An Agent-Based Model for the Management of the Emergency Department During the COVID-19 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 significant mortality in healthcare worldwide. A challenge for hospitals is the management of overcrowding in emergency departments, which can be critical for patient survival and effective patient care. Modeling and simulation can provide a more accurate and effective method to test new management techniques without endangering patients. In this paper, we present an improvement/extension of a previous agent-based model proposal that allows imitating the operation of an emergency department to design a simulator that helps to plan and manage a pandemic situation. We have enhanced the model by adding the variables to patient and staff hospital agents participating in the transmission process; and separated emergency rooms for the infected and non infected to evaluate the effectiveness using different combinations such as laboratory tests, isolation, and other control policies. This modeling can help the configuration of the medical staff, nursing, beds, devices, and patient waiting time management. Furthermore, two health personnel levels (emergency intensivists (seniors) and personnel from different specialties (junior)) have been incorporated in the emergency department to treat COVID patients.**

Keywords: simulation, pandemic, COVID-19, agent-based model.

I. INTRODUCTION

A pandemic occurs when an infectious disease spreads and affects many people in more than one continent. Pandemics are caused by viruses that can be easily transmitted from person to person and spreads over a wide geographical area, usually, spreading in to many countries or attacking almost all individuals in a locality or region.

The unpredictability, uncertainty, fear, and restrictions related to the COVID-19 pandemic have represented particular challenges, mainly due to government's measures of quarantine, confinement, and social distancing, among others. The pandemic has also affected the economy worldwide, generating critical situations in companies around the world, unemployment, and economic difficulties for most families and individuals.

During the pandemic, management of hospital's emergency departments have played a key role for patient survival. Improving such services without knowing in advance how changes made can affect patient care cycle remains challenging. One of the critical points in managing the emergency department is improving its ability to contain the spread of contagious diseases. For instance, we could seek to understand how changes made to specific variables in the emergency management cycle could help reduce the spread of the virus.

The three main approaches used in the simulation of an emergency department are agent-based simulation, discrete event simulation, and system dynamics [1] [2]. The advantages of using simulation is to facilitate 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 agent-based models for modeling the management in an emergency department [3]–[6]. Agent-based model is an approach to model systems in which

 ISBN: 978-1-68558-001-8

individual agents interact. It offers ways to more easily model interactions of individuals and also how these interactions affect other agents in the system [7].

In this paper, we propose designing and developing an agent-based model that allows modeling the management of an emergency department during the COVID-19 pandemic. Our work presented here builds upon the work of Jaramillo et al. [6] that developed a simulator for planning and management of Methicillin-resistant Staphylococcus aureus (MRSA) spreads among hospitalized patients 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). Jaramillo's [6] work is a simulator with a design that allows the spread of infections by contact (MRSA). It does not work in a pandemic situation. The pandemic has emerged, and some requirements must be added to make it work in a pandemic situation.

We have modified the Jaramillo et al. [6] agent-based model to be useful for COVID-19 emergency rooms. First, we have incorporated COVID-related variables for each patient that includes their state of infection, symptoms, viral load, and Polymerase Chain Reaction (PCR) test result. And variables for each hospital staff that include acuity level, age, location, infected or not, symptomatic or not, vaccinated or not, viral load, and PCR test. Second, we have made the simulator more flexible to include: (i) the management of multiple emergency rooms within the same hospital; (ii) multiple PCR test results for each patient; and (iii) separate emergency rooms for the infected and non-infected.

Our emergency clinical staff has been modeled incorporating two possible levels of experience: juniors (with limited or low experience) and seniors (with experience). This is very important because during a significant part of the "Covid attack", in addition to emergency intensivists (seniors), some health personnel from different specialties (juniors compared with the intensivists) were incorporated into the emergency department.

A set of synthetic input data has been prepared for the simulation, which is why the distribution of arrival patients had to be generated. COVID and NO COVID with different levels of severity and the general distribution of simulated patient ages.

Our simulator describes the behavior of the emergency department during the COVID-19 pandemic and can assist doctors and administrators as a decision support system for emergency department management. Our simulator allows us to build virtual scenarios to understand the transmission phenomenon of COVID-19, and the potential impact of implementing different policies on the rates of viral spread.

The rest of the paper is organized as follows. In Section II, we explain state of the art. Section III presents the description of the emergency department model. Section IV describes the initial simulation. Section V presents the experiments and discussion, and Section VI presents the conclusions and the future work.

II. State of the Art

A problem stands out in the 21st century: the increase in microbial resistance and oncological diseases to the appearance of new infectious diseases, such as COVID-19. Some viruses have caused severe pandemics. According to World Health Organization (WHO) data, many emerging and re-emerging infectious diseases are of zoonotic origin. The coronavirus is a big family of viruses that can cause disease in animals and humans.

COVID-19, also called novel coronavirus disease, is caused by severe acute respiratory syndrome coronavirus 2. The high probability of infections in high population density places made the initial transmission faster and stronger. This pandemic put health systems in different parts of the world in uncertainty; they had few resources to face a pandemic of such magnitude.

COVID-19 is transmitted by direct contagion from person to person, by droplets of respiratory secretions emitted when breathing, speaking, yelling, coughing, sneezing, kissing, etc., from one to two meters away. The deposit of secretions generates droplet aerosols that remain in the air at greater distances.

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 infectious, affected tourist cities, spread in health systems [8], patient flow improvement [9], how simulation modeling can help reduce the impact of COVID-19 [10], among others.

Some simulation methods found that were used in the area of COVID-19 simulations are discrete events [9] [11] [12], artificial intelligence [13] and agent-based simulation [14]. 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 [15].

The studies about the emergency department deal with the practice of protocols or objects for medical procedures. Another job in the emergency department talks about managing the resources in intensive care, intensive care beds and their devices, but there is not a similar work as ours at the time.

Some of our works in the emergency department area are: Create a simulator for the emergency department with the participation of the Sabadell Hospital emergency team [3]. Active agents, passive agents, and the environment are identified, and an initial simulation is created using NetLogo [3]. Another task is to optimize the emergency department's performance [4]. Extensive search optimization is used to find the optimal configuration of emergency department staff, a multi-dimensional, multi-objective problem [4]. An index is proposed to minimize the patient's length of stay in the emergency department. The results obtained using alternative Monte Carlo and Pipeline schemes are promising [4]. This paper presents a layer-based application framework for discovering knowledge of an emergency department system by simulating micro-level behaviors of its components [5]. This paper proposes the use of a simulation tool, the MRSA Simulator to design and conduct virtual clinical trials to study contact transmission of MRSA among hospitalized patients [6].

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 devices. 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. Description 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 the functionality of the simulator to be extended to adapt it to changes in the operation of the emergency department when there are exceptional situations such as pandemics, in such a way that it helps in the planning and management of the service.

The first step of the work consists of making a conceptual model of the system's 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.

One of the main properties of the agent-based model is its scope; that is, the domain in which it is capable of executing modeling and simulation scenarios. Agent-based models are increasingly used in several scientific areas, in the simulation of large-scale dynamic complex systems and the observation of emergent behaviors. Complex systems can be thought of simply as sets of interacting agents or entities [16].

The agents can be organizations, human beings, companies, institutions, and any other entity that intends to pursue a specific purpose. Agent-based models are mainly used in the case of complex modeling phenomena, where many active agents or entities interact with each other with specific inherent attributes to establish relationships, thus facilitating automated reasoning and problem-solving [16]. Agent-based models are rule-based systems.

Agent-based model simulation tools support researchers and practitioners in investigating how the macroscopic behavior of a system depends on micro-level properties, constraints, and rules. Agents as objects are typified by specific states and sets of attributes, properties, or functional rules; behaviors that can trigger particular actions through predefined parameters [16].

The ultimate goal is to build simulations of complex systems that evolve as a set of artifacts that interact between multiple decentralized modules. Individual objects or agents refer to the elements that live in the environment and have properties that can change over time; agents can manifest as different independent objects under a discrete or continuous configuration. The agents interact, and the system is constituted by the active interaction of entities or agents and conflict resolution [16].

A. Active agents:

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

Patient: They are the essential individuals in the system.

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

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

The triage nurse: They are who calls the patient to carry out the pre-consultation.

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

Nurse: They provide treatment to the patient, takes and sends test to laboratorys.

B. State variables

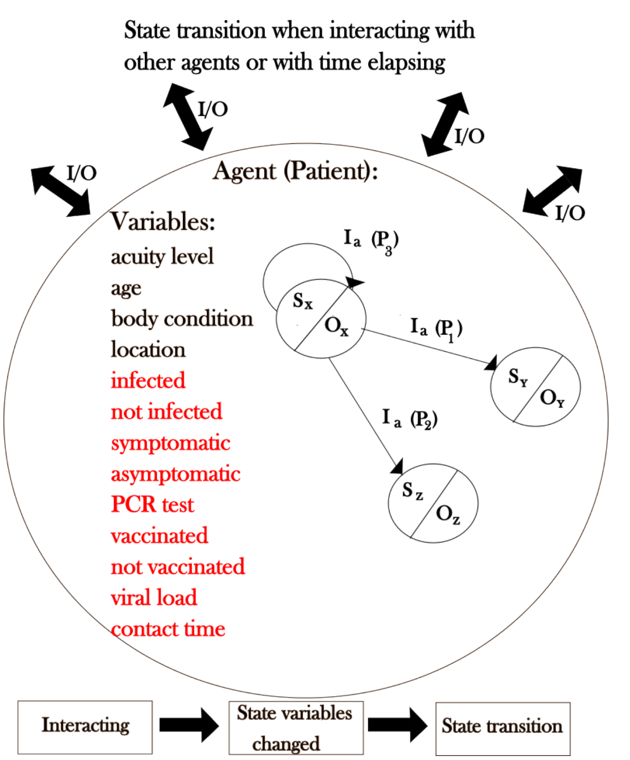

Fig. 1. State transition when interacting with other agents or with time elapsing

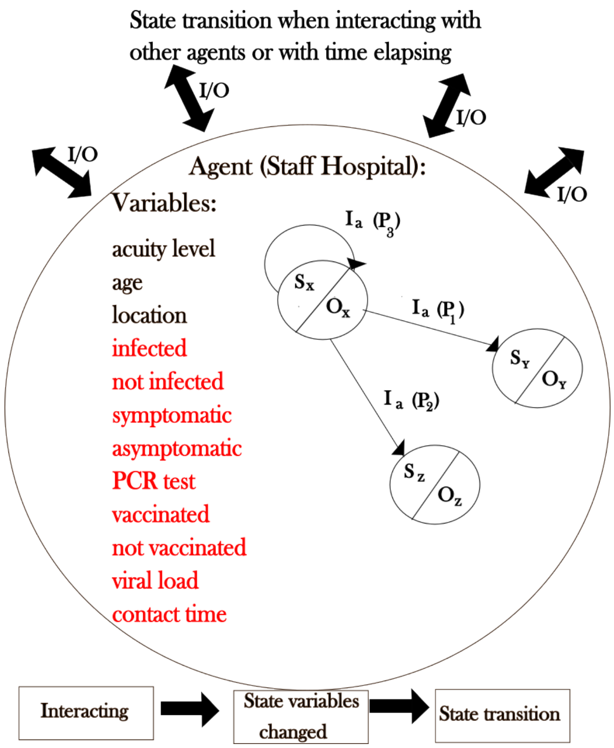

Fig. 2. State transition when interacting with other agents or with time elapsing

The agents move from one place to another by interacting with other agents. During this time, each agent changes its state as a result of the interactions. A state machine perfectly represents this behavior, so they have chosen a state machine to model all agents. Specifically, the agents are represented 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 Figure 2 for the hospital staff (admissions staff, doctor, the triage nurse, laboratory staff and nurse).

The input vector (I) contains a series of input values that includes many different values. The output (O) depends on the state. The transitions between states depend on the current state in time (ST). The agent patient variables are acuity level, age, body condition, location, infected or not, symptomatic or not, vaccinated or not, viral load, contact time and PCR test. The hospital staff (admissions staff, doctor, triage nurse, laboratory staff, nurse) the variables are acuity level, age, location, infected or not, symptomatic or not, vaccinated or not, viral load, 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 defines the situation of a said agent at that time t. The behavior of each agent depends on the category to which it belongs and is defined 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.

These Finite State Machines (FSM) are commonly used to organize and represent a flow of execution. They can be graphically represented as a sequence of nodes and arrows, where nodes are states and arrows are transitions. Each state of the state machines is defined based on the value of the agent's state variables at a given time, considering that each has more than one possible value and a probability associated with each.

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

There is a single-state machine for all the different types of agents in the model, so some combinations of values don't make sense and would never occur during the model operation. Still, it is preferable to have one machine for all agents than different machines because there is the possibility of increasing the model to the point of reflecting the difference between patients with varying levels of knowledge.

C. Output

The agents are represented by Moore machines; each state can have a different output. The output of an agent-based simulator includes the status information (sensors) of the emergency department; some of the outputs are the length of stay (LOS), the length of waiting (LOW) 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 doctor's treatment: wtd, doctor treatment care time: twmd and others), destination, age, acuity level, infected, symptomatic, PCR test, vaccinated, viral load. In this way, the simulator does not directly provide information about the simulated department's behavior. In contrast, cross-analysis through different simulation scenarios is how to obtain information.

IV. Initial Simulation

An initial simulation is created to verify the proposed model designed, using the NetLogo [17] agent-based simulation environment, a high-level platform especially suited for modeling complex systems that develop over time. NetLogo [17] 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 in which different types of 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 arrival of the patient and the registration is completed by the admission staff, based on the seriousness of their situation in the triage, the patients are categorized, taking into account their acuity level. There are five different values, level 1 is for the most critical situation, and level 5 is not urgent [18]. There are different areas in emergency departments (Figure 3):

 ISBN: 978-1-68558-001-8

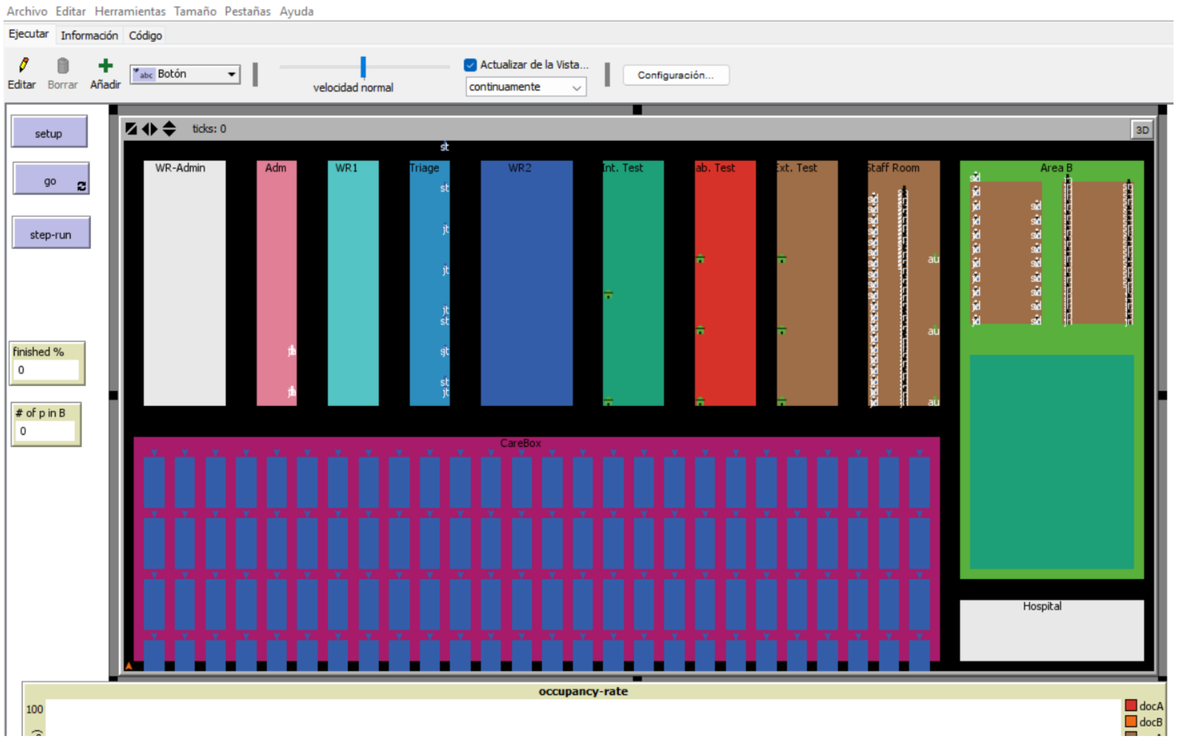

Fig. 3. Simulation display in Netlogo of the emergency department

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.

$$n_{scenarios} = n_{admissions} * n_{timeadmissions} * n_{triagenursing} \\ *n_{timetriagenursing} * n_{nursing} * n_{timenursing} \\ *n_{doctor} * n_{timedoctor} \qquad (1)$$

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

In general, the time to compute a time interval of a simulation based on agents is the product of 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 period each time step the agents operating system. Each time step are 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 a 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. The machine simulation has been chosen as the basis for when the simulator is implemented because NetLogo [17] has all the features needed to implement a model of this type. NetLogo [17] is a simulation environment agent-based model and provides a basis for machine simulation agent based system.

The run time of a simulation step, in an agent based model simulation, is the product of the time it takes to simulate the actions of an agent and the number of agents in the simulation world in this step. In the model described, agents in the simulation are the hospital staff and patients. During simulation, the hospital staff is fixed, does not enter or exit the simulation. On the other hand, patients are constantly in and out of the simulation. This changes the load of each time slot simulation, base on the equation (2) that calculates the running time Ti in step i, with the number of hospital staff h, the number of patients in the simulation in step i and the runtime of a Tagente agent.

 ISBN: 978-1-68558-001-8

We assume that the runtime of an agent is a fixed value. In different simulations, the number of hospital staff can change, but during one simulation, the number of hospital staff is maintained. Concerning the number of patients, this can change from one simulation step to the other because there are patients in and out, but within each simulation step, this number is constant. For a simulation that takes n steps, equation (3) shows the formula.

$$Ti = (h + pi)Tagente \tag{2}$$

$$T = (hn{+}pk)Tagente \tag{3}$$

In order to generalize the process of all patients, the next status will be decided by probability distribution during simulation. The distribution model of the probability was based on the statistical data from the emergency department. Figure 4 indicates the general process during the patients stay in emergency department; P1(%), P2(%), P3(%) and Pn (%) represent the probability of the next state transition separately, equation (4), (5), (6), (7) show the formulae. All of the probabilities follow some probability distributions. The probability density function of the distribution is decided by several key parameters based on the statistical analysis of doctor's decision and patient's behavior, the value of these parameters are estimated by a tuning process from real historical data of the specified emergency department. The uniform forms of the density functions are:

$$Pi = f(LOS, age, level) \tag{4}$$

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

$$P' = f'(TOT, age, level) \tag{6}$$

$$\sum_{i=1}^{n} P'_i = 100\% \tag{7}$$

where LOS is the patient's length of stay and age is the age of the patient, which also has big influence to the probability of status transition. Level is the acuity level of the patient and TOT is the type of test service or diagnosis by doctor. The functions f and f' are the probability density function. These functions will be implemented by analyzing real historical data in tuning process. As the simulator is implementing the general model of the emergency departments, the tuning/calibration process must be carried out for each one of them, in order to adjust its simulation parameters to the specific characteristics of each department (e.g., experience of the specific department staff). Therefore, combined with (1) - (10), every patient will show different behavior during the execution of the model because of the probability distribution and their own differences in body condition. But the statistical property of agents will reflect their common behavior.

In the case of active agents for medical staff, two different levels of experience are considered (LOW, labeled as junior, and high, labeled as a senior). The less experienced user will need more time to carry out their part of the process than the most experienced. The time of the agents is fixed internally by the programmer. Still, 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 have no experience; 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 a lot of 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 is less complicated have been defined. The time of the doctor's attention change according to each patient and its severity level.

V. Experiments and Discussion

Preliminary results obtained with the Instituto de Previsión Social (IPS) Ingavi data are:

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

TABLE I
QUANTITATIVE REPRESENTATION OF THE SIMULATED EMERGENCY DEPARTMENT OF THE HOSPITAL IPS INGAVI

Value of the human resources configuration		
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	Senior Nurse area B	5
JLE	Junior Outside Laboratory	3
SLI	Senior Internal Laboratory	3
JDA	Junior Doctor area A	10
SDA	Senior Doctor area A	10
JDB	Junior Doctor area B	10
SDB	Senior Doctor area B	10

[a]Value of the human resources configuration

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

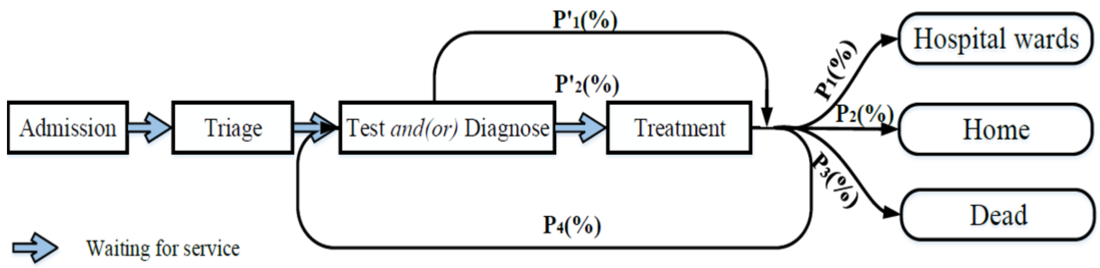

Fig. 4. Waiting for service

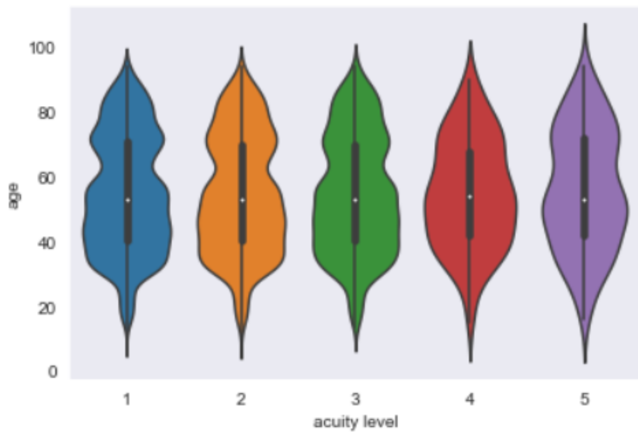

Fig. 5. Overall arrival acuity level and the patient's age distribution

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, the 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 deceased patients were registered daily, and per month they had between 200 and 300 deaths. Table I shows the values of the human resources configuration of the parameters to represent the simulated emergency department.

Netlogo [17] stores information about everything that happens during the execution of the simulator 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 simulator's behavior against the variables that influence the emergency department; several simulations have been carried out with different values to observe what results we could get.

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.

A set of synthetic input data has been prepared for the simulation, which is why the distribution of arrival patients had to be generated. COVID and NO COVID with different levels of severity, the general distribution of simulated patient ages and the patient arrival rates distribution due to hours of the day.

Patient arrival is the emergency department simulator's input, directly influencing the system's 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 arrival patients, in the Figure 7 shown 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.

One of the simulator results is that the distribution of L (acuity) among arrival patients was obtained through statistical analysis of the actual data and the overall patient age distribution, as shown in Figure 5 and Figure 6. Levels 1,2,3 are the most serious, and 4,5 are milder symptoms. As can be seen in Figure 5 and Figure 6, at severity level 1,2,3,4,5, the age range that most visits the hospital in the emergency area is between 40 and 80 years old.

VI. Conclusion

As a result of our research, we present an improvement/extension of a previous agent-based model for managing the emergency department during COVID-19. Based on such an emergency department and after carefully analyzing the care process, we have enhanced the model by adding the variables to patient agents and hospital staff participating in the transmission process. We manage different scenarios to adapt the simulator to pandemic situations, for example, separate emergency rooms for the infected and non-infected, to evaluate the effectiveness using different combinations such as laboratory tests, isolation, and other control policies.

In addition, our emergency clinical staff has been modeled incorporating two possible levels of experience: juniors (with limited or low experience) and seniors (with experience). This is very important because during a significant part of the "Covid attack", in addition to emergency intensivists (seniors), some health personnel from different specialties (juniors compared with the intensivists) were incorporated into the emergency department.

A set of synthetic input data has been prepared for the simulation, which is why the distribution of arrival patients had to be generated. COVID and NO COVID with different levels of severity, the general distribution of simulated patient

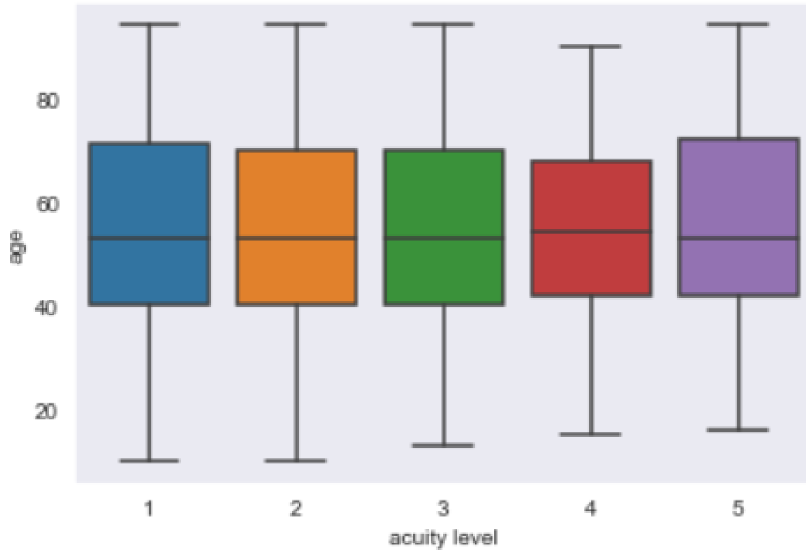

Fig. 6. Overall arrival acuity level and the patient's age distribution

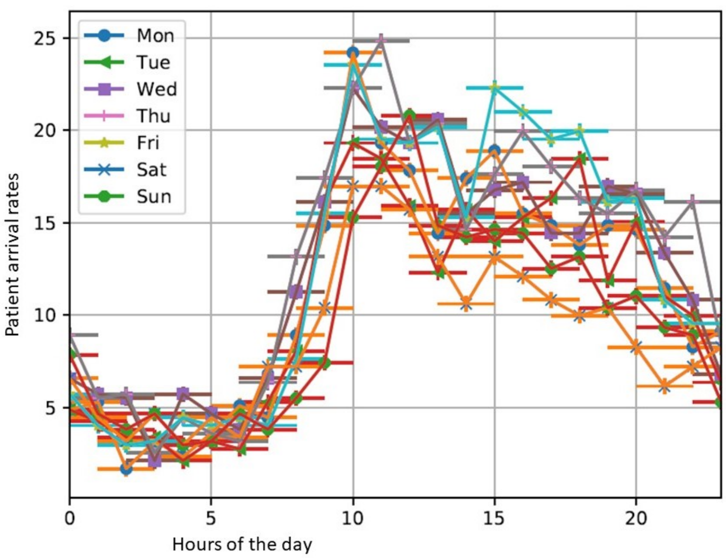

Fig. 7. Patient arrival rates distribution due to hour of day

ages and the patient arrival rates distribution due to hours of the day.

One of the significant differences between our job and the others is that this model/simulator of "COVID-19 in the emergency department" allows the emergency department managers to analyze and evaluate potential solutions for the clinical staff, boxes/beds, and devices.

Our future work is to make a digital twin of the Hospital, to validate and add more details to the agent-based simulator to make it as consistent and close as possible in a pandemic situation, and to build different scenarios for decision-making.

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).

This research has been funded through the scholarship by Carlos Antonio Lopez of Paraguay (Becal)

REFERENCES

[1] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," *Proceedings of the national academy of sciences*, vol. 99, no. suppl 3, pp. 7280–7287, 2002.

[2] P. Escudero-Marin and M. Pidd, "Using abms to simulate emergency departments," in *Proceedings of the 2011 Winter Simulation Conference (WSC)*, pp. 1239–1250, IEEE, 2011.

[3] 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.

[4] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] J. Le Lay et al., “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.
[12] 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.
[13] 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.
[14] 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.
[15] 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.
[16] S. Abar, G. K. Theodoropoulos, P. Lemarinier, and G. M. P. O’Hare, “Agent Based Modelling and Simulation tools: A review of the state-of-art software,” *Computer Science Review*, vol. 24, pp. 13–33, May 2017.
[17] U. Wilensky and W. Rand, *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. Mit Press, 2015.
[18] 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.

 ISBN: 978-1-68558-001-8