Operations Research for Health Care 27 (2020) 100274

Contents lists available at ScienceDirect

Operations Research for Health Care

journal homepage: www.elsevier.com/locate/orhc

Safely learning Intensive Care Unit management by using a Management Flight Simulator

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ARTICLE INFO

Article history:
Received 24 January 2020
Received in revised form 10 May 2020
Accepted 2 October 2020
Available online 13 October 2020

Keywords:
Management Flight Simulator
ICU
Decision-making
Learning–training
Simulation in healthcare
Discrete event simulation model

ABSTRACT

This paper presents the development of the first Management Flight Simulator of an Intensive Care Unit (ICU). It allows analyzing the physician decision-making related to the admission and discharge of patients and it can be used as a learning–training tool. The discrete event simulation model developed mimics real admission and discharge processes in ICUs, and it recreates the health status of the patients by using real clinical data (instead of using a single value for the length of stay). This flexible tool, which allows recreating ICUs with different characteristics (number of beds, type of patients that arrive, congestion level...), has been used and validated by ICU physicians and nurses of four hospitals. We show through preliminary results the variability among physicians in the decision-making concerning the dilemma of the last bed, which is dealt in a broad sense: it is not only about how the last available ICU bed is assigned but also about how the physician makes decisions about the admission and discharge of patients as the ICU is getting full. The simulator is freely available on the internet to be used by any interested user (https://emi-sstcdapp.unavarra.es/ICU-simulator).

1. Introduction

An Intensive Care Unit (ICU) is a special ward within the hospital area that provides intensive medicine. These wards are fundamental for patients who present a clinical situation of high severity or require complex monitoring and are likely to recover. The origin of these units is due to the development of techniques capable of supporting different physiological systems of patients.

However, although the purpose of ICUs is well defined, it is not so clear which patients should benefit from this highly specialized care, especially in contexts of scarce resources. In an attempt to clarify this issue, the Working Group on Quality Improvement (WGQI) of the European Society of Intensive Care Medicine (ESICM) established in 2011 [1] the characteristics of patients who could benefit from admission to an ICU:

- Patients requiring monitoring and treatment because one or more vital functions are threatened by an acute (or an acute on chronic) disease (e.g., sepsis, myocardial infarction, gastrointestinal hemorrhage) or by the sequelae of surgical or other intensive treatment (e.g., percutaneous interventions) leading to life-threatening conditions.
- Patients already having failure of one of the vital functions such as cardiovascular, respiratory, renal, metabolic, or cerebral function but with a reasonable chance of a meaningful functional recovery. In principle patients in known end-stages of untreatable terminal diseases are not admitted. Sometimes the need for palliative care requiring intensive care measures may be considered.
- Patients with brain death or in whom brain death is expected to occur and in whom organ donation is considered may be admitted.

Despite these efforts to define the characteristics of patients that are susceptible to be admitted to an ICU (high severity, complex monitoring, and reasonable expectations of recovery), in practice, few hospitals use admission criteria [2]. On the one hand, ICU admission criteria are usually very general and susceptible to interpretation by physicians. On the other hand, issues such as the reasonable chance of recovery, the prognosis, the quality of life at hospital discharge are not well-established concepts for all the pathologies that motivate ICU admission, and therefore they are subjected to variability among physicians.

The lack of a strict admission protocol and the subjective component in the decision process motivate the research on patient admission and discharge policies in the medical literature. Several studies show that when there is a shortage of beds in the ICU, the admissions and discharges of patients are subject to triage

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https://doi.org/10.1016/j.orhc.2020.100274

processes [3–5]. Costa et al. [6] observe changes in the management policy of an ICU when it is getting full, and physicians try to limit admissions or early discharge patients in better condition. In general, an ICU with high occupancy of beds increases the number of rejected admission requests and the severity threshold for the admission of a patient to the ICU; and shortens the length of stay (LoS) of patients [7,8]. The main objective is often to free ICU beds [9–13]. Other consequences of an excessive occupancy rate of beds are cancellations of scheduled surgeries and transfers of patients to another hospital. Therefore the patient discharge is a process not only influenced by factors related to the patient's health but also by environment and certain organizational problems [14].

Another factor influencing the ICU bed management is the high cost of each ICU bed. The average cost per ICU patient was determined around €1200 per day in Germany, Italy, the Netherlands, and the United Kingdom [15]. Lefrant et al. [16] estimated the daily cost of ICU stays analyzing 23 ICUs from French National Hospitals in €1425 (95% CI = €1323 to €1526). Most ICU costs are fixed (independent of the level of occupancy); thus, from an economic point of view, it is preferable high bed occupancy of the ICU to avoid the underuse of an extremely costly service [17]. However, situations of lack of beds trigger the undesirable consequences listed before: suspensions of scheduled surgeries, delayed or refused admissions to the ICU, and early or inadequate discharges of patients to free up their beds, which are associated with poorer prognosis [18,19] and a higher risk of mortality [20–22]. Thus, from a clinical point of view, high occupancies will be avoided.

Performing a comparative analysis of the physician decisions on the admission and discharge of ICU patients helps to investigate all this. Retrospective statistical analysis of the ICU administrative records can be very difficult to carry out. The decisions are made in unique scenarios and, besides, not all circumstances affecting the decision making are recorded nor the physician responsible for the decision making. However, simulation techniques allow for the reproduction of scenarios and the control of all factors influencing the dynamics and the decision making in complex systems.

This paper presents a computational tool useful for the analysis of the decisions made by physicians related to the admission and discharge of patients in an ICU. The analysis of patient-admission and inpatient-discharge decisions can be done safely in virtual environments that reproduce with high fidelity the characteristics and dynamics of an ICU. In this paper, a Management Flight Simulator (MFS) that mimics a real ICU is presented. The main features that distinguish this simulator from others are the simulation of the patients' stay by evolving their health status (instead of using a single value for the LoS) and the recreation of real discharge and admission processes. Both elements are determinant for creating credible virtual scenarios allowing the users the management of the ICU as they would do in a real ICU, that is, with the same information and environment. The simulator records all the admission/discharge decisions made by users. The analysis of the recorded data about canceled surgeries, early discharged inpatients, admissions delayed, diverted patients, etc. can be used to characterize bed management policies implemented by users. Furthermore, differences among users can be detected and quantified as well as the identification of scenarios in which decisions differ the most. These controversial scenarios are of special interest for physicians because they support the discussion to elaborate consensus protocols for triage decisions in the hospital that can help to reduce variability in medical practice. Therefore, the purpose of the developed flight simulator is double: firstly, to characterize how physicians made decisions and to assess the variability among physicians in making such decisions; secondly, providing a training tool for the management of ICUs.

The main contributions of this paper are summarized in the following points:

- The development of the first MFS of an ICU, which allows analyzing the decision-making process and its management, as well as being a useful learning–training tool.
- The development of a discrete event simulation model (DES) that mimics real admission and discharge processes in ICUs.
- The recreation of the health status of the patients by using real clinical data recorded by the Metavision® software (iMD Sof, Tel Aviv, Israel), instead of using a single value for the LoS. Using 275 health indicators, the status of real patients is monitored, giving an extended and realistic description of their evolution, which can improve or get worse.
- The design of a flexible tool that allows recreating ICUs with different characteristics (number of beds, type of patients that arrive, congestion level) that presents at the beginning of the simulation a scenario that is representative of the stationary state of an ICU.
- Showing through preliminary results the variability among physicians in the decision-making concerning the dilemma of the last bed.

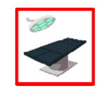
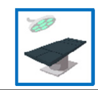
The rest of the paper is organized as follows: in Section 2, the dilemma of the last bed is presented, including an illustrative example with real patients. In Section 3 related literature is reviewed about the use of simulation models in ICUs, as well as the use of MFS. The mathematical modeling of the ICU dynamics and its implementation in a DES is presented in Section 4. Section 5 focuses on the simulator itself, detailing different features of this tool such as the definition of virtual ICUs, the initialization process, the interface, and the recorded data. Section 6 exposes preliminary results of the simulator. Finally, the paper closes with a discussion and the conclusions in Section 7.

2. The dilemma of the last bed

Teres [23] posed as one of the great ethical dilemmas a situation that he described as the ritual of the last bed. This situation occurs when the occupancy of the ICU is at the limit, and the physicians must decide on the admission of a new patient. The increase in the ICU occupancy rate and access block rates are leading to complete or even overwhelmed ICUs [24,25]. The average occupancy rate of ICUs in the US is 90% [26], where it is reported that 90% of ICUs cannot provide beds when required [27]. In this paper we consider a broad definition of the dilemma of the last bed, as it is discussed in [28]; it is not only how to assign the last available bed but how is the physician decision making respect to the admission and discharge of patients as the ICU is getting full. Physicians have to assess the benefits that receive patients already at the ICU and confront them with the benefits that could receive future patients coming from scheduled surgeries and other potential emergency patients. Clearly, no physician wants neither to divert an emergency patient nor cancel a surgery nor to discharge in advance a patient, but these decisions may be inevitable in high bed-occupancy situations.

There is a broad medical literature in which patient discharge decisions and their consequences are implicit. Some mathematical literature also mentions the importance of such decisions, but then they are not modeled [5,6]. Only a few mathematical models include this decision-making process, which is usually called "bumping" [4], "demand-driven discharge" [29], "premature discharge" [30], or "early discharge" [31].

Table 1
Patients to manage in the example of the dilemma of the last bed.

Location	Patient	Age	Principal diagnostic	Icon
Bed 1	Peter	56	Herpex Simplex Virus-1 meningoencephalitis	
Bed 2	Cate	63	Severe community-acquired pneumonia due to Streptococcus pneumoniae	
Bed 3	Phil	78	Postoperative control of aortic valve replacement cardiac surgery	
Bed 4	–	–	–	
Ambulance	Harvey	28	Polytrauma with severe traumatic brain injury secondary to motor vehicle accident	
Waiting for operating room 1	Paul	52	Acute coronary syndrome with ST-segment elevation	
Waiting for operating room 2	Anne	37	Right occipital glioblastoma multiforme	

The discharge decision problem has been addressed by developing optimization models trying to minimize the number of rejected admissions and the LoS shortened for patients in the ICU [32,33]. They formulate a stochastic optimization problem that is solved by using a simulation-based optimization methodology. The solutions determine the service rates at which the queue model representing the ICU should work to achieve the goals and they are interpreted as probabilities of discharging patients in advance, which are dependent on the bed-occupancy level. These models provide normative policies that can be classified into three types [32]: aggressive, equitable, and cautious.

Mathematical models usually propose “aggressive” discharge policies, that is, no actions are taken until there are no free beds and one of them must be released to admit a new incoming patient. Nevertheless, physicians consider another more “cautious” policy, which is more representative of the decision-making that occurs in practice. They claim that early discharge of patients is more frequent as more beds are occupied, but these decisions are made before the ICU is complete. In situations of high occupancy, they advance the discharge of a patient in time in order to anticipate future emergency and scheduled patients’ arrivals. In this way, physicians avoid extreme occupancies in which patients are discharged at unconventional hours, which increases mortality if the discharge occurs at night [34]. Mallor et al. [33] propose a queuing model with LoS dependent on occupancy level. However, in this model, the exchange between a patient who is discharged and another who enters is considered instantaneous.

An illustrative example of the dilemma of the last bed. The problem of the last bed is not just a theoretical concept, but it occurs many times at hospitals: whenever several patients need treatment at the ICU at the same time, but there are no available beds for everyone. A specific situation is presented below, with real patients, to illustrate better this problem. The chosen scenario is a real situation that ICU physicians usually face.

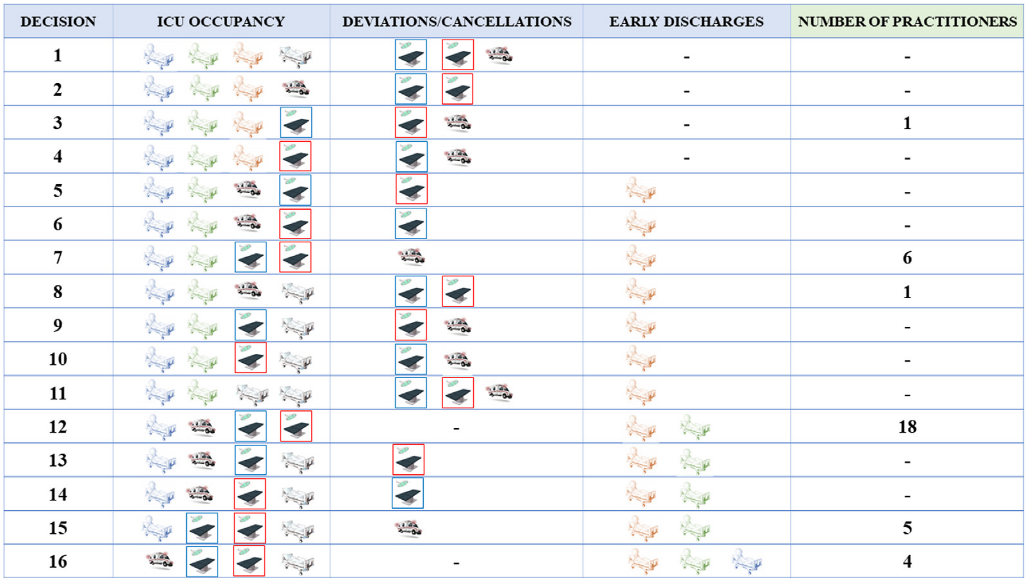
An ICU with only 4 beds is assumed, and 3 of them are occupied by three patients who have different diseases and ages, which are not totally recovered. In the first bed, there is a 56-years old patient (Peter) who has a brain infection due to a virus. In the second bed, a 63-years old patient (Cate) with a lung infection due to a bacterium is allocated. In the third bed, there is a 73-years old cardiac surgery patient (Phil).

ICU physicians, during the clinical morning session, must discuss whether these patients continue to be treated in the ICU or are early discharged. At that moment, physicians are informed about an ambulance that is coming to the ICU with another patient (Harvey, 28), who has suffered a traffic accident and he has head trauma. Besides this, two scheduled surgeries need admission for the ICU that day. The first one is for a patient (Paul, 52) who has suffered a heart attack, and the second one is to treat a patient (Anne, 37) with a brain tumor. So, in this situation, not only discharge decisions have to be made, but physicians also must decide whether the incoming patient is accepted or diverted to another hospital, and which surgery is confirmed or canceled.

In summary, what physicians have to decide is which patients must be treated in these four beds. Table 1 shows all the relevant information of patients that must be managed at that moment (detailed clinical information of these patients is provided in Appendix A).

Over this situation, an ICU physician can differentiate 16 reasonable decisions based on clinic, as it is sown in Fig. 1 (if all combinations were considered, the possibilities would rise to 57, which are provided in Appendix B, but many of them are unlikely in a real context, as discharging all inpatients and admitting no new patient). For example, decision number 2 consists of admitting only the emergency patient that is coming in the ambulance, and both surgeries are canceled. In addition, no inpatient is early discharged with this election. However, decision number 15 is based on confirming both surgeries. Now, the incoming patient is diverted to another hospital, despite the fact that two inpatients have been early discharged (bed 2 and 3). With this election, physicians would reserve a free bed for future emergency patients considered in more severe conditions. Therefore, it is clear that in order to manage these situations, physicians can (1) refer patients to other hospitals, (2) cancel scheduled surgeries, and (3) shorten the inpatients’ LoS.

When this situation was presented to different physicians and nurses of an ICU, they made different decisions, as it is exposed in Fig. 1. The majority (18 out of 35) decided to admit the three incoming patients and assign two early discharges (decision number 12). So, the ICU would be with the four beds occupied. 4 physicians also admitted the three incoming patients but decided to discharge all inpatients in an early way, in order to reserve a bed for a future patient (decision number 16). A group of 11



DECISION	ICU OCCUPANCY	DEVIATIONS/CANCELLATIONS	EARLY DISCHARGES	NUMBER OF PRACTITIONERS
1			-	-
2			-	-
3			-	1
4			-	-
5				-
6				-
7				6
8				1
9				-
10				-
11				-
12		-		18
13				-
14				-
15				5
16		-		4

Fig. 1. Selected decisions based on clinics in the example of the dilemma of the last bed. The last column includes the number of physicians and nurses out of 35 that would make each decision in a real ICU.

physicians decided to divert the emergency patient, with the difference that 6 of them only assigned an early discharge (decision number 7) and the other 5 assigned two (decision number 15). By last, one person decided to cancel both surgeries, assigning an early discharge (decision number 8), while another canceled one of the surgeries and diverted the emergency patient without discharging patients (decision number 3).

Therefore, the responses to this simple realistic example show the variability in the decision making related to the admission and discharge of patients and motivate the need to create a tool that facilitates the analysis of such decisions. The tool presented in this paper not only generates scenarios like the previous one, but it evolves the ICU over time by implementing the decisions of the users. In this way, the user can see the consequences of their decisions and learn by doing. The success of the MSF depends on its ability to recreate this dynamic environment mimicking the real dynamic of the ICU and to include all necessary information to support the decision making.

3. Related literature

In this section, we review relevant literature related to the use of simulation models in ICUs, as well as the use of MFS (flight/virtual/serious game simulators) in general and in health care services in particular.

3.1. Simulation in ICU

Simulation is a very suitable tool to study stochastic and complex systems such as hospitals and, in particular, ICUs. Bai et al. [35] review operations research methods used in ICU management, which include simulation. Mathematical studies include simulation models for analyzing ICU capacity problems [36–38] and ICU admission and discharge processes [39]. Furthermore, Kim et al. [40] compare bed allocation rules using bi-objective optimization and Griffiths et al. [41] propose a bed management optimization making a distinction between emergency and scheduled surgery patients. Other studies analyze changes in the patient-flow circuit with the use of intermediate care wards [10, 42]. Griffiths et al. [43], given a current bed occupancy, present a simulation model to adjust staffing; and Steins et al. [44] assess bed occupancy and patient transfers to other ICU facilities in view of a shortage of resources. All these models have the ultimate goal of minimizing the rejection of patients arriving at the ICU while maintaining a manageable occupancy level.

There are also some studies [38] in which early discharge is suggested as a bed management tool, but they are not explicitly modeled. In order to obtain valid simulation models, it is necessary to include the process of physicians' patient-discharge decision-making [45,46]. Azcárate et al. [47] perform a sensitivity analysis of the effects of such discharge decisions on ICU rejection rates and LoS of patients. Mallor et al. [32] assess by simulation modeling the optimal discharge strategies obtained in [33].

The literature reviewed shows that some researches can propose mathematical solutions to problems associated with ICU capacity and bed management. However, as far as we know, there are no articles that provide an analysis of how physicians' decisions are really made in ICUs.

3.2. The use of management flight simulators

MFS, also known in the literature as virtual simulations, can be used both as a learning–training tool and for research [48]. For research, this kind of simulators enables to analyze key processes, detect biases, and recreate decision-making processes, testing theories about them. As a learning–training tool, these MFS have a close connection with serious games, which are not only intended to entertain but are also used for pedagogical purposes [49]. According to Zyda [50], a serious game is "a mental contest, played with a computer in accordance with specific rules, that uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives." Long before the term "serious game" began to be used, some games were already developed with a purpose other than entertainment.

An example of this is The Beer Game (or the Beer Distribution Game), which was developed in the 1960s at the Massachusetts Institute of Technology's (MIT) Sloan School of Management. Since Sterman [51,52] popularized this simulation game, one of the most popular games used in logistics management and production management class, many applications have appeared in which The Beer Game has been utilized in order to research the behavior of participants [53–55]. In other cases, the original game has been modified to investigate new approaches [56–58].

In addition to The Beer Game, there are more management games in the economic context in which researchers analyze the behavior of a group of people, as well as the participants learn from the experience [59–65]. Besides, the use of this type of simulations as a learning tool is usual in other contexts such as politics [49,66] and environmental care [67–70]. All these applications focus on management learning for general situations, and new concepts acquired by participants can be applied at any time in the real processes. Furthermore, there are other types of simulators, designed for specific situations as defense, aviation, and construction, where decision-making processes are crucial for specific situations. Virtual Reality (VR) simulators are developed here to include a real description of the environment. In the defense area, simulators to better respond bombs and learning–training tools for marine officers or firefighters can be found in [71–75]. In aviation, new types of simulators are arising to capture flight skills, which provides stronger sensations than traditional ones [76–78]. In terms of construction applications, both computer-aided-learning tool [79] and VR training systems for industrial training [80,81] have been found.

Although no articles have been found in which these methods are used in healthcare to learn about the complexity of the ICU management, many healthcare applications have been developed in which virtual simulation has a relevant role in order to teach students at universities and especially to learn from the experience of using [82]. Most of these are traditional simulations, and they use patient care manikins or play-role patients. Sherwood and Francis [83] made a systematic review of the effect of this kind of mannequins in terms of learning for nursing, midwifery, and allied healthcare practitioners. Other types of works, not as popular as previous ones, are those which develop VR simulators or implement a decision-making process in management games. Sauré and Puterman [84] developed an easy to use teaching game to learn how to manage patients appointment scheduling, whereas Vliegen and Zonderland [85] designed a classroom game to introduce Operations Management (OM) in healthcare.

VR simulators developed in the healthcare context intend to transfer skills, as they do in other contexts Brown et al. [86] designed and developed a virtual world for teaching and training Intensive Care nurses in the approach and method for shift handover. VR simulators are also used in urological training, replacing traditional training approaches [87]. But, where this tool is commonly used in healthcare is at operating rooms, with the objective not only for the learning of beginning surgeons but also as a training to reduce the operating time. Jain et al. [88] developed a VR surgical simulator that facilitates trainees for functional endoscopic sinus surgery. The positive effect of these kinds of simulators is also demonstrated in [89–91].

Management games in healthcare, mainly known as hospital management games, gained importance because of the increment of health care costs due to expensive technology, aging of the population, and the increasing number of demanding patients. This type of games first appeared during the 1970s and Kraus et al. [92] made an extensive review of different hospital management games. These games simulate situations of the real world modeling complex decision-making processes, which are influenced by the external hospital environment. In the review, the authors distinguish functional games that are applied to specific hospital departments and general games, which focus on the main function of the hospital. As a functional game, Hans and Nieberg [93] developed the "Operating Room Manager Game" illustrating operating room management, whereas Rauner et al. [94] designed an internet-based management game ("COREMAIN") to illustrate the economic and organizational decision-making process in a hospital.

We also found other examples of game-based simulators in the healthcare area not related to hospital management. Brown et al. [95] designed an educational video game to improve self-care among young people with diabetes. Grunewald et al. [96] developed an interactive Web-based training program for radiology, which offers radiographic anatomy cases and exercises, with the possibility of selecting different levels of difficulty. The "HealthBound" model and game was developed to help people think widely about health reform options and discover for themselves a promising solution [97–100]. Katsialiaki et al. [101] developed a game that simulates the supply chain of donor blood units to patients based on a real case study.

Finally, some studies have been revised that focus on the decision-making processes in resource management. Rodriguez et al. [102] present a decision support system to help humanitarian NGOs better manage resources during a natural disaster response. Rauner et al. [103] developed a policy management game to provide a learning–training tool for mass casualty incidents. Bean et al. [104] programmed a patient flow simulator with which professionals and students can learn important concepts of patient flow and healthcare management.

Reviewing the literature about MFS we realized that those works that focus on management issues, then they are driven by theoretical concepts and models fail to reproduce with high fidelity characteristics of real situations. In these models, many assumptions are made in order to simplify them for the user and to avoid misunderstandings. By contrast, VR simulators, which transfer skills to the user, are very realistic, but then they do not present management-related features in broad contexts. Just as flight simulators in the aviation sector generate in pilots exactly the same autonomic responses when faced up with an emergency, whether this is real or simulated, medical simulations must generate autonomic, cognitive and behavioral responses in participants equal to those observed around medical tasks in the real world [105]. Fidelity is very important if we want to recreate participant's experience with total realism. In this paper, we present an ICU simulator that combines, for the first time, these two different approaches (management decision processes are implemented in a real simulation environment.

4. Modeling an ICU

In this section, the mathematical modeling of the ICU dynamics is presented. In the first subsection, the modeling of the patient flow is exposed, explaining the discharge and admission process, discharge decision times, and the patient's health status. The second subsection focuses on the implementation of these features in a DES model, and the third subsection describes how to sample initial scenarios from the steady state.

4.1. Modeling the patient flow and admission/discharge decisions

An ICU can be mathematically modeled into the framework of queuing models. The queue model representation of the ICU considers that the servers are ICU beds, the clients are the patients that arrive randomly for emergency patients or according to a known schedule for those coming from elective surgeries, there is no waiting room and the queue discipline is "first come, first served". The service is individually provided with duration modeled by a probability distribution. This description leads to a queuing model G/G/c/c, where c is the number of the beds in the ICU.

Nevertheless, this model fails in modeling the dependence between patient LoS and the congestion level, allows for admissions and discharges at any time, the diversion of patients can occur only at full occupancy and the servers (beds) can switch instantaneously from one patient to the next one. In addition, the queueing model does not represent the real admission and discharge processes. These drawbacks preclude the use of this basic queue model to build the simulation model. Therefore, we extend the mathematical modeling of the ICU to represent more accurately both discharge and admission processes and to reproduce the patient's health status while their stay in the ICU. The purpose of the mathematical modeling is to be implemented in an interactive simulator allowing the users to make informed decisions in a virtual environment as physicians do in real practice.

4.1.1. Discharge and admission process

Both the discharge and the admission of a patient are complex and not automatic processes. The discharge process needs the coordination of the ICU medical staff with their counterpart in the destination ward. Moreover, the necessary time to free up the bed depends on its necessity. In cases of imminent patient admission, the process speeds up and the discharging process could take around one hour, for example. However, when there is no urgency, the entire discharge process with peace could last from three to four hours.

The admission of the patient is virtually instantaneous when a patient arrives at the ICU and there is a totally cleaned and disinfected bed. When an admitted patient arrives at a full ICU and no recently freed up bed is ready yet, the patient is temporarily located in a special room where he or she can temporarily be treated.

The flow diagram in Fig. 2 shows the admission and the discharge processes as they are considered in the simulation model. On the left side, the emergency and scheduled patients' arrivals are represented. Medical staff must decide whether to reject or admit them to the ICU. Scheduled patients first occupy a bed in the operating theater area (dark blue icon). Admitted patients occupy a free bed (white icon) in the ICU, when they are available, when not, the patient is placed in a bed in the above-mentioned special room (light blue icon). The right side represents the ICU where the beds can be in 7 different occupancy states: an occupied bed by a patient that is in the process of being discharged (dark gray icon); a bed occupied by a deceased patient (brown icon); bed under cleaning process (light gray icon); available bed (white icon); and occupied beds by patients in severe, stabilized and recovered health status (red, orange and green icons, respectively).

4.1.2. Discharge decision times

Patient discharge decisions normally occur only at a few scheduled times of the day. These moments are denominated clinical sessions and depending on the ICU they can take place once, twice, or even three times a day (morning, afternoon, and evening). During clinical sessions, physicians analyze the inpatients' clinical conditions and decide which ones are going to be discharged. They also propose possible patients who would be discharged if an emergency patient had to be admitted and there were no beds available. At the same time, in the morning clinical session, physicians manage the surgeries of that day, by either confirming or canceling them.

Therefore, the patient cannot be discharged at any time, as it is implemented in classic queuing models. Essentially, the discharge decision process is periodic and throughout the day no more patients are discharged, except in the following case. When an emergency patient arrives at ICU, physicians decide on his/her admission, which in the case of admission in a situation of full ICU implies the discharge decision of an inpatient (the arriving patient is temporarily located in the special room).

The simulator reproduces the dynamics of the ICU and stops at such decision times waiting for the discharge and/or admission decisions of the user. The simulator continues simulating the ICU assuming the decisions made.

4.1.3. Patient's health status

Queuing models represent the LoS of a patient as a certain random variable with a probability distribution fitted usually by using historical data. Therefore, a sampled time from this probability distribution determines the event in which the patient is automatically discharged. However, the implementation of this approach in the simulator would not allow the users to make the discharge/admission decisions clinically grounded and informed. They should rely on probability properties of the probability distribution as for example the expected remaining time, as it is the case of many simulation models (see discussion in [28]).

To overcome this strong drawback, we model the health status of a patient by using 275 health indicators (medical and nursing reports included), all recorded by the software Metavision®, which is a dedicated software to monitor the health of admitted patients of ICU. These variables (described in Appendix C) give an extended and realistic description of the evolution of the patient health status. They provide enough information to assess the health condition of a patient in order to decide whether the patient is stable enough to be transferred to a lower level of care. These health indicators include neurological, hemodynamic, respiratory parameters among others such as provenance and principal diagnosis. All of them are presented to the user of the simulator mimicking the way in which their information systems do.

4.2. The discrete event simulation model

The proposed DES model is designed to incorporate the characteristics of a real ICU described in Section 4.1. A DES model is defined by the set of state variables, which provide at any time a complete description of the simulated system, and the set of events, which modify through time the value of these state variables. We propose three different kinds of state variables to describe the ICU at any time, and a set of events grouped into four different categories.

4.2.1. State variables

The first set of variables is composed of three variables, $X = (X_1, X_2, X_3)$, which describe the number of patients in the ICU (X_1), the number of patients that are waiting in the special room to be admitted (X_2), and the number of patients coming from surgery already accepted but not admitted to the ICU yet (X_3). Observe that the number of total patients admitted (N) in the ICU at time t is the sum of these three state variables ($N = X_1 + X_2 + X_3$).

The second category describes the health status of patients and it is composed of 275 state variables per each inpatient, $Y_{hi}h = 1, \ldots, 275;\ i = 1, \ldots, X_1$. These variables can be continuous as the temperature (°C) or the systolic blood pressure (mmHg), discrete as the heart rate (rpm), binary as being intubated (yes or no), or qualitative as those describing prognosis of physicians and nurses. During the simulation, these variables change in order to recreate the health status evolution of each patient. Therefore, they are considered important indicators to differentiate which patients can be discharged.

Finally, the third group of state variables describes the bed occupancy state. Each one is associated with an ICU bed, $Z_j j = 1, \ldots, c$. They are qualitative variables that can take the following values:

- *Free*: the bed is completely available for the admission of a patient.
- *With a deceased patient*: there is a patient who has just died and is waiting for discharge.
- *With a severe patient*: there is a very serious patient who cannot be discharged under no circumstances.

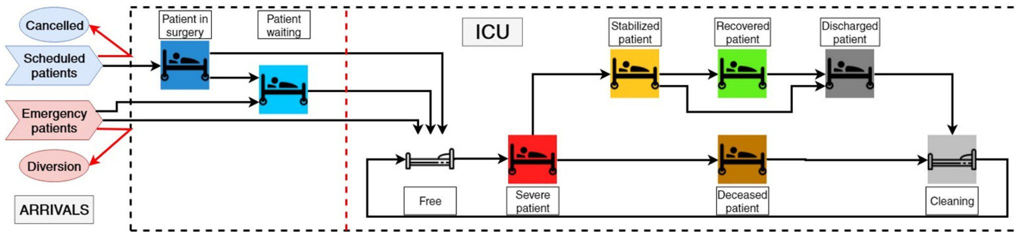


Fig. 2. Representation of the dynamics of an ICU through the change of the bed's state. The two types of patients are distinguished (scheduled and emergency ones) and also the direct entry to the ICU from a delayed one.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

- *With a stabilized patient*: there is a stabilized patient who could be considered eligible to be discharged under circumstances of high occupancy pressure.
- *With a recovered patient*: there is a patient who has recovered and is ready to be discharged.
- *With a discharged patient*: there is a patient who is waiting for transfer to a lower level of care. A discharge decision has already been made.
- *Cleaning*: the bed is undergoing cleaning tasks to condition it for the admission of a new patient.

Therefore, the vector (X, Y, Z) describes at any time t the situation of the ICU (the number of patients admitted in the ICU, the number of patients waiting for an imminent admission, the health description of each one of these patients, and each bed occupancy state).

4.2.2. Events

There are four different types of events modifying through time the value of state variables. The first set of events E_A are associated with the patient's arrival times classified in emergency and scheduled patients. The probability that a patient is of the emergency type is p_E, and of the scheduled type is p_S $(p_E + p_S = 1)$. On the one hand, emergency patients' arrivals occur 24/7, which are modeled by using a Poisson Process (PP) with arrival rate λ_E. These patients are classified into illness groups whose percentages define the type of ICU that is being modeled. In our model we consider 6 different groups (E_1: urgent surgery, E_2: polytrauma, E_3: patient hospitalized in Medical Service, E_4: patient hospitalized in Surgical Service, E_5: emergency/observation patient, and E_6: patient admitted for organ donation/others) and probabilities $p_{E_i} i = 1, \dots, 6$ of belonging to each illness group, which determine the mix of emergency patients $\left(\sum_{i=1}^{6} p_{E_i} = p_E\right)$. When an emergency patient arrives at time t_i, the next arrival occurs at time t_{i+1} obtained from Eq. (1). Aside from assigning the arrival time, the type of emergency patient who arrives is selected. The patient will belong to the type E_i with a probability of p_{E_i}/p_E.

$$t_{i+1} = t_i - \frac{1}{\lambda_E} \ln u_i; \, with \, u_i \rightsquigarrow U(0, 1) \tag{1}$$

On the other hand, once per week, the number of scheduled surgeries for each day of next week is simulated. It is assumed an average number of scheduled surgeries of λ_S per week. We distinguish patients that recover from standard surgery procedure, S_1, with probability p_{S_1}, which can be in the ICU for an expected short stay, and patients that can be for an expected long stay due to a complicated surgery or critical condition of them, S_2, with probability p_{S_2} $\left(p_{S_1} + p_{S_2} = p_S\right)$. During the first clinical session in the morning scheduled patients are presented to physicians. Those patients who are admitted arrive at ICU when the surgery is finished (this time is previously defined for each scheduled patient). Under the assumption of the number of scheduled surgeries each working day is uniformly distributed throughout the week, and no surgeries are scheduled on weekends, the expected number of surgeries in each labor day is $\lambda_{S*} = \lambda_S/5$, and the expected number of arrivals for each type of scheduled patients is $\lambda_{S*_i} = \lambda_{S*} p_{S_i}/p_S$. From these expected values, we simulate the number of arrivals of each type of patient S_i as $\lfloor \lambda_{S*_i} \rfloor$ patients with probability $\lfloor \lambda_{S*_i} \rfloor + 1 - \lambda_{S*_i}$, and $\lfloor \lambda_{S*_i} \rfloor + 1$ with probability $\lambda_{S*_i} - \lfloor \lambda_{S*_i} \rfloor$ (where $\lfloor . \rfloor$ denotes the integer part of the number). These simulated arrivals represent the number of surgeries that the decision-maker must confirm or cancel. When the surgeries are confirmed, those patients are the ones who finally enter the ICU. The diagram of the two types of patients' arrivals is shown in Fig. 3.

The second set of events E_B produces changes in the value of the patient's clinical variables. The sequence of these events describes the health status of each patient described by 275 clinical variables recorded by the Metavision® software. Some of these variables, such as health indicators (the temperature, the heart rate, etc.), change their status every hour. Others related to Analytics, Gasometry, or physicians' reports, change their status every day.

The third category of events E_C is associated with discharge/admission decision-making. These events stop the simulation when there is a clinical session programmed, and discharge and admission decisions must be made by the user in order to continue. Observe that these decisions also appear when an emergency patient arrives at the ICU.

Finally, the last events E_D modify the beds' condition. Some of the previous events can trigger the change of an ICU bed's state. Changes in patient clinical variables can generate that the patient transits to a stabilized health or a recovery condition and then his/her bed does too. The bed's status also changes after the user's admission or discharge decisions. In the first case, when a patient is admitted, the bed's status change from *free* to *with a severe patient* (see Fig. 2). In the second case, if a patient is discharged, his/her bed associated changes to *with discharged patient*. However, two transitions are independent of the other events and must be simulated. On the one hand, once a patient has been discharged, the departure time of the ICU is simulated depending on whether the bed is urgently required or not. Also, in deceased patients, the transfer time may depend on whether the organs are to be previously removed for donation. On the other hand, when a patient leaves the ICU, a bed cleaning time is simulated until the bed is free again. Fig. 4 outlines the simulation model of the ICU.

4.3. Sampling initial scenarios from the steady state

The simulation starts at time zero by creating an initial scenario representative of the ICU stationary state, which means to assign value to all state variables and simulate the time for the first event of each type. The ICU is defined by the user

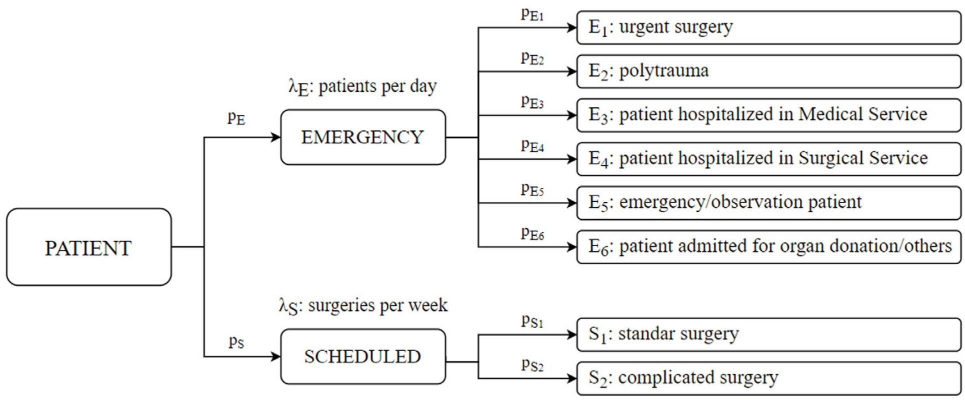


Fig. 3. Diagram of both emergency and scheduled patients' arrivals.

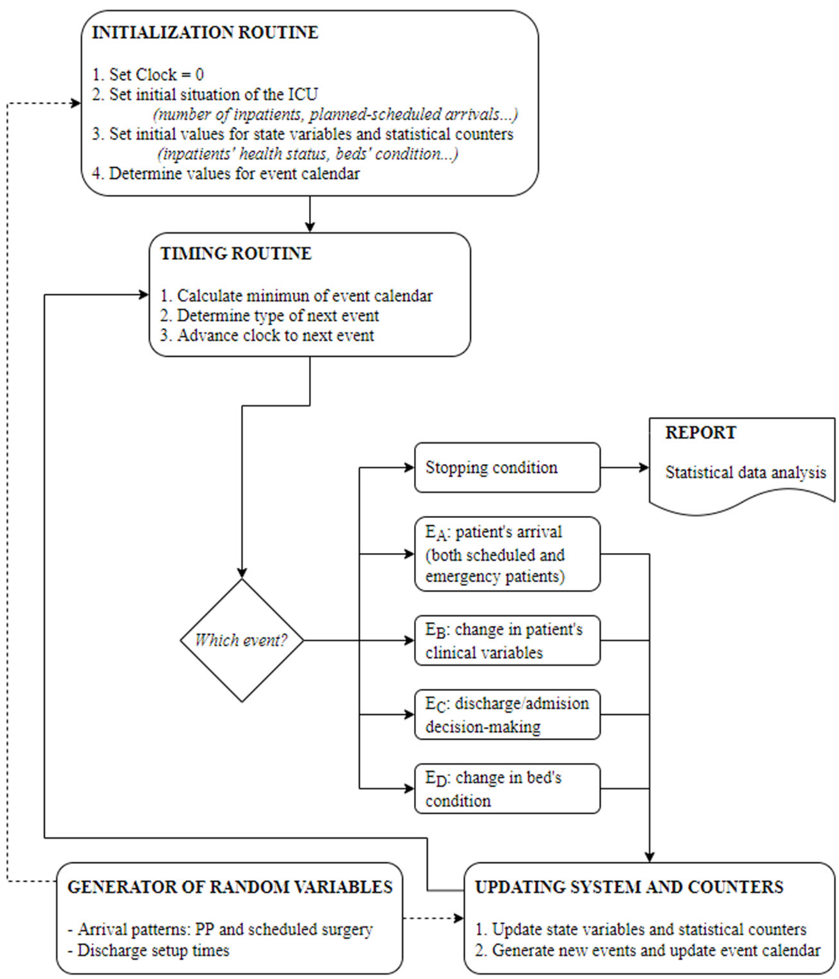


Fig. 4. ICU simulation model.

through a set of parameters, as we expose in Section 5.2. The parameters necessary to generate the ICU scenario at time zero are the number c of ICU beds, the probabilities p_i that define the mix of patients, and the *traffic intensity* ρ.

The *traffic intensity* is the ratio of the arrival rate λ to the departure rate μ, where λ is the number of arrivals per day and μ the number of departures per day. The *traffic intensity* is a measure of the congestion of the system. It is used to determine the patient arrival processes (for both emergency and scheduled patients) and the number of occupied beds at time zero.

Determining patient arrival rates. The total arrival rate is calculated as $\lambda = \rho\mu$. The departure rate μ_b of one bed is estimated from the expected days in ICU of each category of patient, $LoS\ (E_i)\ i = 1, \ldots, 6$, and $LoS\ (S_i)\ i = 1, 2$:

$$\frac{1}{\mu_b} = \sum_{i=1}^{6} p_{E_i} \mathrm{E}\left(LoS(E_i)\right) + \sum_{i=1}^{2} p_{S_i} \mathrm{E}\left(LoS(S_i)\right) \quad (2)$$

where E ($LoS(E_i)$) is estimated from historical data and the probabilities of each patient group are set by the simulator user to define the mix of patients.

Therefore, the total ICU departure rate is $\mu = c\mu_b$, and $\lambda = \rho\mu$. Then, the arrival rate is calculated for each category of patients as $\lambda_E = p_E\lambda$ and $\lambda_S = 7p_S\lambda$ and the first arrival of patients can be simulated as it is explained in Section 4.2.2 (observe that λ_S refers to arrivals per week).

Number of occupied beds at time zero. It is determined from the expected value ρc in the stationary state (assuming no early discharge is assigned, and no patient is diverted). To get an integer value for the number of occupied beds the lower or the upper integer is selected at random: $\lfloor \rho c \rfloor$ occupied beds with probability $\lfloor \rho c \rfloor + 1 - \rho c$, and $\lfloor \rho c \rfloor + 1$ with probability $\rho c - \lfloor \rho c \rfloor$. When the congestion rate ρ is greater or equal to 1, then the number of occupied beds at the beginning is c.

Simulating the type of patient that occupies each bed at time zero. The probability θ_i that a patient of a certain group of patients $P_i \epsilon \{E_1, \dots, E_6, S_1, S_2\}$ occupies a bed is calculated as the expected time that a bed is occupied for that group of patients; that is, $\theta_i = \lambda_i LoS(P_i)/\sum_j \lambda_j LoS(P_j)$, where $\lambda_i = \lambda_{E_i} = \frac{p_{E_i}}{p_E}\lambda_E$ is the arrival rate for emergency patients of type E_i, and $\lambda_i = \lambda_{S_i} = \frac{p_{S_i}}{p_S}\lambda_S/7$ is the arrival rate for scheduled patients of type S_i.

Sampling the patient that occupies a bed at time zero. Once the type of patients P_i is assigned to occupy a bed, a specific patient j is selected at random from the set of patients (see Section 5.2) according to a probability φ_{ij} which is proportional to the LoS, that is, $\varphi_{ij} = t_{ij}/\sum_k t_{ik}$, where t_{ik} is the LoS of the kth patient of type P_i.

Assigning values to the health status state variables Y_{hj}, $h = 1,\dots,275$. Once the patient jth of type P_i is selected to occupy a bed, the LoS already consumed at time zero is considered uniformly distributed in his/her total LoS t_{ij}. Therefore, the health status of the patient is described by the state variables recorded at time ut_{ij} of the LOS of that patient, where $u \rightsquigarrow U\,(0, 1)$.

5. The ICU management flight simulator

This section focuses on describing the simulator developed, detailing its main features, such as the definition of virtual ICUs, the interface, and the information recorded.

5.1. Main features of the simulator

The main purpose of this simulator is to mimic a real ICU, providing an extended and realistic description of the evolution of each patient and recreating real discharge and admission processes. To fulfill these characteristics, the simulator has to generate a familiar environment that is almost indistinguishable from that of the ICU physicians when consulting the monitoring screens of admitted patients' data. To achieve this level of similarity, the simulator presents the following features:

- The simulator generates emergency and elective patients' arrivals according to real arrivals patterns to the ICU.
- For each patient, the simulator shows enough clinical information to make decisions about discharge. Specifically, information about the patient's antecedents, principal diagnostic, and system monitoring values are displayed (as we mentioned in Section 4.1.3 and described in Appendix C). Information about scheduled surgeries for the following days is also shown in a calendar. The information displayed for each simulated patient corresponds to real patients, which have been completely anonymized.
- The visualization of each patient's data mimics the screen of Metavision® software presented in Fig. 5, which is used in a real ICU.
- The simulator moves the time forward generating the events described in Section 4.2.2 and evolving the health of status of each admitted patient (vital signs, analytical parameters, life support measures, medications, etc.). When a decision-making type of event occurs, the simulation stops and waits for the user's instructions about possible patient discharges or admissions. The simulator updates the status of the ICU according to these decisions and it moves the time forward until the next decision-making event.
- The randomness of the simulation is controlled by the initial seed of the random generator and the use of the common random numbers technique. Therefore, the simulator can run the same scenario (identical sequence of patient arrivals and with the same typology) so that it can be evaluated by different users.
- This simulator allows the definition of different ICUs by setting a set of parameters (see Section 5.2). Therefore, the simulator has enough flexibility to define numerous ICUs with different characteristics.
- The simulator collects all decisions made by the users.

To facilitate the medical staff using the simulator, it must be easily accessible, and also from different locations. Therefore, the simulator is freely available on the internet to be used by any interested user (https://emi-sstcdapp.unavarra.es/ICU-simulator); only the username (ICU-simulator) and the password (ICU_S1mulat0r*) are required in order to access it.

5.2. Setting up the ICU characteristics

The simulator is adaptable enough to create different ICUs according to its number of beds, the percentage of different types of patients, the congestion level, and the discharge/admission decision process. We can modify all these parameters as it is shown in Fig. 6. Furthermore, it is possible to save all created scenarios and open them later. Thus, everyone faces the same situations and at the same moments during the simulation.

The size of the ICU is defined by the number of beds. The mix of patients is established by assigning a percentage for emergency and scheduled patients as we mentioned in Section 4.2.2. It would be necessary to select the appropriate percentages for each type of patient and fill in the ones that are not included with zeros. Patients' health status is simulated using 200 clinical reports of 200 real patients treated in the ICU of Hospital Compound of Navarre, who have been completely anonymized. 112 out of the total are emergency patients, and they are distributed among the 6 categories mentioned in Section 4.2.2. The rest, 82 scheduled patients, are distinguished by their expected stay (short or long).

Three congestions levels are considered (*high*, *very high*, and *extreme*), which refers to the value of the *traffic intensity* ($\rho = \lambda/\mu$). The *high* congestion determines a *traffic intensity* $\rho = 0.85$ and the *very high* congestion a value of $\rho = 0.95$. The *extreme* level ($\rho > 1$) causes many situations in which the dilemma of the last bed occurs. This level has been selected to evaluate which decisions users make in each of those situations. Other complementary parameters that can be modified are the day of the week on which the simulation begins and the number of days that the simulation lasts.

Finally, on the lower-left side of Fig. 6, the discharge/admission decision process is defined. It is possible to configure different timetables of clinical sessions, as well as those moments in which physicians can assign a discharge. For example, the schedules in Fig. 6, indicate that every day there is a clinical session at 8 a.m., in which it is assessed which patients are discharged and which

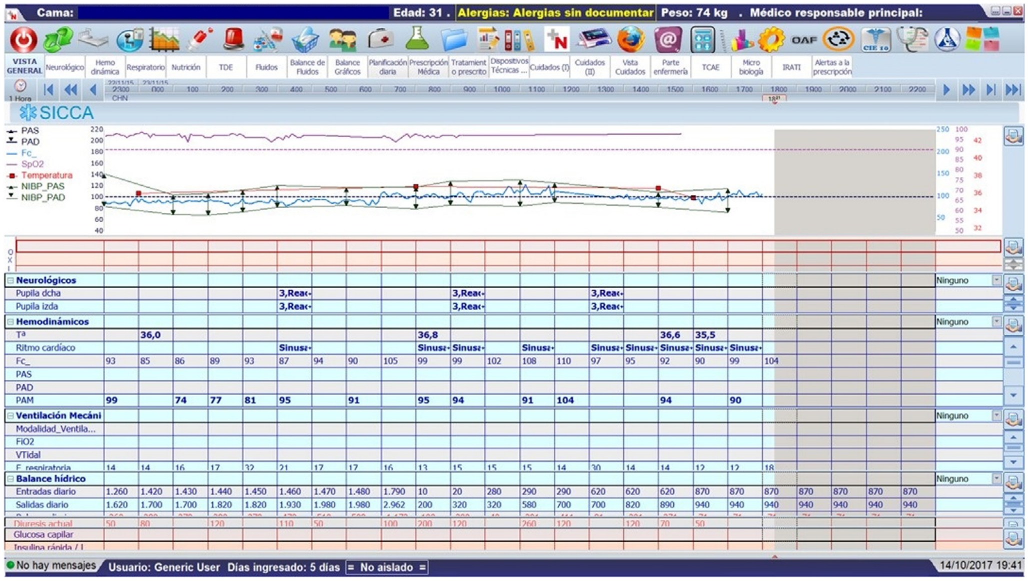


Fig. 5. Real ICU data screen of Metavision® software.

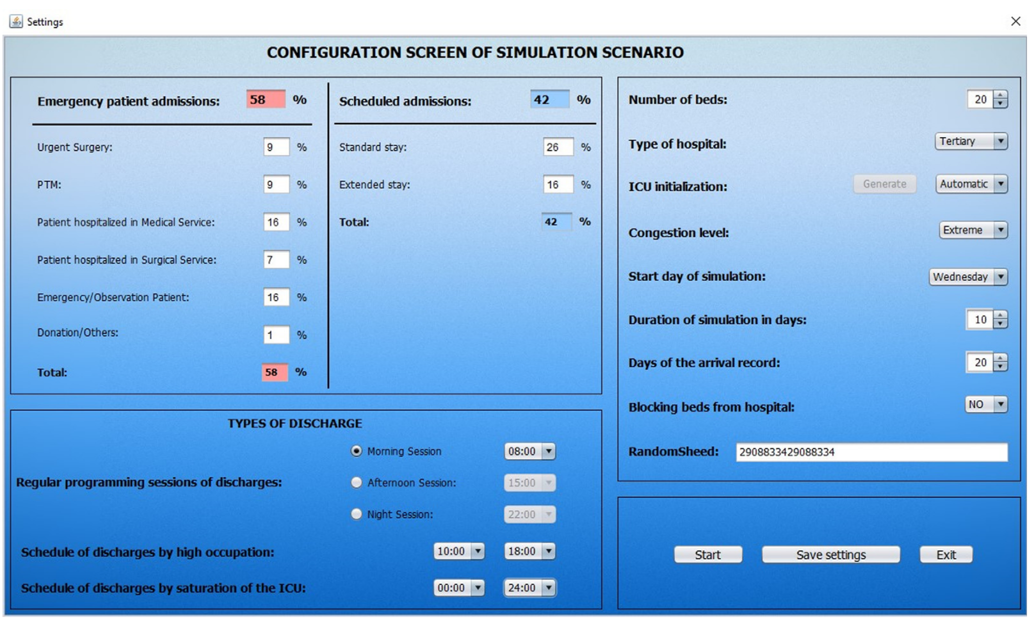


Fig. 6. Configuration screen of the simulation scenario.

surgeries are confirmed. Also, between 10 a.m. and 6 p.m., it is possible to discharge patients in situations of high occupation, to free up beds for future patients. The last defined schedule indicates that at any time it is possible to admit an incoming patient, even if there are no free beds in the ICU, as long as there is the possibility of assigning a discharge.

5.3. Interface

The user must interact with the simulator in order to manage the ICU. At decision times, those patients who are occupying the ICU are presented to the user and he or she must make discharge decisions by using all data provided by the ICU information technologies. This information is based on the health status of the inpatients, the occupancy level, and the forecasted scheduled patients.

The simulator's main screen is shown in Fig. 7. In the lower part, there is a history of the number of emergency patient arrivals for the last days (left) and a panel with the scheduled surgeries of the following days (right). In the upper-right part, events related to the change of health of patients appear, as well as information about admissions and discharges. On the top left side, the occupancy of the ICU is shown in a panel that represents the beds with a color code. Clicking on a patient, all the clinical history to date is shown (the evolution of the 275 variables describing the health status as well as the medical and nursery reports). In fact, the health status is reported on a different screen of the simulator that mimics and provides the same information that is displayed and recorded by the dedicated software Metavision® (see Fig. 8). Thus, the simulator creates a totally realistic and credible ICU environment. Users will be able to access the values of these variables in the case of all stabilized and recovered patients. The volume of information provided is simplified by preventing the consultation of the data of those patients who finally die and those who remain in serious conditions since the data of the patients that clearly cannot be discharged is meaningless.

As we said previously, we have collected variables of 200 real patients of an ICU. The objective of the simulator is to collect information on how each user manages an ICU in which the congestion level is *extreme*. It is not intended to assess the user's medical knowledge. Consequently, some ICU physicians collaborating in the development of the simulator, to shorten the time to assess the clinical status of all inpatients, analyzed the medical records of all patients to define three states along their stay, which help the user to make decisions. On the one hand, we consider in severe conditions to be discharge a patient who has just been admitted in the ICU (red color in Fig. 2). On the other hand, patients who has finished their LoS are considered totally recovered and they should be discharged (green color in Fig. 2). Finally, an intermediate state is established for each patient (orange color in Fig. 2), which indicates the moment from which the patient is sufficiently stabilized to be discharged, although risks to his/her health are assumed.

5.4. Information recorded

When simulation finishes, all decisions and general results (number of patients admitted, number of surgeries canceled, number of early discharges…) are recorded. Given that a well-done simulation run could last many minutes, this simulator allows the user to save the simulation and finishing it later.

Two documents are automatically sent to each user after a simulation is completed. The first one records general information regarding the number of emergency patients diverted, the number of surgeries that have been canceled, the number of discharges assigned in an early way as well as the average time of shortened LoS in hours. The second document shows the evolution of the number of occupied beds along the simulation. It also has information about those specific moments in which emergency patients are admitted or diverted, and the same for scheduled patients.

The simulator, in addition to sending those two types of documents, also generates files that record all the information associated with the individual decisions of the users. The decisions consist of determining at what moment the user has decided to discharge each patient and if patients who need care in the ICU are admitted or diverted, both emergency and scheduled. These files, which can also be opened by the simulator, allow reproducing step by step one simulation that is already finished. As we already mentioned the simulator controls the, so we can reproduce two different simulations in order to compare bed management with each other.

6. Preliminary results

In this section, preliminary results of the simulator are introduced. The objective is not to provide a full analysis of management typologies, but to present their potential to carry out extended research in this direction. Two types of measures are proposed for the analysis of the user decision-making: global indicators and dynamic indicators. The first category accounts for the global results of the management while the second one takes into account the dynamics of the decision-making. Last, a qualitative assessment of the ICU Simulator by users is exposed.

Table 2
Comparison of simulation global results recorded by 18 ICU physicians. Users faced a 24-bed ICU, which was initialized with 23 patients in different health statuses. Over three weeks, 34 emergency patients and 23 scheduled patients arrived at the ICU.

Physician	Diverted emergency patients	Canceled surgeries	Shortened stays (Total discharges)	Average time of shortened LoS (h)
Phy_1	13	2	4 (34)	47.21
Phy_2	9	6	14 (33)	23.78
Phy_3	9	8	14 (30)	31,25
Phy_4	6	7	18 (34)	38,61
Phy_5	7	6	11 (33)	42,62
Phy_6	6	4	21 (38)	43.81
Phy_7	16	0	0 (34)	0.00
Phy_8	11	3	7 (35)	22.16
Phy_9	7	5	16 (34)	29.51
Phy_10	7	3	27 (39)	43.61
Phy_11	9	0	23 (39)	39.32
Phy_12	13	3	5 (32)	30.69
Phy_13	12	5	8 (33)	32.72
Phy_14	10	1	10 (35)	28.92
Phy_15	10	1	21 (35)	37.71
Phy_16	4	4	21 (37)	39.04
Phy_17	10	1	24 (38)	41.14
Phy_18	11	2	13 (35)	35.93

6.1. Global performance measures

Not every physician nor nurse have the same vision when it comes to managing patients at the ICU. With the recorded information it is possible to compare users' results in order to analyze their management *style*. Table 2 summarizes results recorded by 18 ICU physicians. They performed the simulation under exactly the same ICU scenario. These physicians managed a 24-bed ICU with an *extreme* congestion level ($\rho > 1$), which was initialized on Monday with 23 patients in different health statuses. The emergency patients' arrival rate per day was $\lambda_E = 1.38$, and the scheduled patients' arrival rate per operation day was $\lambda_{S*} = 1.51$. Over three weeks, 34 emergency patients and 23 scheduled patients arrived at the ICU. The ICU blocking discharge from wards was not included and during the simulation, there were regular programming sessions of discharges only in the morning at 8 AM. Every user has the same stochastic environment, with the same arrivals and the same patients (note that the total number of discharges by each user is different because it is influenced by the number of patients admitted to the ICU).

Here it is confirmed that physicians make decisions quite differently. Some of them canceled few surgeries but following two different strategies: there are those who decide not to assign early discharges and not admit emergency patients (e.g., physician 7) and others decide to admit more patients assigning early discharges (e.g., physician 11). By contrast, several physicians decided to cancel more surgeries in order to admit more emergency patients (e.g., physician 4). Finally, some physicians try to maximize the number of patients admitted to the ICU (e.g., physician 16).

For each physician, the ratio of diverted patients to total arrivals (34), the ratio of canceled surgeries to total scheduled surgeries (23), and the ratio of shortened stays to total discharged patients (different for each physician) are calculated (data are included in Table 2). A chi-square test of homogeneity has been conducted to compare these ratios among users. Results indicate that there are significant differences in the ratio of canceling surgeries and shortening stays (p-value < 0.01), but no significant differences are found (p-value > 0.1) in the ratio of emergency patients diverted. Table 3 presents the aggregated results for each type of user.

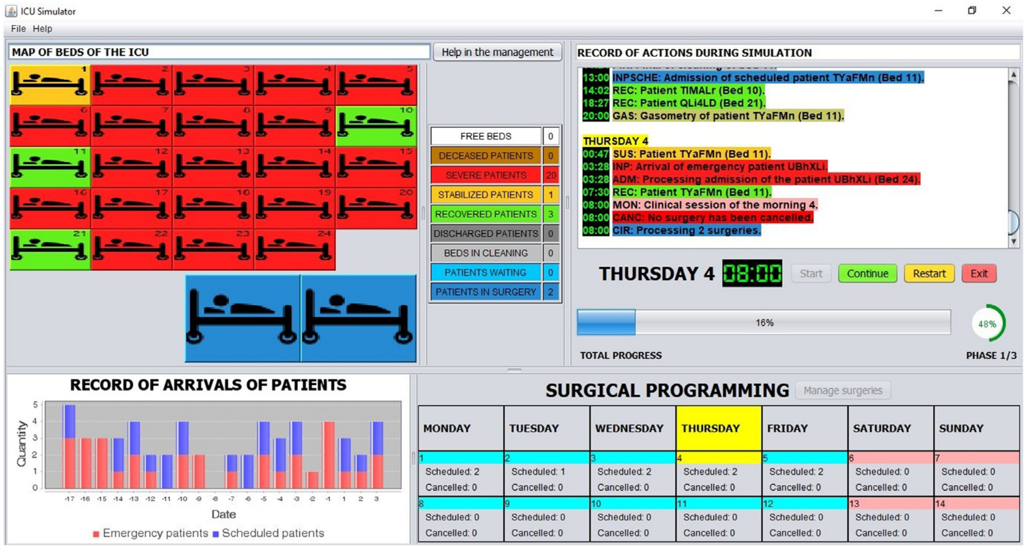


Fig. 7. Simulator's main screen.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

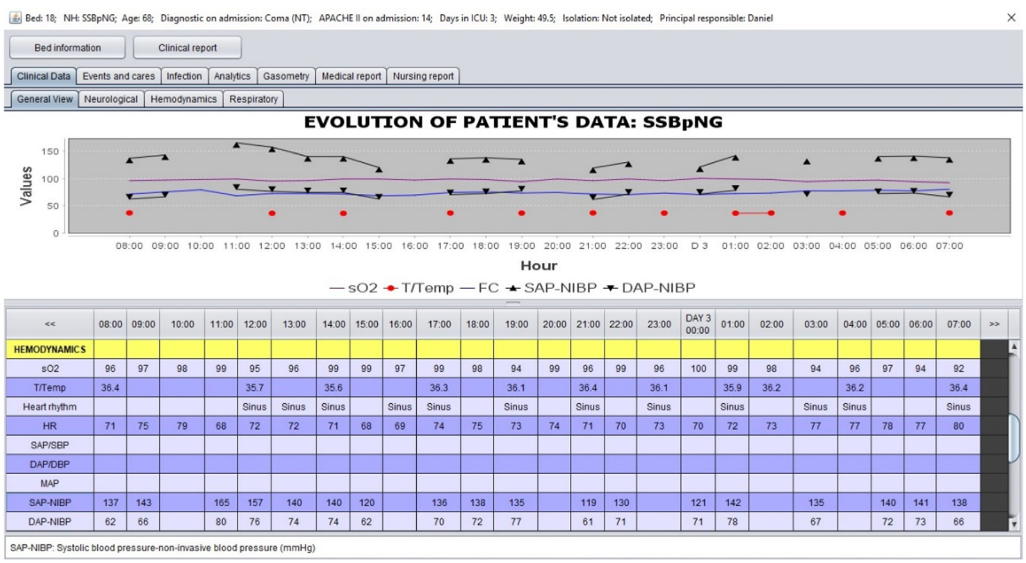


Fig. 8. Information of patient's clinical data, mimicking real screens of Metavision®.

Table 3
Global mean results of all users of the simulator. They are divided by different groups (OM/OR stands for Operation Management and/or Operational Research).

Group (Number of users)	Diverted emergency patients	Canceled surgeries	Shortened stays (Total discharges)	Average time of shortened LoS (h)
Physician (18)	9.44	3.39	14.28 (35.00)	33.78
Nurse (13)	10.77	3.38	10.54 (34.31)	29.61
Nurse tech (4)	13.75	1.25	10.75 (36.00)	34.40
Resident (5)	5.00	5.20	19.20 (36.00)	37.74
Medical student (4)	5.00	5.75	11.00 (35.75)	36.52
OM/OR researcher (4)	7.60	2.80	17.80 (35.60)	35.85

6.2. Dynamic assessment of the ICU management

The performance measures presented in the previous section overview the user decision making and can show that users differ in their ICU management. However, they can show differences even if their global performance measures result to be similar. To describe the dynamic management of the ICU beds we propose to track through time the number of beds that the user keeps available to be assigned to a new patient in a short time if necessary. We name such bed a manageable bed. The number of manageable beds at time t in the ICU is considered the number of those beds in any state but occupied *with a severe patient*, minus the number of patients already accepted but not admitted to the ICU yet (state variables X_2 and X_3).

When a user keeps a low number of manageable beds, then he or she is assuming risks of having to divert emergency patients or canceling surgeries. And the opposite management, having a large number of manageable beds in the ICU can avoid the diversion of emergency patients and cancellation of some surgeries but would require the discharge in advance of some patients or the cancelation of some surgeries not considered as very urgent.

Fig. 9 shows the evolution of two different physicians. The physician number 7 prefers more control over the ICU and reserves at least 3 manageable beds most of the time in order not to cancel any surgeries. However, physician number 10, works on a lower level of manageability, which means that more new patients are admitted, with the risk of running out of manageable beds at certain times. This representation is consistent with the results shown in Table 2. By contrast, Fig. 10 shows the evolution of two physicians who were not so different according to Table 2 (physicians 1 and 12). It is observed that the evolution they have followed is quite different. Accordingly, global results do not fully describe how users manage the ICU, and it is necessary to analyze their evolution.

6.3. Qualitative assessment of the ICU simulator

A questionnaire is provided at the end of the simulation. The users have to respond to four questions using a five-point agree/disagree scale (Likert scale survey). The following questions were used to gather this data:

- Q1: "Did you find that the interactive simulator reflects in a real way how to manage the patients of an Intensive Care Unit?"
- Q2: "To what extent do you agree that the simulator allows you to analyze the decision-making regarding the management of beds in your Intensive Care Unit?"
- Q3: "To what extent do you agree that the simulator can be used as a better learning tool on the management of ICU beds compared to traditional methods such as reports or slide presentations?"
- Q4: "Do you think that the simulator can help you better understand the management of beds in your unit and apply measures to improve it?

Fig. 11 shows the main results of the evaluation, which includes all the participants mentioned in Table 3. The strongly agree and agree scores together have shown a more than 85% satisfaction from the users of the simulator in all questions except from the Q2, which scores a bit lower (82%). Almost all participants agree with the accuracy with which the simulator represents a real ICU (Q1, only 1.96% disagree), and the vast majority find useful this simulator in order to learn on the management of ICU beds (Q3, 56.86% strongly agree).

In general, both physicians and nurses find it more feasible that the simulator allows them to understand the management of ICU beds rather than being able to use it to analyze the decisions made there. This difference may be due to the fact that at this moment a framework has not been developed on the analysis of decision making from the simulator, and one of the purposes is not yet fully understood by medical users. Completing the analysis, for each question (Q1–Q4) a chi-square test of homogeneity has been conducted to determine whether frequency counts are distributed identically across different groups. In all cases, the test does not reject the hypothesis that the distribution of responses is the same in each type of participant (p-value > 0.05).

7. Discussion and conclusions

In ICU management and, by extension, in hospital management in general, it is essential to use all resources efficiently. Furthermore, the bed occupancy rate is very variable and not very predictable, since it depends on both programmed factors, such as surgery that requires that the postoperative period to be referred to the ICU, as well as random factors such as urgent admission of patients. This implies that in certain cases management policies focused on high occupancy, in order to avoid wasting an expensive resource, have to face the problem of lack of bed for a patient who requires it.

The transfer of a patient to an area of less care should be carried out when he or she is stable enough, and the assessment should be fully based on clinical judgment. Clinicians are aware of the risks involved in discharging a patient in advance to be able to admit another when the ICU is full, however, these decisions depend not only on the patient's health status but also on organizational and teamwork issues [14].

According to the SCCM guidelines for ICU admission, discharge, and triage [106], more research is needed on all aspects of critical care rationing to address current deficiencies. This paper contributes to this research by developing, for the first time, an MFS of an ICU that reproduces the necessary operational processes to handle the patient flow and interacts with the user by presenting the same patient clinical information and in the same way as the ICU information technologies do in real ICUs. Specifically, the simulator allows representing the information related to the uncertain, complex, and dynamic features of the ICU and their patients' admission and discharge processes. The purpose of this simulator is to design a decision tool that collects informed decisions of the user to help in the analysis of the decision-making variability to reduce it. The simulator is able to present conflicting scenarios, that is, scenarios that generate discrepancies among physicians.

The MFS is flexible to recreating any type of ICU, defined by its size, mix of patients, congestion level, etc. It is also possible to introduce bed-blocking from wards, although it has not been considered so far in the simulations performed by physicians. In situations of blockage, the patient cannot be discharged whether the user wants it or not. Therefore, we avoid these forced situations to collect the decisions that the user freely make. The simulator has been used and validated by ICU physicians and nurses of the three hospitals of the public network of the Spanish Autonomous Community of Navarre (Pamplona, Tudela, and Estella) and of a private one of concerted management of Guipúzcoa.

The study conducted by de Freitas [107] demonstrated that these types of simulators have a learning function. Other more recent researches also show that the use of MFS has a positive effect on the learning of participants [108,109]. Based on this, we also propose this ICU simulator as a learning tool from two different points of view.

On the one hand, both medical and nursing students could use this simulator at universities in order to learn how ICUs are managed. When students run the simulation, they will take part in the decision-making process of the ICU for the first time, but in a safe environment, in which their decision will not have bad consequences for patients. Apart from this, students can compare their own results with those that are supposed to be the best, that is, decisions about patients of simulations performed by experienced ICU physicians. They can also watch step by step how the simulation has been performed. The success of using this type of tools can be seen in [96].

On the other hand, physicians who work in the ICU not only could use the simulator in order to improve their knowledge of bed management individually, but they could also learn in a collective way. Comparing all results of the decision-making process generated by simulations performed by many physicians of the same ICU, it would be possible to identify which situations cause the greatest disparity among them. These scenarios could be labeled as conflicting scenarios because the decisions that physicians make when managing these situations differ.

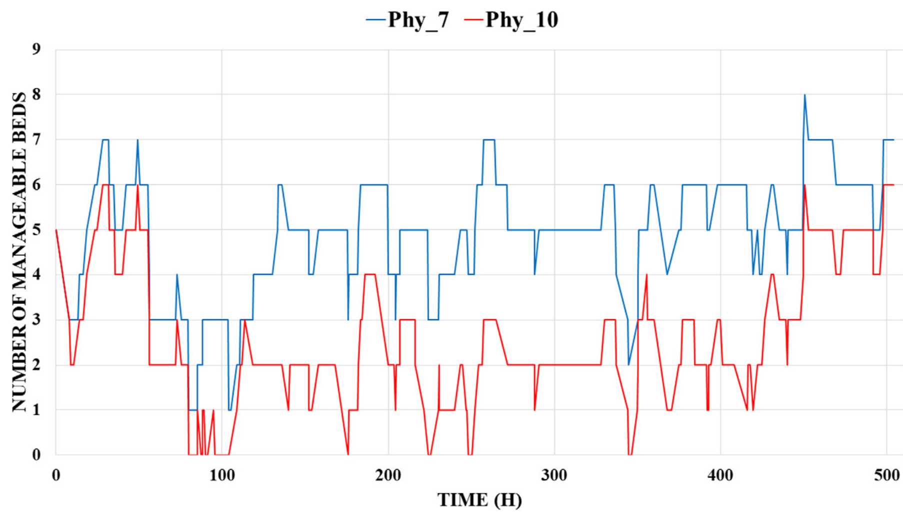


Fig. 9. Graph with the evolution of the number of manageable beds of two different physicians (physicians 7 and 10).

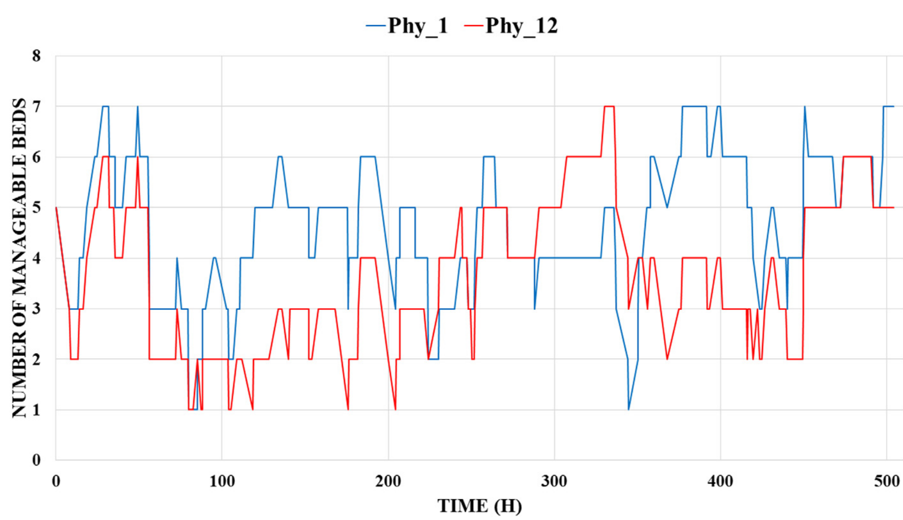
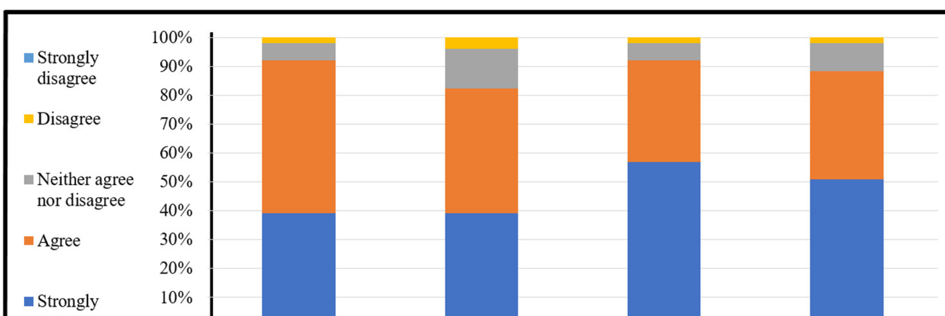


Fig. 10. Graph with the evolution of the number of manageable beds of two similar physicians according to their global results (physicians 1 and 12).



	Q1	Q2	Q3	Q4
Strongly disagree	0.00%	0.00%	0.00%	0.00%
Disagree	1.96%	3.92%	1.96%	1.96%
Neither agree nor disagree	5.88%	13.73%	5.88%	9.80%
Agree	52.94%	43.14%	35.29%	37.25%
Strongly agree	39.22%	39.22%	56.86%	50.98%

Fig. 11. Main results of the questionnaire.

In addition, it would be possible to detect which patients are complicated to treat, because there are no unified decisions about them (decision about admission, time to discharge...).

Our future research includes to develop a methodology that facilitates the analysis of the data recorded by the simulator. At this moment, evaluation criteria are the number of diverted emergency patients, canceled surgeries, shortened stays, and average time of shortened LoS (h); and we focus on these parameters to identify differences among users. These comparisons are made with the overall results of the entire simulation. The tool also saves all the decisions of each user and in which situations, and this will allow a dynamic comparison of the management of the ICU. It is necessary to define metrics to measure the dynamics of the management, as it is presented in Figs. 9 and 10. Mallor et al. [33] obtain different management policies (aggressive, equitable, and cautious) as result of a normative analysis of the decision-making by solving stochastic optimization problems. Physicians' behavior could be classified following this type of policies or other similar ones. In summary, our purpose is to use the simulator to collect data about the management of ICUs that enable us to test theories about physicians' decision-making, analyze triage processes, and detect biases and patterns.

CRediT authorship contribution statement

Daniel Garcia-Vicuña: Methodology, Software, Formal analysis, Investigation, Data curation, Writing. **Laida Esparza:** Conceptualization, Validation, Resources, Investigation, Data curation. **Fermin Mallor:** Conceptualization, Methodology, Writing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This paper has been supported by grant MTM2016-77015-R (AEI, FEDER EU, Spain). The authors are grateful to the medical staff of the main hospital in Navarre for using the simulator and for their help in validating it (Hospital Compound of Navarre, Pamplona) and to the medical staff of the other hospitals for using the tool too (García Orcoyen Hospital, Estella; Reina Sofía Hospital, Tudela; and Guipúzcoa Polyclinic, San Sebastián).

Appendix A. A real patients' description

Peter, 56 years old.
Admitted for Herpex Simplex Virus-1 meningoencephalitis.

- Intubated and connected to mechanical ventilation.
- Neuromonitoring of intracranial pressure.
- Intracranial pressure control by first level measures.
- In treatment with acyclovir.
- Precise norepinephrine in continuous infusion.

Cate, 63 years old.
Admitted for severe community-acquired pneumonia due to Streptococcus pneumoniae.

- Intubated and connected to mechanical ventilation.
- Supported with veno-venous extracorporeal membrane oxygenation.
- In treatment with meropenem and linezolid.

Phil, 78 years old.
Admitted for postoperative control of aortic valve replacement cardiac surgery.

- Hemodynamically stable without requiring vasopressors or inotropes.
- Chest tube with a rate of drainage less than 100 mL/d.
- Acute kidney injury without oliguric and creatinine and urea levels of 1.8 mg/dL and 80 mg/dL, respectively.

Harvey, 28 years old.
Polytrauma with severe traumatic brain injury secondary to a motor vehicle accident.

- Intubated and connected to mechanical ventilation
- Fitted with a rigid cervical collar and pelvic stabilization device
- Dilated unreactive right pupil
- Hemodynamic instability, with worsened hypotension (blood pressure, 80/50 mmHg) and persistent bradycardia (heart rate, 40 beats/min). An inadequate response to fluid resuscitation.

Paul, 52 years old.
Admitted for acute coronary syndrome with ST-segment elevation.

- Cardiac catheterization with left main coronary artery and three-vessels disease.
- Echocardiography with moderate ventricular dysfunction (EF 40%) and segmental alterations, with extensive anterior hypokinesia and apical akinesis.
- Support with dobutamine in perfusion due to low cardiac output with renal dysfunction.

Anne, 37 years old.
Admitted for right occipital glioblastoma multiforme.

- She has nausea and vomiting, headache, that is difficult to control with common analgesics, and visual disturbances.

Appendix B. All combinations of the example of the dilemma of the last bed

See Fig. B.1.

Appendix C. Set of patient variables

- Informative patient's data: age, gender, weight, LoS, provenance, principal diagnostic, personal history, and type of patient (Fixed values for each patient and considered outside the 275 variables).
- Neurological parameters (10): both pupil size in millimeters and reactivity, Glasgow Coma Scale (Glasgow-Motor response, Glasgow-Eye response, and Glasgow-Verbal response), external ventricular drain, and RASS scale.
- Hemodynamic parameters (17): oxygen saturation (%), the temperature in degrees Celsius (°C), type of heart rhythm, heart rate (rpm), systolic blood pressure (mmHg), diastolic blood pressure (mmHg) (invasive are non-invasive), mean arterial blood pressure (mmHg), pacemaker rhythm (y/n), type of pacemaker, pacemaker operating modes, pacing rate (rpm), pacing capture threshold (mA), etc.
- Respiratory parameters (14): spontaneous breathing trials, tracheotomy (y/n), fenestrated cannula/speaking valve (y/n), tracheostomy cap (y/n), conventional mechanical ventilation (y/n), noninvasive positive pressure ventilation (y/n), reservoir mask (y/n), Venturi mask (y/n), nasal cannula

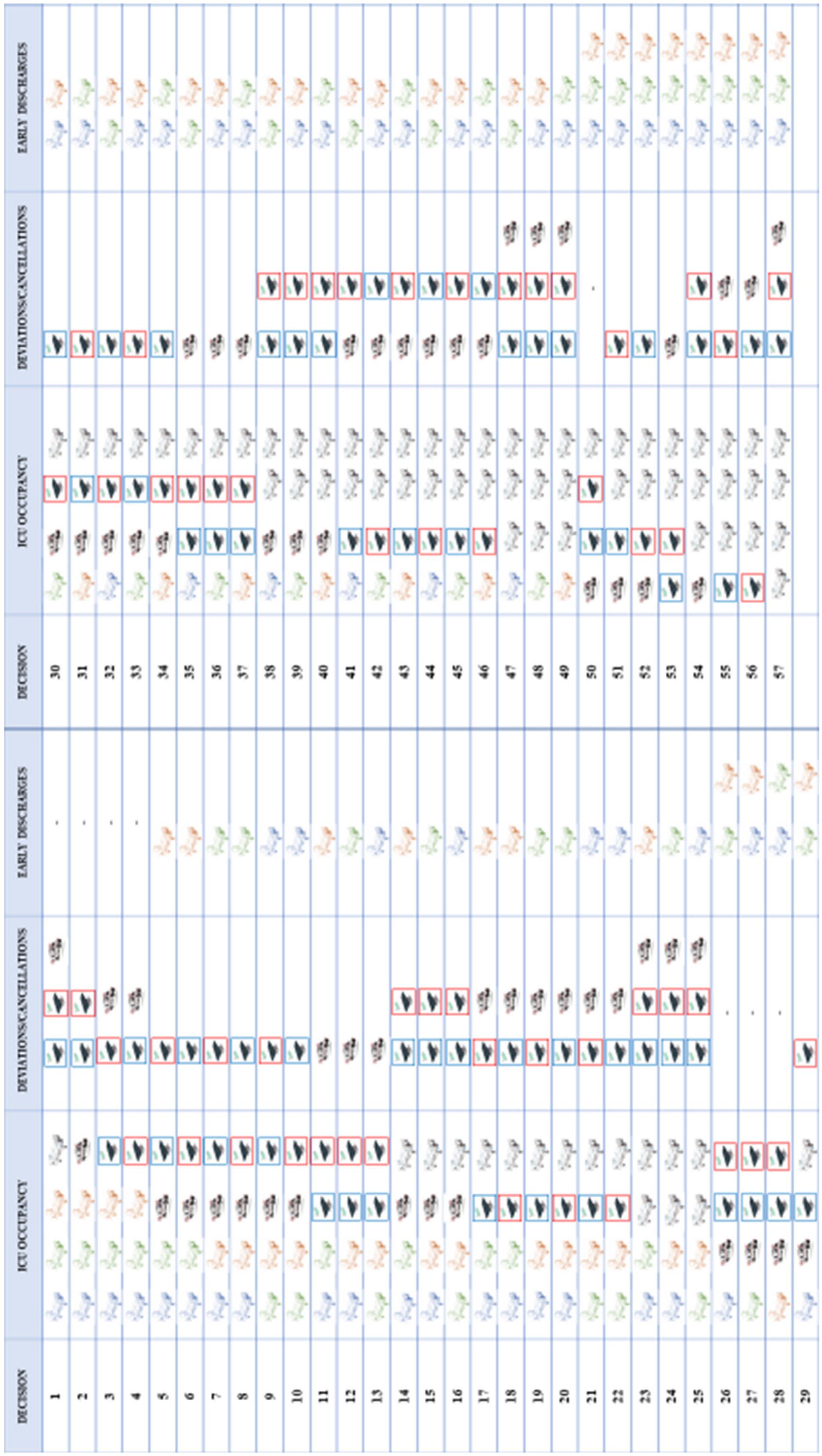


Fig. B.1. All 57 possible combinations of the example of the dilemma of the last bed.

(L/minute), inspired gas flow with high-flow nasal cannula oxygen therapy (L/minute), fraction of inspired oxygen with high-flow nasal cannula oxygen therapy (%), fraction of inspired oxygen (%), extrinsic positive end-expiratory pressure (cmH2O), and respiratory rate (rpm).

- Kidney parameters (2): continuous renal replacement therapies (y/n) and intermittent hemodialysis (y/n).
- Balances (2): diuresis (mL) and chest drainage (mL).
- Medication (123): plasmalyte (mL/h), propofol 2% (mg/Kg/h), midazolam 50 mg (μg/Kg/h), remifentanil/ultiva (μg/Kg/min), morphic chloride (mg/h), intravenous fentanyl (μg/Kg/h), etc.
- Events and care (54): percutaneous tracheostomy, cardiopulmonary resuscitation, defibrillation, electrical cardioversion, pharmacologic cardioversion, transcutaneous pacing, pericardiocentesis, pulmonary embolectomy, etc.
- Infections (5): type of infection, origin, inflammatory response, germs, and antibiotics.
- Analytics (37): hemoglobin (g/dL), hematocrit (%), leukocytes (X109/L), neutrophils (%), Lymphocytes (%), monocytes (%), eosinophils (%), basophils (%), etc.
- Gasometry (7): pH, pCO2 (mmHg), pO2 (mmHg), lactate (mmol/L), saturation (%), HCO3 (mmol/L), and base excess (mmol/L).
- Reports (4): admission, medical, nursing, and clinical reports.

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