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## ► To cite this version:

Yinling Liu, Thierry Moyaux, Guillaume Bouleux, Vincent Cheutet. Hybrid simulation modelling of emergency departments for resource scheduling. *Journal of Simulation*, 2023, pp.Latest Article. 10.1080/17477778.2023.2187321 . hal-04031528

**HAL Id: hal-04031528**

**<https://hal.univ-lorraine.fr/hal-04031528v1>**

Submitted on 8 Feb 2024

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# Hybrid Simulation Modeling of Emergency Departments for Resource Scheduling

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## ARTICLE HISTORY

Compiled March 1, 2023

## ABSTRACT

This paper addresses the problem of resource scheduling of emergency departments in an uncertain environment. An innovative approach based on Agent-Based Simulation (ABS) and Discrete Event Simulation (DES) is proposed. To do so, this paper first proposes a framework integrating ABS and DES. Subsequently, we provide a detailed description of the DES and ABS parts of the model of the ED. Five combinations of strategies – namely, “FIFO+Random” (*i.e.*, FIFO: the queue of patients operates in FIFO; Random: the patients are randomly assigned to doctors), “FIFO+Centralised”, “Random+Centralised” (“Centralised” implies the assignment of the most appropriate doctor to a patient is only determined by the *Platform* agent via optimising all the resources), “Random+Random” and “Autonomous” – are implemented to schedule the resources of the ED. Finally, experiments analyse the efficiency of the five combinations of strategies on the duration of patients’ stay. The results show that “FIFO+Centralised” outperforms others regarding the average for the duration of patients’ stay without hospitalisation: 3.75% of the time has been saved; “Random+Centralised” outperforms others regarding the average for the duration of patients’ stay with hospitalisation: 0.57% of the time has been saved.

**Keywords:** Emergency Department (ED); Resource scheduling; Hybrid simulation modelling; Agent-Based Simulation (ABS); Discrete-Event Simulation (DES).

## 1. Introduction

Emergency Departments (EDs) are complex healthcare delivery systems characterized by time-varying arrivals, multi-stage service, and multi-class patient population Alayan et al. (2019). EDs are increasingly crowded in 2020 because of the outbreak of COVID-19. For example, there were 468,069 confirmed cases with 31,416 deaths until September 22, 2020 in France<sup>1</sup>. Most COVID-19 patients are treated in EDs. ED overcrowding is considered to be a major issue in hospitals. Overcrowding means that the demands for emergency services exceed the available resources in EDs<sup>2</sup>. Scheduling resources (doctors, nurses, equipment, treatment rooms) that work simultaneously in

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<sup>1</sup><https://www.gouvernement.fr/info-coronavirus/carte-et-donnees> accessed on 22 September 2020

<sup>2</sup><https://www.acep.org/practre.aspx?Id=29156> accessed on 22 September 2020

an uncertain environment remains a major challenge in EDs. On the one hand, lacking sufficient resources such as staff, equipment, etc., has a negative impact on timely and suitable services, causing longer stays of patients, patient dissatisfaction, the increase of the probability of patients leaving EDs without a treatment, bad patient outcomes, etc (Vanbrabant 2020). On the other hand, the flow of coming patients is not predictable. Classical mathematical approaches help deal with scheduling problems with low complexity or in a relatively static environment, they have a limitation in describing interrelationships between resources and adapting the analysis to dynamic change (Araújo, Pajares, and López-Paredes 2010; Song et al. 2018).

Much work has emerged in order to face this challenge. Most researchers concentrate on modelling the flow of patients in the ED via simulation approaches. These simulation methods principally include DES and ABS (Duguay and Chetouane 2007; Bair et al. 2010; Wang 2009; Wang et al. 2011; Carmen et al. 2014; Liu et al. 2017). Some work attempts to extend simulation methods, for instance by combining Value Stream Mapping and DES (Bal, Ceylan, and Taçoğlu 2017), incorporating data mining into DES (Ceglowski, Churilov, and Wasserthiel 2007), or integrating DES and ABS (Kaushal et al. 2015). The literature review discovers that the lack of clear evidence that a computer model had been developed led readers to make a leap of faith about how the model was encoded, and the results (Brailsford et al. 2019). In this paper, we model the healthcare team with ABS and the flow of patients with DES. We are dedicated to building a hybrid simulation system with details supporting the application of any resource scheduling strategies in EDs, instead of only focusing on how to improve the efficiency of ED analysed in the work of Kaushal et al. (2015).

DES has been a common approach for modelling EDs for over 30 years (Günel and Pidd 2010). DES is dedicated to modelling the queuing simulation or the complex network of queues (Siebers et al. 2010). The patient flow in EDs can be recognized as one of the complex networks of queues. The part of AnyLogic supporting DES provides a large variety of “Blocks” such as *Source*, *Sink*, etc. which are located in the process modeling library of AnyLogic. However, this approach is insufficient to model EDs close to reality. For example, it is difficult to model the decision process with human thinking. Patients, doctors, etc., in the model, are not autonomous. In other words, the behaviors of patients and doctors are scripted, not originating from the interaction between themselves and the environment. Therefore, we are motivated to introduce ABS into DES. ABS is a bottom-up approach to model systems, which can significantly clarify the solution structure, illustrate the dynamic properties of the model, serve to test the dependence of results on parameters and assumptions, and be a source of counter-examples (Macal 2016). It is generally employed when the complexity of the system being modeled is beyond what static models or other techniques can fully present (Helbing 2012). Agents in ABS are autonomous, which perceive their surroundings and make their own decisions. Patients, doctors, nurses, etc., may be modeled as agents. System-level behaviors are based on the interaction of ED agents and resources. Additionally, ABS offers important insights into the model. It allows investigating every detail of the simulation. Thus, the trace can be found when uncertain events happen in the simulation. Above all, we choose to combine DES with ABS to model EDs.

This work models the ED at CHU (University Hospital Centre) in Saint-Etienne, France. This CHU plans to create a Digital Twin of its ED for resource scheduling, which first requires gaining important insights into the ED from both global and detailed points of view. A simulation is hence necessary to become the backbone of this Digital Twin, and future work will connect the physical ED and our simulation

in both ways (*i.e.*, the physical ED will send information to the simulation, and the simulation will propose actions to the ED) in order to create this Twin. Consequently, we propose a prototype of the hybrid simulation of this ED.

Furthermore, a framework for modelling the ED is firstly proposed, in order to illustrate how to combine DES with ABS. Based on this framework, a hybrid simulation for ED is developed. The modelling processes involve DES and ABS modelling and how to incorporate ABS into DES in a system. In the end, simulation experiments will be performed to validate the feasibility of the proposed approach. The main contributions of this work are illustrated as follows:

- Proposing an innovative framework for the hybrid simulation in EDs;
- Developing a concrete simulation system using ABS and DES to support resource scheduling in EDs;
- Designing an efficient algorithm to realise five resource scheduling strategies in EDs.

Based on our simulation system, hospital managers can run different maintenance scenarios in our simulation system in order to investigate the impact of key factors on the length of patients' stay and waiting time. The impact of the number of doctors on the ED's performance can be equally analysed. Predicting uncertain issues is also possible based on part of real data and the data generated from simulation experiments. Finally, the virtualization of the treatment process allows us to have an insight into any ED details.

The remainder of this paper is structured as follows. Section 2 reviews the work of resource scheduling in EDs. Section 3 explains the process for modelling EDs via the hybrid simulation approach. Section 4 conducts a simulation experiment on the impact of the combination strategies on the duration of patients' stay in hospitals. Section 6 concludes the paper with future perspectives.

## 2. Literature review on resource scheduling in EDs

In this section, we will provide a significant analysis of resource scheduling in EDs. The literature indicates that a variety of aspects concerning scheduling have been investigated: nurse scheduling (D'souza et al. 2021), patient scheduling (Hutzschenreuter et al. 2008; Rachuba and Werners 2014; Hsieh and Lin 2014), physician scheduling (Jones and Evans 2008; Lo and Lin 2011), staff scheduling (Ogulata, Koyuncu, and Karakas 2008; Alayan et al. 2019), medical test scheduling (Di et al. 2012; Jeric and Figueira 2012), supply chain scheduling (Fan and Lu 2015), employees (for cleaning hospitals) scheduling (Campana et al. 2021). Various approaches have been applied to conduct resource scheduling in EDs, including constructing scheduling systems, mathematical approaches, and simulation approaches.

Constructing scheduling systems has been widely used in scheduling resources. D'souza et al. (2021) developed an automated nurse scheduling system to generate daily, weekly, monthly schedules, nurse face sheets, duty allocation charts, etc., for nurses. The system improved managerial control and saved a considerable amount of time for nurses to prepare the schedule. This approach has also been applied to scheduling physicians and supply chain (Lo and Lin 2011; Fan and Lu 2015). Lo and Lin (2011) proposed a Particle Swarm Optimization-based intelligent scheduling system to help solve the physicians' work scheduling problems. Fan and Lu (2015) studied the supply chain scheduling problem in the hospital with periodic working time on a

single machine. They all solved scheduling issues. Unfortunately, none of them takes the complete flow of patients in hospitals into consideration. In other words, the impacts of other processes on the specific scheduling issues cannot be evaluated.

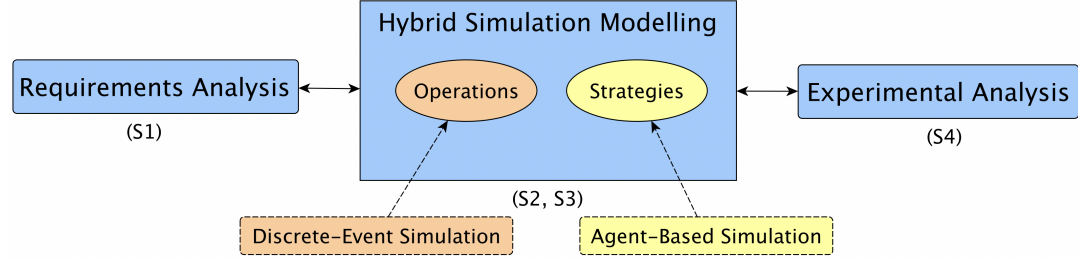
Mathematical approaches have also been commonly employed in scheduling resources in EDs, ranging from patient scheduling (Rachuba and Werners 2014), physician scheduling (Gendreau et al. 2006), staff scheduling (Ogulata, Koyuncu, and Karakas 2008), medical test scheduling (Di et al. 2012; Jeric and Figueira 2012), to employee scheduling (Campana et al. 2021). More specifically, Rachuba and Werners (2014) proposed a robust approach for patient scheduling in hospitals using multiple objectives. Gendreau et al. (2006) used studied physician scheduling problems by a combination of tabu search, column generation, mathematical programming, and constraint programming. Ogulata, Koyuncu, and Karakas (2008) utilized a hierarchical mathematical model to generate weekly staff scheduling. Di et al. (2012) proposed a scheduling strategy to reduce the total time of medical tests in EDs for a given number of patients. Jeric and Figueira (2012) formulated the issue of scheduling medical treatments for patients as a multi-objective binary integer programming model to find efficient scheduling strategies. Campana et al. (2021) used mathematical models and meta-heuristic algorithms to determine a schedule for the employees who will clean the whole hospital. Mathematical approaches always give us very precise results. However, they are basically based on very strict constraints. For example, Di et al. (2012) said the algorithm for the scheduling strategy was limited to a maximum of 10 patients. Ogulata, Koyuncu, and Karakas (2008) needed to select patients in advance. Jeric and Figueira (2012) didn't realize that some medical procedures could be blocked because of lacking resources. These strict constraints prevent us from gaining important insights into the system.

Besides, simulation is another prominent approach to resource scheduling in EDs (Gul and Guneri 2015). Gul and Guneri (2015) reviewed 106 articles on ED simulation and found that DES was the most used modeling method and ABS was becoming an emerging method. Doudareva and Carter (2022) also reviewed DES for ED modeling and focused particularly on the validation methods. Vanbrabant et al. (2019) equally conducted a comprehensive review on the simulation of ED operations and paid attention to KPIs and improvement options. The simulation approaches such as ABS and DES are principally used for patient scheduling (Hutzschenreuter et al. 2008; Hsieh and Lin 2014), physician scheduling (Jones and Evans 2008; Alayan et al. 2019). For instance, Hutzschenreuter et al. (2008) developed an agent-based simulation system for patient admission scheduling in hospitals. Hsieh and Lin (2014) proposed a viable and systematic approach to develop a distributed cooperative problem solver for scheduling patients based on the multi-agent system in order to minimize patient stay in hospitals. Jones and Evans (2008) described the development of an agent-based simulation tool for scheduling physicians in EDs. Alayan et al. (2019) developed a DES to model the time-varying complete patient flow in the emergency department with a multi-class multi-stage queuing network. The existing work seems that it doesn't take the advantage of DES and ABS. For example, Jones and Evans (2008) didn't consider the autonomy of agents. In other words, the agents were not allowed to take their own decisions. Hsieh and Lin (2014) didn't consider the uncertainty in the simulation model. They might also make some unrealistic assumptions: physicians having the same skill level and sufficient physical resources (Alayan et al. 2019). Making full use of simulation approaches not only helps schedule resources in EDs but enables us to model the flow of patients that is close to reality. It is capable of detecting unknown issues in EDs as well.

### 3. Hybrid simulation modeling for EDs

#### 3.1. Hybrid simulation modelling framework

The framework for building the ED simulation system consists of requirements analysis, hybrid simulation modelling, and experimental analysis, which is shown in Fig. 1. This framework is an instance of the conceptual framework for hybrid simulation pro-



**Figure 1.** Framework for hybrid simulation, where  $S_i$  stands for Stage  $i$

posed by Brailsford et al. (2019). Their framework is composed of 4 stages: Real-world problem (Stage 1), Conceptual modeling (Stage 2), Computer modeling (Stage 3), and Solution and understanding (Stage 4). These four stages have been mapped to our framework. We choose this conceptual framework because it ensures a rigorous methodological approach and provides the structure for a set of good practice guidelines for modellers.

The first step is to analyze the requirements of EDs. Based on these requirements, the conceptual model of the ED simulation system is designed. This model involves the basic concepts of the system and the corresponding simulation approaches. In our case, this system principally includes the concepts *operation* and *strategy*, which can be described by DES and ABS respectively. Concept *operation* means the behavior of a system-of-interest comprises a set of processes. Concept *strategy* implies the support of the decision-making needed among the processes. These two concepts are intertwined because operations need the instructions from the strategy analysis to go smoothly; the strategy analysis needs the real-time data from operations to provide the instructions. The hybrid simulation modelling is thus demanded. We use DES to describe the operations of the system of interest. We employ ABS to analyse the real-time situation of the system regarding its environment. The object passing through the operations of the system is the agent. This agent communicates with other agents via sending messages. Finally, different scheduling strategies can be evaluated via this simulation system.

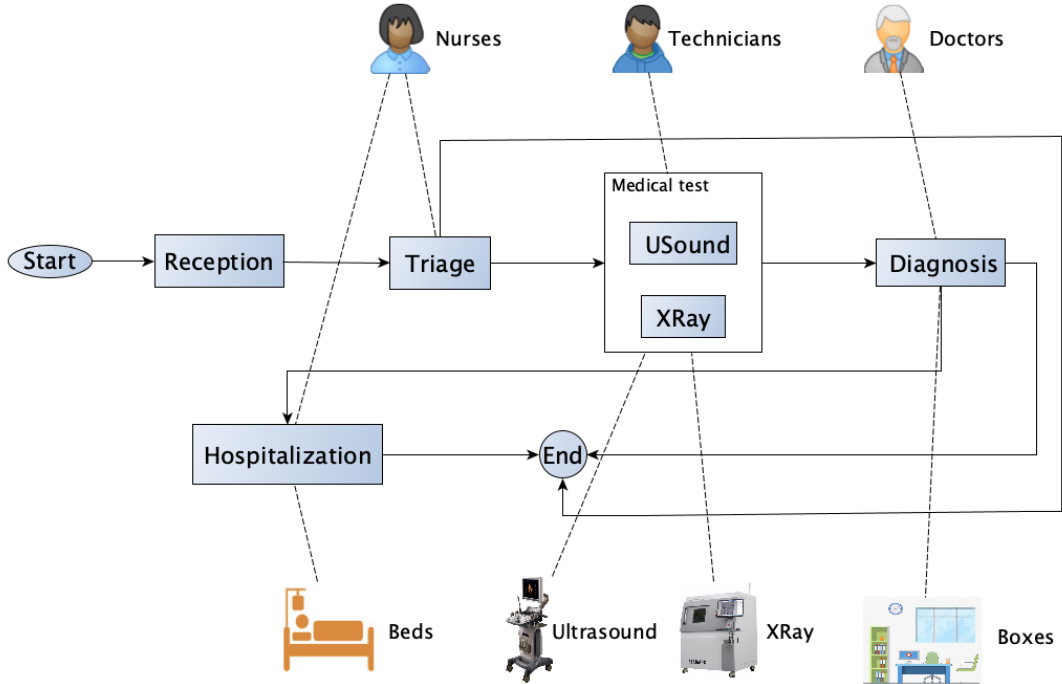
Our framework for developing the ED system clarifies the practical value of the work. It describes the ED system with abstract concepts, which allows us to use the same idea to build another system of interest that can be expressed by similar abstract concepts. We could reuse this approach to deal with different aspects of the system. For example, we can detail every process needed, propose corresponding strategies, and run the simulation with different configurations of the system. This framework could also motivate us to integrate other aspects of the system with the appropriate approaches, in order to fully describe the system of interest. In other words, new processes can be flexibly added to the system. For example, we could trace the whole duration of patients until they are totally recovered. We could also add supply chains for the medicines or equipment, etc.

### 3.2. ED resource scheduling simulation system

#### 3.2.1. The flow of patients

The flow of patients in EDs is shown in Fig. 2. This flow indicates the patient paths in EDs. Rectangles denote the processes. Solid lines imply the potential paths for admitted patients. Dashed lines mean resources are associated with relevant processes. Resources are used in this flow, including nurses, technicians, doctors, beds, ultrasound, xray, treatment rooms. If the resources of human beings are related to processes, it suggests these processes need human intervention.

This figure provides an overview of processes for patients, including registration, triage, medical test, diagnosis, and hospitalization. Patients need to register when they arrive at the hospital. The ways how they arrive at the hospital can be: self-presentation, ambulance, selection, etc. The registered patients are then sorted by nurses via patients' severity. The sorted patients are divided into three groups, *viz.*, internal, surgical, and orthopedic. They need to wait in the waiting room until they are called. Until now, the process of triage is finished. As for treatment, resources such as doctors, nurses, treatment rooms, medical equipment, etc., are required. Doctors are categorised as either interns or senior doctors. Interns are situated in the corridors in order to bring patients to treatment rooms in which they will be treated and they perform a preliminary analysis about patients. On the other hand, senior doctors are located in their treatment rooms when they are waiting for patients to finish these basic tests. After being diagnosed by senior doctors, patients either go home or need hospitalisation. It should be noted that all the resources mentioned in our simulation systems are limited. The details of modeling will be discussed in the following sections.



**Figure 2.** The flow of patients in EDs

### 3.2.2. DES part of our model

The DES module is principally used for modelling the patient flow. Figure 12 (in Annex A) shows the details of the DES model. This DES model is derived from Fig. 2 because DES analyzes the flow of patients from the operational perspective.

This module is mainly built using the “Blocks” of the Process Modelling Library in Anylogic<sup>3</sup>. The “Blocks” involved include *Source*, *MoveTo*, *Delay*, *Queue*, *SelectOutput*, *Hold*, *ResourceTaskStart*, *Seize*, *ResourceAttach*, *Release*, *ResourceTaskEnd* and *Sink*. A summary of modules and blocks is provided in Table 1. User-defined processes are used to describe the examination of *UltraSound* (Fig. 3) and *XRay* (Fig. 4). The advantages of defining our own processes are: (1) we can define our expected behaviors of the processes; (2) It facilitates the modeling of complex systems; (3) we can draw the presentation of these processes, making the whole process more readable. Inside the two self-defined processes, we still use general blocks to call technicians and size the relevant equipment to accomplish the examination.

**Table 1.** Mapping between modules and blocks.

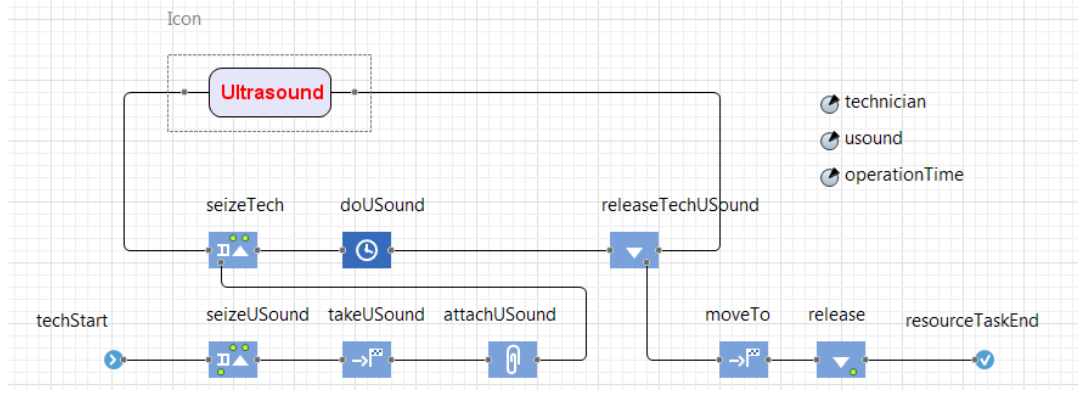
Module	Relevant Blocks	Description
Arrivals	<i>Source</i>	It generates the patients from either self-presentation or ambulances in a random way.
Registration	<i>Delay</i>	The registration process is simulated by a random time of delay.
Triage	<i>MoveTo</i> , <i>Queue</i> , <i>SelectOutput</i>	The patients are triaged into <i>Internal</i> , <i>Surgical</i> and <i>Orthopedic</i> by the FIFO strategy.
Wait	<i>MoveTo</i> , <i>SelectOutput</i> , <i>Delay</i> , <i>Hold</i>	This module involves the interaction between patient agents and other agents, in order to prepare the resources needed for the treatment.
Treatment	<i>SelectOutput</i> , <i>MoveTo</i> , <i>UltraSound</i> , <i>XRay</i>	This module shows the process of treatment such as ultrasound and x-ray examination.
Evaluation	<i>Delay</i>	A synthesis analysis of patients' condition will be made to determine the following treatment.
Hospitalisation	<i>Seize</i> , <i>MoveTo</i> , <i>Delay</i> , <i>Release</i>	Unstable and severe patients are demanded to be hospitalised before discharge or transferring.
Discharge	<i>Sink</i>	Patients leave the ED.

### 3.2.3. ABS part of our model

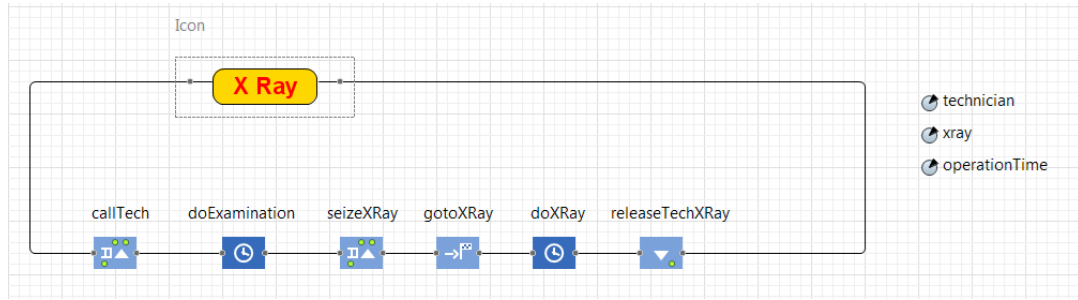
The ABS part of our model aims at analysing the strategies for scheduling the resources, which involves *Patient*, *Nurse*, *Doctor*, and *Platform* agents. The relationship of agents is shown in Fig. 5. *Platform* agent is the center for receiving resource requests from *Patient* agent and for scheduling resources so that the requirements of *Patient* agent can be satisfied. Agents communicate with each other via sending messages. In the following, we will discuss each patient in detail.

<sup>3</sup><https://www.anylogic.com> accessed on 1 November 2022



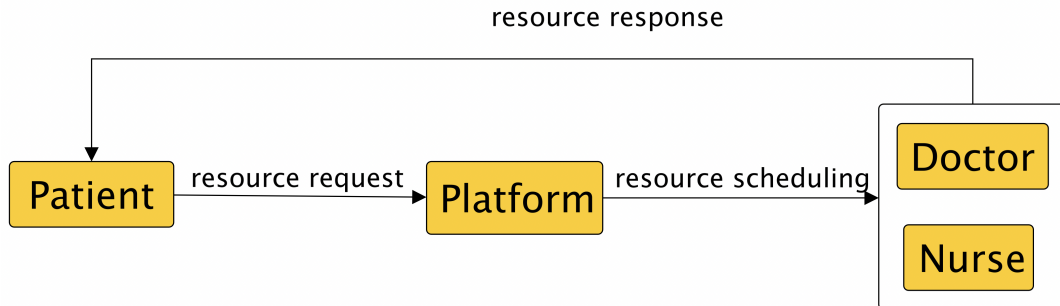


**Figure 3.** DES model of ultrasound examination.



**Figure 4.** DES model of X-ray examination.

*Patient* is the agent type in the DES model. In other words, the objects the DES model processes are *Patient* agents. They are generated in the *Source* Block of Fig. 12. The parameters of this type of agents are shown in Table 2. The idea of designing *Patient* agents is to show the characteristics of patients and facilitate the communication between *Patient* agents and others. For example, we use discrete uniform distribution *uniform\_discr* to generate random numbers which will be assigned to parameters *agent* and *severity*. This distribution is a discrete distribution bounded on  $[\min, \max]$  with constant probability at every value on or between the bounds. Parameter *box* implies treatment rooms where doctors will see the patients. Parameter *waiting* is used as an indication of whether the assignment of resources for patients is ready, which



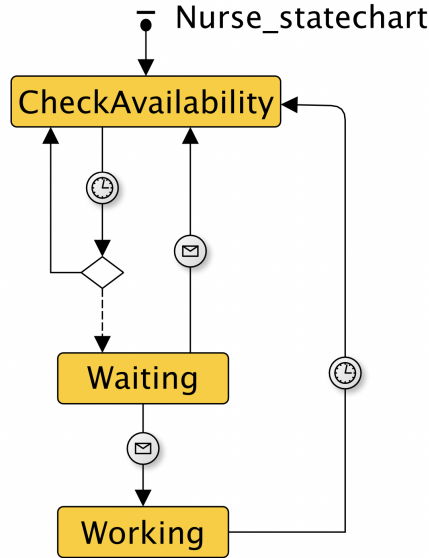
**Figure 5.** The relationship between agents

**Table 2.** The parameters of agents

Agent type	Parameters
<i>Patient</i>	name:String, age:Int, severity:Int, box:Node, waiting:Boolean, admissionTime:Double, dischargingTime:Double
<i>Nurse</i>	name:String, age:Int, state:Int, availability:Boolean, UG:Node, UF:Node
<i>Doctor</i>	name:String, age:Int, state:Int, availability:Boolean, autonomy:int[], competence, membership, doctorRoom:Node, UG:Node, UF:Node
<i>Platform</i>	indexNurse:Int, indexDoctor, indexUF:Node, indexUG:Node, patient:Patient, modePatient:Int, modeDoctor:Int, internalUG:ArrayList<Node>, internalUF:ArrayList<Node>, surgicalUG:ArrayList<Node>, surgicalUF:ArrayList<Node>, orthopedicUG:ArrayList<Node>, orthopedicUF:ArrayList<Node>

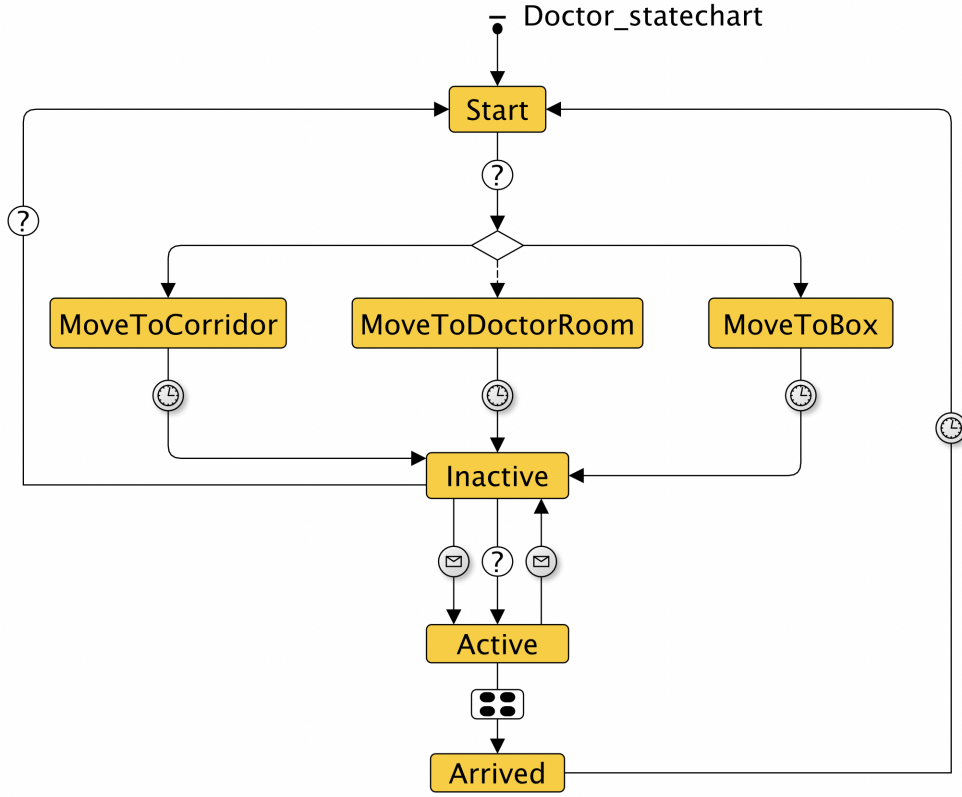
helps stop/continue the patient flow. Parameter *admissionTime* serves not only to calculate the length of stay but as the unique identity of patients. It should be noted that we are not providing a statechart to describe the states of patients. Because we suppose the blocks in Fig. 12 reflect the states of patients.

*Nurse* agents are used for assisting the work of doctors. The design decision of this kind of agents is rather simple. The number of nurses is not fixed, we can configure it at run-time. The schedule of nurses is simple as well. Once nurses are available (they work at that time) and free (they are not occupied), they can be scheduled to work. That's why we use parameters *state* and *availability*. Figure 6 shows the statechart of *Nurse* agents. It should be noted that different images of arrows imply different transition conditions. If the image is a clock, it means the transition needs a self-defined duration of the delay. If the image shows a letter, it says the transition happens when this agent receives specific messages at the appropriate time. The image can also be a mark of a question, it tells the specific condition should be satisfied. The last type of images is like a "paw" (in Fig. 7), denoting that the agent has arrived at its destination.

**Figure 6.** Statechart of *Nurse* agent.

*Doctor* agents describe the behaviors of different kinds of doctors. We consider

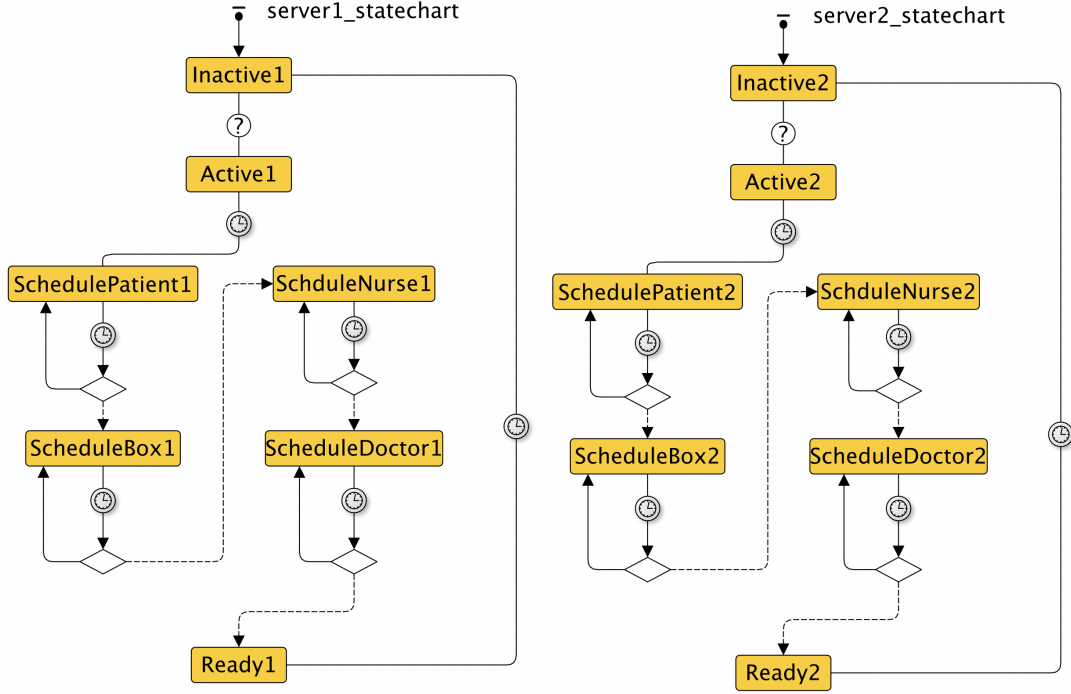
three types of doctors: interns, normal doctors, and senior doctors. Different kinds of doctors are located in different places and are in charge of different issues. Interns are distributed in the corridor to guide patients to the right treatment room. They work with nurses to do some preliminary tests. Normal doctors imply they are neither too young nor old. They wait for patients in the doctor's room. In other words, they will go to the treatment rooms at the same time as patients and interns. Senior doctors have no need to move during working time. They stay in the treatment rooms to treat patients. All the senior doctors stay in treatment rooms except that there are no treatment rooms available. This situation happens when we run the “what-if” scenarios to see the impacts of senior doctors on scheduling efficiency. The details of state transitions for *Doctor* agent are shown in Fig. 7. It should be noted that senior doctors will never reach state “Arrived”. When they finish the treatment, their states will return to state “Inactive”. Of course, if they become unavailable, they will return to state “Start”.



**Figure 7.** Statechart of *Doctor* agent.

*Platform* agent serves as servers to deal with scheduling issues. As shown in Fig. 8, there are two independent servers statecharts inside this agent. The idea of providing more than one server is attempting to avoid unnecessary waiting time when dealing with demands. They share resources like nurses, doctors, and treatment rooms. We suppose resource conflicts don't exist in our system. Once resources are assigned, their states will be changed immediately. As for the concurrent mechanism (see “Event Processing at the Simulation Engine” part of Anylogic Help), Anylogic ensures there are no resource conflicts in scheduling resources by saying “Several events may be scheduled to occur at the same time. If there are several current events, AnyLogic

chooses one and executes it. This is repeated until there are no current events. Thus, several event steps may be made in succession, whereas a time step is always followed by an event step. Simultaneous events may depend on each other or be truly concurrent. The serialization of concurrent events is called interleaving a model.”



**Figure 8.** Statechart of *Platform* agent.

This agent is dedicated to scheduling patients, treatment rooms, nurses, and doctors. Four strategies are used in scheduling resources, including *FIFO*, *Random*, *Centralised* and *Autonomous*. These scheduling strategies are commonly used in healthcare (Hannebauer and Müller 2001; Vermeulen et al. 2007; Wright and Mahar 2013). For example, the *Centralised* strategy was used to schedule nurses to simultaneously improve schedule cost and nurse satisfaction in the Midwestern United States (Wright and Mahar 2013). Vermeulen et al. (2007) developed a multi-agent pareto-improvement appointment exchanging algorithm (Strategy *Autonomous*), to improve patient schedules in response to the dynamic environment. Strategies *FIFO* and *Random* are also supposed to be two fundamental methods for scheduling resources in healthcare (Vermeulen et al. 2007).

Since nurses and treatment rooms are able to be scheduled whenever they are available and free, and free, respectively, we avoid discussing the strategies for them in detail. In terms of scheduling *Patient* and *Doctor* agents, five combinations of these strategies are taken into account, including C1:*FIFO+Centralised*, C2:*FIFO+Random*, C3:*Random+Centralised*, C4:*Random+Random*, and C5:*Autonomous*. The meaning of the five combinations of strategies is explained in Table 3. We assume that qualified doctors are able to treat patients of different levels of severity. The difference of competences of doctors lies in the time they use for the treatment. The more skilled the doctors are, the less time they will use for the treatment. On the other hand, we didn’t use the strategies of other combinations. They are either not close to reality or less interesting for us to investigate. For example, we do not consider Combination

*FIFO+FIFO* because we argue *FIFO* strategy is included in *Autonomous* strategy because under *Autonomous* strategy, *Platform* agent chooses the doctors using *FIFO* strategy. That’s why *FIFO* strategy is not used by doctors. The strategies for scheduling patients can be restricted to only *FIFO* and *Random*. It could be difficult to apply *Centralised* strategy to choose patients because the arrivals of patients are not predictable. We couldn’t make it centralised. On the contrary, the number of available doctors is relatively stable. As for *Autonomous* strategy, the fact that patients are able to autonomously choose their doctors in EDs sounds quite infeasible. So, we choose not to use *Autonomous* strategy for patients.

The core algorithm to accomplish the combination of strategies for patients and doctors is given in Algo. 1. It should be noted that the assignment of the *Autonomous* strategy for doctors is intertwined with the assignment of the strategy for patients. In fact, we simply would like to determine the index of patients at the state of “choosePatient” in Fig. 8, conforming to the semantics of the name of the state. The assignment of *modePatient* and *modeDoctor* depends on which combination the manager of the hospital wants to test. In addition, the statement of line 20 of Algo. 1 does not show the preference in detail. In our case, we choose to use *MOOD*, *TIME*, *AGE* and *SEX* as preferences. For example, random numbers are generated to indicate the emotion of doctors. If doctors have a positive mood, they are more likely to choose to treat patients with serious symptoms. It is because emotions have been demonstrated to affect work in many aspects (Paterson et al. 2010). The positive mood has been associated with increased helpfulness, behaviour-related judgments, and expectations of success. While negative mood can increase self-defeating behaviour, decrease job satisfaction, and increase the probability of making an error. The preferences are assigned in a random way when initializing doctors. The idea of introducing preferences helps model decision-making closer to reality. This may provide an opportunity to study the scheduling issues in EDs from the soft aspect.

**Table 3.** The five combinations of assignment strategies for *Patient* and *Doctor* agents compared in this article.

No.	<i>Patient</i>	<i>Doctor</i>	Description
C1	FIFO	Centralised	<i>Platform</i> agent deals with patients’ requests via the First-in-First-out strategy. It assigns doctors to patients in a centralised way, meaning choosing the doctor with whom the absolute value of the difference between the patient’s severity and the doctor’s competence is minimum. In other words, it assigns the most appropriate doctor to the patient by optimizing resources.
C2	FIFO	Random	<i>Platform</i> agent uses the same strategy as C1 to choose patients. It assign doctors to patients in a random way, meaning a random number will be generated to choose doctors from a set of available and free doctors.
C3	Random	Centralised	<i>Platform</i> agent randomly chooses a patient and assign the most appropriate doctor to him.
C4	Random	Random	The selections of patients and doctors are both random.
C5	<i>null</i>	Autonomous	<i>Platform</i> agent allows doctors to choose patients in an autonomous way.

---

**Algorithm 1:** The implementation of fives combinations strategies

---

```
input      : ArrayList < double > collectionDemands;
// This collection is used for receiving messages sent from patients,
// which are only identified by the patient's admission time.
output     : int indexDoctor, indexPatient;

1 int modePatient, modeDoctor;
2 double admissionTimeFIFO = collectionDemands.get(0);
3 double admissionTimeRandom = collectionDemands.get(uniform_discr(1,100) %
  collectionDemands.size());
4 indexDoctor = indexPatient = -1;
// Assign strategies to patients.
5 if modePatient == 0 then
  // Patients are treated by the FIFO strategy.
6   indexPatient = findFirst(main.patient, p -> p.admissionTime ==
    admissionTimeFIFO);
7   collectionDemands.remove(0);
8 end
9 else if modePatient == 1 then
  // Patients are treated by the Random strategy.
10  indexPatient = findFirst(main.patient, p -> p.admissionTime ==
    admissionTimeRandom);
11  collectionDemands.remove(r % collectionDemands.size());
12 end
13 else if modePatient == 2 then
  // Doctors are allowed to choose patients in an autonomous way.
14  for i = 0 to main.doctor.size() do
15    if main.doctor.get(i).availability == true and main.doctor.get(i).state == 0
      and main.doctor.get(i).membership == 1 then
16      indexDoctor = i; main.doctor.get(i).statue = 1; break;
17    end
18  end
19  if indexDoctor != -1 then
20    indexPatient = findPatientWith(preference);
21  end
22 end
// Assign strategies to doctors.
23 if modeDoctor == 0 then
  // Doctors are scheduled in a centralised way.
24  int difference = 100;
25  for i = 0 to main.doctor.size() do
26    int temp = Math.abs(main.doctor.get(i).competence-patient.severity);
27    if main.doctor.get(i).availability == true and main.doctor.get(i).state == 0
      and main.doctor.get(i).membership == 1 and difference > temp then
28      difference = temp; indexDoctor = i;
29    end
30  end
31 end
32 else if modeDoctor == 1 then
  // Patients are scheduled in a random way.
33  Doctor doctor = randomWhere(main.doctor, p -> p.availability == true and
    p.state == 0 and p.membership == 1);
34  if doctor != null then
35    indexDoctor = doctor.getIndex();
36  end
37 end
```

---

## 4. Experimental analysis

Simulation experiments are carried out to demonstrate the feasibility of the ED system by evaluating the impact of the five combinations of strategies on the duration of the patients' stay in the ED.

### 4.1. Simulation scenario

There are around 100 patients coming to the ED to get treatment every day. The level of patients' illnesses can be divided into: mild, normal, and serious. All the patients follow similar treatment processes. Before the triage, the patients should still respect the *FIFO* rule to wait to be called. After sorted, patients are allowed to leave for some reason. Five combination strategies C1-C5 (in Table 3) can be used to schedule resources. Before going to see the doctor, patients are asked to do Ultrasound/XRay tests. Every type of illness has two treatment rooms. One is for patients with mild and normal symptoms; the other is for patients with serious symptoms. Interns stay in the corridors which are not far from treatment rooms. Doctors of different ages and competences share these treatment rooms. All the patients will be healed before they are discharged. The health information of healed patients will not be traced.

### 4.2. Estimated parameters

Some of the estimated parameters (EP) of the simulation consist of:

- (1) The arrival rate of patients is equal to 0.07/min;
- (2) Patients choose to leave the hospital after the triage with a probability of 0.1.
- (3) Patients are hospitalised after the diagnosis with a probability of 0.1.
- (4) The definition of preferences of doctors is supposed to be:
  - Time** morning, afternoon, night;
  - Sex** male, female;
  - Age** [1,10], [11,20], [21,50], [51, +∞];
  - Emotion** depressed, normal, happy.

The first EP implies the arrival rate is equal to exponentially distributed inter-arrival time with "mean = (1/rate) = 14". In other words, the ED will possibly receive one patient every 14 minutes. So, the ED can receive around 100 patients one day. This data comes from ACEP (James J. Augustine 2016). For the second EP, we simply think the possibility of leaving the ED after the triage is very low. The third EP is provided because we just argue the possibility of being hospitalized after the treatment is very low as well. The last EP just lists some possibilities regarding preferences. Indeed, most of the EPs shown above don't have any concrete evidence to prove them. However, the idea of listing them is more dedicated to illustrating that the modeling of our simulation system takes any possible aspects into account to make it closer to reality. In fact, we think that the modeling of different agents includes hypotheses as well. For example, we assume that different kinds of doctors stay in different places to wait for patients. We choose not to list them here to avoid repetition.

The data of the ED simulation system is principally illustrated in Tables 4 and 5. Table 4 shows the resource configuration of the ED simulation system. The design of the values of these data is to smooth the flow of patients. For example, this configuration implies 12 doctors need to treat around 100 patients in one day. The time for

doctors is reasonably tight. The duration of diagnosis is listed in Table 5. Note that the duration of diagnosis changes depending on the suitability of the assignment of doctors. This suitability involves the severity of patients and the competence of doctors. The severity of patients is defined as: [1,3] (mild), [4,6] (normal) and [7,9] (serious). The competence of doctors is denoted as: 1 (low), 2 (middle) and 3 (high). The less competent the doctor is, the more time he will take to finish the treatment. For example, if the competence of the doctor is low, however, he has to treat a patient whose illness is serious. In this case, his diagnosis time will be  $T(10,15,20)*3$ . In general, the data we used is adapted from the database of the ED in Saint-Etienne. More specifically, the database was generated automatically from the platform monGHTLoire<sup>4</sup>. This platform not only allows patients to access their reports but allows doctors to input patients' treatment information. We don't directly use their data because we are not dedicated to simulating all the details of patients going to the ED of Saint-Etienne. So, the flow of incoming patients is somewhat different, which leads to a difference in the configuration of the system.

**Table 4.** The resource configuration of the ED simulation system.

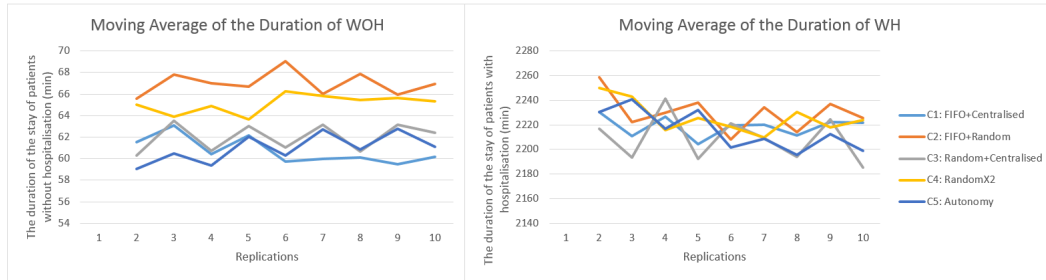
Resource:	nurse	intern	normal doctor	senior doctor	usoundxray	technician	treatment room	bed
Number:	6	6	6	6	10	10	10	16
								12

**Table 5.** Duration of processes where  $T(\min, \text{mode}, \max)$  means triangular( $\min, \text{mode}, \max$ ); the value of  $x$  equals 1, 2 or 3; the unit is minute.

Process:	registration	basic test	diagnosis	hospitalisation
Duration:	$T(3,5,10)$	$T(15, 30, 50)$	$T(10,15,20)*x$	$T(600,2880,3000)$

### 4.3. Experimental results

This simulation experiment is implemented by Anylogic PLE 8.2.3. The configuration of the running laptop is 8G memory and 4 processors (i7-6500U CPU). The simulated duration is one year, which takes about half an hour. The duration of the stay of patients is divided into the durations with and without hospitalisation (WH and WOH). The warm-up period is set to five days in order to avoid initialization bias since the simulation starts without patients.



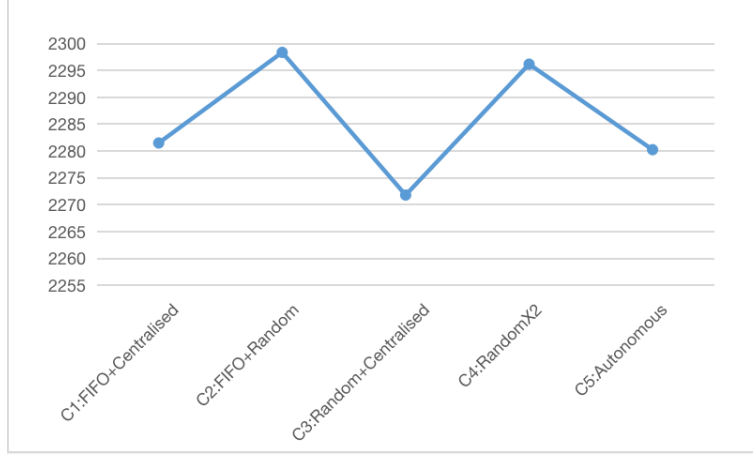
**Figure 9.** Moving averages of patient with/without hospitalisation.

The moving average analysis is conducted to set the required number of replications. According to the results in Fig. 9, after the 7<sup>th</sup> replication, the moving average lines

<sup>4</sup><https://www.viapatient.fr/ght-loire-avec-viapatient/> accessed on 11 January 2023



for both durations tend to be more stable. Since these lines fluctuate with a minimum amplitude around the 10<sup>th</sup> replication, the number of replications will be set to ten in order to ensure that we obtain a better estimate of the average. Box plots are used to show the distribution of the results (Fig. 11). The impact of the five combinations

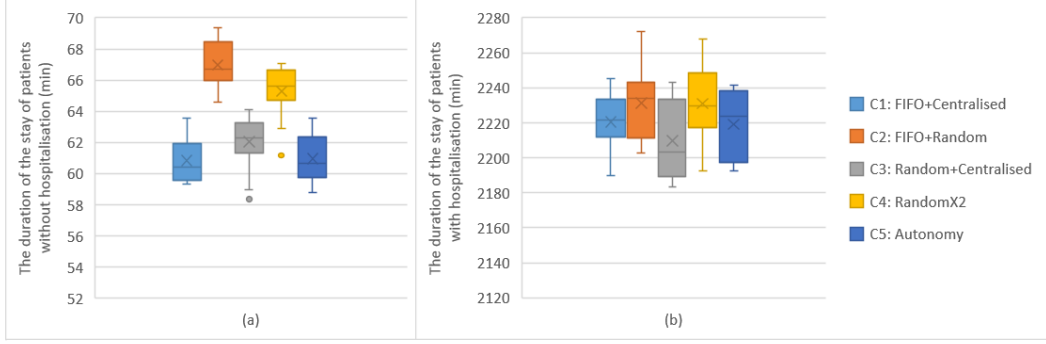


**Figure 10.** Durations of patients in the ED.

of strategies on durations is presented in Fig. 10. This figure suggests Combination “C3: *Random+Centralised*” is the best combination strategy for scheduling patients and doctors, while Combination “C2: *FIFO+Random*” is the worst. It is a little surprising to see Combination “C5: *Autonomous*” is the second-best strategy. Some other interesting results can be concluded from this figure as well. If we fix the strategy for patients as “FIFO” or “Random”, Strategy “Centralised” works quite well. However, if we determine the strategy for doctors as “Centralised” or “Random”, randomly choosing patients seems to be better than Strategy “FIFO”. Since the duration consists of the durations of patients of WOH and WH, we will discuss the two types of durations in detail.

In terms of the duration of patients of WOH (shown in Fig. 11 (a)), it seems that Combination “C1: *FIFO+Centralised*” outperforms the other combinations in general, which is different from the case of the duration of patients. The performance of Combination C5 is approaching that of Combination C1. They share similar averages (60.97029 of C5 against 60.8562 of C1). They are also both left-skewed. They don’t have outliers. Regarding the interquartile ranges and whiskers, the data of Combination C5 is more dispersed than that of Combination C1. So, Combination C1 is more stable. Comparing the largest and smallest observations, Combination C5 performs better than Combination C1 (largest observations: 63.42979 of C5 vs 63.58203 of C1; smallest observations: 58.76172 of C5 vs 59.34006 of C1). For the *Random* strategy assigned to doctors, randomly treating patients saves more time for patients in comparison with Combinations “C2: *FIFO+Random*” and “C4: *Random+Random*”. We didn’t expect to see Combination “*Autonomous*” to achieve high efficiency in scheduling resources, and it just follows Combination C1.

As for the duration of patients of WH (shown in Fig. 11 (b)), all combinations perform differently. Combination “C3: *Random+Centralised*” is the best in general, which is the same as the case of the duration of patients. This combination owns the smallest observation 2183.347, average 2209.758 and median 2203.099. Its data is also left-skewed. The only disadvantage of this combination is that its data is the most dis-



**Figure 11.** Durations of patients with/without hospitalisation.

persed with the second-last largest observation 2242.907 (slightly bigger than the last largest observation 2241.666 of C5). Combination “C4: *Random+Random*” does not have any advantage in terms of the duration in comparison with Combination “C2: *FIFO+Random*”. Combinations “C1: *FIFO+Centralised*” and “C5: *Autonomous*” enjoy similar average durations, but the range of C5 is much larger.

From these results, we may conclude that the best combination of strategies depends on the priority of minimizing the duration of the stay of patients of WOH or WH. If the former is the priority then Combination “C1: *FIFO+Centralised*” would be the best. This combination aims to treat patients equally regarding their arrival time and provides the most appropriate doctors for patients. However, it is restricted by the short duration. If there is a long duration for the patient – in other words, minimizing the duration of the stay of patient of WH is the priority – then Combination “C3: *Random+Centralised*” would be the best. From our point of view, the difference between these two centralized strategies implies that the random way of treating patients is perhaps more like the optimized way, which means this way could prioritize severe patients and provide them with doctors of high capabilities to some extent. Since the number of available doctors is limited, better assigning doctors to patients saves more time.

## 5. Discussion

A simulation system has been designed by using the combination of DES and ABS, which aims to improve the efficiency of resource scheduling for EDs with limited resources under uncertain environments.

The framework for the hybrid simulation modeling provides a global view of how to combine DES and ABS to model EDs. It explains the basic idea of why we choose to combine the two methods. The DES and ABS are contributed to building operations and strategies of the system, respectively. This idea not only makes the approach of the hybrid simulation modeling clearer but helps make the hybrid simulation system more extendable.

We used this framework to build the ED resource scheduling system consisting of the DES and ABS models. The DES simulated the whole process of patients in EDs, meaning from the admission to the discharge of patients. The queuing characteristics of the DES make the relatively fixed procedures easy to be implemented. The

ABS simulated the part of human interventions for the system. Each person appearing in the simulation is an instance of a specific class (agent). Each person has his mind (statechart) to make his decisions. The ABS allows persons to communicate with each other. All the possibilities the ABS provides make the scheduling process close to reality. Any complex algorithms for scheduling can be implemented in the ABS as functions, actions, etc. Therefore, the combination of DES and ABS gives the simulation system for EDs “a strong body” and “a smart brain”.

From the implementation point of view, there are many aspects to be investigated. Our evaluation serves only to illustrate the feasibility of our approach. The configuration of the system should be fully re-analyzed if the system is applied to real cases. For example, the duration of processes could be quite varying. The arrival patterns could need a combination of different probability functions. The decision on the number of doctors, nurses, etc., necessitates numerous runs of the simulation. Hence, we do not completely simulate a real ED. The simplification of our system makes it more flexible and extendable. The implementation of preferences is another issue. Some people may argue it is meaningless to consider the preferences of doctors because they have to try their best to heal patients in any way. From our point of view, since we consider that doctors are able to choose patients in an autonomous way, doctors do more or less have their preferences in their minds when choosing patients. It gives a possibility of analysing the soft aspects of doctors.

The V&V of the simulation system is another issue. Indeed, performing the V&V process of the DES/ABS models is of great importance. However, it would be difficult for us to statistically perform the V&V of the system. On the one hand, we proposed five combination strategies of resource scheduling, which were not used in the hospital when collecting data. On the other hand, we still used estimated parameters because either the hospital didn’t have the data or we considered some new aspects like the preferences of doctors. But we did consider the importance of the V&V of the system. From our point of view, firstly, the simulation system should be self-verifiable. That’s why we provided the details of the statecharts of agents as much as possible. Secondly, we gave the algorithm for the implementation of five combination strategies. Thirdly, we conducted the moving analysis to set the appropriate number of replications, in order to avoid initialization bias. Finally, we compared the performances of different strategies. These make our simulation study reproducible. Since our simulation system is highly extendable, we would argue if the system is correctly modeled and implemented, the validation could be done with sufficient data.

The configurations of simulation systems rely on the cases of interest. From our point of view, one of the most important things is to choose the most appropriate method and build a general system for EDs that is highly extendable. More attention should be paid to the processes and the strategies. In this way, users of the system can save more time to focus on the configuration of the system.

## 6. Conclusion and perspectives

In this paper, we discussed the issue of how to better schedule ED resources with the consideration of the uncertain environment. We firmly believe that building a concrete and proper model for EDs lays the foundation for manipulating EDs, especially for resource scheduling. The proposed system’s dependency on data is very limited. In other words, the system we proposed is rather general, which fully supports the reuse in the healthcare domain.

To do so, we have proposed an innovative approach to building this system via DES and ABS. The hybrid modeling method not only benefits from the efficiency of the classical ED modelling way but introduces a rather new way for modeling dynamic complex systems. We have provided a complete approach to building the system, starting from the proposition of the analysis framework, to concept formulation of the system, to the details of system implementation, and ending with an illustrative case study. The system enables us to gain important insights into the system so that we can run “what-if” scenarios and propose more strategies for scheduling. Besides, we are able to build a system close to reality thanks to the simulation tool Anylogic. This tool supports the connection to ED databases. It also offers interfaces to programs in Java. It provides the 2D and 3D views of the system as well.

As for future work, we plan to transform our simulation system into a Digital Twin by connecting it to the physical ED. The connection from ED to the Digital Twin will require collecting data in the physical ED and feeding it into our simulation. The connection in the other way may be performed by displaying the simulated futures to doctors.

## Acknowledgements

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

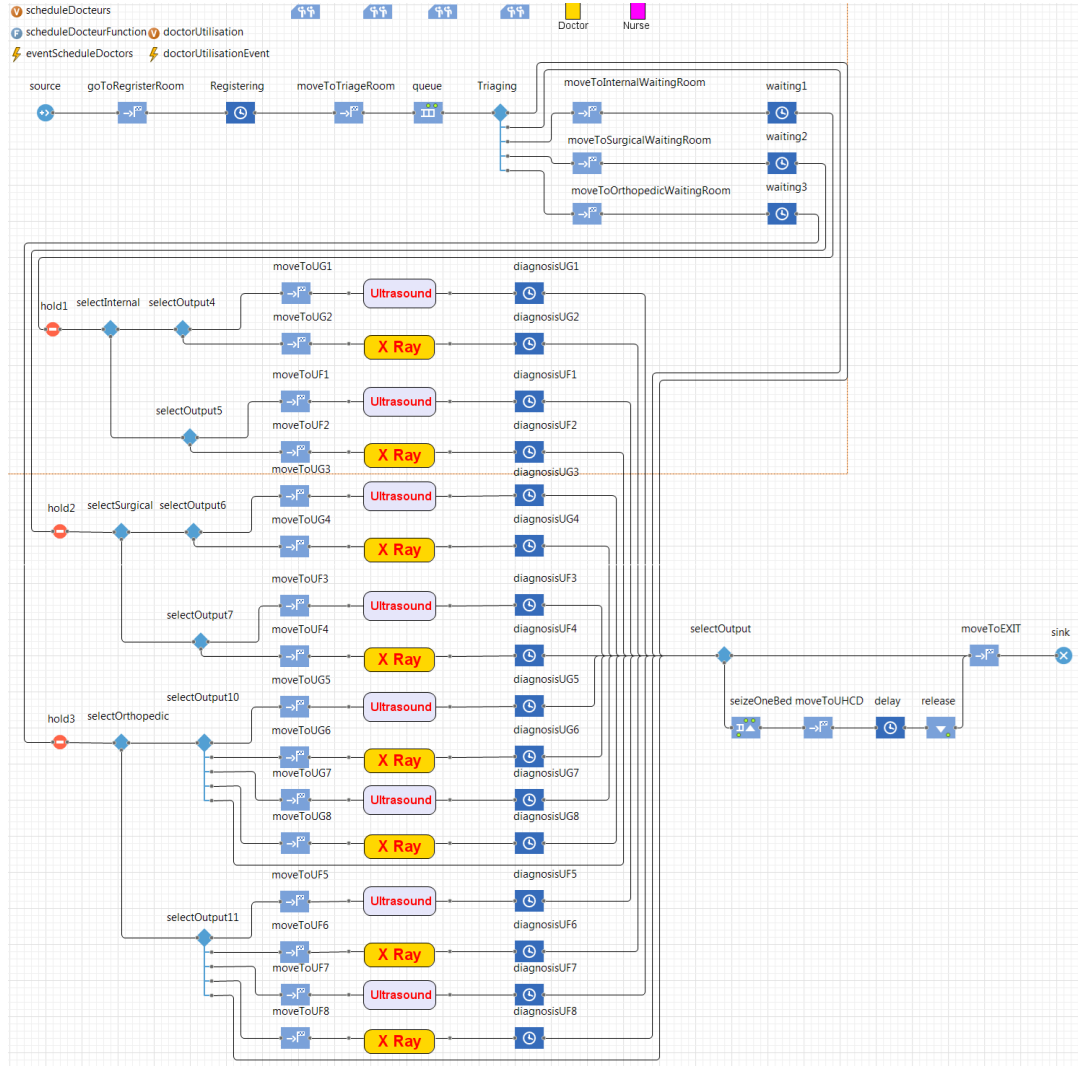
## References

- Alayan, A., Y. Liu, T. Ayer, K. Pasupathy, D. Nestler, and M. Sir. 2019. “Physician Staffing in Emergency Rooms (ERs): Opening the Black-box of ER Care via a Multi-Class Multi-Stage Network.” *Social Science Electronic Publishing* .
- Araújo, José Alberto Araújo, Javier Pajares, and Adolfo López-Paredes. 2010. “Simulating the dynamic scheduling of project portfolios.” *Simul. Model. Pract. Theory* 18 (10): 1428–1441. <https://doi.org/10.1016/j.simpat.2010.04.008>.
- Bair, Aaron E, Wheyming T Song, Yi-Chun Chen, and Beth A Morris. 2010. “The impact of inpatient boarding on ED efficiency: a discrete-event simulation study.” *J. medical sys.* 34 (5): 919–929.
- Bal, Alperen, Cemil Ceylan, and Caner Taçoğlu. 2017. “Using value stream mapping and discrete event simulation to improve efficiency of emergency departments.” *Int. J. Healthcare Man.* 10 (3): 196–206.
- Brailsford, Sally C, Tillal Eldabi, Martin Kunc, Navonil Mustafee, and Andres F Osorio. 2019. “Hybrid simulation modelling in operational research: A state-of-the-art review.” *European Journal of Operational Research* 278 (3): 721–737.
- Campana, Nicolas, Giorgio Zucchi, Manuel Iori, Carlo Magni, and Anand Subramanian. 2021. “An Integrated Task and Personnel Scheduling Problem to Optimize Distributed Services in Hospitals.” In *23rd International Conference on Enterprise Information Systems*, .
- Carmen, Raïsa, Mieke Defraeye, Bilge Celik Aydin, and Inneke Van Nieuwenhuyse. 2014. “Modeling emergency departments using discrete-event simulation: A real-life case study including patient boarding.” *FEB Res. Rep. KBL1420* .
- Cegłowski, R, Leonid Churilov, and J Wasserthiel. 2007. “Combining data mining and discrete event simulation for a value-added view of a hospital emergency department.” *J. Op. Res. Soc.* 58 (2): 246–254.
- Di, L., F. Labeau, X. Zhang, and G. X. Kang. 2012. “Scheduling medical tests: A solution to

- the problem of overcrowding in a hospital emergency department.” In *IEEE International Conference on E-health Networking*, .
- Doudareva, Evgueniia, and Michael Carter. 2022. “Discrete event simulation for emergency department modelling: A systematic review of validation methods.” *Operations Research for Health Care* 100340.
- D’souza, Brayal, Shreyas Suresh Rao, Chepudira Ganapathy Muthana, Reshmi Bhageerathy, Nikitha Apuri, Varalakshmi Chandrasekaran, Deena Prabhavathi, and Sapna Renukaradhya. 2021. “ROTA: A system for automated scheduling of nursing duties in a tertiary teaching hospital in south India.” *Health Informatics J.* 27 (2): 146045822110014.
- Duguay, Christine, and Fatah Chetouane. 2007. “Modeling and improving emergency department systems using discrete event simulation.” *Sim.* 83 (4): 311–320.
- Fan, Jing, and Xiwen Lu. 2015. “Supply chain scheduling problem in the hospital with periodic working time on a single machine.” *Journal of Combinatorial Optimization* 30 (4): 892–905.
- Gendreau, M., J. A. Ferland, B. Gendron, N. Hail, and P. Soriano. 2006. “Physician Scheduling in Emergency Rooms.” *DBLP* .
- Gul, Muhammet, and Ali Fuat Guneri. 2015. “A comprehensive review of emergency department simulation applications for normal and disaster conditions.” *Computers & Industrial Engineering* 83: 327–344.
- Günel, Murat M, and Michael Pidd. 2010. “Discrete event simulation for performance modelling in health care: a review of the literature.” *Journal of Simulation* 4 (1): 42–51.
- Hannebauer, Markus, and Sebastian Müller. 2001. “Distributed constraint optimization for medical appointment scheduling.” In *Proceedings of the fifth international conference on Autonomous agents*, 139–140.
- Helbing, Dirk. 2012. “Agent-based modeling.” In *Soc. Self-Organization*, 25–70. Springer.
- Hsieh, Fu-Shiung, and Jim-Bon Lin. 2014. “Scheduling Patients in Hospitals Based on Multi-agent Systems.” In *Modern Advances in Applied Intelligence - 27th International Conference on Industrial Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2014*, Vol. 8481, 32–42.
- Hutzschenreuter, Anke K., Peter A. N. Bosman, Ilona Blonk-Altena, Jan van Aarle, and Han La Poutré. 2008. “Agent-based patient admission scheduling in hospitals.” In *7th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2008), Estoril, Portugal, May 12-16, 2008*, 45–52. IFAAMAS.
- James J. Augustine, FACEP, MD. 2016. “Emergency Department Benchmarking Alliance Releases 2014 Data on Staffing, Physician Productivity.” <https://www.acepnow.com/article/emergency-department-benchmarking-alliance-releases-2014-data-on-staffing-physician-productivity>
- Jeric, Silvija Vlah, and José Rui Figueira. 2012. “Multi-objective scheduling and a resource allocation problem in hospitals.” *J. Sched.* 15 (5): 513–535.
- Jones, Spencer S., and R. Scott Evans. 2008. “An Agent Based Simulation Tool for Scheduling Emergency Department Physicians.” In *AMIA 2008, American Medical Informatics Association Annual Symposium, Washington, DC, USA, November 8-12, 2008*, AMIA. <https://knowledge.amia.org/amia-55142-a2008a-1.625176/t-001-1.626020/f-001-1.626021/a-069-1.626357/a-070-1.626354>.
- Kaushal, Arjun, Yuancheng Zhao, Qingjin Peng, Trevor Strome, Erin Weldon, Michael Zhang, and Alecs Chochinov. 2015. “Evaluation of fast track strategies using agent-based simulation modeling to reduce waiting time in a hospital emergency department.” *Socio-Econ. Planning Sc.* 50: 18–31.
- Liu, Zhengchun, Dolores Rexachs, Francisco Epelde, and Emilio Luque. 2017. “An agent-based model for quantitatively analyzing and predicting the complex behavior of emergency departments.” *J. Computational Sc.* 21: 11–23.
- Lo, C. C., and T. H. Lin. 2011. “A Particle Swarm Optimization approach for physician scheduling in a hospital emergency department.” In *Seventh International Conference on Natural Computation*, .
- Macal, Charles M. 2016. “Everything you need to know about agent-based modelling and

- simulation.” *Journal of Simulation* 10 (2): 144–156.
- Ogulata, S. Noyan, Melik Koyuncu, and Esra Karakas. 2008. “Personnel and patient scheduling in the high demanded hospital services: a case study in the physiotherapy service.” *Journal of Medical Systems* 32 (3): 221–228.
- Paterson, Jessica L, Jillian Dorrian, Jan Pincombe, Carol Grech, and Drew Dawson. 2010. “Mood change and perception of workload in Australian midwives.” *Industrial Health* 48 (4): 381–389.
- Rachuba, Sebastian, and Brigitte Werners. 2014. “A robust approach for scheduling in hospitals using multiple objectives.” *Journal of the Operational Research Society* 65 (4): 546–556.
- Siebers, P. O., C. M. Macal, J. Garnett, D. Buxton, and M. Pidd. 2010. “Discrete-event simulation is dead, long live agent-based simulation!” *Journal of Simulation* 4 (3): 204–210.
- Song, Wen, Hui Xi, Donghun Kang, and Jie Zhang. 2018. “An agent-based simulation system for multi-project scheduling under uncertainty.” *Simul. Model. Pract. Theory* 86: 187–203. <https://doi.org/10.1016/j.simpat.2018.05.009>.
- Vanbrabant, Lien. 2020. “Simulation and optimisation of emergency department operations.” PhD diss., Springer.
- Vanbrabant, Lien, Kris Braekers, Katrien Ramaekers, and Inneke Van Nieuwenhuyse. 2019. “Simulation of emergency department operations: A comprehensive review of KPIs and operational improvements.” *Computers & Industrial Engineering* 131: 356–381.
- Vermeulen, Ivan, Sander Bohte, Koye Somefun, and Han La Poutré. 2007. “Multi-agent Pareto appointment exchanging in hospital patient scheduling.” *Service Oriented Computing and Applications* 1 (3): 185–196.
- Wang, Lu. 2009. “An agent-based simulation for workflow in emergency department.” In *2009 Systems and Information Engineering Design Symposium*, 19–23. IEEE.
- Wang, Y., W. L. Hare, L. Vertesi, and A. R. Rutherford. 2011. “Using simulation to model and optimize acute care access in relation to hospital bed count and bed distribution.” *Journal of Simulation* 5 (2): 101–110.
- Wright, P Daniel, and Stephen Mahar. 2013. “Centralized nurse scheduling to simultaneously improve schedule cost and nurse satisfaction.” *Omega* 41 (6): 1042–1052.

## A. Appendix - DES model



**Figure 12.** The complete DES model of our hybrid model.