École Nationale Supérieure des Mines de Saint-Étienne, France. He received an MsC in Engineering from Mines Saint-Étienne, Auvergne-Rhône-Alpes in 2017. Currently, he is a research engineer at Centre Léon Bérard. His research interests include modeling, simulation and optimization of health care systems.

**Edgar Alfonso-Lizarazo** holds a Ph.D. in industrial engineering from the École Nationale Supérieure des Mines de Saint-Étienne, France. Currently, he is researcher member of the LASPI laboratory and Associate Professor at Université Jean Monnet, Saint-Étienne, France. His research interests include modeling, simulation and optimization of health care systems and medical decision making.

**Vincent Augusto** is a professor and a permanent faculty member of Mines Saint-Étienne, Center for Biomedical and Healthcare Engineering. He holds a Ph.D in industrial engineering from École Nationale Supérieure des Mines de Saint-Étienne, France (2008) and a “Habilitation ‘a Diriger des Recherches’” (2016) on Health Territories Engineering. His areas of research are the application of industrial engineering techniques, such as simulation and optimization, to health care systems, health data and medical decision aids. He was a visiting professor at CIRRELT (Interuniversity Research Center on Business Networks, Logistics and Transport), Laval University, Québec, Canada in 2009 and 2015. He is co-responsible for the living lab MedTechLab, where approach design, experiments and innovation are combined with health care engineering. He is director of the Center for Biomedical and Healthcare Engineering of Mines Saint-Étienne since January 2020 (70 people).

**Bienvenu Bongue** holds a Ph.D. in pharmacoepidemiology from Toulouse III University. He also holds a Habilitation to supervise research since 2013. Mr Bongue is a research member of the SNA-EPIS Laboratory; EA 4607 of Jean Monnet University (Saint-Étienne, France) and Associate Professor at Montréal University (Québec, Canada). He is also the Chair of “Seniors health - Prevention engineering” of Jean Monnet University of St-Etienne. He is currently supervising 4 PhDs students. Mr. Bienvenu Bongue is a member of numerous scientific councils and the author of numerous scientific papers and reports.

**Thomas Célarier** is an associate professor, geriatric doctor and head of the geriatric MU and clinical gerontology of the University Hospital Center of St Etienne. He is also a medical consultant for the AURA Gérontopole, and he coordinates many studies on interventional research and works on health care modeling.

**Baptiste Gramont** is an internist doctor since 2019 at the university hospital of Saint-Étienne. He is specialized in systemic diseases and polyvalent care. He is also a PHD student in ageing immune system at the team GIMAP-Centre International de Recherche en Infectiologie (CIRI)”

**Malek Masmoudi** is engineer and PhD in industrial engineering. He is currently associate professor at Sharjah University, UAE, and was the head of the industrial engineering Master at Jean-Monnet University, France, from 2013 to 2021. He received the Doctorate of Sciences (Habilitation) from Jean-Monnet University in 2017. His main research interests are the applications of data science and optimization techniques to various engineering and management fields. He published two springer books in data science and more than thirty-two international journal papers in operations research and industrial engineering.

**Xiaolan Xie** is a professor and head of the department of Healthcare Engineering of the Center for Biomedical and Healthcare Engineering, Ecole Nationale Supérieure des Mines (EMSE), Saint Etienne, France. His research interests include data analytics, design, planning and scheduling, supply chain optimization, and performance evaluation of health care and manufacturing systems. He is author/coauthor of 300+ publications, including 110+ journal articles and six books. He has rich industrial application experience with European industries and is PI for various national and international projects. Pr. Xie is a fellow of IEEE, the founding chair of the IEEE RAS-Technical Committee on Automation in Health Care Management and an IEEE RAS 2017 Distinguished Lecturer. He has been an editor/associate editor for IEEE Transactions on Automation Science & Engineering, IEEE Transactions on Automatic Control, IEEE Transactions on Robotics & Automation and the International Journal of Production Research. He has been a Guest Editor of various special issues on health care engineering and manufacturing systems.