Simulation of the Emergency Department Management during the Pandemic

[1,2,4]Ramona Galeano, [1]Dolores Rexachs, [1]Alvaro Wong, [5]Eva Bruballa,
[2]Cynthia Villalba, [3]Diego Galeano, [1]Emilio Luque

[1]*Computer Architecture and Operating Systems Department*
Universitat Autónoma de Barcelona (UAB)
Barcelona, Spain
e-mail: RamonaElizabeth.Galeano@autonoma.cat, Dolores.Rexachs@uab.cat
alvaro.wong@uab.es, eva.bruballa@eug.es, emilio.luque@uab.es
[2]*Facultad Politécnica*
[3]*Facultad de Ingeniería*
[4]*Facultad de Ciencias Médicas*
Universidad Nacional de Asunción
San Lorenzo, Paraguay
e-mail: cvillalba@pol.una.py, dgaleano@ing.una.py
[5]*Escuela Universitaria de Informática*
Escuela Universitaria Gimbernat

***Abstract*—The COVID-19 pandemic has caused disasters worldwide, overwhelming public health systems and generating actions such as movement restrictions and containment orders. It has strained public health systems and exposed the healthcare needs and gaps for marginalized and vulnerable populations. Modeling and simulation can help make a physical or logical representation of a system to generate data and determine decisions or predict a given system or problem. In this paper, we present an adaptation of our previous work on a simulation of an agent-based model to simulate an emergency department for a different hospital in a pandemic situation; we compare some of the results we obtained from the simulations with reality to help the management of the emergency department.**

***Index Terms*—simulation; agent-based model; COVID-19; management**

I. Introduction

Pandemics occur when a new virus emerges for which the necessary natural defenses are not possessed, so it spreads rapidly, sometimes with disastrous results. It is a disease outbreak that spans several countries and continents, affects many people, crosses many borders, exceeds the expected cases, and persists over time. Pandemics are often caused by viruses, such as COVID-19, which can be easily spread from person to person.

The COVID-19 pandemic caused a severe economic, social, and health crisis never seen before. They cause unemployment, leading to an exponential increase in poverty, and their repercussions on developing unprecedented famines.

It constitutes a disruptive situation that generates high individual and collective stress levels. For many people, it implies a tragic situation due to the losses they must face: loss of loved ones, health, housing, property, or employment.

Many countries suffered many consequences from the crisis, with overloaded health systems, unemployment, business failures, and other problems. This is particularly true in the poorest areas, where the pandemic has exposed deep-seated inequalities.

The COVID-19 pandemic generated a shock wave that affected the entire world economy and triggered the biggest crisis in over a century. This led to a drastic increase in inequality within and between countries.

The COVID-19 pandemic affected different aspects of life and caused many collateral problems, such as biological damage and mental health problems. It has also generated unique ethical dilemmas stemming from the various demands on society generated by many of the decisions made and the existing health system.

Health professionals must make decisions about allocating scarce resources that can eventually cause moral distress and affect their mental health and patients.

Another edge has been the restrictions on freedom of movement, which has forced the closure of entire economies to flatten the epidemics' curve. Even the recommendation of good hygiene practices, proper hand washing, and physical distancing, which seem easy to comply with, may be challenging in the poorest societies.

Finally, some will question the ethics behind the search for effective treatments and the development of vaccines; research carried out at a time of uncertainty and anguish.

Most countries have been affected, including developed and developing countries. COVID-19 has caused death and exposed the severe limitations of the countries' health systems.

Emergency departments must be prepared to handle crises and disasters such as the pandemic. During this time, they required a quick solution to give a sustained response to the problem that came ahead.

Simulation can be used effectively to create or improve a system or process. It is beneficial to build hypothetical scenarios; it is used in many areas and also for emergency departments.

The main methods used for simulation in emergency departments are agent-based simulation [1], [2], discrete events [3], and system dynamics [4]. The advantage of simulation is facilitating the automatic search for scenarios that can provide the best solutions given a set of constraints and future states. This automation of the search for improvements to an emergency department can significantly help managers who need answers to problems.

We have previously developed an agent-based model for emergency departments; some of our works are: creating a simulator using NetLogo [5], performance optimization of these emergency systems [6], micro-level behavior of the emergency department for the prediction of characteristics at the macro level [7], contact transmission of MRSA between hospitalized patients [8] among others. An agent-based model is an approach to model systems where individual agents interact. It offers ways to more easily model interactions of individuals and also how these interactions affect other agents in the system [9].

Our work presented here builds upon the work of Liu et al. [10] that developed a simulator for planning and management of the emergency department, which has the advantage of having been verified and validated in several cycles or iterations, taking into account a wide variety of data and configurations, and with the participation of emergency department staff at the Hospital of Sabadell (Spain).

This work adapted an agent-based model that allows modeling the management of an emergency department during a pandemic such as COVID-19. The emergency department incorporated doctors and nurses from other specialties to support the emergency area, manage more resources (adding beds or boxes to increase the number of people who can be treated), and the severity levels of the patients to a pandemic situation (COVID-19), where the patients who attended were the most serious.

To adapt the incorporation of more personnel to the emergency department, our simulator was configured, which has personal resources as a configurable parameter and also considers two levels of junior and senior experience: juniors (with limited knowledge or low experience) and seniors (with experience); we use the two levels that the simulator already has to map the two types of classification on them doctors used during the pandemic. This is very important because during the COVID-19 pandemic, in addition to the emergency intensivists (seniors), health personnel from different specialties (juniors versus intensivists) were incorporated into the emergency department.

For the experimental part, we have prepared a set of synthetic input data for the simulation, arrival distribution of patients with COVID and NON-COVID with different levels of severity, and general distribution by the age of the simulated patients; with these input data, we have analyzed the occupation time of the doctors and nurses, the waiting time of the patients, the service time according to the level of severity. Then we compared it with reality, obtaining very promising results.

Our simulator describes the behavior of the emergency department during the COVID-19 pandemic and can help hospital personnel as a decision support system for emergency department management.

The paper is organized as follows. In section II, we explain related works. In section III, the adaptation of the emergency department model. Section IV describes the simulation. Section V presents the experiments and discussion, and section VI presents the conclusions and future work.

II. Related works

The simulation topics most frequently found in the literature in the COVID-19 simulation area are studies for contact tracing with COVID-19, transmission models of healthy patients with an infectious spread in health systems [11], patient flow improvement [12], how simulation modeling can help reduce the impact of COVID-19 [13], among others.

Some simulation methods found that were used in the area of COVID-19 simulations are discrete events [12] [14] [15], artificial intelligence [16] and agent-based simulation [17]. Some countries used the simulation to predict scenarios, including the behavior of the Delta variant to know the number of deaths, infected, and vaccinated infected; others to see the evolution of COVID-19; others to establish the infected, quarantined, recovered, and dead, using the Susceptible Exposed Infected Asymptomatic Quarantined Recovered (SEIAQR) model [18]. Other work presents an approach in health care in which combined techniques of discrete event simulation, simulation-based multi-objective optimization, and data mining are used [19].

There is an evolution in the literature on applying agent-based models to emergency department operations. The agent-based model (ABM) has grown tremendously over the last 15 years and, more recently, in hospitals and healthcare. One of the main applications of ABM in hospital environments is that it examines the flow of patients in emergency departments [20], [21].

The studies about the emergency department deal with the practice of protocols or objects for medical procedures [22]. Another job in the emergency department involves managing the resources in intensive care, intensive care beds, and their devices [14]. Length of stay and patient waiting times, optimizing resources [19].

Previous works in the emergency department area are: Create a simulator for the emergency department with the participation of the Sabadell Hospital emergency staft [5]. Active agents, passive agents, and the environment are identified, and an initial simulation is created using NetLogo [5]. Another task is to optimize the emergency departments' performance [6]. Extensive search optimization is used to find the optimal configuration of emergency department staff, a multi-dimensional, multi-objective problem [6]. An index is proposed to minimize the patients' length of stay in the emergency department. The results obtained using alternative Monte Carlo and Pipeline schemes are promising [6]. This work presents a layer-based application framework for discovering knowledge of an emergency department system by simulating micro-level behaviors of its components [7]. This work proposes using a simulation tool, the MRSA Simulator, to design and conduct virtual clinical trials to study contact transmission of MRSA among hospitalized patients [8].

The difference between our job and the others is that this model of COVID-19 in the emergency department simulator will allow the emergency department managers to analyze and evaluate potential solutions for the beds and the management of human resources such as nurses and doctors. And also has been considered at two levels with experience and without experience (juniors and seniors); when reinforcing, the health personnel treating COVID have incorporated emergency intensivists (seniors) and health personnel from different specialties (juniors). And to evaluate the effectiveness of different combinations of scenarios. Many countries have been experiencing extreme stress with patients unable to access therapy beds, dying in emergency department corridors while waiting for beds to be released, and a lack of experienced doctors.

III. Adaptation of the Emergency Department Model

This section presents a model for the emergency department during the COVID-19 pandemic. The general objective of this research is to propose a model that allows to expand the simulators' functionality to adapt it to changes in the emergency department operation when exceptional situations occur, such as a health alert, or restrictions, and when extraordinary temporary measures are adopted. As is the case of pandemics spread by air, in such a way that it helps in the planning and management of the service. First, our simulator was adapted to another hospital, verifying its operation, and then it was adapted to the pandemic.

The first step of the work consists in a description of a conceptual model of the systems' operation, from which the computational model that will allow the system to be simulated is elaborated. It is planned to use the simulation environment and a high-level platform.

A. Active agents

The active agents are the individuals who act dynamically; they are all human actors in the emergency department. They are:

Patients: The essential individuals in the system.

Admissions staff: The person, the patient, goes to request an appointment, update their data, and request the opening or search of their medical record.

The triage nurse: Responsible of the assignment of the acuity level to patients.

Doctor: They interact with patients to diagnose and treat them.

Nurse: They provide and supervise treatment to the patient and take and send tests to laboratories.

Laboratory Staff: These are the persons who perform the tests and analyze the patient if necessary.

B. State variables

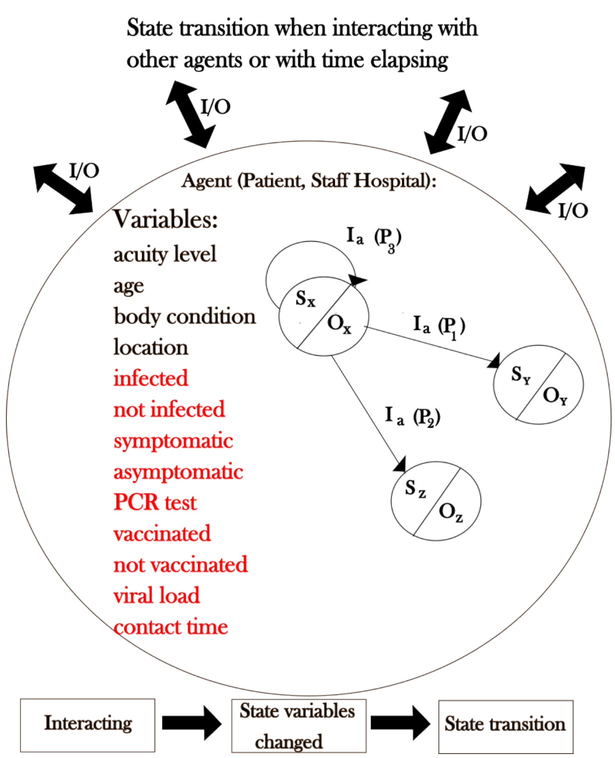

Fig. 1. State transition when interacting with other agents or with time elapsing

The agents move from one place to another by interacting with other agents. During this time, each agent changes its state due to the interactions. A state machine perfectly represents this behavior, so they have chosen a state machine to model all agents. Specifically, the agents are characterized by a probabilistic Moore machine. An initial set of state variables defined through the round of physician interviews is based on the minimum amount of information needed to model each patient and staff. An initial set of state variables is shown in Figure 1 for the agent patient and the hospital staff (admissions staff, doctor, triage nurse, laboratory staff, and nurse) [23].

Variables must be incorporated into each agent; the variables included by the agents' patient and hospital staff (admissions staff, doctor, triage nurse, laboratory staff, nurse) are acuity level, age, body condition, and location. And the new variables are infected or not, symptomatic or not, vaccinated, viral load, contact time, and PCR test.

The agents are divided by their state variables and their behaviors. The values of the state variables of an agent at a given time, t, define the agents' situation at that time, t. The behavior of each agent depends on the category to which it belongs and is determined based on the rules previously assigned to each. To represent the different states of the agents during the attention process are used finite state machines.

The agents' state transition from one state to another will then be determined by (a) the current state and (b) the input value it receives due to the interaction with another agent, always considering that this value will be granted based on a previously defined probability.

C. Output

Some of the outputs are the length of stay (LOS), the length of waiting (LOWT) for each stage (e.g., waiting time for service request: wtsr, time of admission: at, waiting time in admission: wta, waiting time in nursing: wtn, time nursing care: twnc, waiting time in doctors' treatment: wtd, doctor treatment care time: twmd and others), destination, acuity level, infected, symptomatic, PCR test, vaccinated, viral load and the occupations of hospital staff (admissions staff, doctor, triage nurse, laboratory staff, and nurse).

IV. Simulation

An initial simulation is created to verify the proposed model designed, using the NetLogo [24] agent-based simulation environment, a high-level platform especially suited for modeling complex systems that develop over time. NetLogo [24] allows visualizations of actions and agent interactions, an essential aspect considering that a primary use of the tool is gathering feedback from the emergency department.

The emergency department is divided into different zones where other agents can act, maintaining interactions that can also be different. The input to our model is a group of patients arriving in the emergency department. After the patients' arrival and the admission staff completes the registration, based on the seriousness of their situation in the triage, the patients are categorized, considering their acuity level. There are five different values, level 1 is for the most critical condition, and level 5 is not urgent [25]. The original simulator has the following areas, as shown in Figure 2: admissions area, triage area, diagnosis-treatment area, waiting rooms, etc. After triage, patients with diagnosed acuity levels 1, 2, and 3 are treated separately and assigned to Area A, and patients 4 and 5 are treated in Area B. The adapted simulator has the same areas but with different resources, for example, more boxes, doctors, and nurses, as shown in Figure 3 has the same areas but with different resources and added variables.

$$\begin{aligned} n_{scenarios} = & n_{admissions} * n_{timeadmissions} * n_{triagenursing} * \\ & n_{timetriagenursing} * n_{nursing} * n_{timenursing} * \\ & n_{doctor} * n_{timedoctor} \end{aligned} \tag{1}$$

The scenario adopted for this initial stage is to simulate the patients who move through the emergency department. The areas and types of active agents represented in this simulation are patients, admission staff, triage nurses, doctors, auxiliary staff, laboratory tests, internal tests, external tests, ambulance, and carebox. Each combination of values represents a different scenario simulation. Wide varieties of values make up the parameter space. The parameters can generate many different scenarios (1).

There is many parameter value combinations, large enough that there is no possibility of casting each one manually. For this reason, parametric simulations are required, in which the simulator launches a set of simulations with different combinations of parameter values.

In general, the time to compute a time interval of a simulation based on agents is the product of the time it takes to simulate the actions of an agent within the world of simulation in this step. In the model described, agents in the simulation are the hospital staff and patients. The simulator will be conducted by time. Time is divided into discrete, identical intervals and periods at each time step of the agents' operating system. Each time step is divided into two phases. Assuming that the simulator this at time t, the phases are: First, each agent processes the inputs of the last phase (It-1) and, according to that input and the state, as it was during the last step (St -1) and changes to its new state St. Second, each agent emits its output to its current state, Ot. This output uses receivers to switch to the next state. In time each agent changes state. It may change to the same state it was previously, but there is a change nonetheless. The metrics that are to be used for each state input It and output Ot are: waiting time to request service: twrs, time for register a required service: trs, time admission: ta, waiting time in admission: twa, waiting time in nursing: twn, time nursing care: te, waiting time in doctor: Twmc, health care time: tm.

$$Pi = f(LOS, age, level) \tag{2}$$

$$\sum_{i=1}^{n} P_i = 100 \tag{3}$$

$$P' = f'(TOT, age, level) \tag{4}$$

$$\sum_{i=1}^{n} P_i' = 100 \tag{5}$$

To generalize the process of all patients, probability distribution during simulation will decide the following status. The distribution model of the probability was based on the statistical data from the emergency department. Figure 4 indicates the general process during the patient stay in the emergency department; P1(%), P2(%), P3(%), and Pn (%) represent the probability of the following state transition separately, equation (2), (3), (4), (5) show the formulae [23]. All of the probabilities follow some probability distributions. The distributions' probability density function is decided by several key parameters based on the statistical analysis of the doctors' decision and the patients' behavior; a tuning process estimates the value of these parameters from actual historical

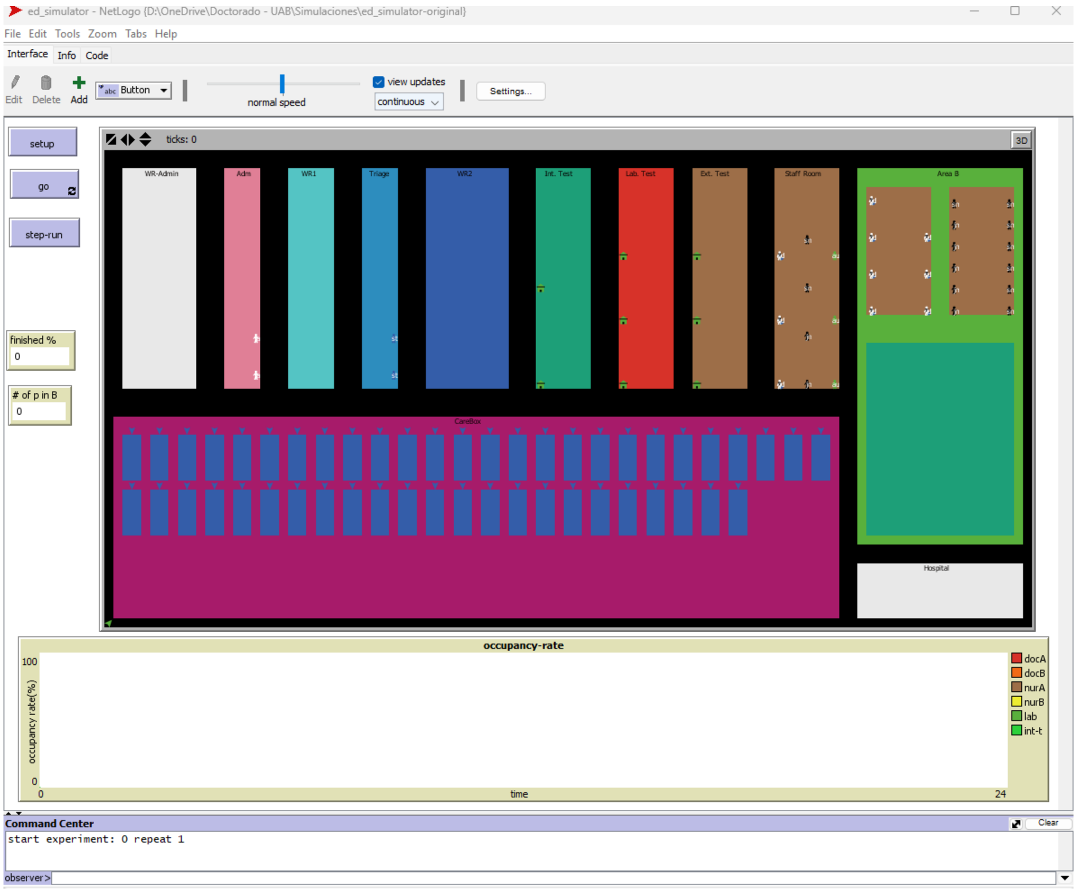

Fig. 2. Visualization of the original simulator in NetLogo before the adaptation

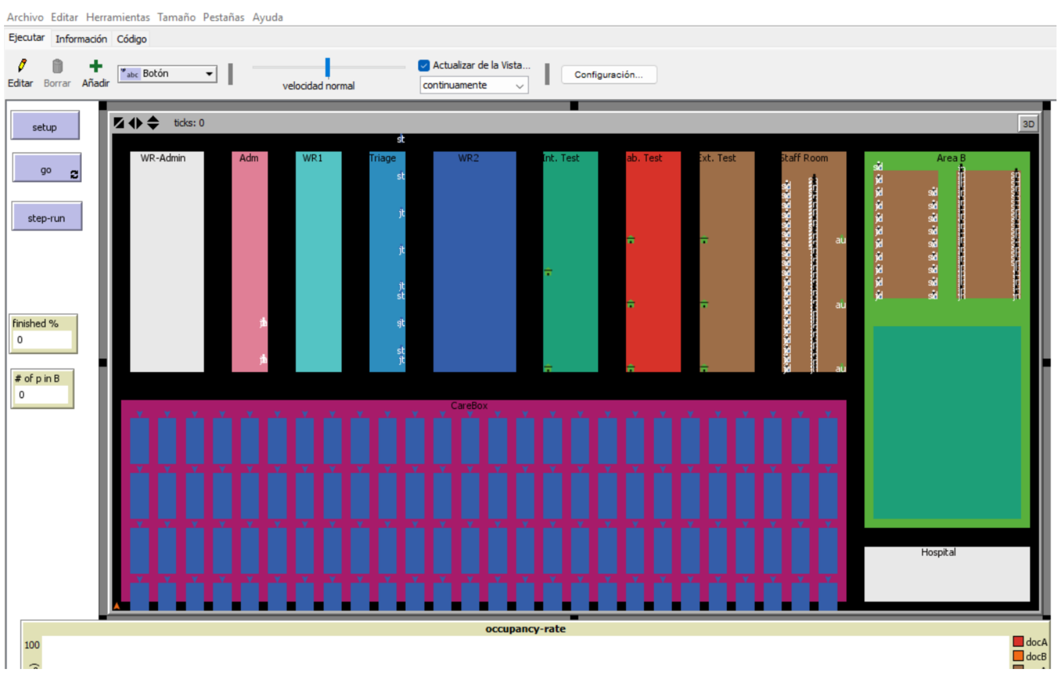

Fig. 3. Visualization of the simulator in NetLogo after the adaptation

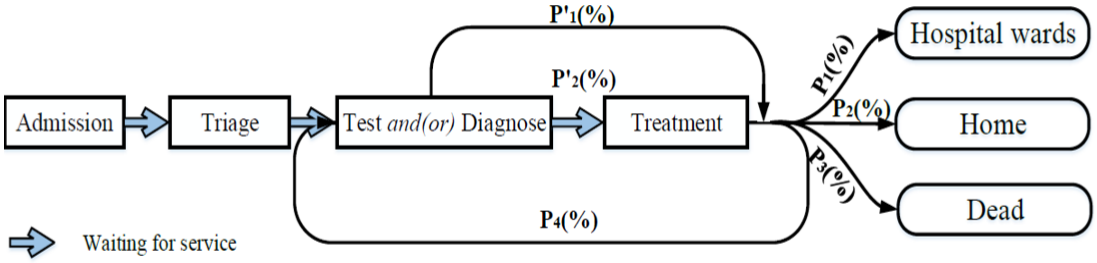

Fig. 4. Main processes in the emergency department

data of the specified emergency department. The uniform forms of the density functions are:

LOS is the patients' length of stay, and age is the patients' age, which also influences the probability of status transition. The level is the acuity level of the patient, and TOT is the type of test service or diagnosis by a doctor. The functions f and f' are the probability density function. These functions will be implemented by analyzing historical data in the tuning process. Therefore, combined with (2) - (5), every patient will show different behavior during the execution of the model because of the probability distribution and their differences in body condition. But the statistical property of agents will reflect their typical behavior.

In the case of active agents for medical staff, two different levels of experience are considered junior and senior. The less experienced user will need more time to complete the process than the most experienced. The simulator user can easily define the number of each type of personnel and their level of experience using the configuration console. The less experienced will use more time to carry out their work because they do not know; they could be a resident doctor who has just finished. The more experienced will take less time. They already know the process and treatment because they have much experience and years of service. To make a preliminary demonstration of how a simulation can be reproduced using only a few parameters, a simplified set of patient attributes and patient flow that is less complicated have been defined. The time of the doctors' attention changes according to each patient and its severity level.

V. Experiments and Discussion

A. Case Study: COVID-19 at the IPS Ingavi of Paraguay

The IPS Ingavi is a modern high-complexity hospital in Paraguay, offering medical care and emergency department to more than 2,000 insured persons per day, with approximately 1,500,000 insured persons. It is one of the reference hospitals for caring for patients with COVID-19 in the country.

From March 2020 to September 2021, IPS Ingavi Hospital treated approximately 15,000 COVID-19 patients, of whom 1,500 died despite medical efforts. In the most critical period of the disease, up to 10 daily deaths were recorded, and there were between 200 and 300 deaths per month. Table II shows the human resources configuration of the IPS hospital after hiring more personnel due to the high demand of patients due to COVID-19, and Table I shows the values of the human resources configuration of the IPS hospital before hiring more doctors and nurses.

TABLE I
Case 1: Low number of Human resources

Human resources configuration before the pandemic		
Label	*Interpretation*	*Number*
JA	Junior Admission staff	3
SA	Senior Admission staff	3
JTN	Junior Triage Nurse	5
STN	Senior Triage Nurse	5
JNA	**Junior Nurse area A**	**5**
SNA	**Senior Nurse area A**	**5**
JNB	**Junior Nurse area B**	**5**
SNB	**Junior Nurse area B**	**5**
JLE	Junior Outside Laboratory	3
SLI	Senior Internal Laboratory	3
JDA	**Junior Doctor area A**	**5**
SDA	**Senior Doctor area A**	**5**
JDB	**Junior Doctor area B**	**5**
SDB	**Senior Doctor area B**	**5**

[a]Human resources configuration before the pandemic

TABLE II
Case 2: High number of human resources

Human resources during the pandemic		
Label	*Interpretation*	*Number*
JA	Junior Admission staff	3
SA	Senior Admission staff	3
JTN	Junior Triage Nurse	5
STN	Senior Triage Nurse	5
JNA	**Junior Nurse area A**	**35**
SNA	**Senior Nurse area A**	**20**
JNB	**Junior Nurse area B**	**35**
SNB	**Senior Nurse area B**	**20**
JLE	Junior Outside Laboratory	3
SLI	Senior Internal Laboratory	3
JDA	**Junior Doctor area A**	**10**
SDA	**Junior Nurse area A**	**10**
JDB	**Junior Nurse area B**	**10**
SDB	**Senior Doctor area B**	**10**

[a]Human resources during the pandemic

The simulator developed with NetLogo [24] stores information about everything that happens during their execution and allows the creation of reports that can be exported and processed with statistics. We did an initial simulation with the data and got to analyze the simulators' behavior against the variables that influence the emergency department; several

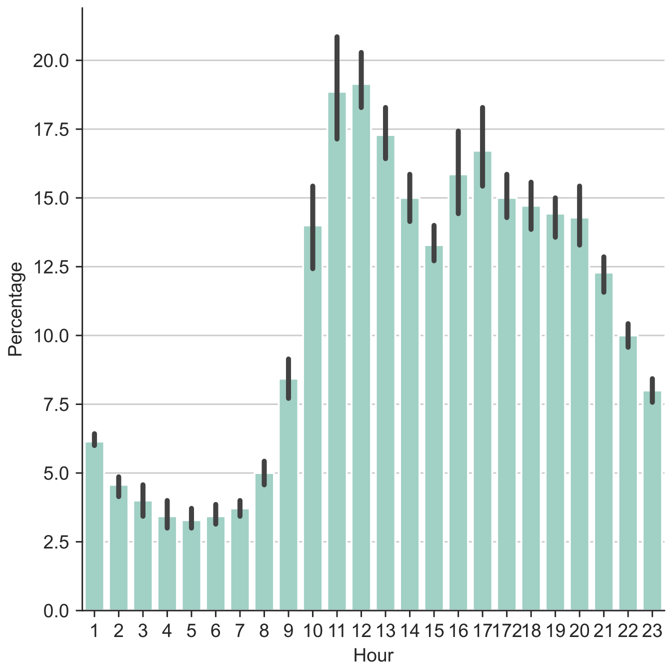

Fig. 5. Arrival of patients per hour at the hospital

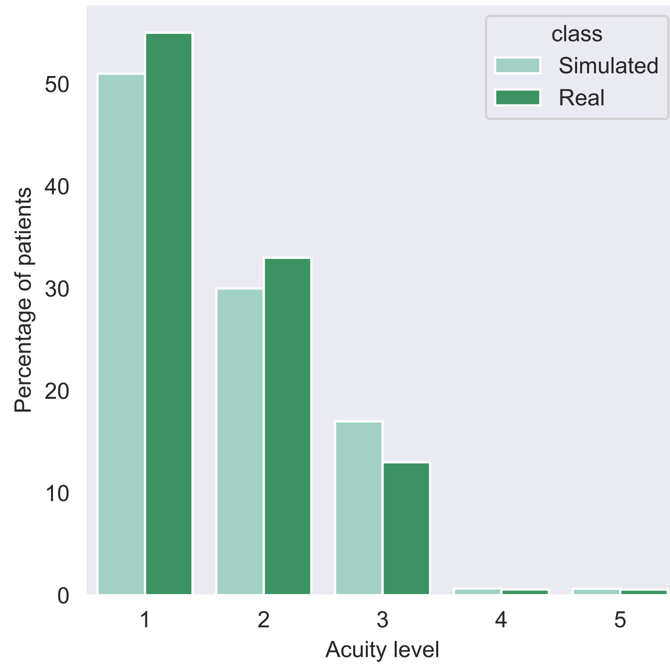

Fig. 7. Acuity level of patients between actual and simulated data

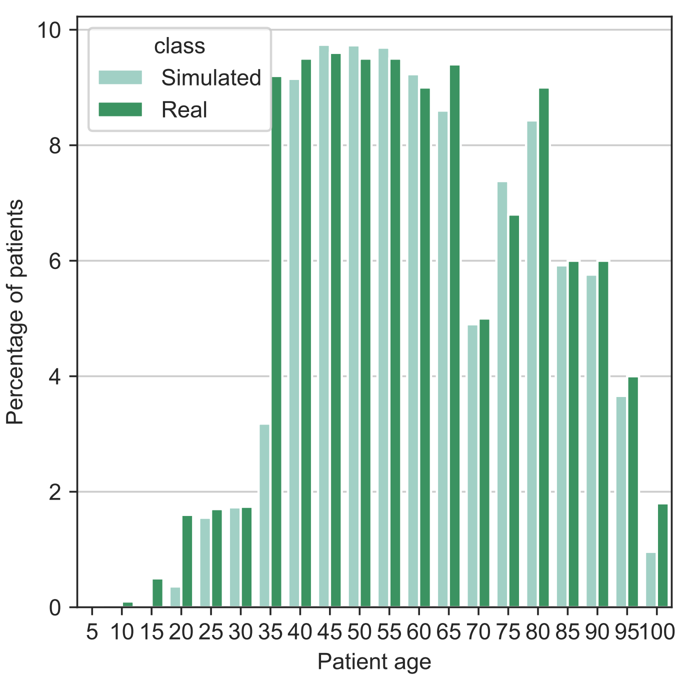

Fig. 6. Comparison of patient age between actual and simulated data

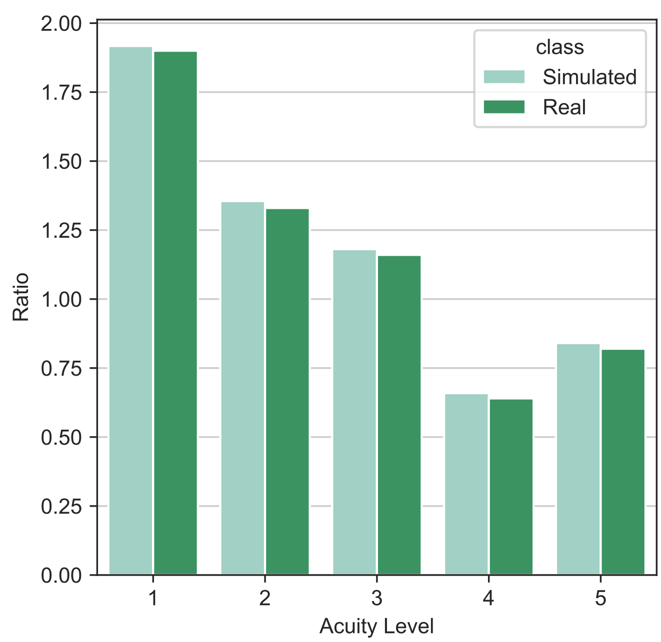

Fig. 8. Doctors' service time for each level of patients

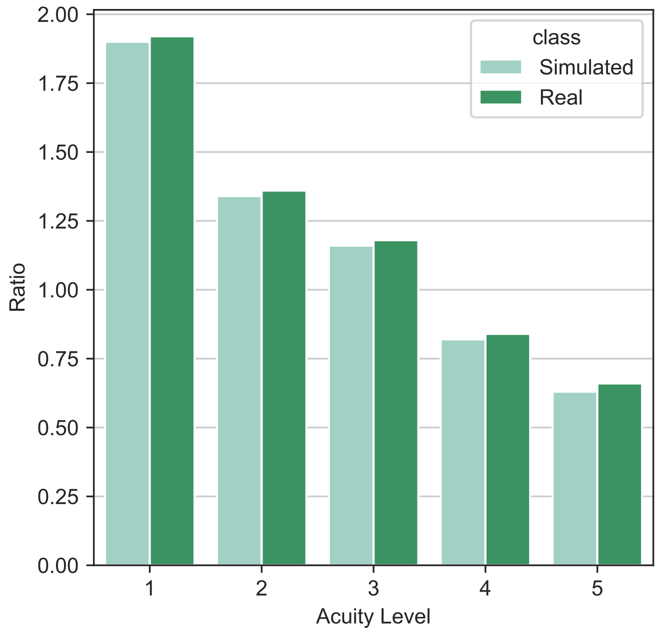

Fig. 9. Nurses' service time for each level of patients

simulations have been carried out with different values to observe what results we could get.

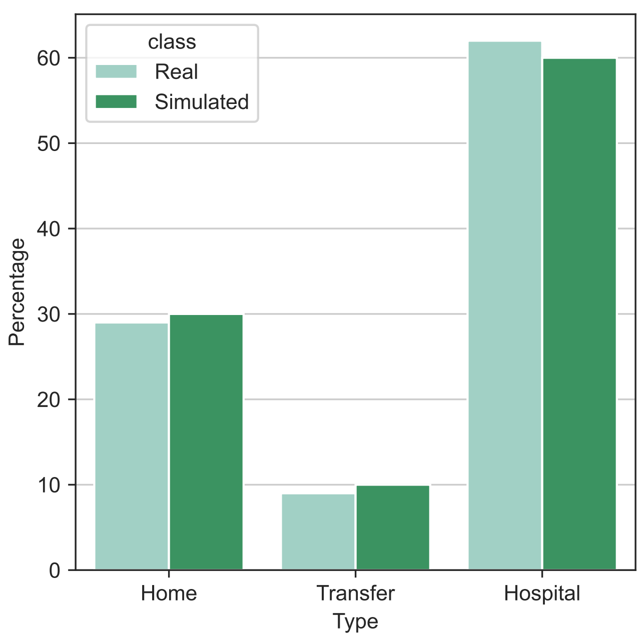

Fig. 10. Destination patient

Patient arrival is the emergency department simulators' input, directly influencing the systems' behavior. A precision model to reflect patient arrival is necessary to simulate and predict the behavior of an emergency department; the patient arrival model includes patients; Figure 5 shows the patient arrival rates distribution due to hours of the day in the hospital. This figure shows the arrival of patients at the hospital according to the time and day of the week, and it can be seen that the range of approximately 6 to 21 hours is the range where patients go to the hospital the most. Figure 6 shows the age range of the actual patients compared to the simulated ones, where you can see the age range of the patients who attended the hospital the most, which shows a rise from twenty-five to approximately ninety-five years.

TABLE III
UTILIZATION RESULTS ANALYSIS OF THE HUMAN RESOURCES (SIMULATION RESULTS).

Utilization results analysis of the human resources (percentage)				
Case	***Human resources***	***Average***	***Maximum***	***Confidence int***
Case 1	Doctor area A	70	100	(68, 70)
Case 2	Doctor area A	37	89	(37, 38)

[a]Utilization results analysis of the human resources

TABLE IV
MAXIMUM, THE AVERAGE SAMPLE SIZE TO ASSESS PATIENT STAY (LOS, LOWT, RELATIVE ERROR: 10%, CONFIDENCE: 95%).

Maximum, average sample size to assess patient stay (hours)				
Case	***Type***	***Average***	***Maximum***	***Confidence int***
Case 1	LOS	284	508	(282, 286)
Case 1	Lowt	282	433	(280, 284)
Case 2	LOS	256	497	(254, 258)
Case 2	Lowt	254	435	(252, 256)

[a]Maximum, average sample size to assess patient stay

The patient arrival model includes patients with severity L (acuity level). To do quantitative verification and validation, we built a patient arrival model according to the actual data from our cooperative hospital. As seen in Figure 7, comparing the simulated datas' severity levels to the actual data shows that levels 1, 2, and 3 are the levels of the patients who attended the hospital the most. The patients with severity levels 1, 2, and 3 are the most serious, and levels 4 and 5 are the mildest.

One of the simulator results is that the distribution of L (acuity level) among arrival patients was obtained through statistical analysis of the actual data and the overall patient age distribution.

The results from the patients' perspective are the LOS and the Lowt; the results from the management point of view are the occupations of the doctors, nurses, admission, and triage.

Patients with severity levels 1, 2, and 3 are the most serious and therefore take longer to be treated due to the seriousness of their situation. Figure 8 and Figure 9 show the comparison between the actual and simulated values of the ratio attention time of the doctors and nurses according to the severity level of the patients, where it is observed that the most extended attention times are between levels 1,2 and 3.

One of the outputs of the simulator is the destination of the patient after entering the emergency department; in Figure 10, you can see the comparison of the actual and simulated values of the percentage of patients who went home after the

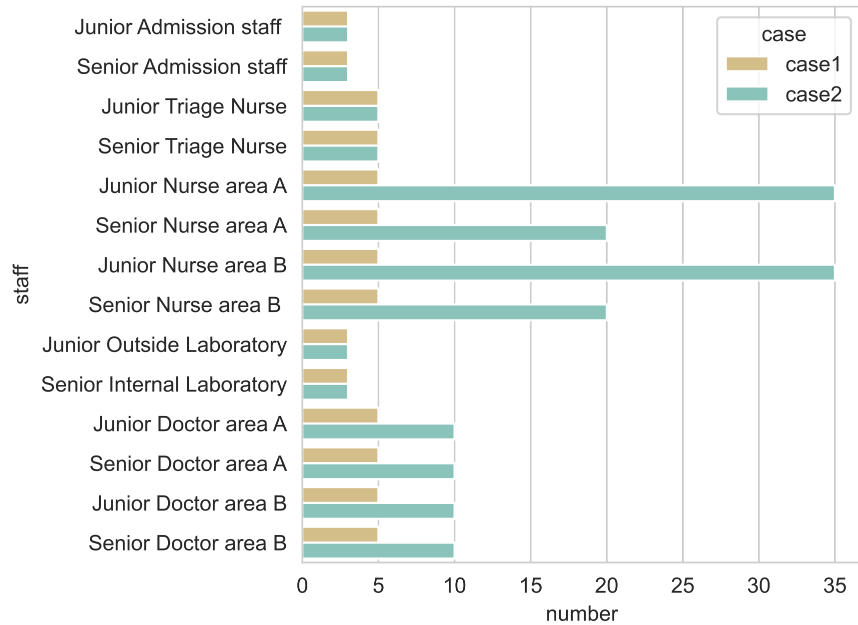

Fig. 11. Value of the human resources configuration case 1 and 2

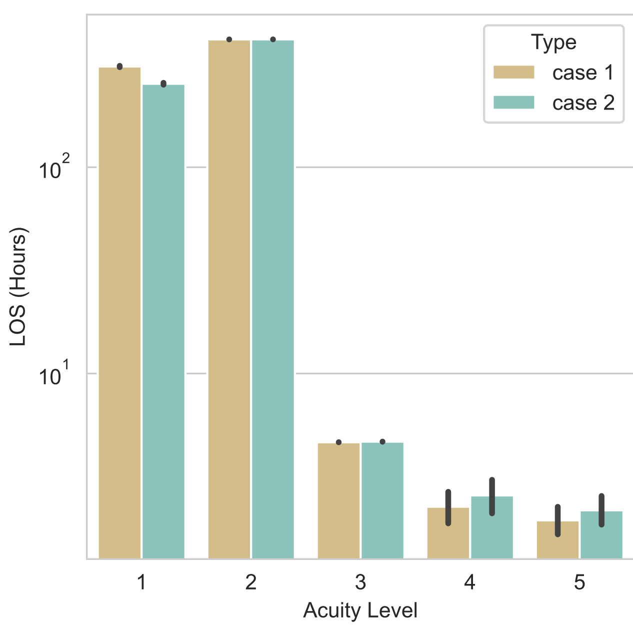

Fig. 12. Length of stay according to acuity level (LOS).

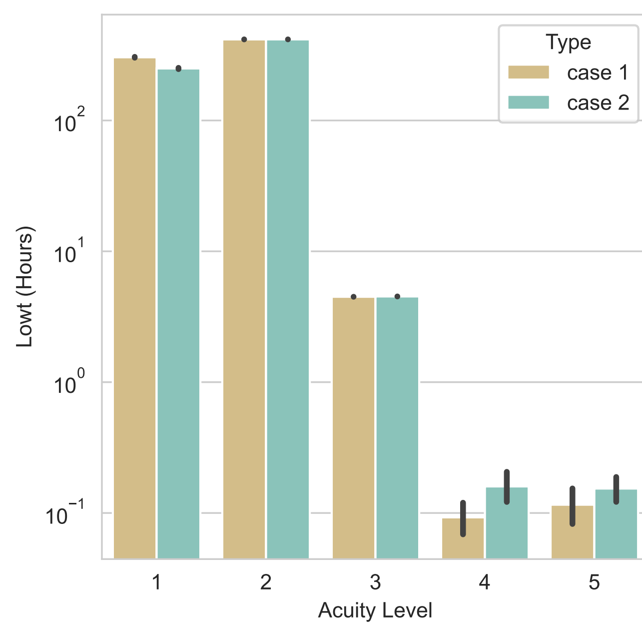

Fig. 13. Length of patient waiting time according to acuity level (Lowt).

emergency consultation, that is the case in which the patients were not seriously ill, the rate of patients who remained in the hospital to continue with their treatments and the percentage of those transferred.

Figure 11 shows the human resources configuration for cases 1 and 2 of the simulation; case 1 has a low number of doctors and nurses before hiring more hospital staff; case 2 has a high number of nurses and doctors after hiring more staff. Regarding the length of stay (LOS) and (Lowt) with the simulations carried out with cases 1 and 2, it can be observed that patients with severity levels 1 and 2 are those who have a longer waiting time to be treated in the hospital; this is seen in Figure 12 and Figure 13. This is because severity levels 1 and 2 are the most serious currently in the hospital; his critical condition requires further attention from hospital staff.

Regarding the percentage of occupation of doctors and staff,

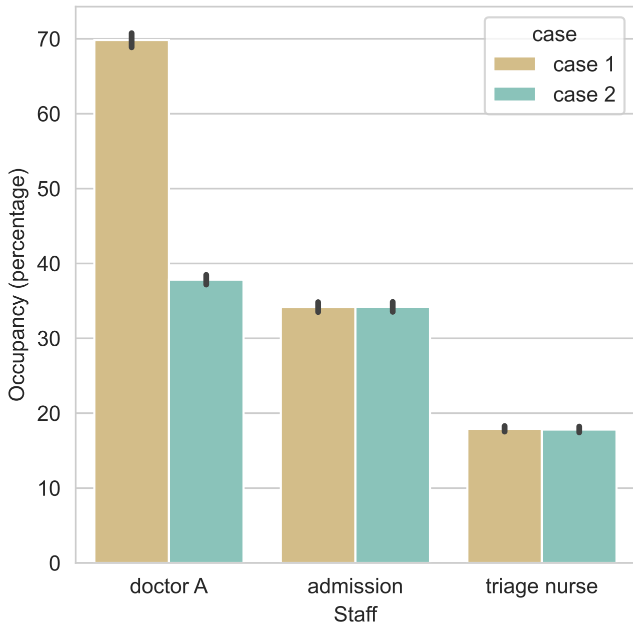

Fig. 14. Staff occupation time

the calculation is essential to determine when the system is about to be saturated, and it is necessary to hire more personnel; Also, when doctors are very saturated, their performance of patient care may decrease, and not care for patients correctly, in case they are already fatigued.

Figure 14 shows the occupation range of doctors, triage nurses and admission staff. It can be seen that the occupation range of the doctors for case 1 goes to approximately seventy percent; as the patients arrive, the occupation of the health personnel increases, and with an occupation range of about forty percent on average for case 2 by hiring more extra doctors and nurses due to the number of patients that are arriving due to the pandemic.

Table III shows the maximum value, the average (percentage), and the 95 percent confidence intervals of the doctors' area A for cases 1 and 2. When more health personnel are hired, the values of maximum and average occupations decrease. And when more health personnel are not engaged the occupations' average and maximum value increase.

Table IV shows the maximum value, the average, and the confidence intervals at 95 percent of the value of the LOS and Lowt for cases 1 and 2. It can be distinguished that when there is more health personnel hired, the values of the mean, maximum, and confidence interval of the LOS and Lowt (hours) waiting times of the patients are lower, and when there are fewer personnel, values of the means, maximum and confidence interval of the LOS and Lowt waiting times of the patients are higher.

VI. Conclusion

As a result of our research, we present an adaptation of an agent-based model for emergency department management. We handle different scenarios to adapt the simulator to pandemic situations, for example, using combinations such as hospital human resources and patient increases.

We used a set of synthetic input data for the input of data to the simulator for the arrival of COVID and NON-COVID patients with different ages, levels of severity, and the distribution of the arrival of patients by hours of the day, with these input data we have analyzed the occupation time of the doctors, the length of waiting time of the patients, the service time according to the level of severity and then we compare with reality. One of the advantages of our work is that this "COVID-19 in the emergency department" model/simulator allows emergency department managers to analyze and evaluate possible solutions to analyze the number of hospital staff, boxes/beds.

Our future work is to add the airborne spread of COVID-19 in the emergency department to validate and add more detail to the agent-based simulator to make it as consistent and close as possible in a pandemic situation and build different scenarios for decision-making. It will allow us to build virtual scenarios to understand the transmission phenomenon of COVID-19 and the potential impact of implementing different policies on viral spread rates.

Acknowledgment

This research has been supported by the Agencia Estatal de Investigacion (AEI), Spain and the Fondo Europeo de Desarrollo Regional (FEDER) UE, under contract PID2020-112496GB-I00 and partially funded by the Fundacion Escuelas Universitarias Gimbernat (EUG).

References

[1] R. E. Galeano Galeano, D. I. Rexachs del Rosario, A. Wong Gonzalez, E. Brugada, C. E. Villalba Cardozo, D. A. Galeano Galeano, and E. Luque Fadón, "An Agent-Based Model for the Management of the Emergency Department During the COVID-19 Pandemic," *The Fourteenth International Conference on Advances in System Simulation (SIMUL)*, pp. 54–62, Oct 2022.

[2] J. M. Adleberg, C. L. Catlett, R. E. Rothman, K. Lobner, and Y.-H. Hsieh, "Novel applications of agent-based modeling in emergency medicine research–a systematic literature review," *The American journal of emergency medicine*, vol. 35, no. 12, p. 1971, 2017.

[3] X. Zhang, "Application of discrete event simulation in health care: a systematic review," *BMC health services research*, vol. 18, no. 1, pp. 1–11, 2018.

[4] M. R. Davahli, W. Karwowski, and R. Taiar, "A system dynamics simulation applied to healthcare: A systematic review," *International Journal of Environmental Research and Public Health*, vol. 17, no. 16, p. 5741, 2020.

[5] M. Taboada, E. Cabrera, M. L. Iglesias, F. Epelde, and E. Luque, "An agent-based decision support system for hospitals emergency departments," *Procedia Computer Science*, vol. 4, pp. 1870–1879, 2011.

[6] E. Cabrera, E. Luque, M. Taboada, F. Epelde, and M. L. Iglesias, "Abms optimization for emergency departments," in *Proceedings of the 2012 winter simulation conference (WSC)*, pp. 1–12, IEEE, 2012.

[7] Z. Liu, D. Rexachs, E. Luque, F. Epelde, and E. Cabrera, "Simulating the micro-level behavior of emergency department for macro-level features prediction," in *2015 Winter Simulation Conference (WSC)*, pp. 171–182, IEEE, 2015.

[8] C. Jaramillo, D. Rexachs, F. Epelde, and E. Luque, "Virtual clinical trials: A tool for the study of transmission of nosocomial infections," *Procedia Computer Science*, vol. 108, pp. 109–118, 2017.

[9] C. Macal and M. North, "Introductory tutorial: Agent-based modeling and simulation," in *Proceedings of the winter simulation conference 2014*, pp. 6–20, IEEE, 2014.

[10] Z. Liu, E. Cabrera, M. Taboada, F. Epelde, D. Rexachs, and E. Luque, "Quantitative evaluation of decision effects in the management of emergency department problems," *Procedia Computer Science*, vol. 51, pp. 433–442, 2015.

[11] R. Moss et al., "Coronavirus disease model to inform transmission-reducing measures and health system preparedness, australia," *Emerging infectious diseases*, vol. 26, no. 12, p. 2844, 2020.

[12] M. Zeinalnezhad, A. G. Chofreh, F. A. Goni, J. J. Klemeš, and E. Sari, "Simulation and improvement of patients' workflow in heart clinics during covid-19 pandemic using timed coloured petri nets," *International journal of environmental research and public health*, vol. 17, no. 22, p. 8577, 2020.

[13] C. Currie et al., "How simulation modelling can help reduce the impact of covid-19," *Journal of Simulation*, vol. 14, no. 2, pp. 83–97, 2020.

[14] J. Le Lay, V. Augusto, X. Xie, E. Alfonso-Lizarazo, B. Bongue, T. Celarier, R. Gonthier, and M. Masmoudi, "Impact of covid-19 epidemics on bed requirements in a healthcare center using data-driven discrete-event simulation," in *2020 Winter Simulation Conference (WSC)*, pp. 771–781, IEEE, 2020.

[15] G. Fava, T. Giovannelli, M. Messedaglia, and M. Roma, "Effect of different patient peak arrivals on an emergency department via discrete event simulation: a case study," *Simulation*, p. 00375497211038756, 2021.

[16] V. Ahuja and L. V. Nair, "Artificial intelligence and technology in covid era: A narrative review," *Journal of Anaesthesiology, Clinical Pharmacology*, vol. 37, no. 1, p. 28, 2021.

[17] M. Laskowski, R. D. McLeod, M. R. Friesen, B. W. Podaima, and A. S. Alfa, "Models of emergency departments for reducing patient waiting times," *PloS one*, vol. 4, no. 7, p. e6127, 2009.

[18] Z. Chen, Z. Shu, X. Huang, K. Peng, and J. Pan, "Modelling analysis of COVID-19 transmission and the state of emergency in Japan," *International Journal of Environmental Research and Public Health*, vol. 18, no. 13, p. 6858, 2021.

[19] A. G. Uriarte, E. R. Zúñiga, M. U. Moris, and A. H. Ng, "How can decision makers be supported in the improvement of an emergency department? a simulation, optimization and data mining approach," *Operations Research for Health Care*, vol. 15, pp. 102–122, 2017.

[20] S. S. Jones and R. S. Evans, "An agent based simulation tool for scheduling emergency department physicians," in *AMIA Annual Symposium Proceedings*, vol. 2008, p. 338, American Medical Informatics Association, 2008.

[21] M. R. Friesen and R. D. McLeod, "A survey of agent-based modeling of hospital environments," *IEEE Access*, vol. 2, pp. 227–233, 2014.

[22] S. Diebel and E. Boissonneault, "A pan-canadian narrative review on the protocols for covid-19 and canadian emergency departments," *International Journal of Medical Students*, vol. 9, no. 2, pp. 157–161, 2021.

[23] Z. Liu, E. Cabrera, D. Rexachs, and E. Luque, "A generalized agent-based model to simulate emergency departments," in *Sixth Int Conf Adv Syst Simul*, pp. 65–70, 2014.

[24] U. Wilensky and W. Rand, *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. Mit Press, 2015.

[25] E. Bruballa, A. Wong, D. Rexachs, E. Luque, and F. Epelde, "Evaluation of response capacity to patient attention demand in an emergency department," *Int. J. Adv. Syst. Meas*, vol. 10, no. 1-2, pp. 11–22, 2017.